A STUDY OF HUMAN BEHAVIOUR IN LIBYAN HEALTHCARE

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A thesis submitted in partial fulfilment of the requirements of The Manchester Metropolitan University for the degree of doctor of philosophy

Faculty of Sciences and Engineering/ School of Engineering

Manchester Metropolitan University

2014

Abstract

Overcrowding in Emergency Departments (ED) results in increased Lengths of Stay (LOS) and longer Waiting Times (WTs) for patients. These are ever-growing concerns in all hospitals around the world. Published literature shows many causes of this problem. This study, explores and identifies that one of the prominent causes can be attributed to human behaviour within EDs. It appears that patient behaviour has not been included in previous work as a cause of overcrowding.

This thesis aims to present a method referred to as Discrete Event Simulation (DES) in an effort to explore and understand the effects of patient behaviour in the overcrowded ED of Tripoli Medical Centre (TMC). Firstly, a descriptive study was adopted, which collected data from different hospital sources, i.e. ED reports, ED's services time, staff and managers' opinions, and the observations of patients attending the ED of TMC. This identified the most significant behaviours impacting LOS and WT. Secondly, four different DES models were developed and analysed. Ultimately a hybrid model comprising of DES logic and Bayesian Network (BN) modelling was developed to capture and analyse a more accurate occurrence of human behaviour.

Analysis of the hospital data reveals four behavioural factors are responsible for increasing WTs and LOS, leading to disruptions in patient flow. These factors include confrontation, challenges, passivity and illness belief. These behaviours are often appearing amongst the minor and non-urgent patients, who represent approximately 75% of all ED patients. The examination area within ED was found to be the place most commonly impacted by difficult behaviours, which is shown by the prolonged WTs in this area.

A new strategy termed as Patient Behavioural Control (PBC) has been devised, developed and modelled. The PBC strategy aims to detect patient behavioural problems early and implements a revised patient flow procedure that results in overall reductions in LOS and WTs. This thesis contributes to the knowledge in this arena through consideration being directed towards patient behaviours from an operational perspective, utilising DES models in an effort to establish cause and effects, thus helping to devise a new approach in the healthcare sector. This new approach is not restricted in terms of application in only the healthcare arena, but can be adopted across other sectors for the management of human behaviours.

Declaration

This is to certify that:

(I) The thesis includes only my original work.

(II) Due acknowledgement has been made in the text to all other material used.

Signature: Entisar Aboukanda

Date: 4/8/2014

Publications

This section provides a range of publications that are considered part of the work of this thesis:

1- Aboukanda, E & Latif, M. Characteristics of Patients Attending the Emergency Department at the Tripoli Medical Centre. Journal of Management research, 2013. Vol. 5: 333-344. ISSN No: 1941-899X.

2- Aboukanda, E & Latif, M. Exploiting Simulation to Reduce Patient waiting Time Using A Streaming Strategy in An Emergency Department. International Journal of Advanced Technology and Engineering , 2013. Vol. 3(2): 79-86. ISSN No: 2250-3536.

3- Aboukanda, E & Latif, M. The Effect of Patient Behaviour on Wait Time in Emergency Department. International Journal of Business and Commerce, 2014. Vol. 3(6): 18-31

4- Aboukanda, E & Latif, M . Exposing Human Behaviour to Patient Flow Modelling. Proceeding of the 37th International MATADOR conference, Manchester, UK 2012:247-250.

Acknowledgements

I would like to acknowledge the financial support that was provided to me, through Libyan Government. It has actually given me support throughout the period of my academic study.

There are several people who have supported and encouraged me during the completion of this work. Firstly, The author gratefully acknowledges helpful comments and contributions received from my supervisor, Dr Muhammad Latif who has provided invaluable advice and incredible patience with the delays and diversions that have occurred during my studies.

My appreciation goes to all of my family and friends, who have supported and encouraged me during the last four years.

I also sincerely thank the volunteers, who must remain unnamed, and provided the knowledge for data collection phase in this thesis.

Last but by no means least, I would like to thank my sister, Samira Aboukanda, who probably did not realize the importance of what she has done for me during the period of my study. Her patience and care have got me through many difficult periods, and while I wouldn't go so far as to say that I couldn't have done this without her, I'm very pleased that I didn't have to.

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LIST of ABBREVIATIONS

No.	ABBREVIATIONS	MEANING
1	TMC	Tripoli Medical Centre
2	ED	Emergency Department
3	IU	Inpatient Unit
4	DES	Discrete Event Simulation
5	WTs	Waiting Times
6	LOS	Length of Stay
7	PBC	Patient Behaviour Control
8	RAT	Rapid Assessment and Treatment
9	LWBS	Leave Without Being Seen
10	POCT	Point of Care Testing
11	FT	Fast Track
12	HBR	Human Behaviour Representation
13	SDs	Standard deviation
14	SME	Subject Matter Experts
15	BN	Bayesian Network
16	CPD	Conditional Probability Distribution
17	CPT	Conditional Probability Table
18	CI	Confidence Interval
19	ITF	Innovative Time Form
20	SPSS	Statistical Package for the Social Sciences
21	χ^2	Chi Square
22	KPI’s	key performance indicators
23	MRI	Magnetic Resonance Imaging
24	CT	Computerized Tomography

Chapter 1: Introduction

1.1 Introduction

An Emergency Department (ED) is a medical treatment provision, specialising in the acute care of patients who attend without a prior appointment having been made—either by their own means or via ambulance. Because of the lack of predictability in regard to patient attendance, it is imperative that the department delivers a range of treatments covering a vast arena of different injuries and illnesses; importantly, some of these may be considered life-threatening, and may therefore necessitate immediate, urgent action. Nevertheless, EDs are experiencing many different obstacles and issues owing to the fact that there has been a significant surge in patient demand; this has subsequently induced the need to ensure services and their overall quality is improved. The most serious obstacle that EDs face today around the world is the overcrowding of areas within the department. This problem of overcrowding alone can easily lead to the demise of a healthcare service. Over crowdedness affects EDs from an array of different avenues that only lead to a deficiency in activity and processes. This problem has an on-going reverse affect from the very start, i.e. as the problem persists, the quality of service provided degrades and the time needed for tasks increases. This reverse affect is then passed down through to other patients and circulates throughout the departments. Hence, both patients and the service provider are simultaneously affected in the worse possible way as it is very difficult to control.

Overcrowding is the subject of this study to see the cause and effects of this problem and then explore the best solution to the problem. The ED in Tripoli Medical Centre (TMC) within a developing country (Libya) has been chosen to be the subject of study. TMC is within the capital city of country and is the hub for all medical centres and facilities within Libya.

Chapter 1 discusses the background and outlines the motivation for pursuing the study. This is followed by the aim and objectives of study, the problem statement and research questions that aided the succession of this study. In addition this chapter highlights the contributions of this thesis, a description on how this thesis is organised concludes the chapter.

1.2 Background

1.2.1 Emergency Department Overcrowding:

Within hospital emergency departments, one of the most significant, urgent operational obstacles facing such units is patients overcrowding, which is recognised as threatening public health and patient safety. Considerable attention has been devoted to the study of overcrowding in critical hospital departments in Europe/USA on the root causes of overcrowding and their effects on healthcare services.

Markedly, overcrowding is commonly considered as a circumstance wherein there are a greater number of patients than treatment beds and staff, and also where waiting times necessitate patients to endure long delays [Hoot *and Aronsky*., 2006; Trazeciak *et al*., 2003; Fatovich *et al*., 2005; Mahmoud *et al*., 2012].

Notably, overcrowding commonly comprises three types of patients: those seeking to be admitted to the emergency department; those being assessed and/or monitored in non-treatment areas; and those requiring transfer to the inpatient unit (IU) [Walshe *and Smith*., 2006].

The matter of ED overcrowding is not new, as this problem surfaced in the emergency medicine literature about 20 years ago. The Literature review shows that many studies have been done over the past decade; the majority of the reviews concentrated on the incidence of the problem, its causes and the consequences on the health services [Andrulis *et al*., 1991; Fromm *et al*., 1993; Varon *et al*., 1994; Nelson *et al*., 1998; Lambe *et al*., 2002].

This problem has been compounded recently, a literature review carried out in the United States over a period of 4 years, highlights findings that the emergency departments have more than 114 million patients annually, that have been affected because of this serious problem of over crowdedness [Bolton *and Johnson*., 2011].

The increase in the ED overcrowding problem has motivated researchers to delve into the issues surrounding the causes and effects, as well as how to establish a solution for this problem.

As is the case with any successful application of such studies, an understanding of the underlying environment is essential. Moreover, within the ED environment, the concept of patient flow is fundamental. Therefore, the following contains an explanation of the work environment in different emergency departments, and how the patients move from one stage to another within a patient flow system.

1.2.2 Patient Flow

Overall, patient flow is viewed as being the transfer of patients throughout various different locations in specific relation to a healthcare facility [Litvak, 2010]. Various different studies have also established that a patient flow system is a valuable tool for examining and evaluating hospital performance. Furthermore, a patient flow system has the capacity to establish the overall potential of hospitals to provide patients with quick and efficient services as they progress from one phase of care to another [Hall, 2006; De Silva, 2013]. Importantly, the patient flow system comprises various physical flow stages, all of which concern the flow of existing materials, such as decision flow, information flow, the number of doctors and nurses available, test results, treatment materials, and waiting-list operation departments. Occasionally, it is recognised that information flow may also include decision flow [Moskop et al., 2009]. Patient flow is first initiated at the time at which a patient is diagnosed with a condition or illness or otherwise at the time at which the patient is first admitted to the healthcare facility. In the same vein, after the condition or illness has concluded, or otherwise if the patient is discharged or chooses to leave the healthcare facility, the patient flow is recognised as being terminated. Between the time of admission and patient flow conclusion there are various different activities, conditions, locations and/or services the individual may experience. Furthermore, during such points, the patients may require the utilisation of various different healthcare resources, namely beds, examining rooms, medical procedures, nurses, and physicians. This therefore suggests that the overall patient flow system may be described as a network [Hall, 2006]. Figure 1.1 illustrates the patient flow process, [Zhao and Lie., 2008].

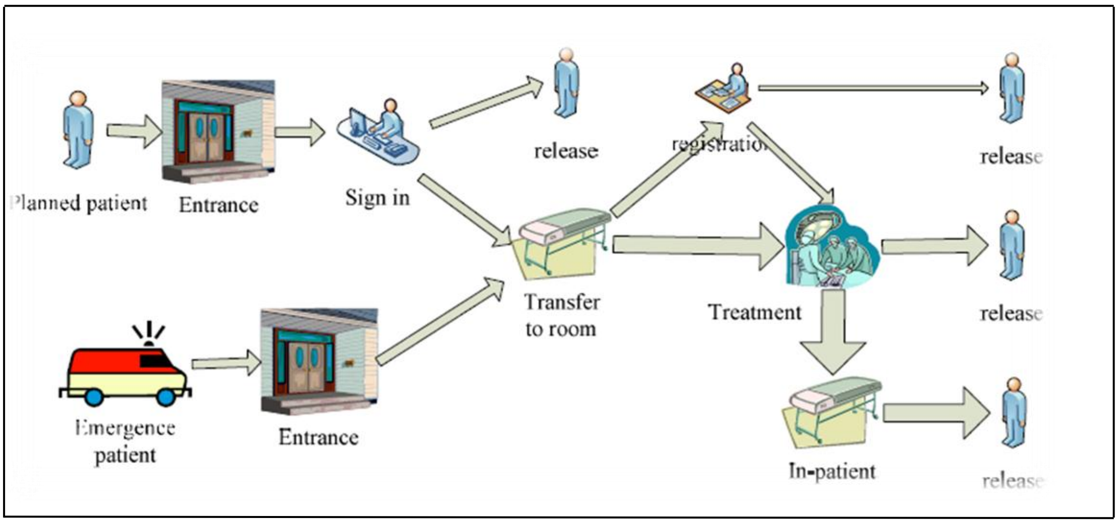


Figure 1.1 Patient flow of the emergency department [Zhao et al., 2008]

In part, patient delays depend on how she/he physically flows through the network, and also on the ways in which information, equipment and other objects flow through it. In actual fact, the problem in hospitals is that such movements throughout the patient flow network have been stopped or otherwise progress slowly owing to many different reasons, which cause an increase in waiting time that subsequently, leads to patient dissatisfaction [Jense, 2006; Jensen *et al*., 2010]. Previous studies, which have been carried out in America and Europe, demonstrate that the measurement of patient flow in ED can prove to be a very valuable tool in terms of analysing the influence of various factors in regard to overcrowding. Consequently, improving patient flow which is an essential issue in hospitals' EDs, as well as all over the world [Hoot *et al*., 2008; McHugh *et al*., 2011].

The following section is an account of the most important causes of emergency overcrowding that have been monitored by previous studies. The section also will list the most important effects that are caused by overcrowding.

1.2.3 Causes of ED Overcrowding:

Many previous studies have indicated that there are multiple factors that contribute to creating a situation of overcrowding in emergency departments. The most common causes leading to overcrowding have been listed by researchers as: an overall increase in patient volume. increased complexity and acuity of patients to the ED, lack of beds for patients admitted to the hospital, avoiding inpatient hospital admissions by intensive assessment and treatment in the ED, delays in the service provided by radiology, laboratory, and ancillary services, shortage of staff, and a shortage of physical space within the ED [Lambe *et al*., 2003; Andersson *et al*., 2001; Derlet *et al*., 2000; Schneider *et al*., 2003; Der Linden *et al*., 2013].

1.2.4 Effects of ED overcrowding:

There has been much published in the academic literature surrounding the negative consequences of ED overcrowding, for example, increased risk of clinical deterioration, prolonged patient wait times, subsequently leading to prolonged pain, increased patient complaints, decreased staff satisfaction and decreased physician productivity, increased pressure in terms of managing the hospital effectively, and poor service quality [Ahmed *et al.*, 2009; Peck *et al*., 2010; Hwang *et al*., 2008; Derlet *et al*., 2001; Baer *et al*., 2001].

In actual fact, previous studies of ED overcrowding is solely based on ideal patients, as they assume patients attending the ED come with a certain condition and follow the designated patient flow patterns to acquire the necessary treatments. Hence patients are only categorised by their condition and acuity level. This indirectly implies the cause of overcrowding is mainly based on patient numbers attending and the condition in which they attend in i.e. the acuity level and treatment needed.

Therefore, many studies highlight the lack of facilities and inefficient management of the available resources.

This study, takes a totally new and original approach, which is in essence a more realistic and logical approach, as it considers patient behaviour to be a root cause that inevitably develops overcrowded EDs.

In developing countries like Libya a more realistic patient flow model is needed to take into account the effects of patient behaviour on the patient flow system. It is recognised that under stressful conditions, particularly during overcrowding, patient's behaviour deviates substantially from ideal, especially when rules and regulations are not formally known or enforced. From this point, the current study proposed the problem statement as patient behaviour, being a key driver of overcrowding in ED within Libyan EDs resulting in poor levels of patient healthcare.

1.3 The problem statement:

This problem study can be expressed by considering the following research question:

- Are problematic patient behaviours directly responsible for affecting the patient flow system, and subsequently inducing emergency service delays?

To answer this question, additional related questions have to be raised and considered. These questions have been summarised as follows:

- What are the most important behaviours that are considered by EDs' staff to be undesirable, and are considered a reason to block the patient flow system and increase the time within EDs?
- What patient types attending the ED show undesirable behaviour?

- Are there any specific areas and processes within the ED that experience increased difficulties due to behavioural factors?
- What are intervals/times of the day that the most undesirable behaviour takes place?
- Are there any important differences between normal patients and patients with undesirable behaviour, in terms of service times?
- Are there any other factors, (e.g. staff behaviour, WTs, ED areas, age of patient and so on) that contribute to the development of difficult behaviour?.

Answering these research questions should then help to identify a more suitable and proper technique in modeling human behaviour by developing a greater understanding. The selection of an inappropriate technique could easily lead to an unsuccessful modeling process and produce undesirable artificial results, which will not meet the aims and objectives of study and further be a waste of valuable time and effort**.**

Due to the complexity of emergency departments, majority of previous research studies based on healthcare providers and hospitals EDs, have used Discreet Event Simulation (DES). DES has been deemed to be the most suitable technique to be used as it provides fast efficient results without jeopardizing the service provider directly and the simple capabilities of DES that can consider all influencing factors [Connelly *et al*., 2004; Raunak *et al*., 2009; Duguay *et al*., 2007]. This thesis describes the research work based on modelling human behaviour and using the simulation technique DES. Chapter two (literature review)will comprise wider explanation for the reasons of using EDs in this work.

1.4 Research Aim:

The overall aim of this thesis is to develop and analyse a new DES model for a Libyan hospital, taking into account the impact of difficult patient behaviour effecting the length of stay (LOS) and waiting times (WT).

1.5 Research Objectives

In order to accomplish this aim, several measurable objectives must be achieved:

- Review past and current approaches to patient flow systems, and understanding of patient interactions within an ED environment.
- Gain experience with DES software and understanding of the modelling of a patient health care system.
- Explore and investigate patient behavioural factors and develop a knowledge base.
- Develop improved models of a patient flow system that incorporates human behaviour, capable of accurately predicting levels of ED during overcrowding.
- Validate the models, developing the necessary test and comparison methods appropriate to the health industry.
- Use the simulation models and compare them against current hospital management procedures.
- Explore future use of the developed simulation model and define areas where it may be of significant benefit to the health service providers and the research community.

1.6 . Thesis Contribution

- In this study, patient behaviour is considered as an additional cause of ED overcrowding and an integral additive to the root cause. No previous studies have been carried out or literature is available where patient behaviour is an influencing factor that negatively affects the services throughout the ED. This point is a new detection that helps in reducing patient waiting time (WT) and then reduces length of stay (LOS), which can be assumed to lead to improving the utilisation of available resources. Thus, reducing expenses resulting from increased service time. Also by taking this factor into consideration and developing a new strategy that reduces waiting time and LOS, patients and staff will be satisfied with the service as the service provider will reap the benefits of a more efficient facility. This study seeks to complete and improve other working tasks in many aspects in relation to the ED to enhance services and reduce patient WT and LOS.
- Another novel point to be considered in this study is, this is the only one of its kind to be carried out in Libya; there exists no previous study based on overcrowding and studying the effects of this problem in Libya using DES.
- This study will show the LOS and WT in the TMC ED, for the first time, because there is no system in ED of TMC that account for time that patient spend in ED. This study uses the time frame as innovative idea to find the very important data needed to understand the working environment in ED, and thus enhance the services.
- This study further uses Bayes' theorem to find out the probability of having difficult patients for the first time, Bayesian theory was deemed to be the best fit in order to calculate these random occurrences as it considers the

influencing factors. Bayesian theory displays the most accurate true to life representation of behaviour occurrences within patients. The Bayesian approach is then implemented within the simulation model to provide a dynamic platform that is visually available to view.

- A new strategy was developed, Patient Behaviour Control (PBC), which is based on the redesign of the patient flow. This is an innovative attempt to improve patient flow in order to decrease WT and LOS into EDs.

1.7 Research Structure

This thesis consists of eight chapters, structured as follows:

Chapter 2: Gives an account of the literature reviews undertaken in this study which can be segregated as follows: Simulation modeling in healthcare and ED, and patient behaviour in healthcare and ED. The chapter starts with an investigation into the theory of DES modelling, modelling concepts, advantages and disadvantages and lists some of the available simulation software packages and their applications. The literature review discusses the existing studies that use DES in modelling healthcare and ED problems. The chapter also presents the introduction of human behaviour and the cause and affects in relation to over crowdedness in healthcare and ED.

Chapter 3: Describes the research methodology that was used to gather data from the existing hospital records and field research undertaken of TMC. The chapter further discusses in detail the conceptual DES modelling techniques and application with reference to the research. This chapter includes the validation and verification process followed throughout the thesis.

Chapter 4: Brings forward all the aspects of model building from chapter 3. The Bayesian Network (BN) Modelling aided by Hugin software is introduced and the application of the Bayesian approach to the simulation model is depicted in greater detail to show how the Bayes theorem has been applied to DES model to enable the occurrences of difficult behaviour to be considered accurately.

Chapter 5: Presents and discusses the results that have been obtained through the analysis of historical data. The characteristics of the patients are discussed, all the procedures and processes within the TMC's ED. The results of questionnaires and personal interviews that were conducted with professionals from within TMC, to explore their experiences, opinions and attitudes are discussed. The last part of this chapter is devoted to explain and discuss the results of observation that targeted patients.

Chapter 6: This chapter presents and collates all the DES model developments. Five DES models were developed as follows: Logical, Basic, Actual, Behaviour and Bayesian model. All the results are presented and collated together to develop greater understanding based on the collective research undertaken and changes applied. The results are presented to show a structural comparison from one DES model to another based on the changes applied as the DES models are developed.

Chapter 7: Based on the results collated in chapter 6, the results are used to establish an accurate strategy that will be used to reduce LOS and WT. Patient behaviour control is introduced, a strategy that uses the Bayes theorem to monitor and predict difficult patient behaviour is used to segregate the difficult patients from the normal patients in order to enable a more proficient system of processing patients.

Chapter 8: Presents an overall conclusion of the thesis with reference to the findings of the study, the chapter looks back at the aims and objectives of this study to ensure viability and correlation with a new developed patient behaviour control (PBC) strategy.

The contribution to the healthcare and DES in this study is presented. The chapter finishes with future work in this area for further development.

1.8 Summary:

This chapter gave an introduction and background to EDs services. Overcrowding within the health service is discussed and further, the effects of overcrowding within the ED, that inevitably results in an inefficient system and processes. The problem statement is discussed and the research aim and objectives war highlighted along with the research contribution and structure outline of the thesis is also covered.

Chapter 2: Literature Review

2.1 Introduction

Previous research considers overcrowding in EDs as a result of other problems that EDs have confronted on a daily basis. The most fundamental problems that are known to create overcrowding—whilst at the same time potentially caused by overcrowding—are increased WTs and prolonged LOS. There are several reasons behind the creation of this problem, including the patient's behaviour. Many strategies have been innovated during the last decade in an effort to reduce the effects of overcrowding on EDs' services, such as by using the simulation technique. This chapter will comprise several parts.

- Primarily, a Literature Review will consider the general concepts of EDs' services and time, and their relation to overcrowding.
- Secondarily, the general concepts for simulation will be presented. At the same time , there is the provision of more specialised reviews relating to the most important utilisation of this technique in the field of healthcare, and specifically in the context of EDs.
- Thirdly, there is the presentation of the general concepts for patient behaviour and how these create services problems.
- Fourthly, the chapter will provide the reviews relating to the simulation of human behaviour in different sectors.

2.2 Emergency Departments' Processes and Time Definitions

This work in ED cannot advance without providing definitions of the key processes that EDs encompass. As the specialty identifies best practices, it is beginning to collect data on important ED processes, which lead to facilitating understanding of the terminology used in this study later. The important processes are defined below:

- ***Registration***: The approach to establishing and detailing information in mind of creating a patient record. Such details including data relating to socio-demographics and financial responsibility, the main objective of which is associated with billing. It should be noted that registration differs to patient identification (Gorelick *et al*., 2005).
- ***Triage***: The method of evaluating patients in an effort to prioritise care in line with the urgency of the need and complexity of the services required. It is common for triage to be carried out by a registered nurse, who progresses through various stages of information-gathering. One of the most fundamental aspects of this stage is triage scale assignment, with the 5-level Emergency Severity Index/Canadian Triage and Acuity Scale (ESI/CTAS) commonly adopted (Carson *et al*., 2010; Fitzgerald *et al*., 2010; Moskop *et al*., 2007).
- ***Intake***: The approach centred on receiving and sorting patients in relation to the required medical care. Triage is one intake model, with others including physician in triage, rapid medical screening and team triage (Welch *et al*., 2010; Welch *et al*., 2012).
- ***Medical Examination***: This is an evaluation performed with the aim of establishing whether or not there is urgency in the medical condition (Walsh *et al*., 2007).

- ***Discharge***: The approach centred on releasing patients from the emergency department following the conclusion of treatment, including the distribution of the relevant paperwork (Walsh *et al*., 2007).
- ***Boarding***: This involves patients being admitted to the hospital for longer periods. This includes the time spanning from admission through to departure (Sun *et al*., 2013; Singer *et al*., 2011).

The processes adopted by the ED, which create patient flow systems, commonly experience a number of challenges and disruptions as a direct result of overcrowding, with longer waiting times resulting in greater LOS in the ED. It has been established through prior research that LOS is recognised as an indicator of ED overcrowding, and is further recognised as a key factor in the quality assurance approach concerning EDs (Chan *et al*., 1997; Yoon *et al*., 2003; Herring *et al*., 2009; Rathlev *et al*., 2012).

It is well known that , so far, most studies consider overcrowding in emergency departments all attempt to decrease WTs and the LOS of patients in EDs in order to solve this problem. In order to do so, they focus first on understanding the time spent by the patient in the ED. This study also focuses on understanding EDs' times as a starting stage in studying overcrowding in ED TMC.

The following is a definition of processes' time for ED TMC. These definitions have been adopted after consultation with the TMC staff and a review surrounding the regulation and laws of the TMC. In actual fact, the definition of processes' time is alike in other hospitals.

- ***Arrival time***: The time that the patient first arrives at the ED for the purpose of requesting emergency care. This is the first contact and not necessarily registration time or the triage time.
- ***Treatment area time***: The time of placement in a treatment area. 'Treatment area' is any space the hospital describes as an area for providing emergency care.
- ***Provider contact time***: The time of first contact of the physician or the provider with the patient to initiate the medical screening examination, but specifically not the triage nurse.
- ***Disposition decision time***: The time that the order relating to the disposition of the patient (transfer, observe or discharge) is documented.
- **Admit decision time:** The time that the admission order is documented by the provider. This time is applied only to those patients who are admitted.
- ***Departure time***: The time of the physical departure of a patient from the ED treatment area. The time is represented by leaving the department for all categories of patient, including those who are admitted, discharged and observed.
- **ED length of stay:** The arrival time spanning through to the departure time.

Figure 2.1 below describes the LOS interval in ED TMC.

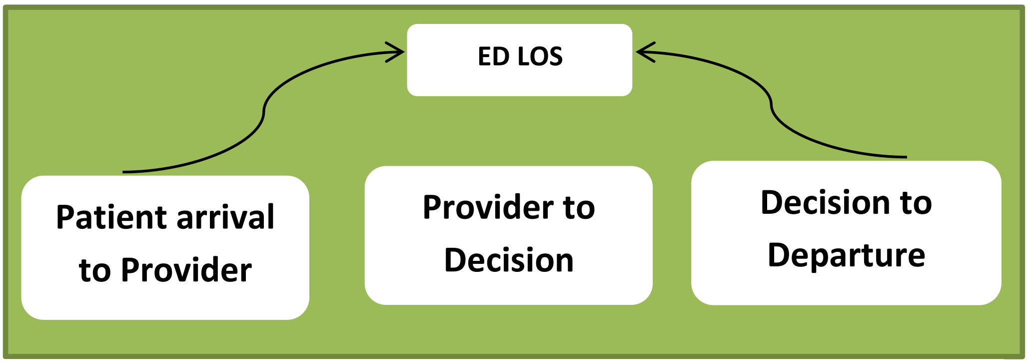


Figure 2.1 The interval of ED LOS

The literature shows that simulation is the effective tool used to study EDs; however, there are a number of interesting questions to be posed, such as, ‘What is simulation?’, ‘Why are simulation techniques widely used to study different systems?’, ‘Are there different types of simulation?’, ‘Is simulation used in the healthcare sector?’, as well as many other questions that will be answered in the following sections.

2.3 General Concepts of Simulation

2.3.1 What is Simulation?

Simulation has been defined by various researchers, some of whom describe simulation as being a technique, not a technology, to replace real experiences with guided experience, and which suggests or reiterates important aspects of the real world in a totally interactive way [Ingalls, 2008]. Other researchers, on the other hand, define simulation as ‘’the process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behaviour of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system’’ [Shannon, 1975]. Another source defines simulation as ‘’the imitation of the operation of a real world process or system over time’’ [Latif, 2011].

From the various definitions of simulation, it is very clear that those detailed above suggest that simulation is related to a scientific system used to transfer all processes and procedures that arise in a real system to a computer system for the reason of examining and determining real issues.

Computer simulation grew hand-in-hand with the fast development of the computer, which underwent its first large-scale use during the period of the Manhattan Project in World War II with the aim of modelling the procedure of the nuclear explosion. This encompassed the simulation of 12 hard spheres, utilising the Monte Carlo algorithm [Pidd, 2002].

2.3.2 Why Use Simulation?

There are many advantages associated with simulation, which makes it a scientific method that is very important in mind of solving the problems of many of the systems used in all areas. The literature review has been carried out in order to establish the key advantages associated with using simulation. Importantly, the benefits of particular importance in this study have been listed as follows [Altiok *et al*., 2007; Ross, 2006; Tulsian *et al*., 2006; Sokolowski *et al*., 2009]:

1. It allows access to system internals that otherwise may not be observable.
2. The changes occurred in the informational, environmental and organisational setting can be simulated, with the results of these modifications on the model's behaviour able to be observed.
3. Observations based on the simulations give great insight into system behaviour, and are able to determine which variables are most significant and how they can be linked.
4. Simulations allows experiments with new plans or policies prior to execution.
5. Bottleneck examination is possible.
6. By using simulation, organisations are able to examine, in a risk-free environment, possible changes relating to the system.
7. Simulations consider all the resources and limitations involved in the system.

2.3.3 Types of Simulation

There are various types of computer simulation, all of which have common features that seek to generate a sample of representative situations for a model during which the entire details of all possible states of the model would be prohibitive or not possible [Liang *et al*., 2001; Law *et al*., 2000].

The literature shows that there are four types of simulation, namely stochastic, deterministic, discrete event and continuous simulation. All of these types will be discussed below.

1. Stochastic is a simulation model with one or more than one random variable as inputs, where the final output is the random output. There elements are sometimes related by probabilistic statements.
2. Deterministic is different compared to the one above. This approach does not contain any random variable. It needs a known set of inputs, which result in a unique set of outputs, meaning the elements are correlated by absolute statements.
3. The discrete event approach is a simulation modelling that contains state variables change just at a countable number of points in time. The relationship is discrete and random before smooth and predictable: for example, the number of patients waiting in line.
4. Continuous simulation modelling is a simulation containing the state of the variables changing continuously in respect to time.

This work, in fact, directs attention to the use of a simulation technique in one of the healthcare centres in Libya, with focus on the ED in order to examine and analyse the real system in an effort to suggest solutions of the problems the centre faces every day. Therefore, similar previous works that have been carried out in the healthcare centres and EDs all around the world will enrich this study.

2.4 Simulation in Healthcare and EDs

According to the literature review, many previous studies have shown that simulation has been applied in health sectors from the early 1970s. According to the report conducted by Dublin Institute of Technology (2009), there were many researche projects centred on the use of simulation in the health sector, which were conducted during the period 1973–1977. There were 62 research projects published during the years 2003–2007. The report also showed that the total number of publications of simulation in the healthcare sector for the period 1993–1997 was 28 [Thorwarth *et al*., 2009].

Likewise, many areas of healthcare have been studied with the use of simulation during the recent decade. For example, Harper (2002) applied a generic framework for the modelling of Royal Berkshire and Battle Hospital resources, which aimed to establish the needs of the user and real-life hospital processes. The model was built using several programs, such as the simulation shell (TOCHSIM) and the data collection tool named Apollo. There were three scenarios examined in the project with the aim of illustrating the consequences of possible decisions by the hospital management. Such different scenarios include hospital beds, operating theatres and the use of Human Resources, such as nurses, doctors and anaesthetists. The model helped hospital managers to understand and assess the consequences of planning and management politics. Furthermore, the developed model illustrated that it could be used to study a variety of hospital planning issues and possibly enhance the efficiency and effectiveness of the limited resources available [Harper, 2002].

Vissers *et al*. (2007) established a platform that could compare the performance of the admission systems of hospitals. This theoretical model is based on the assumptions of a basic hospital. Maximum Resource Use (MRU), Zero Waiting Time (ZWT), Coordinated Booked Admission (CBA) and Uncoordinated Booked Admission (UBA) are some of the admission plans examined; these plans are measured according to the resource utilisation of beds, intensive care beds, operating theatres and nursing staff. In addition, the paper proposed the possibility of recognising the most appropriate admission strategy [Vissers *et al*., 2007].

In Greenville Memorial Hospital, U.S.A, Late starting surgeries have been shown to be a reason of process and scheduling disruptions, and are a most important contributor to dissatisfaction among patients and staff. The pre-operative system requires the preparation of a large number of patients with an individual set of features and array of required tasks before surgery. Staff do not have a prescribed sequence of activities nor mutually exclusive duties. According to Pearce *et al*. (2010), the novel discrete system prepares for simulating the various activities of pre-operative procedures, demonstrates significant processes, and tests mitigating policies. At present, it examines the prescriptive approach of resources set on the agent approach, selecting and permitting the task, and similarly attaining the effort for the agent [Pearce *et al*., 2010].

Similarly, many studies have been implemented using simulation techniques to examine EDs' overcrowding. Previous work in this field demonstrate that discrete event simulation (DES) is an effective tool for EDs management in the reduction of LOS [Jacobson *et al*., 2006; Gunal *et al*., 2010; Wang *et al*., 2012]. A review of studies that consider reducing WTs and LOS in EDs identified that 22 studies of 29 used DES [Lim *et al*., 2012]. For example, McGuire showed in a study conducted in a SunHealth Alliance hospital how staffing alternatives could be tested, and accordingly selected a solution centred on significantly reducing the LOS for the ED using simulation technology [McGuire, 1994]. Moreover, Miller and his colleagues developed a DES model for the simulation of potential process improvements in an effort to reduce the LOS [Miller *et al*., 2003]. In addition, Connelly *et al*.(2004) present a discrete event simulation model known as EDSim, developed using Extend, a general purpose commercial simulation tool, to investigate the ability to predict actual patient care times using simulation. Another simulation study implemented in the ED of the University of Kentucky Chandler Hospital has shown that the diagnostic test is the bottleneck in the ED [Brenner *et al*., 2010]. The work at a community hospital in Lexington, KY, identifies a similar procedure as bottleneck, and investigates the impact of the nurse floating policy (i.e., two nurses sharing the work together) on ED efficiency. It has been shown that such a policy is able to help reduce patient LOS and waiting times [Zeng *et al*., 2012].

In addition, prior work shows a number of innovative strategies that have been trialled to reduce WTs and LOS in order to find a solution for ED overcrowding. In an effort to clarify this, many authors have emphasised that WTs can be reduced through the better use of existing resources, i.e. the number and type of staff and how these can be scheduled to become more compatible with the number and time of patients present in the emergency department. For example, Weng *et al*. (2011) in their study aimed to identify the most optimal allocation of resources in ED by using simulation to improve the patient flow system. The creation of a model based on real situations of the ED can represent WTs and LOS in ED; therefore, researchers were able to build a model that is recognised as compatible with National Emergency

Department Overcrowding Scale (NEDOCS) to increase the performance in ED and re-manage the patient flow system. The results show an increase in ED performance through the new allocation of human resources. This study also recognises increases in patient satisfactions [Weng *et al*., 2011]. Moreover, another study carried out by Tan *et al*. (2002) expected that modifications to the current doctor schedule would decrease the WTs patients spent in the facilities. They suggested a new schedule that would incorporate an extra doctor for each time slot. The shifting bottleneck issue was considered in this study. The current and proposed doctor schedules were tested with the use of a discrete event simulation model, simulated on Arena. The result of the simulation stated that the proposed schedule decreased the WTs of patients. Additionally, sensitivity analysis was performed, with the next bottleneck resource identified [Tan *et al*., 2002].

Other researchers consider that those hospitals that focus on only studying issues in the emergency departments in order to reduce WTs and LOS will not be completely successful. They explain that ancillary departments, such as for X-rays, and the lab, need to be reviewed and analysed in order to establish whether they meet the needs of the emergency department. To illustrate, Yoon *et al*. (2003) carried out a study that aimed to identify and measure the principal ED patient care time intervals, as well as the impact of important service processes, i.e. laboratory testing and imaging on LOS for different types of patient. The results showed that the use of diagnostic imaging and laboratory tests was associated with prolonged LOS [Yoon *et al*., 2003].

Many other interventions are inspired by lean healthcare thinking, with focus directed towards improving patient flow in emergency departments [Ahlstrom, 2004; De Koning *et al*., 2006].

As stated in the literature review, the interventions strategies were grouped into team triage, point-of-care testing, i.e. performing laboratory analysis in the emergency department, and streaming. In the following sections there is the provision of more in-depth explanation of these strategies, with the way in which they are used in order to decrease ED overcrowding also demonstrated.

In terms of the team triage strategy, in some hospitals, this is known as Rapid Assessment and Treatment (RAT), defined as triage, handled by a team led by a senior doctor. The purpose of this strategy is to increase accuracy and efficiency in the initial process of patient investigations and treatment [ECIST, 2012].

Many studies have been carried out during the last decade that have considered team triage and its ability to decrease time spent with patients in different services. For example, a study in the USA—more specifically, the state of Hawaii—implemented team triage to improve ED efficiency and patient satisfaction, and to mitigate the effects of overcrowding by considering a set of data, i.e. mode of arrival, LOS and WTs. This study showed that, by using team triage, the number of patient arrivals was increased during the study period whilst the WTs decreased for outpatients; however, the overall LOS for outpatients remained the same [Haruno *et al*., 2012]. Holdroyd *et al*. (2007) conducted a study in Canada that aimed to evaluate the effects of triage liaison physician on LOS and patient leave without being seen (LWBS). This study stated that cooperating physician in triage smoothed patient flow. Additionally, LOS was reduced by 11% whereas LWBS was reduced by 20% [Holdroyd *et al*, 2007]. Partovi *et al*. (2001) conducted a study in the United States that aimed to examine the effects of a senior emergency physician in the triage team. They reported that the average LOS was reduced by 82 minutes, and revealed that the effect was mainly the result of team triage strategy with the involvement of no other factors; in other words, patients needing to be admitted and x-rayed had an impact on the results [Partovi *et al*., 2001].

Another study from Northern Ireland was carried out by Subash *et al*. (2004), which randomly tracked approximately 1,000 patients to team triage or ordinary triage. They found that WT to see a doctor and WT to x-ray were statistically reduced. Nonetheless, the study demonstrated no reduction in LOS [Subash *et al*., 2004].

Although the successes of the team triage strategy in reducing the number of patients LWBS by a physician, the literature review shows that team triage has limited effects in terms of reducing WT and LOS [Oredsson *et al*., 2011].

In regard to Point-of-Care Testing strategy (POCT)—sometimes referred to as Patient Bedside—this centres on moving laboratory analysis to the ED. The purpose of this strategy is to generate a result quickly, which obviously leads to the speeding up of the diagnosis process, thus meaning the clinical and/or economic outcome in the ED will be improved [Price, 2001; Kendall *et al*., 1998]. There have been many studies that have considered POCT in ED around the world: For example, Lee-Lewandrowski *et al*. (2003) was carried out in the USA and reported a shorter time from ordering laboratory tests to the time when results were ready for the attending physician. They also achieved a reduction and demonstrated increased staff satisfaction LOS through the use of the POCT strategy [Lee-Lewandrowski *et al*., 2003]. In a US study carried out by Parvin *et al*. (1996), approximately 95% of the patients who attended the ED needed central laboratory analyses to complement POCT. Consequently, POCT had no effect on the patients' LOS [Parvin *et al*., 1996]. Singer *et al*. (2008) examined the impact of a POCT on ED LOS in a before-and-after study that was conducted at an academic ED with 75,000 twelve-month patient visits. They found that the implementation of the POCT was associated with a significant reduction in the median ED LOS by almost 1 hour. However, the results of their study showed that the effect of the POCT strategy on ED LOS was less noticeable for discharged patients [Singer *et al*., 2008].

Based on the studies assessed, the effect of POCT on turnaround time is supported by relatively strong evidence. It can be asserted that the POCT strategy has remarkable effects in relation to patient turnaround time. However, its effects on LOS are supported by only limited evidence.

In consideration to streaming strategy, this refers to the intervention where patients have to be pushed to triage or for a brief assessment after dividing them into different paths according to more or less defined criteria. The most common example of streaming is usually referred to as Fast Track (FT), which is a strategy that works on separated patients based on their conditions, adopting different processes. Scientific evidence on the effect of FT on WTs, LOS and LWBS were moderately strong [Devkaran *et al*., 2009; Der Linden *et al*., 2013].

Owing to the effectiveness of the FT strategy to decrease overcrowding in EDs all over the world by reducing WT and LOS, the current study will implement this approach, albeit with some modifications to enable fit to the variables considered in this study. Consequently, this study will contain a chapter centred on clarifying the FT in details, and will also show the previous work done when using FT. In this same vein, the chapter will display the current work in terms of using FT to reduce overcrowding in ED TMC.

Although these strategies—as well as many others—have been attempted all over the world to improve the services of emergency departments and reduce overcrowding, all previous studies, however, assumed a range of causes of overcrowding in EDs. They studied these causes in order to develop solutions. Moreover, all causes of this problem—which the literature review has clarified—have been discussed in the previous chapter. This study will also address another factor that is seen to contribute to the creation of overcrowding, which is that of patient behaviour during the period of waiting to receive emergency services.

This study seeks to analyse this factor in an effort to identify its impacts on patient flow in terms of increasing WTs and LOS. The FT strategy, as an idea, will be used to reduce WTs and LOS, which have been significantly affected by patient behaviour in ED TMC.

The simulation package used in this study to develop the models of Emergency Departments within TMC is WITNESS. This package has been chosen owing to its availability within the School of Engineering at Manchester Metropolitan University (MMU).

The following section will be concerned with explaining the patient behaviours considered in this study, as displayed in the literature review. This section will help the reader to gain more understanding of behavioural factors that have an impact on WT and LOS.

2.5 Patient Behaviours

Waiting is an unavoidable part of modern life. Waiting causes not only inconvenience but can also prove to be frustrating, demoralising, painful, annoying, time-consuming and extremely expensive [Newstron *et al*., 2010]. Moreover, waiting in a service facility (e.g. store, bank, laboratory, hospital and so on) has significant effects on customers' overall perceptions of the quality of service they seek; hence, the waiting process has drawn great attention—and subsequently has become a critical element in regard to business operation management [Arnold *et al*., 2010]. In fact, numerous mathematical and operations researches have been carried out with the aim of improving the overall efficiency of the waiting process; however, previous researches have solved only part of problem as they do not take into consideration human factors. As waiting involves people, time and the environment, it is fundamental to incorporate issues relating to both the social and psychological perspectives in an effort to reduce the negative impacts of waiting on customer satisfaction and perceived quality.

To monitor the most significant factors of patients' behaviour that have a negative impact on the time of service and patient flow system, the literature concerning patient behaviours while they are waiting for service have been reviewed. It has been found that most of researchers assign a label of 'difficult patient' to those patients who show undesirable behaviours whilst waiting for services. The concept of a difficult patient has been defined in the literature as "a patient whose behaviour causes difficulties for others" [Duxbury, 2000]. The literature review shows that difficult patients share common features: for example, they can be demanding, noncompliant, whiny, entitled or manipulative [Duxbury, 2000; McCarty *et al*., 1996; Roberts *et al*., 2003; Sharon *et al*., 2007]. With this in mind, it can be seen through the majority of past studies that patient behaviours are generally grouped into four different arenas: challenging, confrontational, passive and withdrawn. Furthermore, another two groups are assigned to each difficult patient, as being those illustrating defensive behaviours and those showing protective behaviours [Sohr, 1996].

Difficult patients, in fact, can affect health services in the following ways [Milliken, 1987; Parliamentary Office of Science and Technology, 2001; Stewart, 2005]:

- They may lead staff to lose their tempers;
- Medical staff may, to some degree, be forced to respond in displeasing ways;
- Medical staff may be unable to carry out their roles efficiently;
- Medical staff may be manipulated to utilise and adopt dishonest approaches to meet needs;
- Medical staff may become angry, worried or defeated, or may otherwise experience other negative emotions.
- Difficult patients may remain passive and require staff to do more work.

From the above, we can conclude that a difficult patient behaviour causes obstructions in the service system because such behaviours create a state of chaos and confusion in the system, which negatively affects service providers and thus leads them to experience weaknesses and sometimes failures in the provision of service. However, this aspect has been ignored by researchers, with focus instead directed towards other aspects where we can find numerous studies on the subject of communication. Notably, others exist in terms of addressing the reasons for violence towards nurses and doctors, and how the occurrence of such can be reduced. Moreover, there are many studies concerned with managing difficult patient behaviours within health institutions [Laurie *et al*., 2010; Smith, 1995; Jackson *et al*., 1999; Pomm *et al*., 2003; Fallowfield *et al*., 2004; Wasan *et al*., 2005].

Furthermore, as a result of previous studies that have failed to address the impacts of patient behaviours on the delay of health services provided and increase patient waiting times—which subsequently increases overcrowding in the centres of health service delivery—following the stabilisation of the highlighted factors. Table 2.1 has been created in an attempt to illustrate the fundamental elements known to play a role in service delivery negativity.

Table 2.1. The significant patients factors affecting the service in emergency departments.

Patient Behaviour Factors		
No.	**Factor**	**How Services can be Impacted**
1	**Defensive behaviour, including:** a. *Challenges*, including: - Interfering - Over-involvement - Demanding. b. *Confrontation*, including: - Anger - Arguing - Aggression - Lack of respect - Intoxication (alcoholism).	- Capacity issues - Disturbance of service because of the complaint and objection - Requires a long time to deal with them.
2	**Protective behaviour, including:** *a. Passivity:* - cultural influences (discrimination, lack of respect the rule, e.g. jumping the queue - Communication difficulties.	- Increase service time
3-	*Illness Believes (additional factors*)	- Capacity issues. - Requires a long time to deal.

In the following, it may be necessary to provide an explanation for each of the highlighted factors, and to accordingly explain why these are recognised as affecting the delay of service and increasing patient waiting times.

2.5.1 Defensive Behaviours: Challenging and Confrontational Patients

As has been highlighted through the work of Duxbury (2000), the terms 'challenging' and 'confrontational' can be used interchangeably in order to emphasise the issue as providing a challenge to service providers. Essentially, this particular concept references those behaviours considered to be non-desirable to the surrounding community, and may take the form of anti-social, aggressive, disturbed, disruptive or violent behaviours [Duxbury, 2000]. Importantly, such behaviours are the most difficult behaviours to deal with. In actual fact, most researches known to have conducted works in the healthcare sector have shown that long waiting times, anxiety and fear are significant factors commonly creating challenging and confrontational behaviours, which cause glitches in the waiting system. Markedly, waiting can be associated with difficult patient behaviours: for example, patients may feel helpless waiting for an unidentified duration or an unknown result. Anxiety and fear usually lead to patients in waiting queues asking themselves many questions, such as, 'When will the wait end?', 'will service provider require anything of me?' and 'will others receive their service before me?' [Russell *et al.*, 2003].

Waiting for services whilst under pressure and experiencing fear can cause anxiety, subsequently leading patients to illustrate difficult behaviours. These types of behaviour are generated through the long waiting times, and are referred to as 'defensive behaviours', which contain those behaviours outlined in Table 2.1.

Through insight into such behaviours, we can state that the presence of one or all of these behaviours is a significant reason for disrupting the flux patient system and thus leading to the disruption of services. To illustrate this point further, it might be better to provide an example of delivering the service at the reception.

Previous studies have indicated that the mean time for a patient or his/her relative to give details to reception is 3.5 minutes, which statistically means that every patient should give his/her details in a time between 1.5 and 5.5 minutes; however, if there is a patient who illustrates challenging or confrontational behaviours, such as arguing or demanding behaviours, then this kind of behaviour leads to an increased time for giving details. Clearly, if these behaviours are repeated amongst many patients, the service of other patients will be delayed by hours.

2.5.2 Protective Behaviour: Unwillingness to Disclose Information relating to the Situation

Some patients of the ED show behaviours of unwillingness to disclose all information relating to their condition, which has caused their presence in the Emergency Department. This behaviour usually appears as a result of the following reasons (Sobolev *et al*., 2008):

1. Depression and grief resulting from the health status and lack of desire to speak or even explain their illness to the doctor or nurse.
2. The embarrassment of providing some of the information; in other words, the sensitivity of some issues.
3. The inability to explain because of a disability problem, such as speech problems, which may cause the patient to prefer silence.

Such behaviours facing medical staff in the Emergency Department may be considered to be one of the factors causing patient flow to be impeded, which subsequently causes delays in services within the department. To illustrate, a patient with this type of behaviour demands additional time for being dealt with, which then needs to be allocated by the nurse and/or doctor to convince and encourage the patient to respond and give the information needed so that the team can provide medical assistance.

The literature review shows that there is a lot of work to be done in order to simulate human behaviours in various arenas. In fact, the famous simulation used concerning human behaviours is DES. In the following section, there will be brief clarification of the use of DES in the simulation of human behaviour.

2.6 DES Technique

DES is recognised as one of the more valuable and widely accepted simulation forms, which has been implemented since the 1950s, as highlighted by Robinson (1996). DES may be described as a discrete, dynamic and stochastic simulation approach [Banks *et al*., 2005]. The simulation time, in the case of DES, is recognised as critical (dynamic model), with DES, as a stochastic framework, comprising a number of random input factors. Furthermore, DES is recognised as discrete owing to the fact that the state of entities in the system undergo change and modification at a discrete time [Carson, 2003].

2.6.1 The DES Modelling Technique

The DES modelling approach involves process flowcharts, which is the same approach implemented by various simulation packages, including Anylogic and ARENA, with the aim of solving various issues in the service and manufacturing sector. Process flowcharts centre on the interaction flow between block charts, entities and resources, as displayed in Figure 2.2 In the latter figure, Entities are created as a source block, which then shifts from one block to the next until they are removed from the system, as shown by the sink block. The DES framework utilises a top-down approach, which has facilitated viewing the model from a complete perspective, thus enabling the development of understanding the system performance as a whole [Banks *et al*., 2005]..

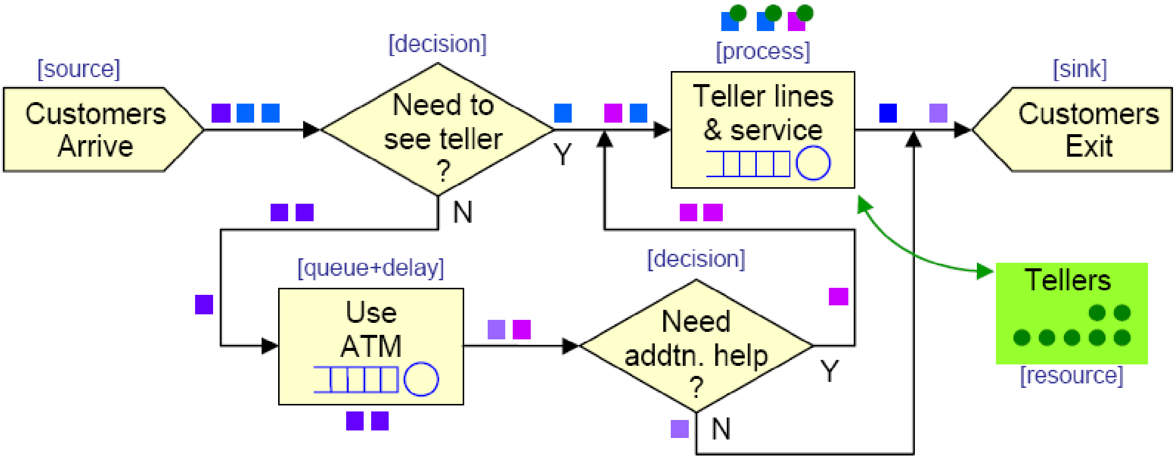


Figure 2.2 Discrete event model, Bank kiosk in Arena TM [Borshchev et al., 2004]

2.6.2 Advantages of DES

The benefits of utilising the DES approach as an instrument for delivering decision support across various applications have been detailed and documented across various sectors, including academia and the military, as recognised by Dubiel *et al.* (2005). Importantly, the DES framework offers the unique benefit of modelling a system in a sequenced form, which is one aspect of the processes in service and manufacturing sectors [Siebers, 2010].

One further benefit of this model is its propensity to be utilised in combination with other simulation techniques, including continuous simulation, for example [Zaigler *et al*., 2000], and agent-based simulation when examining more complicated systems [Parunak *et al*., 1998; Darley *et al*., 2004]. An aeroplane's movement is a good way of displaying this point: in the air, the craft changes its movement, which is a continuous process spanning a long period of time; however, upon arrival at the airport, the craft arrives at a discrete—or random—point in time.

2.6.3 Application Areas and Simulation Software of DES

Since the development of the DES model, its implementation has been wide-ranging, such as in the design and application of queuing systems [Komashie *et al*., 2005], business strategic [Hlupic *et al*., 2005], banking [Banks, 2000], healthcare [Werker *et al.*, 2009], managing inventory systems [Brailsford *et al*., 2007], manufacturing and distribution systems [Semini *et al*., 2006], transportation [Cheng et al., 2004], disaster planning [Mahoney *et al*., 2005], and military [Nehme *et al*., 2008] uses. Simulation packages are utilised widely, such as those of AutoMOD, Anylogic, ProModel, Quest, Simul8, Arena and Witness.

2.7 Human Behaviour Modelling

2.7.1 Modelling Human Behaviour using Simulation

As noted by Pew & Mavor (1998), HBR (Human Behaviour Representation)—also referred to as human behaviour modelling—is centred on the use of computer-based models, which are concerned with replicating the behaviours of people, either on an individual or a team basis. In the modern world, examination into the behaviours of people is well-documented across the world, and is considered and discussed from various perspectives. Simulation, in this sense, seems to be recognised as a preferential route in the modelling of human behaviours [ProModel, 2010]. This is owing to the assortment of different behaviours of people, which are accurately highlighted through the use of simulation [ProModel, 2010].

Throughout the course of the literature, DES is recognised as one of the most valuable approaches to modelling and simulating behaviours. Of those researches carried out in this arena, DES use is considered by various scholars [Brailsford *et al*., 2006; Nehme *et al*., 2008; Baysan *et al*., 2009]. Nonetheless, owing to the various dependent aspects incorporated within the DES framework, the pedestrian movement pattern throughout the course of the simulation is limited only to fixed, pre-arranged routes.

As well as modelling behaviours through the application of DES, there has been much research carried out into the various ways of predicting the effects of imperfect situational awareness in the context of military vehicle operators, for example. It is suggested that the DES framework can be adopted in an effort to understand human behaviours, such as through aligning the DES framework results with human subjects.

Overall, the researches considered in this paper suggest that DES is an appropriate tool when seeking to capture human behaviours, although the approach is more difficult when considering complicated behaviours.

Studies published on the application of simulations for simulating patient behaviours in the context of EDs could not be identified in specific consideration to the impacts of increasing LOS and WTs. Accordingly, this particular research aims to simulate patient behaviours during the period of waiting at ED facilities.

Moreover, studies concerning the application of simulation technology for analysing hospital issues, specifically in the context of Libyan hospitals, could not be identified. Accordingly, this research will be the first to be carried out in Libya.

Chapter 3 will provide a more in-depth discussion of the study methods utilised for gathering data, creating ED simulation frameworks and simulating patient behaviours.

2.8 Summary:

Previous works have shown that there is much interest in studying overcrowding in EDs as this leads to many other problems. Researchers have been successful in reducing overcrowding in many EDs through the application of different strategies. The literature review has shown that there is interest in utilising simulation technology to implement most of these strategies. Studies have demonstrated that the technique is very useful in cases such as observing the complex issues surrounding patient flow in EDs. Moreover, this technique is used to study some of the issues like resources requirements and equipment, ambulance services and human behaviour problems in healthcare.

Since the introduction of simulation, the development of several simulation packages has been aimed towards reflecting the scientific evolution that occurs in the simulation field. These packages have been used in different areas, with each of these packages providing their own advantages. Additionally, a great deal of work has been identified as considering simulating human behaviour in different sectors.

Chapter 3: Methods, Design and Implementation

3.1 Introduction

The previous chapters emphasised the importance of studying causes and effects of overcrowding on patient flow in EDs by using simulation technique which is commonly used in this type of investigation. The previous knowledge provides an initial awareness of patient behaviour in EDs as a significant factor affecting patient flow. To build on this knowledge, this study aimed to ascertain exactly how different kinds of patient behaviour effect patient flow and patient waiting time, along with which activities are more affected by patient behaviour, and the real delays caused by undesirable behaviour. In order to achieve this goal, ED TMC has been chosen to investigate this factor. This chapter includes a description of the general methodology used to address the research questions and explore the aims and objectives outlined in chapter 1 of this thesis. This chapter is divided into three main sections. The first section gives a description of the hospital that has been chosen as the subject of this study, and describes the ED of the hospital in detail. The second section describes the methods and tools that have been used to collect data from the field study, and their application to this study. The final section analyses the five phases that have been followed to build a DES model for the ED of the hospital under study.

3.2 Field study

As explained in the previous chapters, one of the major problems faced by the healthcare managers of various hospitals in Libya is the congestion experienced by emergency departments within the hospitals. To investigate this, one of the most important hospitals in Libya was selected as the subject of substantial data collection and observations that would allow the aim and objectives of this study to be achieved. The following is a summary of the hospital that has been chosen, with further detail of the emergency department, which is the focus of the attention of the study.

3.2.1 Hospital under study

Tripoli Medical Centre (TMC), an urban teaching hospital, is considered one of the most advanced health establishments in the provision of high quality medical care. It is also an advanced centre for medical education and training of the medical and para-medical staff, established under Directive No.169 of the year 2002, issued by the General People's Committee. TMC is one of the largest hospitals in Libya, located on the Eastern entrance of the city of Tripoli with a total number of 1,438 beds. This hospital includes an emergency department, one of the most important in the country as it serves the residents of Tripoli, an estimated population of over one and a half million.

3.2.2 The Emergency Department (ED) in Tripoli Medical Centre (TMC)

The ED in TMC receives approximately 85,000 adult ED visits per year. The ED service is provided on a 24-hour basis, led by consultants delivering specialised services, such as cardiology.

Once the patient arrives at the emergency department of TMC, regardless of their condition or degree of injury, the patient (or one of their relatives) goes directly to the reception area and gives the necessary information. Then, the patient is directed to a specific path according to their condition, as shown in Table 3.1. Sometimes these paths are intersected because of similarities between patients' conditions, creating complexities in the patient flow system within the ED. In depth discussions were carried out with the staff members in order to understand the different categories of patients. The patients are classified into five categories according to their condition:

1. Immediate cases, which are directed immediately to an urgent area comprising a resuscitation room, observations rooms and cardiology. This type of patient should be seen in less than 1 minute.
2. Emergency cases, which are directed to an urgent area. This type of patient should be seen within 1–14 minutes.
3. Urgent cases are commonly directed in the same way as emergency patients, but are seen within 15–60 minutes.
4. Minor cases (referred to as semi-urgent in some hospitals) are directed to the main ED area, and should be seen within 1–2 hours.
5. Non-urgent cases are sent to the main ED area and should be seen within 2–4 hours. Every patient (or their relative) has to register in at reception upon arrival at the ED.

Each of these categories reclassifies itself (is sub-divided) based on the patient condition in that category, from the most serious condition to the least serious condition. Table 3.1 provides more details about the sub-classified patients' categories.

Table 3.1. Details of the sub-classified categories.

No.	Patient's Condition	Level of condition in each category (sub-classified)	Path of each group of patients
1	Immediate cases	4 →	Passed away / stay in Resuscitation area
		3 →	Send to ward as inpatient
		2 →	Transfer to another health centre
		1 →	Sent to Immediate care area
2	Emergency cases	4 →	Passed away / send to Resuscitation area
		3 →	Stay in immediate care area (Observation room or Cardiology room)
		2 →	Transfer to another health centre or ward
		1 →	Send to waiting area to wait with Minor patients
3	Urgent cases	Commonly directed in the same way as emergency patients, but are seen within 15–60 minutes.	
4	Minor cases (trolley or walking)	one category →	Send to Examination area
			Transfer to another health centre
			Discharge
5	non-urgent cases (walking patients)	one category →	Send to Examination area
			Transfer to another health centre
			Discharge

3.2.2.1 Staff classification

In the Emergency Department, medical staff are divided into three Categories, juniors, seniors, and specialists. If the ED requires a consultation due to the complexity of a patient's condition, consultants are called from one of the inpatient departments of the hospital. Other staff categories in the ED of TMC include nurses, receptionists, and porters.

3.3 Data collection methods and materials

Qualitative research has been used for this thesis because of its suitability to achieve the aim of this study and analysis of the study's questions. To clarify what is meant by this, it is perhaps important to discuss the concept of qualitative research.

Some researchers defined qualitative research as ‘’describing social phenomena as they occur naturally. No attempt is made to manipulate the situation under study as is the case with quantitative experimental research’’ [Denzin *et al*., 1994]. Others have said that ‘’qualitative research is concerned with the opinions, experiences and feelings of individuals, producing subjective data‘’ [Hancock, 2002]. While others defined qualitative research as attempting to understand the unique interactions in a specific situation. The goal of understanding is not necessarily to predict what might occur, but to understand in depth the characteristics of the situation, the meaning brought by participants, and what is happening to them at that moment. The aim of qualitative research is to truthfully present findings to others who are interested in what you are doing [Patton, 2002].

Regarding the various definitions of qualitative research, it can be summarized that qualitative researchers consider gaining understanding of the situation through a holistic perspective. It studies the phenomenon through gaining experiences, opinions and feelings of individuals regarding all aspects of the subject under study. This represents precisely what is being conducted during this study. As described in the aim that has been shown in first chapter, this study is seeking to investigate the phenomenon of overcrowding that frequently occurs in EDs all around the world. Collating the opinions, experiences and feeling of ED staff, is the most educational way to understand the causes and effects of the overcrowding problem, along with analysis of the study hypothesis. In addition, observation of patients while they are in the process within the ED is the only way to collect necessary data to contribute to the understanding of the problem. Therefore, it can be said that because of the interpretive nature of this research, a qualitative approach is the most appropriate for this study. Qualitative methods were used to collect the essential data from the hospital under study.

Five primary qualitative methods were employed in this study: document analysis, designed time forms, questionnaires, interviews, and observations. These methods were implemented in an integrated fashion as the research process unfolded. The five research methods will be discussed separately in the following paragraphs.

3.3.1 Document analysis

Document analysis is an important indicator of events, processes and a source of information. ‘’Documents indicate, among other things, what an organization produces and how it certifies certain kinds of activities, categorizes events or people, codifies procedures or policies, explains past or future actions, and tracks its own activities’’ [Lindlof, 2002]. In this study, ED records for all patients (both electronic and manual) that have been visited the ED during May 2012 have been reviewed in order to obtain information that describes the ED visits and activities. The importance placed on ED records made it possible, and indeed necessary, to access all available documents in order to assure that no important data were overlooked.

3.3.2 Using the Time Form

Even though the electronic and manual records were reviewed, these records contained inadequate information with the capacity to demonstrate other aspects of the ED. For instance, patients' waiting times, and the time spent delivering the different care services. Therefore, the time form was designed to assist in the collection of important data for the study that was essential for building an ED simulation models. This information was actually related to the time spent waiting for the service (see Appendix A).

Three assistants were trained for three days, (28-30 April 2012), in the use of the form prior to the collection of data. They were also trained in observing the daily operations and activities within the ED. The method was centred on dividing patients into two categories.

The first category included patients with minor and non-urgent conditions who, upon arrival at reception, were asked whether they were prepared to participate. The researcher then explained the form prior to giving it to each patient (or relative) to complete before returning it upon leaving the ED (to be admitted, discharged, or referred to other centres). The second category concerned patients with extreme emergencies and urgent cases. The assistant's task was to observe, collect, and complete the form for this category.

Data were collected using the time form throughout the month of May 2012, from 8 am to 6 pm each day. The reasons for collecting data for one month are explained as follows:

- Historical data from previous years has been reviewed and found that there is no important variation.

- One month has been chosen as a period of study to avoid any seasonal variation.

3.3.2.1 Participants of the time form:

Although efforts were made to ask every patient admitted to the emergency department between 8 am and 6 pm to complete the designed form, several patients could not be included for various reasons (as described in Figure 3.1).

Altogether 7,100 patients were found to have attended the ED of the TMC. Figure 3.1 showed that more than one-third (38 %, n = 2719) participated in the research. In regard to the overall size of the sample, 38 % is considered to be a very good representation of population [Bartlett *et al*., 2001].

3.3.2.2 Data analysis for first and second methods

Data gathered by the first and second methods was entered into a Microsoft Excel spread sheet. Categorical variables were reported as percentages, however continuous variables were reported as means and standard deviations (SDs).

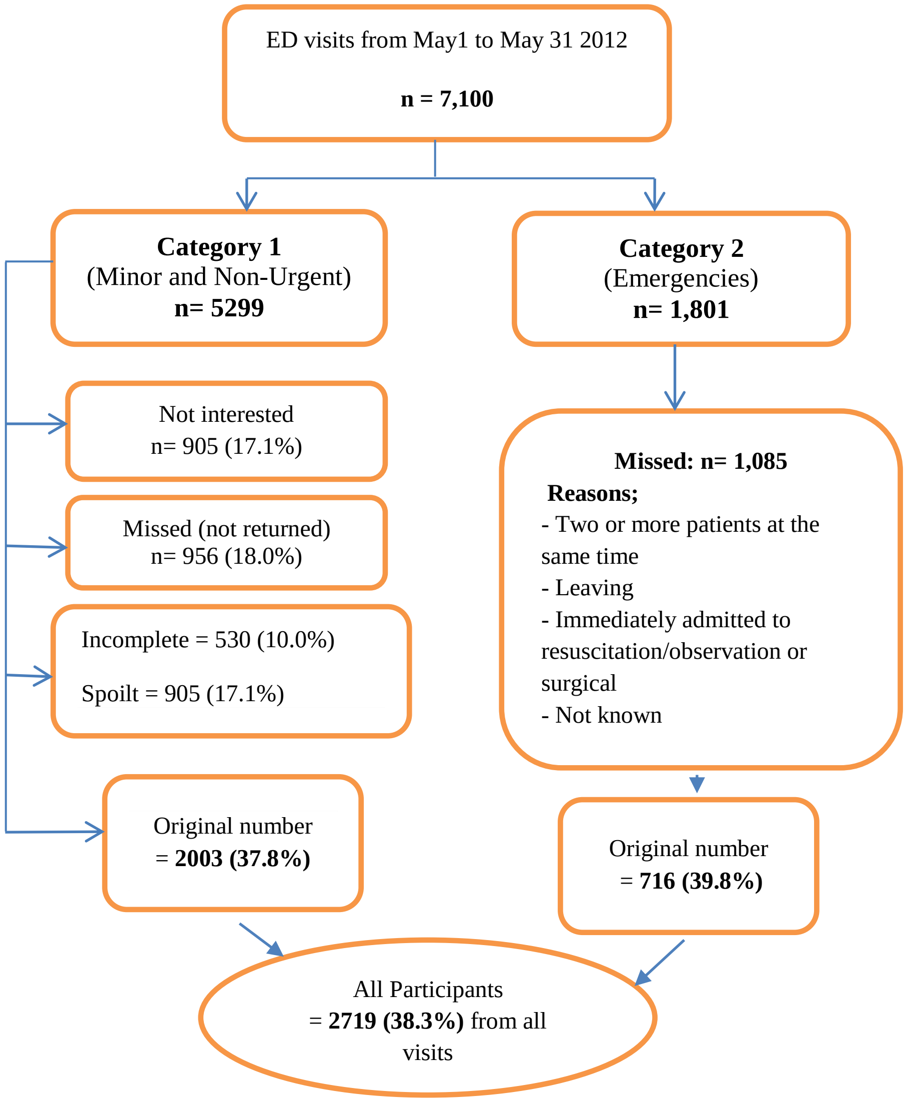


Figure 3.1 The patient recruitment flow diagram, May 2012

3.3.3 Questionnaires

A closed-ended questionnaire, See appendix B), is the third tool of data collection, targeted toward each doctor and nurse working in the ED of TMC during the data collection period. The purpose of the questionnaire was to obtain as many staff perspectives as possible. For this reason, the questionnaire was constructed with three different sections, which are given as:

a. The first section of the questionnaire includes questions aimed at the collection of data regarding staff members' opinions of the overcrowding problem, its causes, and its negative effects.

b. The second part of the questionnaire consists of questions dedicated to capturing the key factors of human behaviour deemed by the staff as having the capacity to disrupt the delivery of patient services.
c. The third section of the questionnaire has been allocated to indicate any further comments the staff want to make.

The questionnaires were personally distributed to doctors and nurses in early February 2012, and were carefully explained to the participants. The participants have been asked to return the questionnaires within fifteen days. A brief summary of the study's importance was also included with each questionnaire as an incentive for participants. The rate of response was approximately 75 % (9 out of 12 questionnaires) for doctors and approximately 84.6 % (11 out of 13 questionnaires) for nurses.

3.3.3.1 Data analysis for the questionnaire method

The first step for the analysis of data obtained through the questionnaire was coding. This is where the researcher encodes the data by giving each response a specific numerical code which is meaningful to the researcher, facilitating the extraction results into a software program. The analysis of the findings involved utilising the Microsoft Excel computer application for entry of all the responses into individual fields within a spreadsheet. The spreadsheet system enabled data to be collated into synthesised themes and graphs. It also permitted comparison of responses across categories. For instance allowing the responses of nurses to be extracted independently and compared to those of doctors respondents.

3.3.4 Interviews

Multiple semi-structured interviews have been conducted for various purposes. Semi-structured interviews were used because of the flexibility of being able to ask a set of prepared questions, while also providing the freedom for the researcher to ask additional follow-up questions as they see fit. The interviews consist of meeting with participants one on one (See Appendix C).

1- Interviews were conducted with 6 doctors and 8 nurses working in the ED of TMC. This was firstly to gain a deep understanding of all processes, rules and procedures that exist in the ED, and secondly to help ensure the validity and accuracy of the information that was collected by questionnaires. This method also enabled the construction of a conceptual model for the ED.
2- Interviews were conducted with 5 managers working in the ED of TMC in order to gather information about ED that would help to understand additional operational aspects.
3- Interviews were conducted with 4 receptionists in order to gather their opinions regarding the effect of patients' behaviour on reception services

3.3.5 Observation

Observation is a common method used by researchers interested in understanding different aspects of human behaviour. This method is often used when an understanding of on-going behaviour is required. For example this may entail observing officers conducting their business, observing parents dealing with interruptions from their toddlers, observing teachers and/or students during classroom, observing people in crowding places, or observing people dealing with emergency situations. From the standpoint of researchers it has been said that "the observational method of research usually involves people watching people doing things. Often when people in public places do things in full view of many other people, it can be considered that they are accessible for live observation without getting any permission" [Olsen, 2012]. However, in many research studies the use of observations, conversations, questions, statements, and sometimes interviews are combined with observations. It is considered the best way to collect explicit and quantifiable data [Flick, 2011].

Based on the above, in this research, observation was chosen as a method to gather data about human behaviour. The aim of this phase of the study is to obtain evidence to prove the contribution of unacceptable human behaviour on delays in service throughout the ED of TMC, and to know the exact added waiting time that occurs due to patients' difficult behaviour.

3.3.5.1 Observation Design and participants:

Observations targeted minor and non-urgent patients who visit the ED of TMC from 26th April, 2012 to 31 May, 2012. These two categories have been selected to be observed based on the results of the questionnaires and interviews that were aimed at doctors and nurses, who assured that minor and non-urgent patients are the only two categories that have difficult behaviour which lead to confusion in patient flow throughout the ED.

The researcher worked very closely with three assistants. The assistants were fully trained for two weeks to show them how the observation checklist worked and how it should be completed in the most effective manner. Observations were carried out on three key areas as follows; the reception, the triage room and examination room.

The results of the interviews and questionnaires identified many behaviours that were believed to be the reason behind confusion in patient flow through the ED. These behaviours; i.e. confrontation, challenges, passivity and illness belief were given the highest of consideration when carrying out the observation and in the development of the checklist, (See Appendix D).

Another important step in this phase is to determine the sample size required for observation. The population i.e. visitors number of minor and non - urgent patients during May, is not known precisely, however, it ranges between 4000 and 6000 based on population size for the previous months of the study i.e. Jan 2012 - April 2012 .

To find out the appropriate sample size, the Cochran's sample size formula for categorical data has been used [Cochran, 1977]. it is given as follows:

$$n_0 = \frac{(t)^2 * (p)(q)}{(d)^2}, \quad n_0 = \frac{(1.96)^2 * (0.5)(0.5)}{(0.05)^2} = 384$$

- Where t = value for selected alpha level of 0.025 in each tail = 1.96.

In this study, the alpha level of 0.05 indicates the level of risk the researcher is willing to take that the true margin of error may exceed the acceptable margin of error.

- Where (p)(q) = estimate of variance = 0.25.

The research will identify some variance, as the research has not actually administered the survey yet, the safe decision is to use 0.5 – this is the most forgiving number and ensures that the sample will be large enough.

- d = acceptable margin of error for proportion being estimated = 0.05

To calculate the final sample size, Cochran's correction formula has been used. The calculations are as follows:

$$n_1 = \frac{n_0}{1 + n_0 / \text{population}} \quad , \quad n_1 = \frac{(384)}{1 + 384/6000} = 361$$

Where, 6000 is the upper limit of the number of patients (minor and non-urgent) per month, as confirmed by the data of the previous months of the study.

In addition, researcher interaction consisted mostly of casual conversations with participants during observation. These conversations were recorded in the same checklist of each conversation.

Patient behaviours were discussed and defined by the researcher with all members taking part in the research prior to the start of study, and a pilot study was conducted to ensure integrated consistency.

All the patients and only the patients in the waiting room area were observed, no visitors and accompanying family members are observed. Staff members were also excluded from the observational study.

3.4 Roadmap towards building the implementation phase of the simulation model

This section of the chapter describes the methodology that has been used to simulate patient flow in the emergency department at TMC. The methodology for building an ED model involves five standard phases but with somewhat unclear boundaries between individual phases. The result of one phase can force the modeller to revisit the previous stage. The simulation modelling works on an iterative approach between phases and within each phase. Figure 3.2 shows all the simulation phases implemented in order to build the ED model.

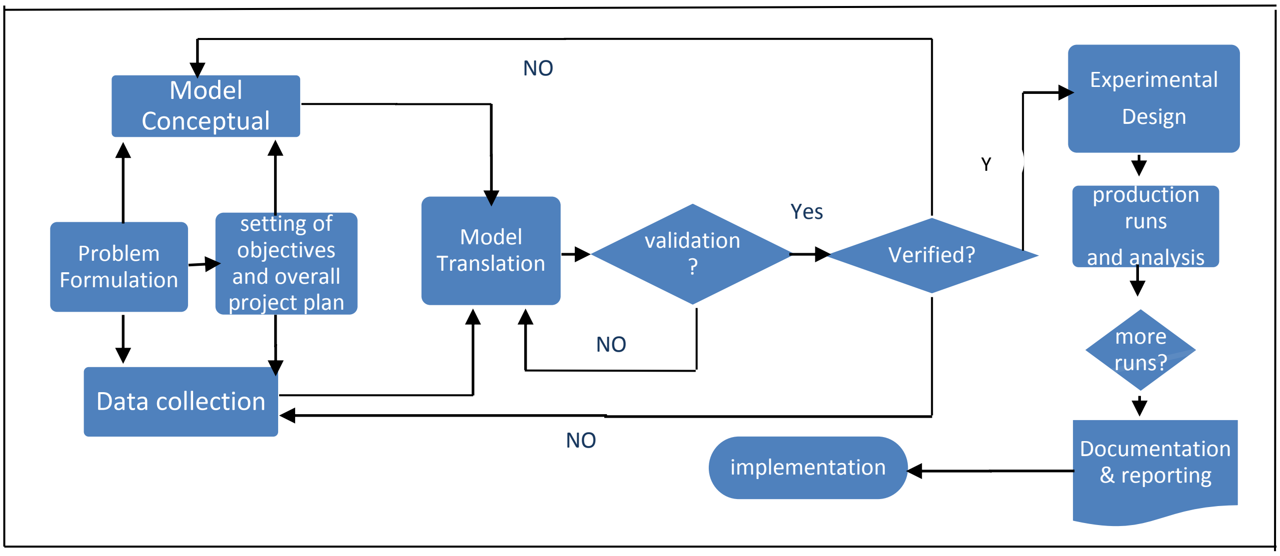


Figure 3.2 The project modelling phases

3.4.1 First Phase: Problem formulation

Problem formulation has been illustrated in detail in the problem statement and research questions section of Chapter 1 of this thesis. However, it may be useful to recall the most important questions guiding researchers to the critical data that should be collected. The following summarises the most important research questions.

- Are problematic patient behaviours directly responsible for affecting the patient flow system, and subsequently inducing healthcare service delays?

3.4.2 Second Phase: Data collection

Data collection in this section refers to the data collected for the purpose of simulating patient flow throughout the ED. In this phase, discussions conducted with ED staff allowed the study to reach the following goals:

Understanding of processes and procedures that take place in the ED, allowing the possibility of representing them.

- Understanding of the patient flow system within the ED.

The data collection phase aid the start of the third phase of building the ED model, developing the conceptual model.

3.4.3 Third Phase: The conceptual modelling of the system

At this stage, a paper-based model is built. The model represents the number of various activities possible for patients while they are in the Emergency Department. There are many activities, leading to a complex network of patient flow. The complexity of the patient flow network for the different categories of patients can be seen in Table 3.2.

Table 3.2. The complexity of the patient flow network within the ED.

Patient	T	R	O	E	X-ray	Lab	CT	MRI	Ultra	D	Tr	Ad	Dg
Reception	X	X											
T		X	X	X	X	X							
R			X	X	X	X	X	X	X	X	X	X	X
O		X		X									
E		X			X	X	X	X	X	X	X	X	X
X-ray		X				X	X	X	X	X	X		
Lab		X					X	X	X	X			
CT		X						X	X	X			
MRI		X							X	X			
Ultra		X								X			
D		X									X	X	X
Tr		X										X	X
Ad												X	
Dg													X

*T = Triage, R = Resuscitation, O = Observation, E = Examination, D = Diagnosis, Tr = treatment, Ad = Admission, Dg = Discharge.

The links of the network can be identified from the above table by first looking at the left hand column. The "X's" in a given row correspond to the linking locations. To illustrate, from Triage (T) a patient may be sent to Resuscitation (R), to have Observations taken (O) or to the Examination area (E), X-ray area, or Lab.

3.4.4 Fourth Phase: Building the DES model

In this stage, the conceptual model of the study is transferred to the computer by using Witness Simulation software developed by Lanner Group due to the capability of the software to develop DES. Once the simulation software has been selected, the next stage is to build and program the simulation model. The structuring of computer model includes four phases defined as the assumption, definition, detail and display phases.

The DES model is firstly developed to replicate the existing TMC ED and all the processes involved in patient processing from admission through to discharge. Once a logical representation is achieved, the DES model aids greater understanding of the causes and effects. This develops opportunity for changes to be applied and further developments to be implemented.

3.4.4.1 Assumptions

In order to replicate a true to life system, the simulation is based on a number of assumptions which aid model building and to improve understanding by simplifying the model. A set of assumptions are made from the research and further assumptions are set to enable a logical processing of elements aided by expert consultation as follows:

- The ED categorises arrival of patients into five types of case: immediate cases, emergency cases, urgent cases, non-urgent cases and minor cases.
- Patients arrive according to statistical averages derived from the research.

- All the labour requirements, i.e. doctors, physicians, nurses and consultants are readily available and work for 24 hours continuously. Hence no shifts have yet been applied to the constructed model.
- All ED staff are fully qualified and capable of handling all medical problems.
- There exists no shortage of medical supplies.
- Patient behaviour is not considered, i.e. patients cannot leave the system abruptly or otherwise cause problematic issues leading to further disruptions.
- Unexpected disruptions are not considered, i.e. power cuts etc.
- The model will only run for a total of 1440 minutes, which equates to a whole day (24 hours).

3.4.4.2 Defining Physical and Non-Physical Elements:

The witness programming software uses basic elements. These elements should be defined at the time of model construction. In the project, elements are characterized into two types: physical element and non-physical element. Each type is defined as the following:

Physical elements:

a- **Entity**: The entity represents parts that flow through the model. Example, patients arriving at the entrance of emergency department, move forward to be examined and treated by the doctor. Following are other examples of entities:

- A project progressing through a large corporation.
- Calls being received and answered in a call centre.
- Application forms being processed from within an office.
- People moving through shops, etc.

b- **Activity**: An Activity is a station where a task is completed, for example, the location where the patients come to register, i.e. reception counter and treatment rooms. Other examples include:

- Numerous typical stages of business processes.
- The sales counter in a shop.
- Handling of an email enquiry.

c- **Queue**: A Queue is a point where an entity is held until it is required or needed, or even a point where a desired waiting time can be applied. For example, once the patients have registered, they have to wait till the nurse is free to examine them. They are held in a queue at a room called as waiting room. It is the required time needed for the completion of previous job. Other examples include:

- Files waiting to be processed.
- Customer in a queue waiting to be served.
- Materials waiting for other materials to arrive.

d- **Resources**: The labours required to perform a desired activity. They are often important and necessary to perform certain operations. These can be people or physical equipment that may be required by other elements for processing at the time of simulation. Example, the receptionists, nurses and doctors required to carry out the task.

- Operatives.
- Technical staff.
- Managerial staff.

e- **Conveyor**: A transporting or moving element, that enables an entity to move from one location to another continuously, for example.

- Parts moving on a conveyor belt.
- Raw materials moving from one machine to another.
- People moving on escalators.

Non-physical elements

a- **Variable**: A variable contains a value (or a set of values, if the quantity of the variable is greater than 1). When a variable is defined, its data type must be specified indicating the type of data contained i.e. integer, real, name or string.

Different types of variables are:

- Integer – it is a variable containing a whole number.
- Real – it is a variable containing a number with a decimal fraction.
- Name – it contains a WITNESS element name.
- String – it is a variable containing a string.

b- **Attribute**: An attribute is an element that represents a characteristic of an individual entity, resource, activity or carrier element. For example, an attribute can be used to characterize colour, size, skill, cost, density, voltage or serial number. The attribute is used to represent different conditions of emergency in which a patient come to department.

3.4.4.3 Details of Each Element

Placing the details of previous element is the next stage. Details help in building a logic model logically connecting the elements to one another as in reality. For example, during the examination process, a doctor or nurse must remain with patient in an examination room for a period of time. The following is a brief explanation of various details entered into different types of element definition:

Details of Physical Elements:

a- Entity: details of arrival time, condition of patients, and the location where the patients must go after entering ED is entered, See Figure 3.3.

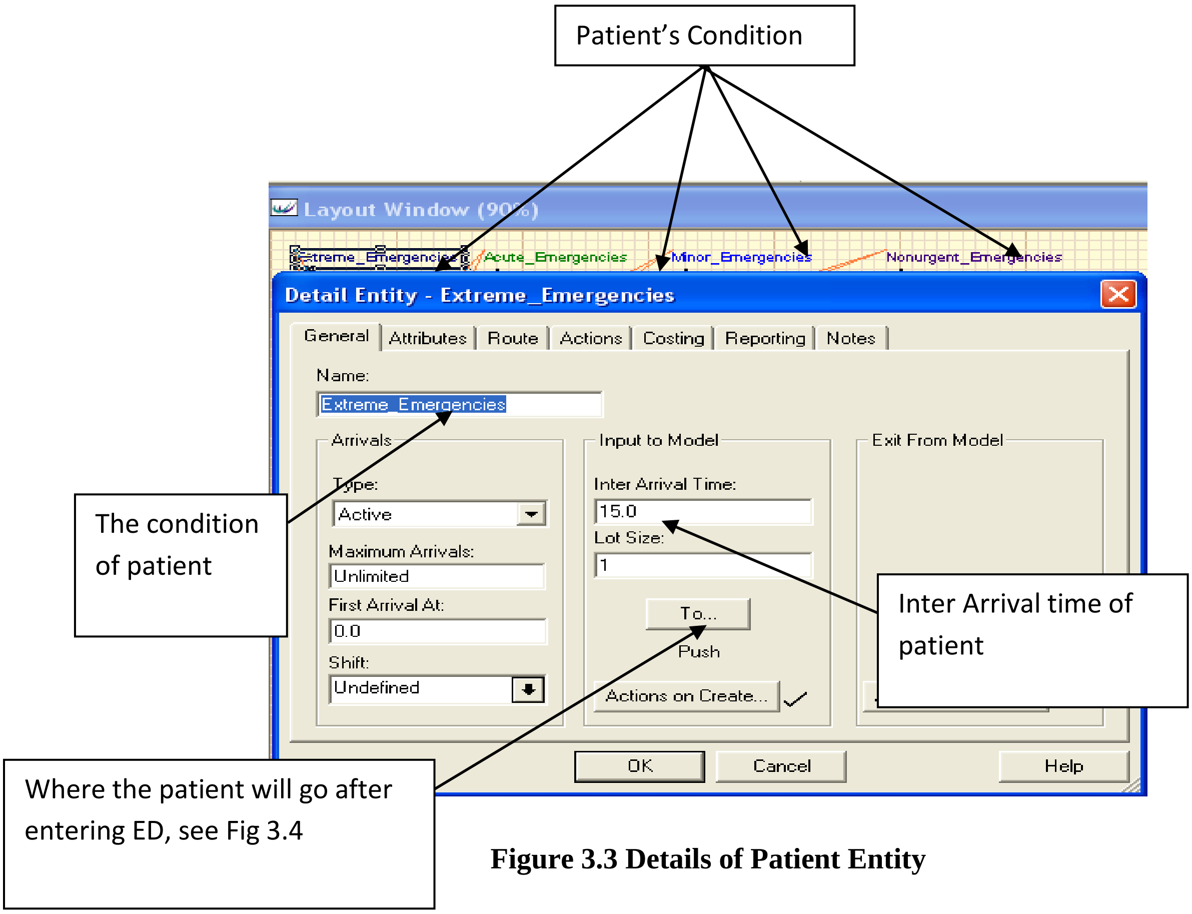


Figure 3.3 Details of Patient Entity

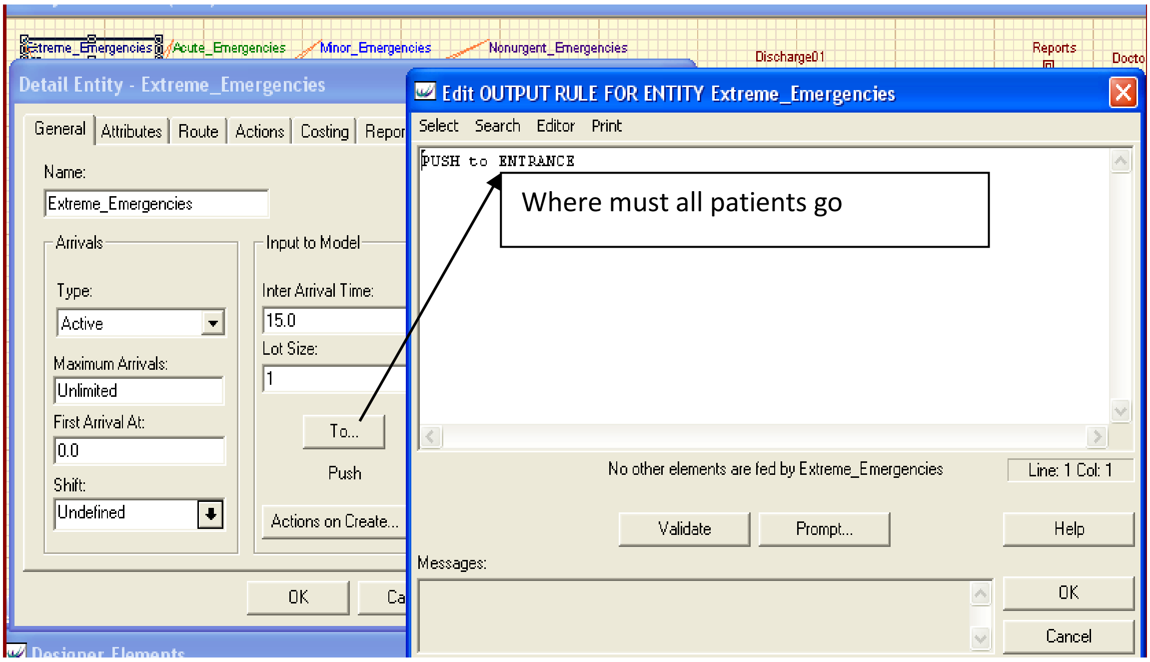


Figure 3.4 Shows where the patient will go after entering ED

b- Activity: all details are added for individual activity element. The information mimicking real life in the emergency department has been entered for each activity. For example, in the reception activity, the entered information includes number of reception activities of the emergency department, location of the patient and the distribution that used to determine the length of time which the process takes. Figure 3.5 shows the screen used in the witness program with all the details regarding the activities of reception.

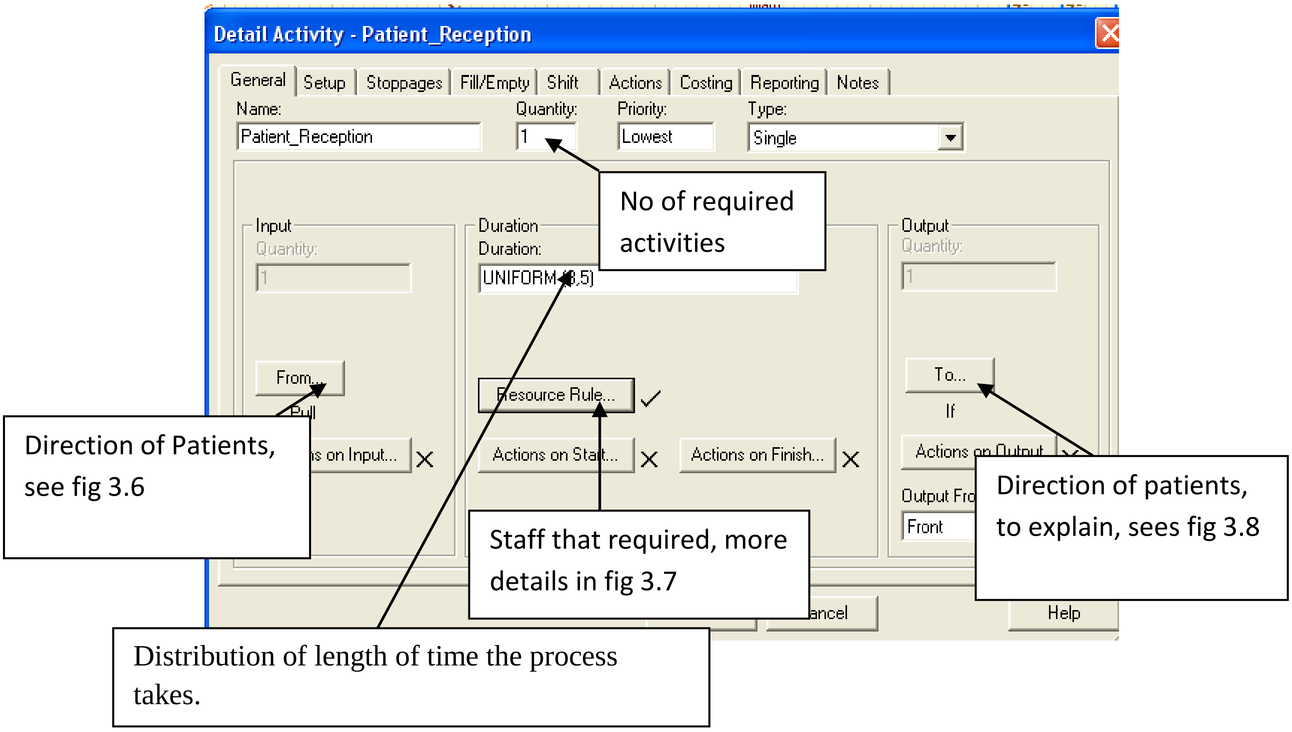


Figure 3.5 Details of reception activity.

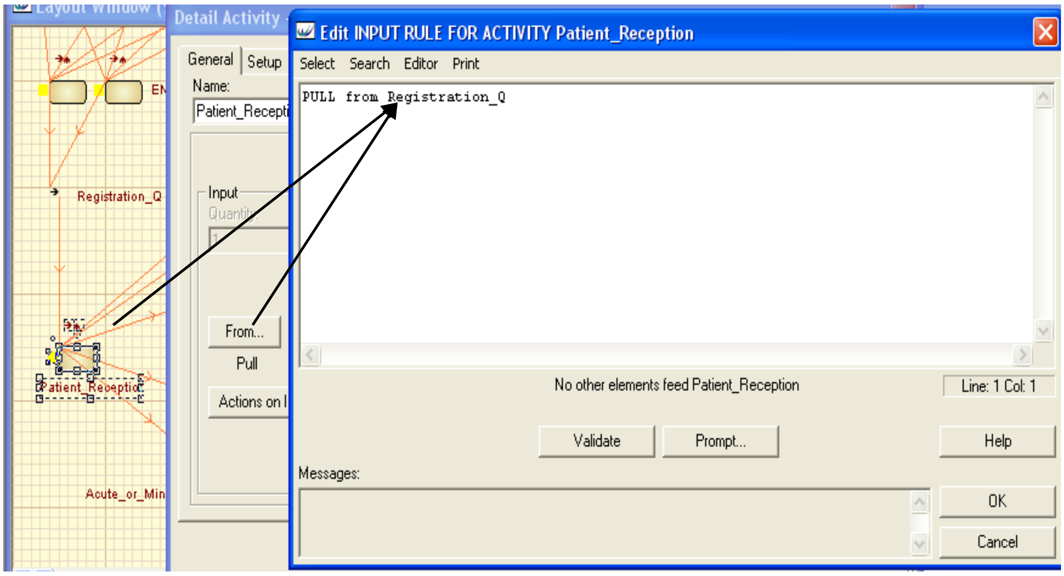


Figure 3.6 Direction of patients (input rules for reception activity).

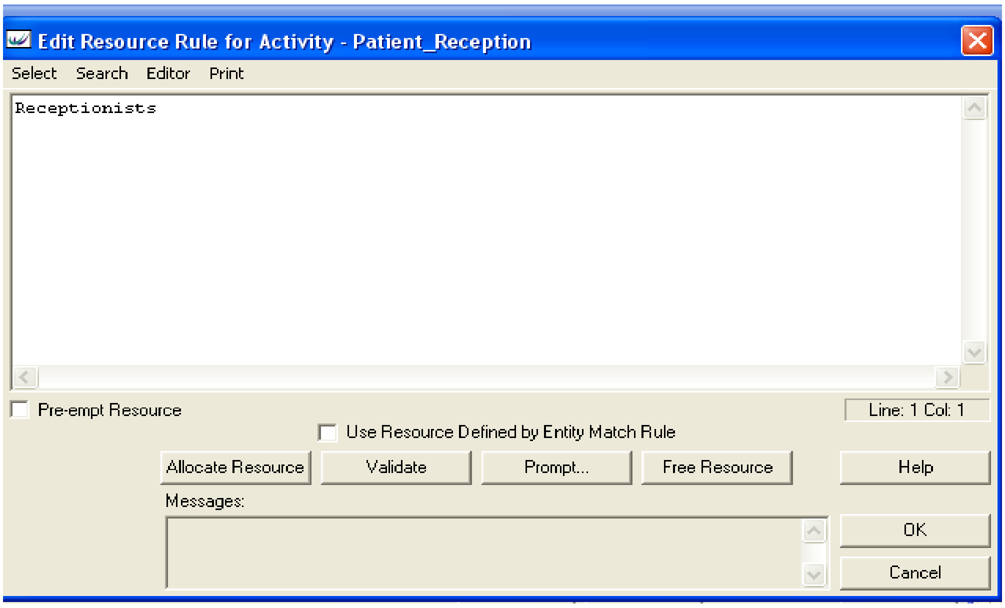


Figure 3.7 Details of Staff required (Resource Rule).

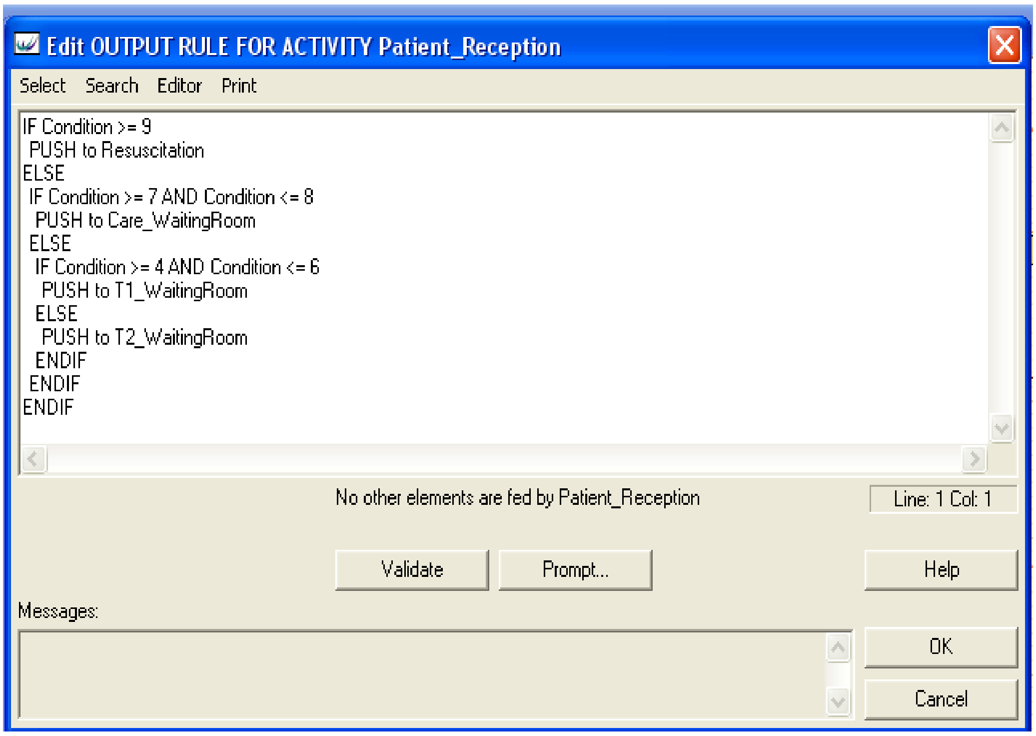


Figure 3.8 Direction of patients (output rule for reception activity).

c- **Queues:** Emergency Departments are characterized by queues network pushed by patients while waiting for service. To build the model, details of the capacity of individual queue must be introduced which is very essential. The present model, details the capacity of individual queue within the Emergency Department.

d- Resources: Doctors, nurses, and other employees in the emergency department are represented with the place of work, See Figure 3. 9.

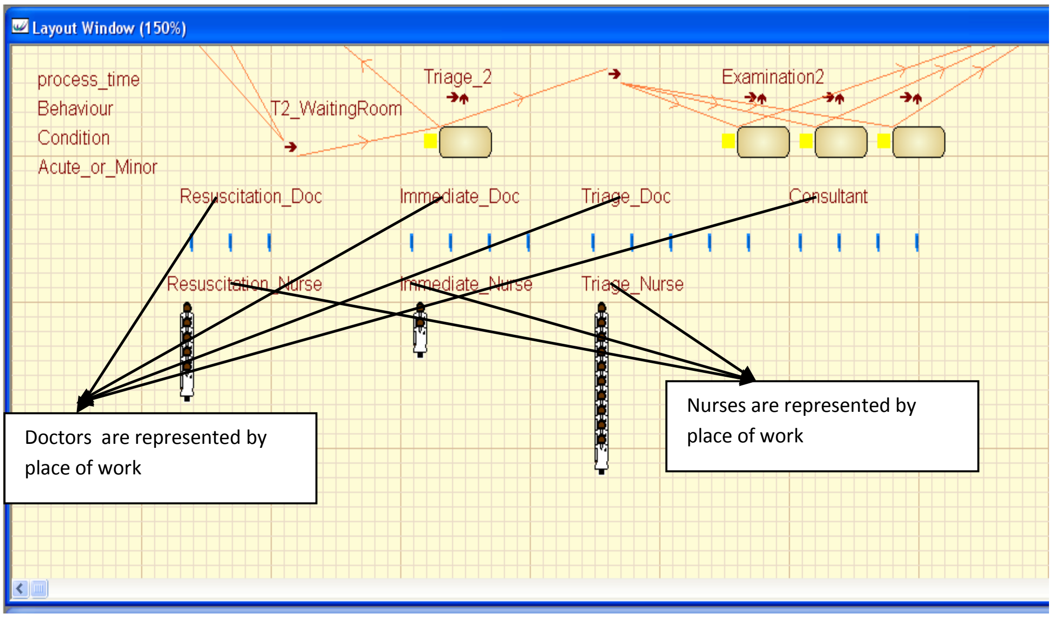


Figure 3.9 Representation of staff by their work place

Details of Non-physical Elements:

a- Dummy activity: A Dummy activity is not physical processes in reality. It is not associated with cycle time or resources and do not form part of the simulation display. It is included in the model to facilitate logic which is very complex to perform within the constraints of the physical elements.

b- Attributes: As patient moves from stage to another within the department, attributes on the patients can be changed which indicates the stage they are at in the process and the decisions that are made with regard to patients condition. To illustrate, After examination a doctor may decide to send the patient for a Lab test which results in the activation of appropriate attributes of the patient being directed to the Lab queue instead of the treatment queue.

3.4.4.4 Distributions used in the model

The following is a brief clarification of the methodology that has been used to choose all distributions that have been used in the simulation models for TMC ED, and applied to all existing activities in ED. Where the methodology was based on:

1- A distribution fitting software was used to transform raw data into a single distribution that best represented the collected data. The aim of distribution fitting is to find the most suitable distribution use based on the collated data. Input data analysis was validated by using INPUT ANALYZER of ARENA. Through this test, a set of distributions have been adopted for each activity according to the data collected i.e. uniform, triangular, normal, beta and negative exponential. For example, figure 3.10 show the result of input analyser of arena to capture suitable distribution i.e. Beta, for triage service time with the presence of difficult behaviour factor.

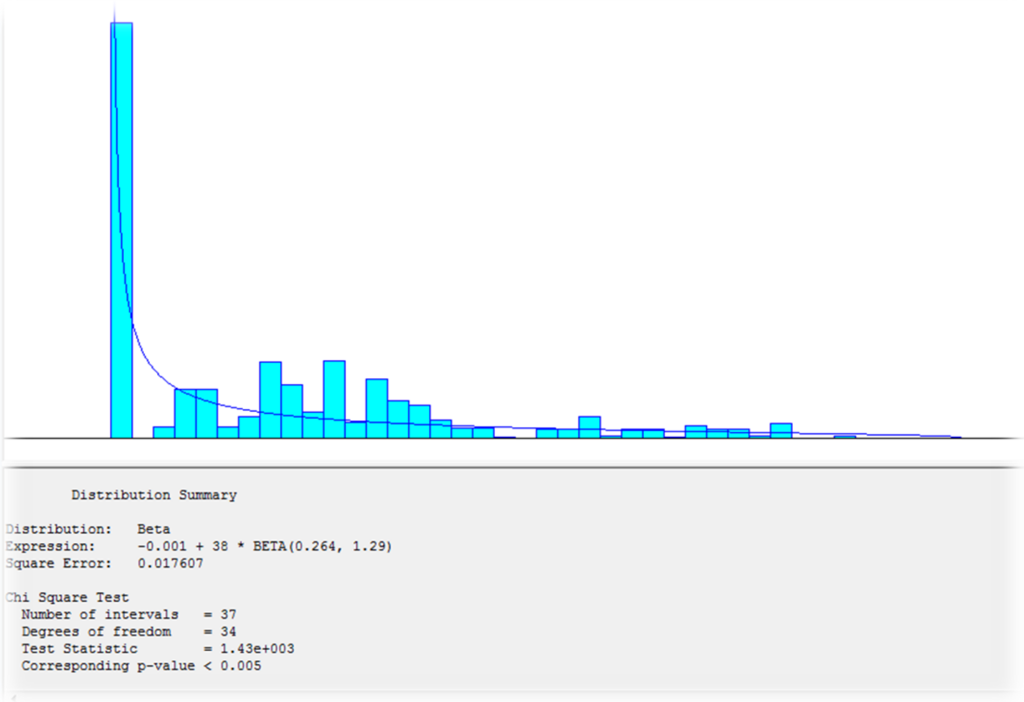


Figure 3.10 Input analyser of arena result

2- Knowledge of appropriate types of distributions that represent EDs activities, based on several previous studies that specialised in developing DES models of EDs. For example, using Poisson distribution to simulate patient arrival [Ahmed and Alkhamis., 2009].

3.4.4.5 ED Activities :

The ED consists of various activities to provide a range of emergency services, it is important to explain what are these activities and how they work, and the purpose of their presence in the ED. The following table summarises the ED activities that have been simulated to build TMC's ED.

Table 3.3. Activities that have been simulated in the TMC's ED

No.	Location and Place	Purpose
1	Entrance (E1, E2, E3, E4 and E5)	This location has no distribution as it only represents patients walking through the entrance. There are however 5 entrances to enable all 5 types of patients to enter simultaneously.
2	Patient Arrival	This variable describes how patients arrive to the ED.
3	Patient Reception	To register all details of the patients conditions.
4	Triage	Where the minor and non-urgent patients are sent in order to be prepared for examination.
5	Examination	Where patient examinations take place, from simple blood tests to a range of other examinations.
6	Lab reception	This is where all patients need to hand in all documentation with regard to emergency and medication notes.
7	ED Urgent Area	Where the urgent and emergency patients go, after which they are sent to cardiology or else observation according to their condition and requirements.
8	Enter Cardiology	Where the patients meet up with cardiology doctors for a review before entering the cardiology area.
9	Cardiology	This is where the cardiology care takes place.
10	Exit Cardiology	Where the patients have to see a doctor before being discharged from cardiology.
11	Resuscitation	Patients are directly sent here to be resuscitated as their case requires immediate care.
12	Observation Consult	Where the patients meet with observation consultants for a review before entering into the observation area.
13	Observation	This is where all the patients are observed for an array of different purposes.
14	Observation Exit Consult	Patients have to see a consultant before they can be discharged.
15	Lab Department	The duration Laboratory takes.
16	X-ray Department	The duration X-ray takes.
17	CT Department	The duration CT scan takes.
18	MRI Department	The duration MRI scan takes.
19	Ultra Department	The duration Ultrasound scan takes.
20	Diagnosis Review	This is where a review is conducted with a doctor and a patient after they have been through the necessary scans.
21	Treatment	The final stage before discharging the patient from the ED is to discuss the agreed treatment required.

4.4.4.6. Display

After the elements have been defined and detailed, the display is established, which is a essential part of Visual Interactive Modelling (VIM). The display is designed to mimic the real life physical representation of the system.

Each entity and activity is displayed, making queues and processes within the department visible to the user. The icons used in the display can be user defined.

3.4.5 Fifth Phase: Model Validation and Verification

The verification and validation processes are performed in order to produce a good representation of real world service systems. The following sections will explain the methodology that has been used in this thesis to carry out model verification and validation:

3.4.5.1 Model Verification

Verification is the process by which it is checked that the developed simulation model performs as proposed**.** Model building should be carried out correctly according to the real time system and its assumptions. Verification ensures that a model is constructed correctly by examining the logic of the anticipated mode [Banks *et al*., 2010; Eng, 2011; Sargent, 2011].

Guidelines for the proper methodology in the verification of the simulation model are provided in Law, [2007] and Banks *et al*., [2005].

The following verification techniques have been used to ensure the proper conversion of the patient processes to the study's simulation model:

1- By starting with a simple framework, the levels of detail were added and debugged successively until the model represented the system under study to a satisfactory condition.

2- The computer program was written and debugged in modules or subprograms.

3- The conceptual model is checked by an expert in the simulation software being used in order to ensure a accurate representation is achieved.

4- The simulation was run under a variety of settings of the input parameters to examine the rationality of the model output.
5- Model output was compared to historical data and expert opinions to ensure accuracy.
6- The simulated system was observed at each process and compared with hand calculations to ensure that the program operated closely to the real time system. This process is called "trace" and allows the modeller to inspect any model object during the model execution.
7- The model was set using simplifying conditions to observe its true characteristics or to simply compute and compare its results.
8- The visual animation of the simulation model output was observed to assure patient flow represented the actual systems.
9- The mean and variance for each simulation input probability distribution was computed for means of comparisons with the historical mean and variance to ensure that the values were being correctly generated from the distributions.

The simulation package, Witness Simulation, was used as its built-in features minimised the number of probable errors occurring during the model's construction. The package also comes with a feature program called WITNESS scenario manager which enables stochastic analysis's to be carried out.

3.4.5.2 Model Validation

Validation is very closely connected to if not interlinked with the verification process. Model validation is an important process in increasing one's confidence in a model, which is concerned with comparing the model to the real time system and ensuring that it behaves with sufficient accuracy to achieve study's objectives [Edward *et al.*, 1996].

Methods for increasing the validity and reliability of a simulation model are provided in Law, [2007] and Banks *et al*., [2005]. Throughout the design and development of the simulation model, several methods were implemented to ensure validity of the model. The multistage validation method, as described by Sargent was used as follows [Sargent, 2009]:

1- **Subject Matter Experts (SME) validity in a model:**

Ensures the researcher obtained a complete and accurate set of information from SME's in order to construct a logical model. By liaising with SME's, the model logic and assumptions were reviewed before and after programming, and model credibility was increased. For this thesis, SME validity was accomplished by observing the actual system and by obtaining historical records to validate results obtained from the simulation model. Further expert opinions where obtained from staff with five years experience and attitudes within the TMC .

2- **Quantitative methods used to test the model's assumptions:**

Although, SME's were used to validate the assumptions to ensure reliability, further quantitative methods i.e. model results were used to finalise the validity of the results. This meant observing the model reaction and distribution according to the SME's opinions. This examines the assumptions made throughout the model's design and development processes. There are a number of ways to achieve this target. Input data analysis was validated by using goodness-of-fit tests carried out by software named Arena input analyser.

3- Evaluating inputs and outputs:

Evaluating the inputs and outputs uses to measure the model's capability to forecast the future behaviour of the actual system. This was achieved as the model's input data set provided output data which closely resembled the expected output data from the actual system.

The results were then compared to data derived from research i.e. historical data and collated research, which was obtained from the same time period. The results of the empirical distributions were compared to the information gathered from the SMEs. These comparisons helped validate the simulation model where a consensus could be seen in matching logical results.

The simulation model data input was also compared to the model's patient arrivals against the actual patient arrivals as gathered from hospital records. The LOS and WTs from historical records was used to compare with the simulation model output.

Key performance indicators (KPI) were used to compare and contrast results and as the logical DES model developed in stages. A visual observational evaluation of how the system performance measure changes dynamically over time aided greater understanding.

4- Stochastic approach

To evaluate the output data of the simulation model with the research data using a stochastic analysis, the model was replicated 100 times to derive an ensemble of results. Confidence intervals of the simulation output was taken at 95 per cent confidence level ($\alpha = 0.05$). The patient overall LOS, classified by patient condition was used as the measure of the model validity in the validation process. Checking these time periods is not only helpful in validating the model but also useful for future improvement efforts.

The data was recorded on a daily basis, 1440 minutes, the simulation model was repeated for a total of 100 times with each replication using a different random number stream to test the variance and find 95% confidence interval. This enabled a thorough stochastic analysis to be carried out and analysed.

3.5 Summary

This chapter depicts the transformation of real life data into the simulation model to represent the current operating processes within TMC ED. The objectives of all the models are to represent reality, which closely reflects the real system in order to observe these interactions and see the cause and affects. The methodologies used in attaining accurate data and their application is highlighted i.e. data collection, research methodology, input data analysis, verification and validation – provided a structured process to construct the simulation model.

Chapter 4: Modelled System

4.1 Introduction

Chapter 4 introduces some further developments of the model and discusses details of the model diagnosis. This enables a deeper understanding and highlights the reasons for certain entities and elements of the model being present. Their purpose is discussed, along with what they intend to replicate in terms of historical data and expert knowledge in relation to the techniques used. This chapter brings forward all the aspects of model building from chapter 3. Bayesian Network Modelling aided by Hugin software is introduced, the chain rule is explained in greater detail and the application of the Bayesian approach to the simulation model is discussed. Live screen shots are used to improve clarity of explanation, and logical programming commands and functions are explained in greater detail with reasoned justification. After identifying the required elements of the Witness software and their functionality in relation to the model development, the simulation models were then constructed. The Actual model and the Bayesian model are both discussed in detail in order to develop a clear understanding of the difference in the two models, their purpose and their approach.

4.2 Bayes Theorem Introduction

Bayes theorem is based on the Bayesian Network (BN) modelling that has been used abundantly throughout the EDs in order to compute the most accurate representation of a probability based on influencing factors [Friedman et al., 2000]. A study that has been conducted in the U.S., Pittsburgh used Bayesian network to assess factors that affecting performance of influenza detection in Emergency department [Ye. *et al.*, 2014].

Another study that has been done in Copenhagen, Denmark aimed to predict the adverse outcomes in the acute cases of adult patients who were admitted to hospital. The researchers built a Bayesian network model by using already existing data to estimate the risk of adverse outcomes, as well as to serve as a decision support system in assessing future outcomes [Barfod *et al*., 2013].

Bayesian Network modelling has also been applied to administrative data, where it has been used to provide the descriptive models to determine the differences in the patient characteristics, process and results of care between the ED triage categories of patients admitted from an ED with a Stroke Care Unit. The result of this study showed the applicability of BN to evaluate the current triage practices and subsequent impact [Nadathur *et al*., 2011].

In the current study, BN is used to populate the conditional and marginal probability based on the influencing factors of patient behaviour types i.e. the probability of a difficult patient or difficult behaviour. Patient behaviour types have been categorised into four types as discussed in further detail within this study. Therefore, these four behaviour types will be apparent in all patients, however the BN allows these four types of cases data to be collated in order to derive a subsequent outcome of either difficult or normal based on the influencing nodes i.e. behaviour types.

The BN modelling has been used as it is based on a unique formula that can be integrated within the Discrete Event Simulation (DES) models to enable a dynamic platform that consists of ever changing behaviour types that are considered on an individual basis displaying different results for each patient replicating a true to life system. The BN modelling is also the most accurate procedure to determine the probability of a difficult behaviour rather than relying on a total random as it takes into consideration historical data and the current behaviour types which collate to give a single outcome [Friedman et al., 2000].

In order to understand this process thoroughly, it is critically important to understand the *Bayesian Network Modelling* process, which uses the Chain Rule and other key variables.

In order to find out the areas in which the most problems are likely to occur within the ED TMC, Bayesian network models are developed.

A brief overview of what BN modelling is and how it works with the aid of the Hugin software is given, and more importantly, the methodology that should be used when constructing Bayesian network models is also given.

A BN model is developed for the 3 different areas within the ED and the results are shown below, indicating the area which has the highest probability of difficult patient behaviour.

4.3 Bayesian Network Modelling

Bayesian network modelling (BN) relies on Bayes' theorem as a rule of inference, i.e. observations and data are used to update the uncertainty of any parameter or node in a BN which in most cases is derived from historical data, field research and expert consultations. Inference in a BN refers to the computation of the conditional probability for some variables given any available information (evidence) regarding the other variables.

Equation 4.1 relates to the conditional and marginal probabilities of two randomly occurring events, which calculates the posterior probabilities given observations of the two events. If events A and B are considered where event A is the influenced node and event B is the influencing node, Bayes' theorem states :

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$ (Equation 4.1), [Bolstad., 2007]

where:

P(A) is the prior or marginal probability of A.

P(A|B) is the conditional probability of A given B.

P(B|A) is the conditional probability of B given A.

P(B) is the prior or marginal probability of B.

This theorem forms the basis of Bayesian network modelling. A Bayesian network (BN) is a directed acyclic graph (DAG) that encodes a conditional probability distribution (CPD) at the nodes on the basis of the arcs received as shown in Figure 4.1. The nodes can represent any kind of variable or event. A BN is therefore a DAG encoded with a CPD. An arc goes from one node to another node making a connection in one direction only (acyclic). A node is shown as an oval that represents the variable or event. The arc is a straight line with an arrowhead illustrating the direction from the source node, often called the parent node, to the target node, often called the child node, representing the probabilistic dependence between the two variables.

An important concept for BN is conditional independence. Consider two sets of variables, A and B, which are (conditionally) independent. Given a third set of variables, C, when the values of the variables *C* are known, knowledge about the values of the variables B provides no further information about the values of the variables A, for example equation 4.2:

$$P(A|B,C) = P(A|C)$$ (Equation 4.2) [Bolstad., 2007]

Now, if every path from a variable in *A* to a variable in *B* contains a variable in *C*, then *A* is conditionally independent of *B* given *C* [Lauritzen *et al*., 1988; Lauritzen et al., 1989].

In order to ensure an accurate representation, a methodology of how to develop conditional probability tables (CPT) must be followed.

4.3.1 Methodology To Develop CPT

1- Establishing relevant and accurate information.

2- Establishing nodes with dependencies.

One of the advantages of Bayesian network modelling is its flexibility in enabling new nodes to be added to an existing model. It also allows existing information to be updated as new information is gathered. An example of a BN is shown in Figure 4.1 which represents the reception area (Parent Node) and the influencing child nodes. The reception desk just like the other existing areas within the ED has been found to have 4 critical parameters (symptoms) which can each lead to disruptions, i.e. difficult patient behaviour.

- Confrontation
- Challenge
- Passivity
- Illness belief

Figure 4.1 shows the 4 child nodes with arrows pointing downwards to the reception indicating their influence on the reception. Furthermore, each node has two states, i.e. 'Normal' and 'Difficult' that can be seen in figures 4.2, 4.3, 4.4 and 4.5. This example models the reception area and shows the dependencies between the child nodes and the parent node.

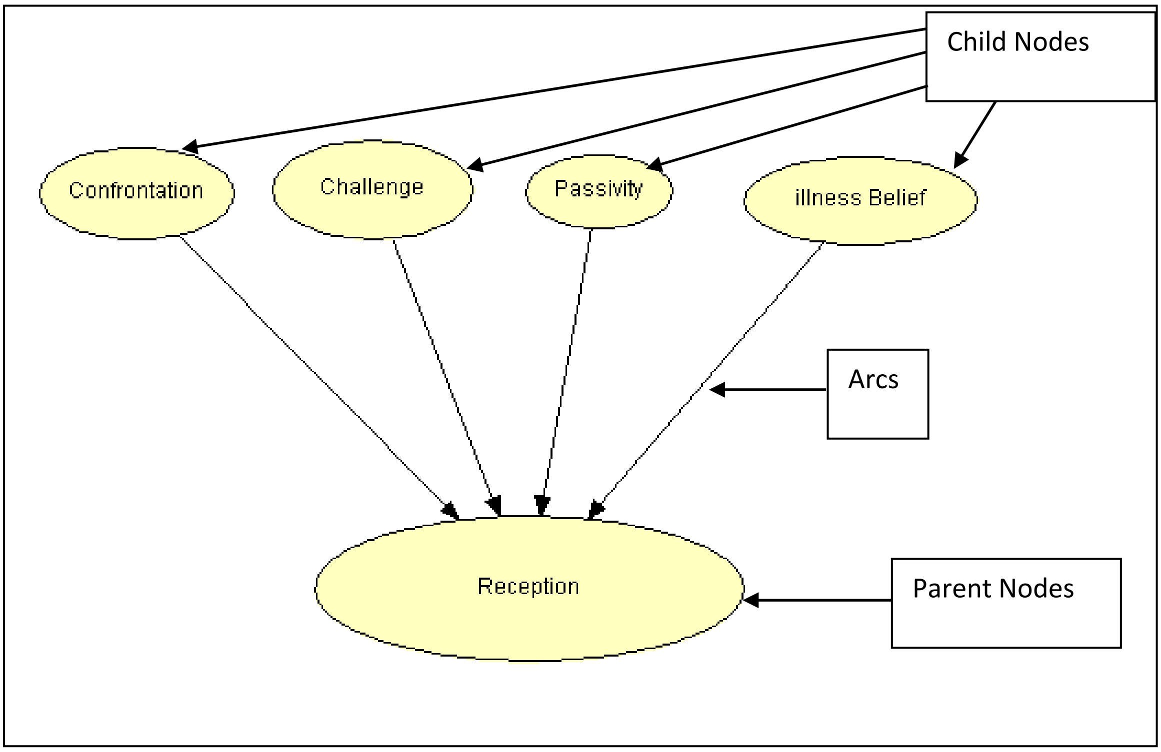


Figure 4.1 Bayesian network modelling of the Reception area

4.3.2 Establishing the Conditional Probability Table (CPT).

A Bayesian network can visually represent the relationship between various nodes or events (qualitative representation), or it can quantitatively represent each node through a conditional probability table (CPT) as shown in Figure 4.6. Furthermore, each parameter state is given a probability, for example Figure 4.2 shows that the confrontation state has a normal probability of 67.7 % and difficulty of 32.3%. The same procedure is followed for Figures 4.3, 4.4 and 4.5. The given probabilities can be based on historical data gathered over time, research, and expert knowledge/opinion. These figures have been derived and represent historical data based on expert opinion with regards to their experience within the ED.

Therefore the probability of patient difficulty is dependent or conditional on the existing parameters in figures 4.2, 4.3, 4.4 and 4.5. This can be seen in figure 4.6' conditional probability table for the reception area.

Confrontation	
Normal	67.7
Difficult	32.3

Figure 4.2 Confrontation State

Confrontation	Challenge
Normal	76.2
Difficult	23.8

Figure 4.3 Challenge State

Confrontation	Challenge	Passivity
Normal	82.4	
Difficult	17.6	

Figure 4.4 Passivity State

Confrontation	Challenge	Passivity	illness Belief
Normal	66.2		
Difficult	33.8		

Figure 4.5 Illness Belief State

Figure 4.6 shows the CPT for difficult patient behaviour in the reception area based on the influencing nodes where, on one hand if all the nodes are ‘Normal’ the probability of no patient disruption is 5%, and on the other hand if all the nodes are ‘Difficult’, the probability of patient disruption is 95%.

Confrontation | Challenge | Passivity | illness Belief | Reception

illness Belief	Normal								Difficult							
Confrontation	Normal				Difficult				Normal				Difficult			
Challenge	Normal		Difficult		Normal		Difficult		Normal		Difficult		Normal		Difficult	
Passivity	Normal	Difficult	Normal	Difficult	Normal	Difficult	Normal	Difficult	Normal	Difficult	Normal	Difficult	Normal	Difficult	Normal	Difficult
Normal	95	90	85	70	70	60	55	50	50	45	40	30	30	15	10	5
Difficult	5	10	15	30	30	25	45	50	50	55	60	70	70	85	90	95

Figure 4.6 Reception Nodes Conditional Probability Table (CPT)

In this example, the parent node ‘reception’ is dependent or conditional on the 4 influencing child nodes which exist and hence have influencing effects on the generated probability. In order to calculate the probability of difficult patient behaviour, the chain rule (Equation 4.1) must be applied.

The child nodes ; confrontation, challenge, passivity and illness belief are termed A, B, C and D accordingly, and the probability of a behaviour disorder is termed P. The term ‘BD’ can also be used to represent the state of behaviour disorder.

Equation 4. 3 – Chain Rule [Darwiche., 2009]

$$P\,(BD) = \sum_{i=1}^{4}\sum_{j=1}^{4}\sum_{k=1}^{4}\sum_{l=1}^{4} P(BD / A_i\, B_j\, C_k D_l)\, P(A_i)\, P(B_j)\, P(C_k) P(D_l)$$

Therefore :

P (Behaviour Disorder) =

P (A ‘Normal’) x (B ‘Normal’) x (C ‘Normal’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Normal’) x (B ‘Normal’) x (C ‘Normal’) x (D ‘Difficult’) x P (Behaviour Disorder) +

P (A ‘Normal’) x (B ‘Normal’) x (C ‘Difficult’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Normal’) x (B ‘Normal’) x (C ‘Difficult’) x (D ‘Difficult’) x P (Behaviour Disorder) +

P (A ‘Normal’) x (B ‘Difficult’) x (C ‘Normal’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Normal’) x (B ‘Difficult’) x (C ‘Normal’) x (D ‘Difficult’) x P (Behaviour Disorder) +

P (A ‘Normal’) x (B ‘Difficult’) x (C ‘Difficult’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Normal’) x (B ‘Difficult’) x (C ‘Difficult’) x (D ‘Difficult’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Normal’) x (C ‘Normal’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Normal’) x (C ‘Normal’) x (D ‘Difficult’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Normal’) x (C ‘Difficult’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Normal’) x (C ‘Difficult’) x (D ‘Difficult’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Difficult’) x (C ‘Normal’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Difficult’) x (C ‘Normal’) x (D ‘Difficult’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Difficult’) x (C ‘Difficult’) x (D ‘Normal’) x P (Behaviour Disorder) +

P (A ‘Difficult’) x (B ‘Difficult’) x (C ‘Difficult’) x (D ‘Difficult’) x P (Behaviour Disorder) + P (Behaviour Disorder) =

(67.7 x 76.2 x 82.4 x 66.2 x 0.95) + (67.7 x 76.2 x 82.4 x 33.8 x 0.90) + (67.7 x 76.2 x 17.6 x 66.2 x 0.85) + (67.7 x 76.2 x 17.6 x 33.8 x 0.70) +

(67.7 x 23.8 x 82.4 x 66.2 x 0.70) + (67.7 x 23.8 x 82.4 x 33.8 x 0.60) + (67.7 x 23.8 x 17.6 x 66.2 x 0.55) + (67.7 x 23.8 x 17.6 x 33.8 x 0.50) +

(32.3 x 76.2 x 82.4 x 66.2 x 0.50) + (32.3 x 76.2 x 82.4 x 33.8 x 0.45) + (32.3 x 76.2 x 17.6 x 66.2 x 0.40) + (32.3 x 76.2 x 17.6 x 33.8 x 0.30) +

(32.3 x 23.8 x 82.4 x 66.2 x 0.30) + (32.3 x 23.8 x 82.4 x 33.8 x 0.15) + (32.3 x 23.8 x 17.6 x 66.2 x 0.10) + (32.3 x 23.8 x 17.6 x 33.8 x 0.05)

= 31.739645 or 31.74% probability.;

The results show that when compared to the actual example model of the reception area's nodes and dependencies, the outcome probability is very much the same. This data has been implemented and modelled using the Hugin software with the states shown in Figures 4.2 to 4.5, for which the results are shown in Figure 4.7.

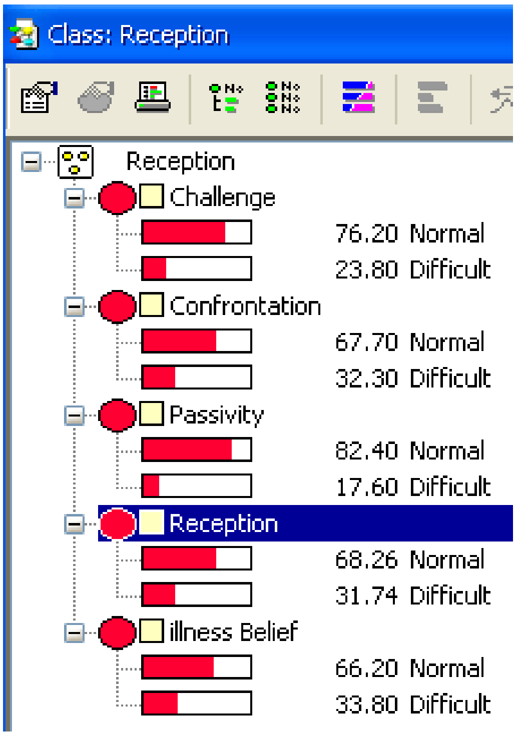


Figure 4.7 Reception area results based on the nodes and states

This example shows that given the above probabilities of the child nodes, a behaviour disorder has a 31.74% probability of occurring and causing disruption. A crucial advantage of the Bayesian approach is that it allows updated information to be considered in order to continually revise probabilities.

The same structure was used to construct BN models for other areas within the ED in order to identify the probability of difficult patient behaviour occurring. Reception has been used as the example and also, examination and laboratory areas are further analysed.

All three areas rely on the same child nodes as the example reception. The same types of patient flow from one area to another. The first point of the methodology is to establish accurate data to be input regarding the child nodes' normal and difficulty ratios. This data is taken from historical data and from the field research carried out.

4.4 Bayesian Simulation Model

The behavioural symptoms are now generated on a random occurrence basis and a behaviour status is applied to each patient via the implementation of the chain rule (Equation 4.3), variables and attributes. The status of the patient behaviour influences the amount of time they spend at one area along with their condition.

The next step was to implement the *Chain Rule* (Equation 4.3) which is used by the BN to formulate probabilities within the developed model. The BN is only able to produce results based on the given information, and hence new results require further data to be input into the *Conditional Probability Table* (CPT), after which the results may be extracted. Different numbered conditions must be applied, and hence changing the CPT for results is an on-going process.

The Witness Simulation model on the other hand will not require the input of any data, since all the data is now dependent on the random variables of the symptoms which cause behavioural problems. The CPT enables the *Chain Rule* to extract variables and calculate the overall probability. This *Chain Rule* will be implemented within the model as will be shown in following sections, to extract probabilities and attach signifying attributes highlighting the key conditions for the model to adhere to and process, abolishing the need of on-going input of data. This will produce a sophisticated dynamic approach and the model will show an array of different probabilities based on the random symptoms of patients.

4.4.1 Actual System (replication) Simulation Model

The Actual model is based on all the historical, observational and researched data gathered in order to represent the existing ED in the truest possible sense. In order to carry out the model building accurately, many working processes and procedures must be represented via programming, as will be discussed in the following:

4.4.1.1 Attributes Applied to Modelling

Each patient is represented by a single entity and each entity may have an array of different attributes according their needs and requirements. All entities i.e. patients, are assigned the attributes of behaviour, condition and patients as shown in figure 4.8. Behaviour represents the patient's behavioural state, condition indicates the emergency level of the patient's condition and the attribute 'patients' is used to allow a single patient to be separated in two entities and re-join where required. The attributes are shown in figure 4.8 and are also apparent in the actual model.

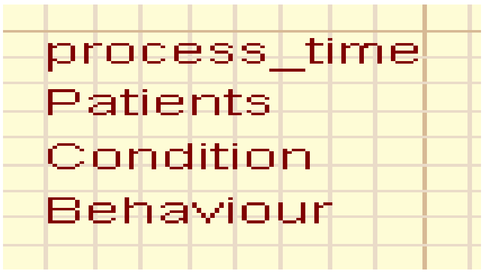


Figure 4.8 The attributes used in the Model.

Figure 4.8 also shows the process time attribute. This is used to allocate different time spans according to patient condition and behaviour.

Each patient is allocated their condition attribute at the very start, i.e. on creation. This attribute highlights the severity of the condition and is assigned according to the information derived from the triage area which classifies patients based on their condition. The triage classifies patients on a scale from 1 to 5, where 1 represents the most severe condition and 5 represents the least severe condition. This condition attribute enables the entities to move forward to their designated area within the ED according to the severity of their condition. For example, an entity (patient) with condition 1 will move forward to the resuscitation area as this is classed as an immediate case which has to be handled with the utmost urgency. All the patients should flow through the model according to their condition in this fashion.

The attribute named ‘process time’, represents the amount of time that an entity (patient) spends within the designated activities. The process time is set according to the research data gathered during the data collection stage, and it changes through the model according to a patient’s behaviour and/or their condition. Process time has been set as an attribute in order to enable the time spent at an activity to change according to each individual patient. Therefore, as soon as a patient enters an activity, the software will signal and give preference to the attributes attached and enable the correct time to be spent in accordance with the condition and behaviour of the patient. The same will apply for all patients. According to their condition they will spend a certain process time within their respective activities which represents an array of different ED tasks. This method was implemented in order to create patients with separate process times according to their requirements.

These attributes are assigned independently to individual entities enabling different durations to be applied at different locations within the model. For example, on the detail entity for immediate cases shown in Figure 4.9, the attributes can be applied via the *Actions on Create* tab. This leads to a further *Edit Actions on Create*, where the attributes can be applied. In figure 4.9, condition = 1, patients = 1 and behaviour

= 0. These are the given attributes that entities are created with, i.e. they are automatically assigned as soon as the entities (which represent patients) enter the model.

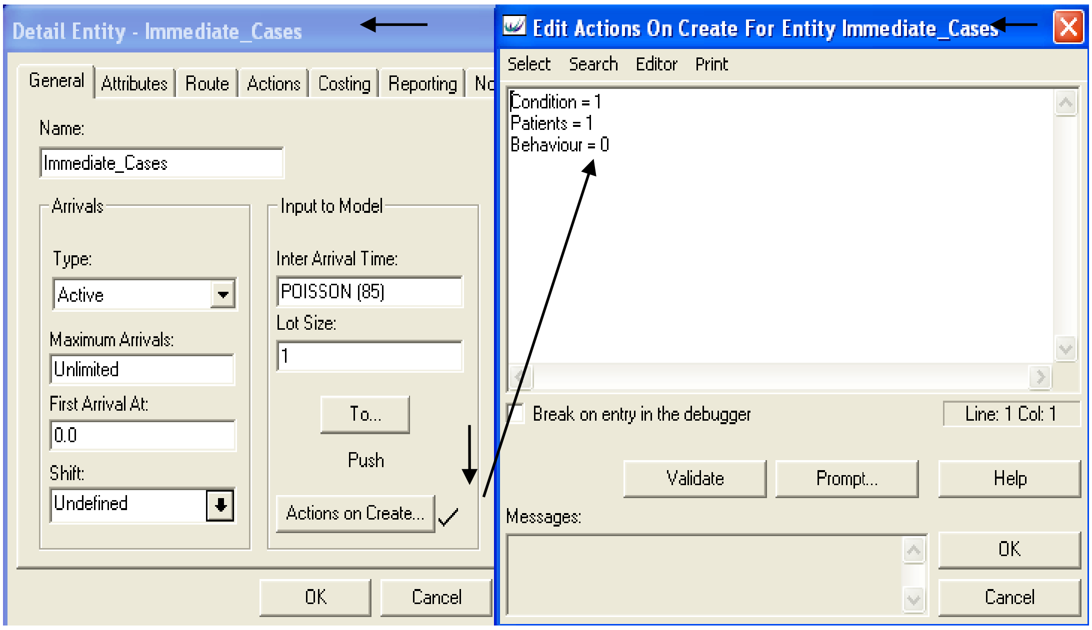


Figure 4.9 Applying attributes to entities.

All patients have different ‘condition’ and ‘patients’ attributes according to need and purpose, however the *Behaviour* attribute remains the same in all entities. This behaviour attribute only remains at 0, however, until patients enter the reception activity. This will be further discussed in detail as it is directly related to how the chain rule is implemented and the behaviour probability is calculated. This probability attribute actually only changes depending on the chain rule to a 1, or else remains a 0.

These attributes have to be implemented within the activities that represent ED tasks according to the level of emergency, which can be looked at as a work station. As entities (patients) enter their designated activities, they are required to spend the allocated duration according to their attributes, and are then directed to different areas within the ED according to their condition attribute. An example of this is shown in figure 4.10 using Patient _ reception Activity.

The duration is attributed as process_ time, and as an entity enters the activity, the software will automatically apply the duration set by the attribute. This is the same case for all the activities which must give attention to all patients that enter the activity.

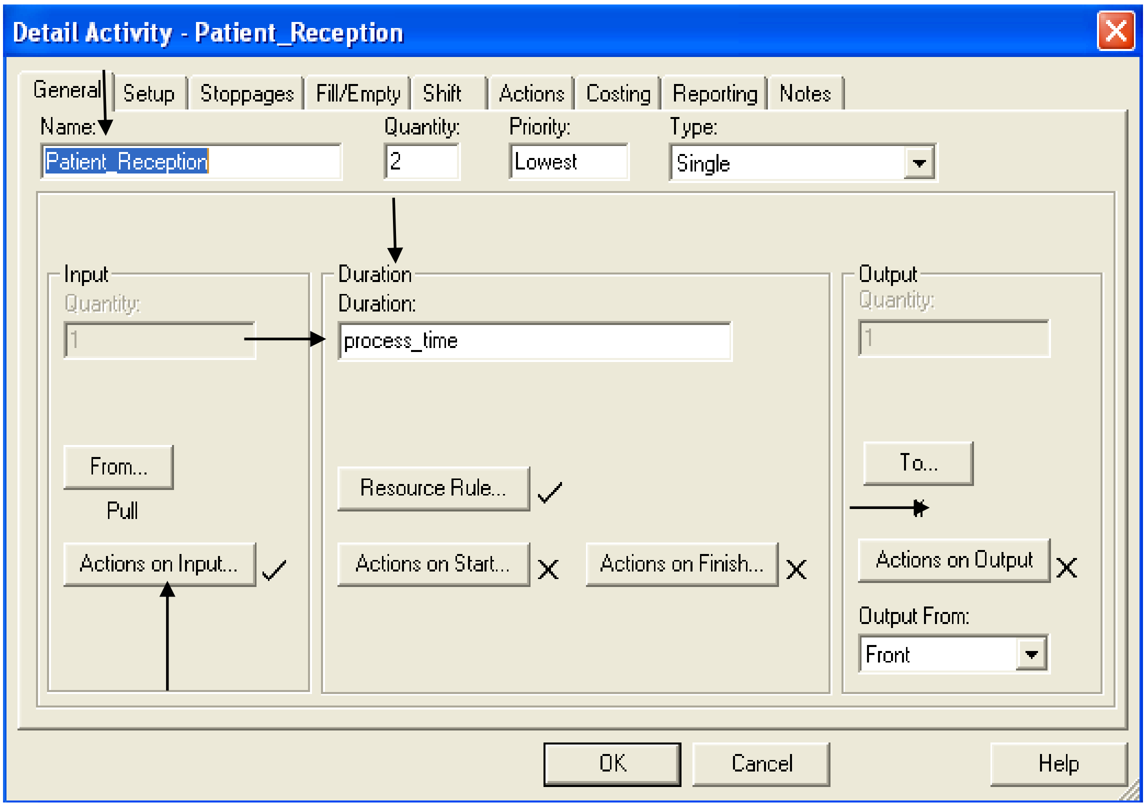


Figure 4.10 The process time implementation.

The patient reception activity also takes into consideration the attribute condition, applying an ‘if rule’ as can be seen in Figure 4.10 just above ‘actions on output’. This enables the activity to check attributes of all patients and forward them according to their need in terms of emergency. In addition, Figure 4.11 shows how the rule has been input based on the condition attributes to determine where the patients are to be sent. For example, as shown in figure 4.11, if the condition of the patient equals 1, they are pushed to the resuscitation queue, or else if the condition equals 2 or 3, they are pushed to the emergency department queue and so forth.

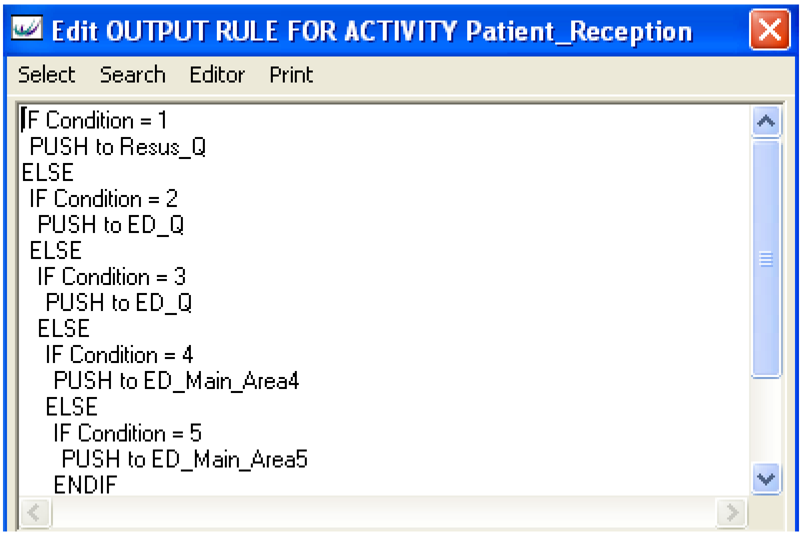


Figure 4.11 Illustrates the reception output rule

4.4.1.2 Operationalization of Human Behaviour in the ED Model

Patient behaviours, as described previously, are categorised into four different types: Confrontation, Challenge, Passivity and Illness Belief. However, there is no system or rule as to how these symptoms of behaviour are observed relative to the process, case type and emergency. Hence, the four behaviour symptoms are best represented as random occurrences just as in real life.

For this reason, the Hugin system based on the Bayes theorem was used to collate all the data and to develop a system where the marginal and conditional probabilities of the 4 symptoms could be considered in order to produce a single probability for difficult behaviour occurrences. The Hugin approach uses the Chain rule to calculate marginal and conditional probabilities. This exact system has been integrated into the simulation model which will be presented and discussed at a later stage.

4.4.1.3 Implementation of random symptoms and the chain rule

Figure 4.12 shows how these random occurrences have been translated into a logical programming system. Firstly, it is important to highlight where this random rule has been input and how it affects the system. It can be seen that it has been integrated into the reception activity ‘action on input’. Hence these random symptoms only develop in the model once the patients reach the reception. Once they reach the reception they are assigned their symptoms as represented by a random variable from 0 to 1.

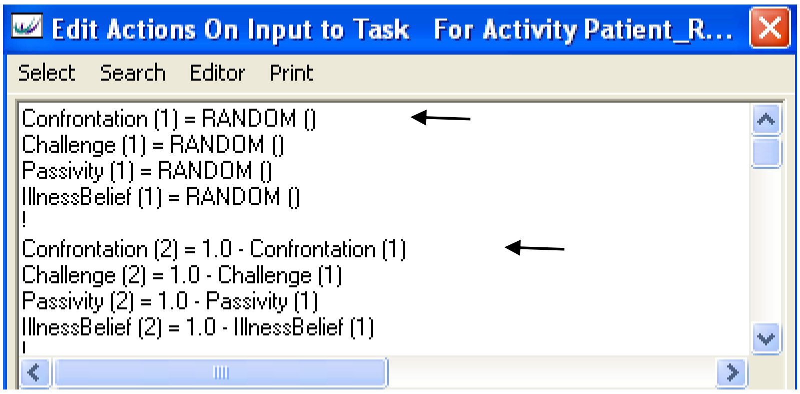


Figure 4.12 Implementing the random symptoms.

Figure 4.12 shows each of the symptoms that represent a random variable, i.e. confrontation (1) = random (), the empty brackets in programming terms represent a chance value between 0 and 1. The symptoms shown in Figure 4.12 also have a (1) and (2) assigned to them. This is simply to aid the process of formulae which can also be seen in Figure 4.13, where a screen shot of the system in place in the model is shown. Firstly, the random variables are developed as discussed, and then the random value is subtracted from the whole number 1 to show the remaining value. For example, confrontation (1) = random (), therefore, confrontation (2) = 1.0 – confrontation (1).

Random variable (1) is given in the top line of Figure 4.13 and (2) is in the bottom line. Once the rule has been applied according to Figure 4.12, the display is available in the actual system as shown in Figure 4.13. The top line represents the chance of occurrences and the bottom line represents the remainder chance.

Confrontation	Challenge	Passivity	IllnessBelief
0.27	0.67	0.34	0.62
0.73	0.33	0.66	0.38

Figure 4.13 The four symptoms in the actual system

Figure 4.13 in essence is the core of the formula which represents the chain rule in order to calculate the marginal and conditional probabilities because these random variables are used to calculate the overall probability which is calculated from 16 different variables as shown in Figure 4.14. These 16 different variables are then combined in order to establish the probability of difficult behaviour caused by the collective symptoms.

Edit Actions On Input to Task   For Activity Patient_Reception

Select   Search   Editor   Print

```
Sum1 = IllnessBelief (1) * Confrontation (1) * Challenge (1) * Passivity (1) * 95
Sum2 = IllnessBelief (1) * Confrontation (1) * Challenge (1) * Passivity (2) * 90
Sum3 = IllnessBelief (1) * Confrontation (1) * Challenge (2) * Passivity (1) * 85
Sum4 = IllnessBelief (1) * Confrontation (1) * Challenge (2) * Passivity (2) * 70
!
Sum5 = IllnessBelief (1) * Confrontation (2) * Challenge (1) * Passivity (1) * 70
Sum6 = IllnessBelief (1) * Confrontation (2) * Challenge (1) * Passivity (2) * 60
Sum7 = IllnessBelief (1) * Confrontation (2) * Challenge (2) * Passivity (1) * 55
Sum8 = IllnessBelief (1) * Confrontation (2) * Challenge (2) * Passivity (2) * 50
!
Sum9 = IllnessBelief (2) * Confrontation (1) * Challenge (1) * Passivity (1) * 50
Sum10 = IllnessBelief (2) * Confrontation (1) * Challenge (1) * Passivity (2) * 45
Sum11 = IllnessBelief (2) * Confrontation (1) * Challenge (2) * Passivity (1) * 40
Sum12 = IllnessBelief (2) * Confrontation (1) * Challenge (2) * Passivity (2) * 30
!
Sum13 = IllnessBelief (2) * Confrontation (2) * Challenge (1) * Passivity (1) * 30
Sum14 = IllnessBelief (2) * Confrontation (2) * Challenge (1) * Passivity (2) * 15
Sum15 = IllnessBelief (2) * Confrontation (2) * Challenge (2) * Passivity (1) * 10
Sum16 = IllnessBelief (2) * Confrontation (2) * Challenge (2) * Passivity (2) * 5
!
Probability = Sum1 + Sum2 + Sum3 + Sum4 + Sum5 + Sum6 + Sum7 + Sum8 + Sum9 + Sum10 + Sum11 + Sum12 + Sum13 + Sum14 + Sum15 + Sum16
!
```

Figure 4.14 Implementing the chain rule in the reception activity

Similarly, this programming implementation is displayed in Figure 4.15. This figure shows how the variables are actually represented in the developed model, the occurrence of random variables that can be achieved, and the resulting final probability. This has all been implemented into the reception activity and occurs as soon as patient enters the system. The random variables of the symptoms are developed and the formula is used to assign variables with probabilities.

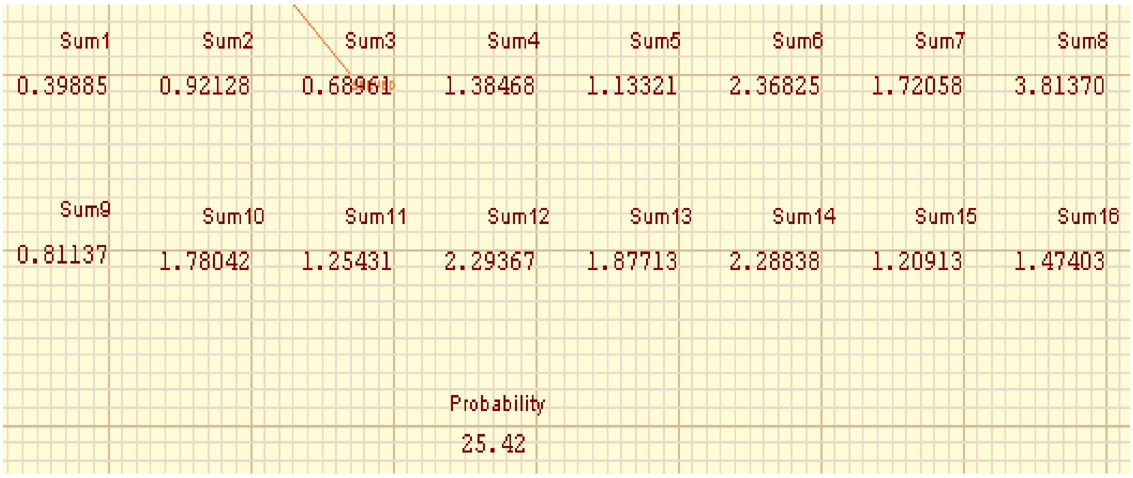


Figure 4.15 The chain rule variables and probability displayed in actual model

Once the chain rule was in place and working sensibly, a probability representing difficult patients had to be attached to each and every patient. A system was put in place to aid the processing of the formulae and programming as will be presented and discussed in Figures 4.16 to 4.18.

Based on all the collated data, it was immediately apparent that a very high number of patients had behavioural issues within the ED. The challenge was how this number could be used as a probability. After many consultations with experts in the field, a consensus was reached that if the probability of difficult behaviour occurrences is above a value of 60 then this can be classed as a patient with behavioural issues (an extensive justification can be found in the methodology chapter). Hence, in figure 4.16, it is stated that if the probability is equal to or less than 59, then the variable behaviours (1) = 1, which implies a normal patient, and behaviours (2) remains 0. However, if the probability is equal to or greater than 60, behaviours (1) = 0 and behaviours (2) = 1, which indicates a difficult patient.

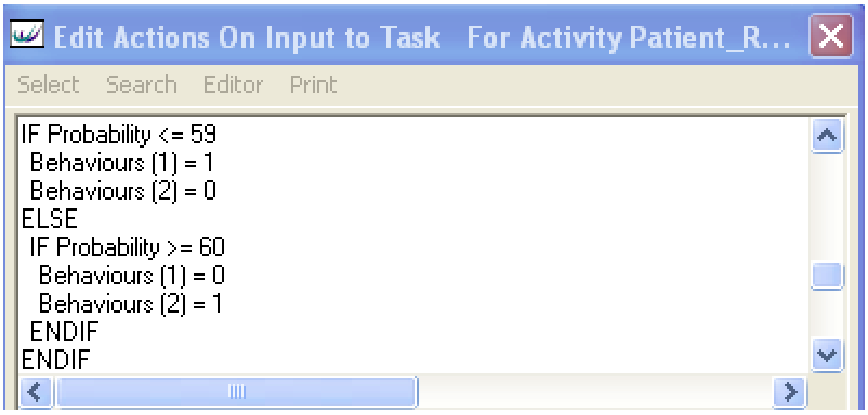


Figure 4.16 Behavioural probability.

This simple process would enable the development of counters to show how many difficult patient probabilities above the 60 threshold had occurred, and also informs the attribute ‘behaviour’ as discussed and shown in Figure 1. Figures 4.17 and 4.18 also highlight the importance of the behaviour variables which aid the processing of formula and logical programming. Figure 4.17 shows the behaviours counter and total counts of behaviours that have been classed as normal or difficult. Normal is below the 59 threshold and difficult is above the 60 threshold.

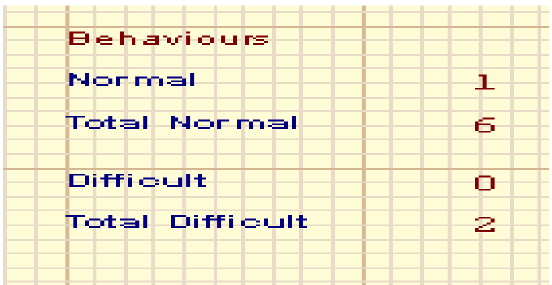


Figure 4.17 Behaviour count.

Following on from Figures 4.16 and 4.17, Figure 4.18 shows how the variables are used to aid and implement a system whereby every patient is processed depending on their probability and with that the process time is also changed accordingly.

Figure 4.18 shows that if behaviours (1) = 1, which represents normal behaviour, a certain process time has to be used, i.e. uniform (3, 5) and the attribute behaviour (not the variable behaviour) is also now equal to 1. If however, behaviour (2) equals 1, which represents difficult behaviour, a different process time is defined i.e. triangle (5, 10, 15), and the attribute ’behaviour’ now equals 2.

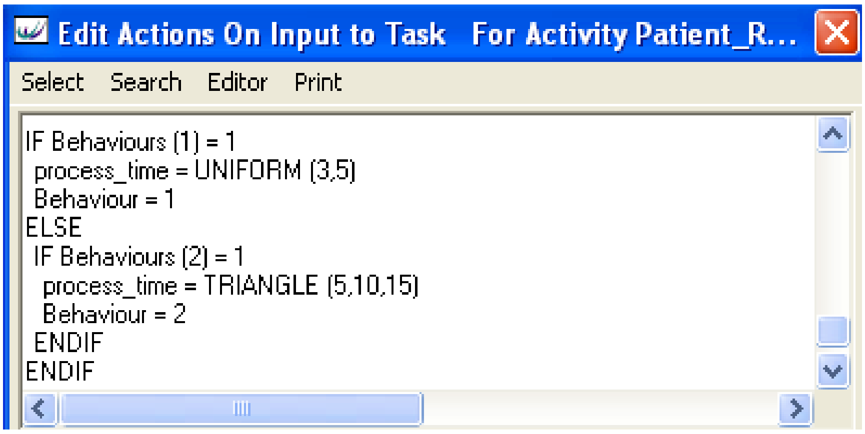


Figure 4.18 Assignment of different process times according to behaviour.

This entire process has been implemented into the reception activity at ‘action on start’. It enables the activity to move, divert and forward all the patients according to their need in terms of emergency level, and minimises the consumption of additional time based on their behaviour.

Similarly, process times change as the patients enter other activities which represent an array of different tasks. For example, the very same ‘if’ rule from Figure 4.18 is used in areas such as triage and observation, albeit with different timing constraints according to the research. This can be seen in Figures 4.19, 4.20 and 4.21.

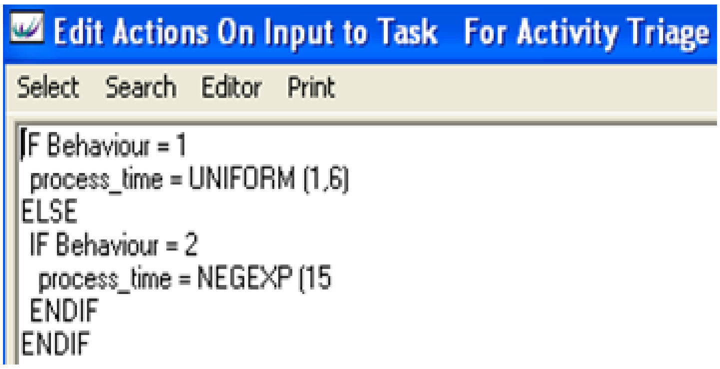


Figure 4.19 Triage process time according to behaviour.

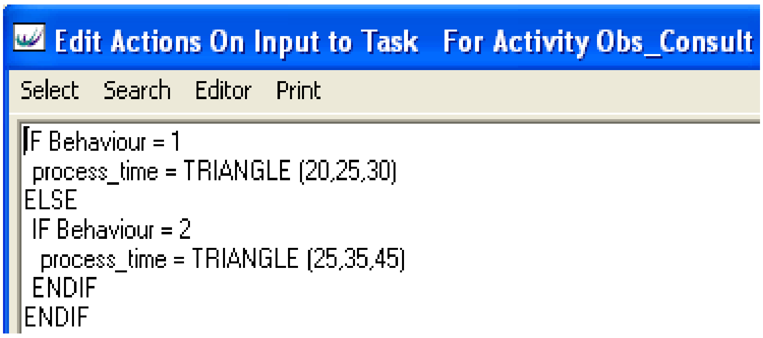


Figure 4.20 Observation process time according to behaviour.

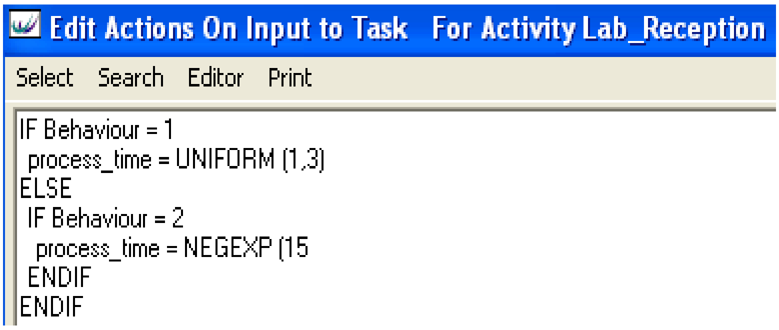


Figure 4.21 Laboratory reception process time according to behaviour.

4.5 Summary

This chapter highlights the difference in modelling in terms of the Bayesian approach and how it affects the actual model in terms of programming application, the changes applied in order to represent the Bayesian system as accurately as possible. Firstly, key elements such as the attributes are identified and discussed in relation to the modelling, their purpose and aim and what processes they intend to replicate. Visual aids are provided throughout the chapter to aid understanding. Thereafter, the Bayesian approach is implemented with the development of random variables and the chain rule equation that calculates the marginal and conditional probabilities depending on influencing factors (random variable (symptoms)).

The Bayes theorem is explained and a step by step guide of how the Hugin software uses the variables of influencing factors is provided to validate the process presented by a methodology that should be adhered to in order to derive the most accurate results. Tests are carried out based on influencing factors (symptoms) using the Hugin software to validate the results further as changes are made to see the affects thereof. A set of results is finally drawn given the random occurrence of influencing parameters.

Chapter 5: Data Analysis and Discussion

5.1 Introduction

Chapter 5 highlights and discusses the available data from hospital records and data gathered from the field research from the experts within the ED of TMC. The purpose and importance of the data is shown and how the data is used and how it affects the study is highlighted. The data is used to develop an accurate simulation model in order to represent a true to life system with comparable results that show an affective correlation. The data gathered primarily serve to develop greater understanding of the ED within TMC and further aid to fill the missing data, where data is not accurate or available from hospital records. The data gathered also gives an opportunity to make comparisons to previous studies to develop understanding further.

5.2 Overview of Hospital Records

This part of data collection focused on the description of the emergency department of the Tripoli Medical Centre (TMC) and the attending patients. In this stage, data was collected by reviewing ED records and administrative records for May 2012. In addition, the researcher used a form that has been designed to collect data that was not available in ED records, the form is designed with the patient in mind, who are attending the TMC ED, to collect data with regards to service times and patient waiting time (form details is shown in chapter 3). Data has been validated by using observation methods, and reviewing the data from previous months of the study as well as expert opinions. The information and data collected from the research is shown and discussed below:

5.2.1 ED TMC Patients Characteristics

Patient characteristics in the study are summarised in Table 5.1. The mean age of all ED visitors is 52 years; 39.2 % were 65 or over; just 10.6 % were between 16 and 24 years. Data also indicates that almost all ED users within the study were Libyan.

5.1. Summary of patients visiting ED, May 2012

Mean Age 52.3 year, SD (7.7)	
variables	**# Number of patients (%)**
Age (year)	
(16-24)	755 (10.6%)
(25-44)	1,500 (21.1%)
(45-64)	2,061 (29.1%)
(65 +)	2,784 (39.2%)
Gender	
Male	4,015 (56.5 %)
Female	3,085 (43.5 %)
Nationality	
Libyan	6,897 (97.2 %)
Non-Libyan	203 (2.8 %)
Severity	
Emergencies cases (Immediate, emergent, and Urgent)	1,801 (25.4%)
Minor & Non-Urgent case	5299 (74.6 %)

Noteworthy (as shown in Table 5.1) the majority of patients who use the ED (to obtain medical services), i.e. 5,299 patients were minor and non-urgent cases (74.6 %). The remaining 1,801 patients made up the extreme and urgent group. This may be interpreted by data presented in Figure 5.1, which describes the access methods to the ED, and shows that most users of ED (82.9%) attended ED based on their decision to seek medical service not by being referred by a healthcare professional. Other health centres in Libya referred just 9% of all visits and almost 6% of patients were directed to ED by private clinics. In TMC ED, similar to most of the EDs around the world, ED's are forbidden to reject patients who attend the ED even if they have a minor or non-urgent case. Actually, the researchers over the years demanded that it has to prevent the provision of non-urgent medical care in the ED, describing their reason as a misuse of hospital EDs by non-urgent patients and create several negative consequences to it, including overcrowding, increase in the cost of medical care, and reducing ED services quality [Cunningham *et al*., 1995; Moskop, 2010; Durand *et al*., 2012].

However, patients with non-urgent medical conditions in ED are likely to continue and, in fact increase as a recent international literature review reported. It shows that roughly 4.8% to 90% of ED patients were non-urgent patients [Durand *et al*., 2011].

Most of non-urgent patients and minor cases that attended the ED in TMC (82.9%) were self-referral as shown in Figure 5.1. In fact, the 'self-referral' problem is well known in EDs around the world and considered a reason for ED overcrowding. For example, a study conducted in the U.S.A (Rochester, NY), found that about 53 % of all patients reported that they attended the ED because they believed that their problems were urgent and required immediate care prompting them to visit the ED. The study reported that most patients who attend ED were self-referral [Kamali et al., 2013]. Another study that has been done in Royal Perth Hospital, Australia, has found that 73.8% of patients attend ED were self-referral [Ng *et al.*, 2012].

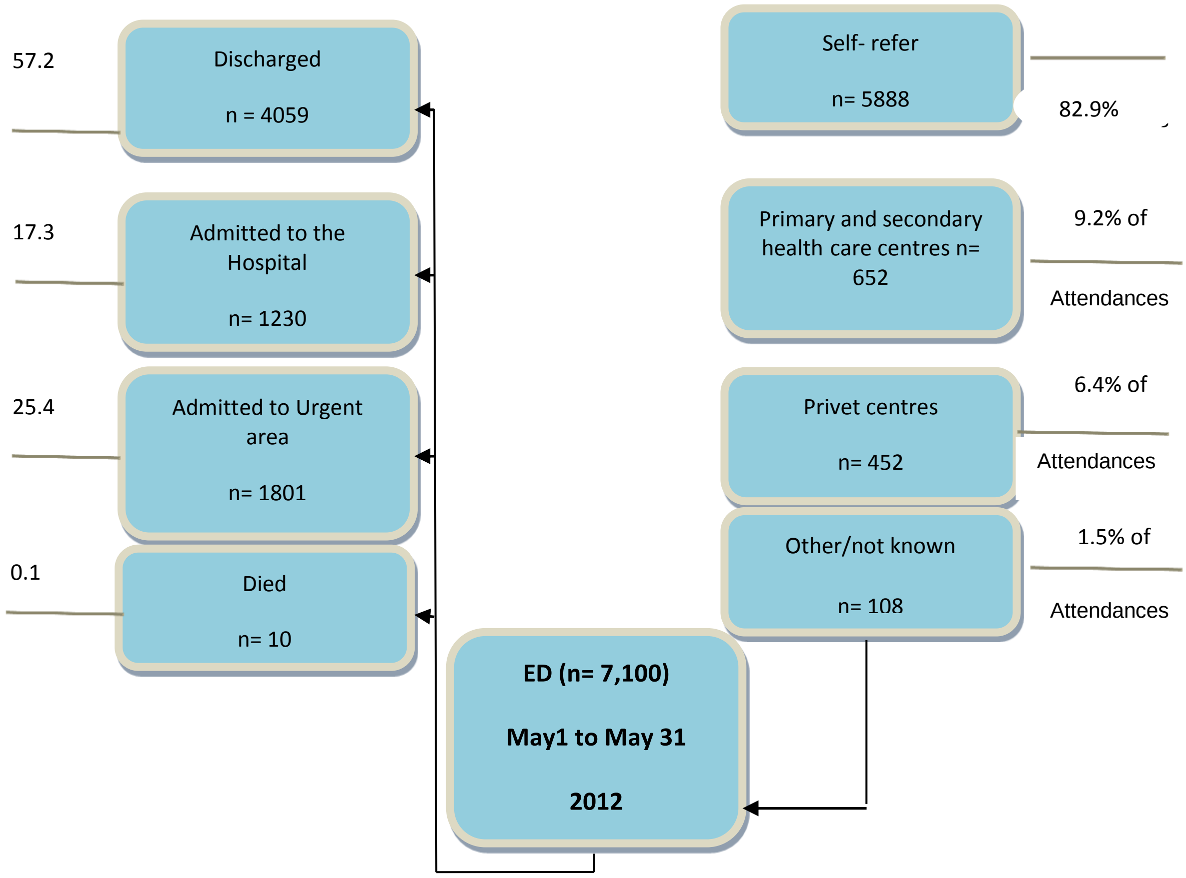


Figure 5.1 The ED patients overview, May 2012.

Figure 5.1 also shows that the ED admitted approximately 17 % to hospital per month. Furthermore, almost 25 % of all users are referred to the urgent area. These cases transferred to the urgent area (especially the observation and resuscitation room) are usually dealt with as inpatients, because the length of their stay in the ED may exceed two days.

Of patients present in the ED during the study period, 10 have since passed away, including four who were dead on arrival. This percentage is similar to that of months preceding the study. The department also discharged (to home or any other health centre) the equivalent of 57% of all users. This result is very logical, because most department users were minor or non-urgent cases.

It is worth mentioning that the data obtained from the ED of the TMC, as presented in Figure 5.1, is somewhat similar to results in previous studies that examined the characteristics of emergency departments in many hospitals worldwide, especially those that suffer from some problems, like overcrowding [Moser et al., 2004; Day et al., 2013].

5.2.2 Patients Arrival Process

The arrival process ensures that the time at which the patient registers within the ED is recorded; varying degrees of detail may be included. In the context of this study, the arrival process will be described in two different ways accordingly to timescale. Notably, Figure 5.2 provides a middle-level monthly illustration, the time unit is days, Figure 5.3, on the other hand, provides insight on a daily basis, with time unit in hours.

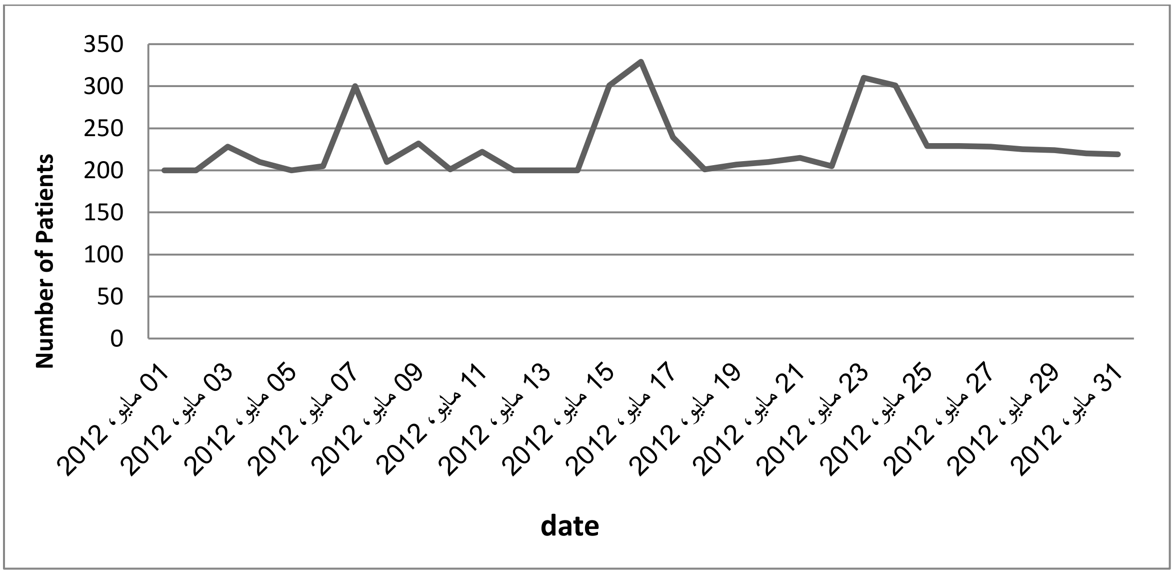


Figure 5.2 Number of patients per day (May 2012)

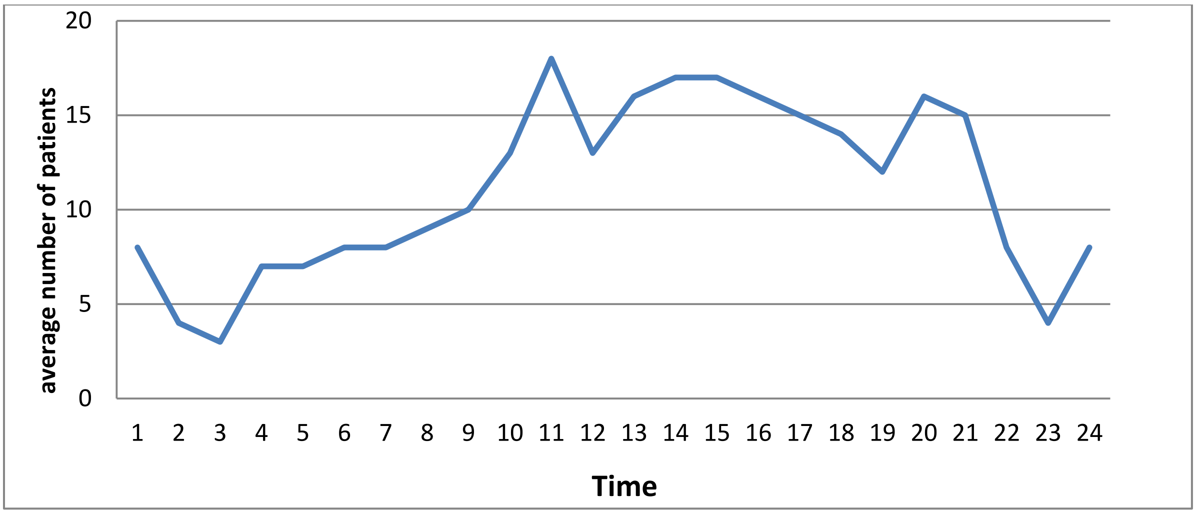


Figure 5.3 Number of patients per Hour (May 2012, Weekdays)

Figures 5.2 and 5.3 show that number of patients arriving daily to the ED is close, where the average daily arrival is 229 patients. Note that the peak time for the patient's influx is between 10:00 a.m to 21.00 p.m

5.2.3 ED capacity

Data contained in Table 5.2 (taken from hospital records and personal observations) displays details of beds and staff in the ED.

One of the more interesting aspects of this study is the shortage of beds compared with other hospitals which are of a similar size and type as the TMC. Table 5.2 shows that the main area in emergency departments contains 14 beds, while there are approximately 23 beds available in other similar hospitals [Delia, 2000]. In addition, urgent areas containing 23 beds distributed to resuscitation rooms (4 beds), observation rooms (17 beds) and cardiology rooms with just 2 beds. This constitutes a serious shortage of beds compared to other similar hospitals [Khare *et al*., 2008; Elshove-Bolk *et al*., 2006].

5.2. ED capacity during study period (May 2012).

ED Area	Facilities	Details
ED waiting area	There is no proportionality between the number of seats in the waiting area and the number of waiting patients	Patients should wait in the waiting area if all ED beds are taken. They are directed to main or urgent beds on a first come, first served, basis relative their condition.
ED Main area Bed staff	 14 beds 4 attending physicians from 08:00 to 20:00 2 attending physicians from 20:00 to 08:00 5 Nurses from 08:00 to 08:00	Patients in the main ED first see a physician and then wait (without a physician) for diagnostic testing and treatment, and then see a physician again before being admitted or discharged.
ED Urgent area Resuscitation Bed Staff Observation Bed Staff Cardiology Bed Staff	4 beds 1 attending physician from 08:00 to 20:00, 1 attending physician from 20:00 to 08:00, and 4 nurses from 08:00 to 08:00 7 beds for males and 10 beds for females. 2 attending physicians from 08:00 to 20:00 and 2 attending physicians from 20:00 to 8 am. 2 Nurses from 08:00 to 08:00 2 beds 1 attending physician from 08:00 to 08:00, 1 attending physician from 20:00 to 08:00 2 Nurses from 08:00 to 08:00	There is no specific time for patient to stay in resuscitation room. Patients admitted to the observation unit are like those admitted to the hospital.
Boarding	No data available about how many beds in hallway	No present limit on how many patients can board

5.2.4 Waiting Time and operation time in ED TMC

This section discusses the waiting and operating times of service procedures, with particular attention to minor and non-urgent patients. The data used were collected by direct measurement (Innovative Time Form (ITF), see chapter 3) and through TMC ED staff interviews.

5.3. Average patient waiting time to see a physician and percentage of visits exceeded the recommended time frame in May 2012.

Patient Condition	Average wait time in minutes	% of patients whose waiting time exceeded the recommended time frame*
Immediate cases (class 1) (should be seen in less than 1 min)	10	55.8
Emergent (class 2) (should be seen within 1 to 14 minutes)	38	53.4
Urgent (class 3) (should be seen within 1 to 2 hours)	53	23.5
Minor (semi urgent) (class 4) (should be seen within 1 to 2 hours)	85	22.5
Non – urgent cases (class 5) (should be seen within 2 to 24 hours)	100	60.3
Recommended time frame is developed by the Emergency Nurses Association. Time patients should spend waiting for doctor depends on a five-level emergency severity. Emergency Department of TMC is used this frame in its regulation.		

Table 5.3 compares the mean time patients wait to see a doctor and that recommended by Emergency Nurses Association, which is implemented in ED's organisational regulation. It can be seen that the mean waiting time exceeds the recommended time available in the hospital regulation. This is particularly so for immediate and emergent cases were the minimum differences were 9 minutes (56%) and 24 minutes (53%) respectively. In the urgent (53 mins), minor (85 mins) and non-urgent cases (100 mins), the mean values were within the recommended time

frames of 1-2hrs and less than 24 hours. Nonetheless, the percentage of patients who are forced to wait for longer than the recommended time was highest for non –urgent cases (60.3%) while that of minor patients was the least with 22.5%.

5.4. Average time (in minutes) spent by class 4 and 5 patients in the triage waiting room before seeing a physician and/or nurse

Categories	Time category	Patients number and percentage [No / (%)]
1	< 60	320 (15.98 %)
2	60-120	690 (34.45 %)
3	>120	1010 (50.42 %)
Overall average time at triage area (minutes)		80 min

The waiting times for class 4 and 5 patients, i.e. minor and non-urgent patients, between registering at the reception and upon first entry into the triage area are presented in table 5.4. The data shows that 50.42 % of patients spend more than 2 hours in the triage waiting room to see a doctor or nurse. Consequently, half of ED TMC patients are treated by physicians/nurses after being delayed for more than the target triage time, which ought to be less than 2 hours for minor patients.

Compared to other studies, a significant difference exists. It was reported that about 78% of all patients and 67% of patients who were triaged to be treated in one hour, were treated by a physician within the target triage time [Horwitz et al., 2010].

Furthermore, approximately 34 % of all minor and non-urgent patients, who participated in this study waited between one to two hours, with just 16 % of them found to have waited for less than an hour. The average waiting time in the triage area, regardless of the patient's condition (minor or non-urgent) was found to be approximately 1hr 20 minutes. This result correlates with the study published by Care Quality Commission in 2012, in which 29% of participants were found to have waited for treatment for over an hour [Care Quality Commission, 2012]. In another study conducted in the U.S., the average waiting time for triaged patients was approximately 55.8 minutes [Stephen *et al*., 2008]. Lyons and his colleagues also reported a mean time of 13.34 mins for patients waiting to initially speak to a triage staff, in a study conducted in the U.S. [Lyons *et al*., 2007].

The review of previous studies reveals that most researchers agreed that patients spent less time waiting for triage compared to that obtained for this research. Prolonged waiting time at triage to see a doctor or nurse could be due to many reasons. As confirmed from questionnaires given to staff participants and previous researches, these reasons could include shortage of facilities, disorganisation and capacity at ED TMC. Several researchers agree with these factors. However, an important factor which could be responsible for huge delays and is yet to be explicitly explored by previous researchers could be a high number of minor and non-urgent patients who attended the ED TMC on a daily basis. the extra time spent on sorting and attending to difficult patients is considering as factor which cause extra WTs, as previously discussed in chapter 2. difficult patients are usually confrontational, challenging, passive and have an illness belief problem. This factor will be explored further in later sections.

Operational times were also studied using the Innovative Time Form (ITF) created. The operational time is defined as the time a patient spent with a doctor or nurse in order to complete the triage process. The statistics presented in table 5.5 showed that the majority (1070,(53.4%)) of patients spent between 5 to 10 minutes, while patients who spent less than 5 minutes represent the minority in this study (493, (

24.6 %)) and patients who exceeded 10 minutes with a triage staff represented 22% (440, (22%)).

In 2007, Lyons et al. found that the average time spent in the triage by patients was 4.17 minutes [Lyons *et al*., 2007]. Similarly, a study conducted in the U.K, for the purpose of finding solutions to reduce waiting time in ED, found that the median triage time before intervention was 7 min [Subash *et al*., 2004]. This result nearly matches the average triage time in ED TMC represented in table 5.5. However, the 2012 study conducted by Wang et al. in the Kentucky, US, stated that operating time (13mins) exceeded the recommended time by 10 mins [Wang *et al*., 2012]. In addition, from table 5.5, the majority of patients who attended the ED TMC were triaged within the recommended triage time; 5-10 minutes.

5.5. Average time spent (minutes) by class 4 and 5 patients in the triage room with a nurse

categories	Time category	Patients Number and Percentage No / (%)
1	< 5	493 (24.6 %)
2	5-10	1070 (53. 4 %)
3	>10	440 (22%)
Overall average time at triage room (minutes)		7.3

Minor and non-urgent patients at ED TMC are usually directed to the examination waiting area where they are examined and treated by a doctor or nurse. The time each category of patient spent between leaving the triage room and entering the examination room are recorded in table 5.6.

5.6. Average time spent (in minutes) by class 4 and 5 patients in the examination waiting room

Categories	Time category	Patients Number and Percentage No / (%)
1	< 60	320 (16 %)
2	60-120	423 (21 %)
3	>120	1260 (63%)
Overall average Time of Examination waiting area (minutes)		140 min (2 h 33 min)

The data indicates that most of patients waiting for more than 2 hours to enter the examination room and the overall mean time was found to be 140 mins.

5.7. Average LOS of ED Patients (in minutes) according to patient's conditions

ED area	Mean (SD)
LOS for Urgent area patients (min) (immediate, Emergent and Urgent)	370 (min) (≈ 6 hours)
LOS for examination area patients (min) (Minor and non-urgent)	274 (min) (≈ 5 hours)
Overall average	207 (≈ 4 hours)

The above table shows that the ED under study suffered from prolonged LOS as many other EDs all around the world. Earlier studies conducted within an emergency department, with similar overcrowding conditions, recorded a comparable LOS as found in this study. In a study conducted by Elmer et al in Boston, U.S., the median ED LOS was 5.1 hours [Elmer *et al.*, 2012]. In 2008, Khare and other researchers found that the mean LOS in ED was 4.1 hours [Khare *et al*., 2008]. Also Affleck and others found that the average LOS of minor and non-urgent discharged patients was about 4 hours, while LOS of urgent and emergent patients was found to be approximately 8 hours [Affleck *et al*., 2013]. Similarly, in another study that was conducted in Netherlands, the researchers found that the average LOS of discharged patients was 119 minutes [Linden *et al*., 2013].

The previous studies tried to find a relationship between LOS of the department and many other factors. For example, increase in the volume of the patients attended to at the emergency department, departments' organization and procedures, the resources i.e. number of doctors and nurses, number of beds and ancillary departments and how they contribute to increase LOS.

A fascinating factor discovered in light of this research, which is yet to be explored to the best of the researcher's knowledge was patient behaviour. Thus, the aim is to find the relationship between this factor and LOS in ED TMC. This will be studied and clarified in later sections of this study.

5.3 Overview of Questionnaires and Interviews

The research question, as was displayed in chapter 1 (The Introduction), has been outlined, which assumes that patient behaviours whilst waiting in a service queue is one of the reasons impeding the smooth operation of the patient flow system. To prove the hypothesis, this study used many strategies. One of them is a survey (questionnaires and interviews) of staff working in the ED of TMC. The survey aimed to find and develop a consensus of staff opinion on the issue of patient behaviour and its impact on service. The following is the result that has been found after a thorough analysis.

From the questionnaire sent to the ED staff in TMC: there were 9 doctor respondents, who represent 75% of the total questionnaires sent, and 11 nurses respondents, who represent 84.6%. The staff were asked about how long they had worked in the ED and most staff who responded (doctors and nurses) had been in their jobs over five years (approximately 67% for Doctors and 73 % of nurses). This result indicates that they have gained valuable experience to be able to present accurate views to consider. Based on this finding, it is reasonable to assume the questionnaire and interview results, hold great value from many years of experience within the ED and enable greater understanding for the problems that TMC ED is facing on a daily basis.

When staff members were asked whether overcrowding existed in the ED, 77.8% of the doctor respondents agreed in addition to 72.7% of the nurses. It was explained that overcrowding is considered to be a very frustrating and aggravating problem that they face daily. These employees illustrated that this problem requires a quick and serious solution. The same response and result was found to exist in studies conducted in other countries. ED staff members had similar complaints and demands as TMC ED staff. For instance, a study implemented in the Netherlands, 2013 showed there was a strong agreement amongst the ED nurse (79 %) and Emergency Physicians EP (73 %) for the feeling of overcrowding and feeling of being rushed [Anneveld *et al*., 2013]. In another survey conducted in 2000 in California, 96% of the ED directors were of the opinion that overcrowding is a threat to efficient work at ED [Richards *et al*., 2000].

Participating staff members were asked about factors considered by previous researches as significant reasons for increased patient's waiting time. Their responses are illustrated in the figure 5.4.

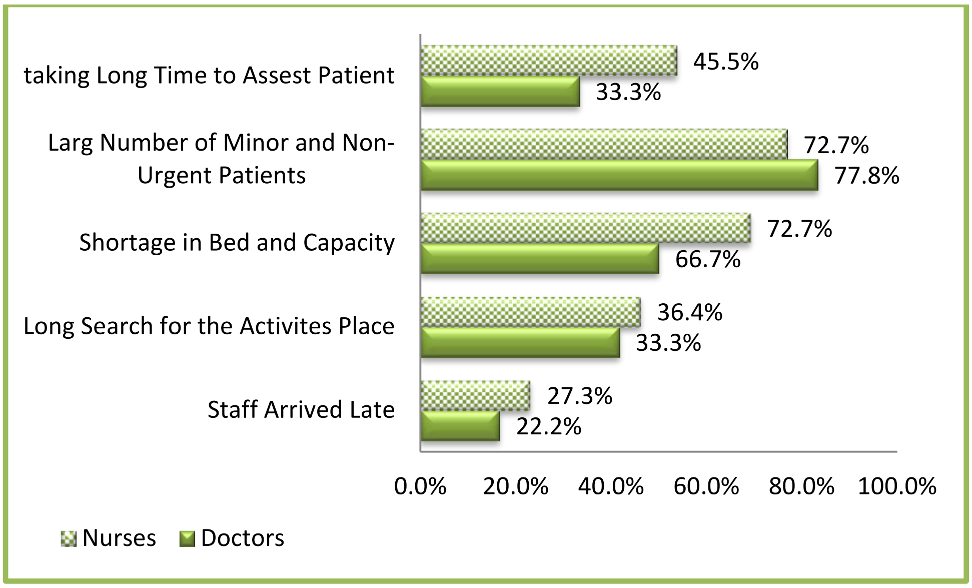


Figure 5.4 describes the staff opinion about overcrowding cases

From Figure 5.4, it is obvious that doctors and nurses who participated in this study believe that a huge number of non-urgent and minor cases who attended ED to receive emergency services are more responsible for creating the overcrowding situation experienced at the ED. This result agrees with previous studies, where it was reported that minor and non-urgent cases are problems faced by ED all around the world.

The staff were also asked to indicate whether they felt that difficult patients' behaviour issues had a negative impact on the work of their ED, and almost seventy eight percent (77.8%) of doctors and 81.8 % of nurses felt that it did. These results obviously show the importance of conducting such a study in order to discover the importance of this problem and work on finding a suitable solution.

The factors that have been found in literature that are considered as significant patient factors affecting the service in emergency departments, (previously discussed in chapter 2), have been discussed with the staff via interviews and questionnaires.

The analysis of interviews and questionnaires showed that almost all responders agree on some factors, and they emphasise that these factors, which are shown in table 5.8, are the fundamental elements known to play a role in service delivery negativity in ED of TMC. Table 5.8 also display the staff opinion about how does each factor effect the services.

5.8. The significant patient's factors affecting the service in emergency departments.

Patient Behaviour Factors		Staff Responses		
No.	**Factor**	**How it could affect the services**	**Doctor**	**Nurse**
1	**Defensive behaviour, including:** c. Challenges, including: - Interfering - Over-involvement - Demanding. d. Confrontation, including: - Anger - Arguing - Lack of respect	- Capacity issues - Disturbance of service because of the complaint and objection - Requires a long time to deal with them.	88.9% 77.8%	72.7% 36.4%
2	**Protective behaviour, including:** b. Passivity: - cultural influences, i.e. discrimination, lack of respect the rule, e.g. jumping the queue - Communication difficulties.	- Disturb patient flow - Requires a long time to deal with them.	55.6%	81.8%
3-	**Illness Belief**	- Capacity issues. - Requires a long time to deal.	55.6%	45.5%

Table 5.8 clearly shows that doctors and nurse strongly agree that the most important behaviour that infuriates them, and disturbs their work is challenges which includes

interfering, over-involvement and demanding, near 89% and 73 % consecutively. The staff say this type of behaviour disrupts the services because of a lot of complaining and objections that patients seem to have due to lack of understanding of the processes involved. Confrontational behaviour which shows almost violence i.e. anger, arguing and lack of respect, takes second place of importance for doctors. However, within the TMC ED nurses do not find the violence to be a problem as they do not face this issue. This aspect of violence where nurses do not consider being a critical problem is different when compared to other studies, Where Physical and non-physical violence against ED workers are a common concern from all members of staff [Gates *et al*., 2011]. For illustration, a study conducted in US found that nearly 25% of respondents reported experiencing physical violence more than 20 times in the past 3 years, also very nearly 20% of nurses reported experiencing verbal abuse more than 200 times during the same period [Smith *et al*., 2009]. Similar study found that approximately 82% of emergency nurses responded that they had been physically assaulted at work [May *et al*., 2002].

Table 5.8 also shows that nurses find passivity and cultural influences can be certainly disturbing and affect their work considerably (about 82%). Doctors on the other hand do not strongly agree with this point as much as nurses do (55.5%).

Majority of the doctors and nurses involved in this study (88.9 % doctors, 90.9 % nurses) agreed that, minor and non-urgent patients were showing the most difficult behavioural issues, which leads to a delay in service and crashes the system. This, in fact, prompted the researcher to focus only on these two groups of patients in observation.

In order to understand staff opinion to the best of abilities about the most difficult behaviour that effect patient flow system, they were asked to highlight factors shown in table 5.8 in order to assess the level of seriousness, starting from major effect on services, ending with no effect on services. The results highlighted that doctors considered over-involvement, demanding, and urging, the most important behavioural factors to cause confusion at work. These behaviours, as interpreted by the doctors surveyed, mean that patients who carry these behaviour, are usually not of an urgent case and emergent, but rather non-urgent and/or minor cases, they tend to interfere in the doctor's decision. For example, patients are trying to get involved with the type of tests that doctors choose and the resulting diagnosis. According to the ED doctors' explanation, staff should investigate and treat all types patients who are presented in the department, regardless of condition; therefore, these behaviours lead to an increased number of patients waiting in queues as increased time is consumed dealing with such patients, which causes the overcrowding. Nursing staff believe that the most important factor that impedes their work is queuing behaviour i.e., jumping the queue and demanding to be at the head regardless of condition and urgency. Nurses also share the same opinion as doctors, where 72.7 % of them believe that the intervention in the treatment and the long arguments with staff are difficult behaviours, which lead to delay in services. See table 5.9.

5.9. Staff opinion about the most serious difficult patient's behaviour that effect services.

Behaviour Factors	Level of Seriousness					
	Doctors %			Nurses %		
	Major effect	Minor effect	No effect	Major effect	Minor effect	No effect
Over-involvement	88.9	11.1	0	63.6	36.4	0
Demanding	77.8	11.1	11.1	72.7	18.2	9.1
Arguing	66.7	22.2	11.1	54.5	27.3	18.2
Lack of respect	55.6	11.1	33.3	81.8	18.2	0
Illness Belief	55.6	0	44.4	27.3	45.4	27.3
Communication difficulties.	33.3	55.6	11.1	45.4	36.4	18.2
cultural influences	22.2	44.5	33.3	18.2	45.4	36.4

The staff were also asked to indicate the negative effects caused by the difficult patients' behaviour on the work in the TMC emergency department, and it was found that doctors (approximately 89 %) and nurses (approximately 82%) agreed that difficult patient behaviour, increased patient waiting time for service. Seventy-eight percent of doctors and 73% of nurses believed that unacceptable patient behaviour disturbs the patient flow system. In addition, 67% of doctors and 55% of nurses responded that difficult behaviour contributes of staff dissatisfaction, which negatively affects the quality of service provided. See figure 5.5.

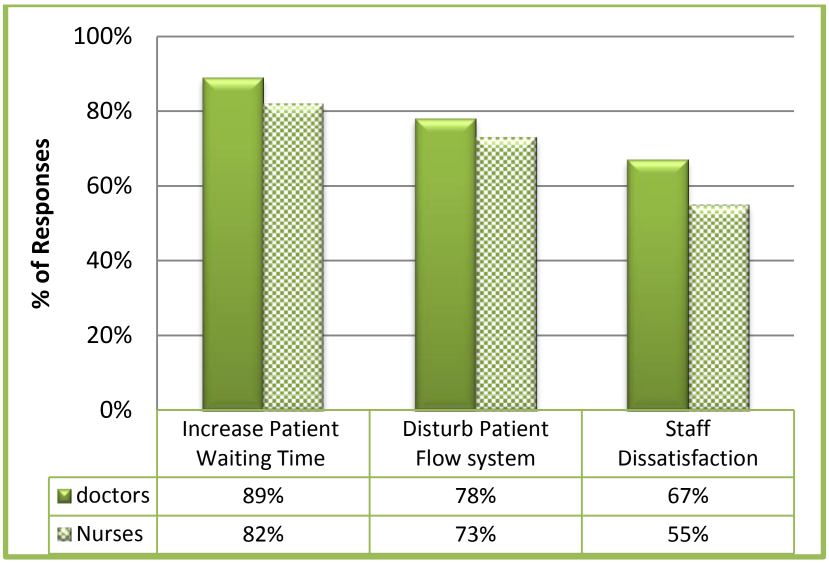


Figure 5.5 The Negative effects caused by the difficult patients' behaviour

Respondents were asked to highlight service areas experiencing unacceptable behaviour. The results show that there were three service areas experiencing delays because of the difficult behaviour of some patients. Table 5.10 shows those areas, and also shows the average real-time service, and the estimated average time that respondents believed that the difficult patient takes in addition to real service time. The purpose of this question is to develop greater understanding based on staff opinion about the more important areas that face difficulties to provide services because of behaviour. The results gathered aids to develop and build the behaviour model of TMC ED in the most accurate manner, it means the model is based on real issues that research has revealed according to staff opinion and experience. ED staff can give the most accurate details to consider due to many years of expertise within the TMC ED. This will also fill the gap of missing data where data is not available from hospital records and enable an accurate representation of a true to life system within the simulation model.

In fact, there is no previous research that can be found to compare with these results, as previous research is nonexistent in this area, where human behaviour is considered and the effects it can have on patient processes.

5.10. The Most important service areas for the recurrence of unacceptable behaviour, and staff estimation of the extra time taken by difficult patients.

Service area	Repeated behaviour	Mean time to provide the service (mins)	mean estimate extra time (mins)
Triage	- Interfering - Arguing - Communication difficulties - Illness Believes - Aggression	6	7
Reception	- Demanding - Aggression - Lack of respect - cultural influence - Communication difficulties - Alcoholism	3	4
Examination	- Communication difficulties - Arguing - Illness Believes	15.5	7

Although observation method was planned to examine patient behaviour as clearly discussed in chapter 3, nevertheless obtaining staff opinion about these factors will be a very important step that will help to understand patient behaviour, as they are the people who face these behaviours in their everyday work. Their experience is absolutely beneficial to establish the reality of these factors. Therefore, their responses will help to focus on the essential issues during the observation stage of this research. In addition, this step will confirm or reject the results from observation method. The details about the factors and staff responses are illustrated in table 5.11.

5.11. Staff Responses to Factors That Affect Patient Behaviour.

Factors that affects patient behaviour	Staff responses	
	Doctors (%)	Nurses (%)
Gender		
• Difficult patients are mostly males	66.7	72.7
• Difficult patients are mostly female	33.3	27.3
Nationality		
• Difficult patients are mostly Libyan	88.9	81.8
• Difficult patients are mostly non-Libyan	11.1	18.2
Age		
• Difficult patients are mostly old	44.4	36.4
• Difficult patients are mostly young	55.6	63.6
Time of Behaviour		
• Difficult behaviour usually occurs during early morning	33.3	18.2
• Difficult behaviour usually occurs during afternoon	22.3	27.3
• Difficult behaviour usually occurs during night time	44.4	54.5
Place of behaviour		
• Urgent area faces serious interruptions due to patient behaviour.	33.3	36.4
• Examination area faces serious interruptions due to patient behaviour.	66.7	63.6

The data in table 5.11 shows that staff members agree that difficult patients are mostly young Libyan men. The staff members also believe that they experience the most unacceptable behaviour at night and least disturbing behaviour in the morning. In addition, they ascertained that the examination area faces more difficult patient behaviour than the urgent area. Accordingly, this was attributed to the fact that the urgent area deals with intensive care patients that need immediate care and usually cannot show any kind of behaviour under examination/treatment.

5.4 Overview of patient behaviour based on observational data

In this section of chapter 5, the results that have been gathered via observation method will be explained and discussed further. The purpose of the observation and the method that has been followed in order to choose the sample size, the participants, and analysis method has been illustrated in detail in chapter 3.

This section is attempted to identify the problem affecting hospital's service time in relation with patient's behaviour. A descriptive analysis summarising the patient's characteristics and other factors in relation with their behaviour is displayed in Table 5.12 (a) and 5.12 (b).

The information that can be extracted from Tables (5.12 and 5.13) and Figure (5.6 to 5.9) is that "Reception" is the most likely place for difficult behaviour, with more likely "Male" patients, age in the band "30 – 40" , where time "12:00 pm – 2:00 pm" is the more likely time that behaviour is observed. The more likely reason of behaviour is the "long waiting time" and "the staff behaviour".

5.12. Distribution of Patient's characteristics by Existence of behaviour

The Factors			The Existence of Behaviour		
			Difficult Behaviour	Normal	Total
The Place	Reception	N (%)	75(49.7%)	18(8.6%)	93(25.8%)
	Examination	N (%)	46(30.5%)	150(71.4%)	196(54.3%)
	Triage	N (%)	30(19.9%)	42(20%)	72(19.9%)
Sex	Male	N (%)	81(53.6%)	114(54.3%)	195(54%)
	Female	N (%)	70(46.4%)	96(45.7%)	166(46%)
Patient Age	20-30	N (%)	38(25.2%)	54(25.7%)	92(25.5%)
	30-40	N (%)	58(38.4%)	58(27.6%)	116(32.1%)
	40-50	N (%)	25(16.6%)	49(23.3%)	74(20.5%)
	> 50	N (%)	30(19.9%)	49(23.3%)	79(21.9%)
Time of Observation	8:00 am - 10:00 am	N (%)	22(14.6%)	26(12.4%)	48(13.3%)
	10:00 am - 12:00 pm	N (%)	33(21.9%)	33(15.7%)	66(18.3%)
	12:00 pm - 2:00 pm	N (%)	64(42.4%)	90(42.9%)	154(42.7%)
	2 : 00 pm - 4:00 pm	N (%)	29(19.2%)	55(26.2%)	84(23.3%)
	4:00 pm - 6:00 pm	N (%)	3(2%)	6(2.9%)	9(2.5%)
Confrontation Behaviour (B1)	Yes	N (%)	53(35.1%)	0(0%)	53(14.7%)
	Normal	N (%)	0(0%)	210(100%)	210(58.2%)
	Not Applicable	N (%)	98(64.9%)	0(0%)	98(27.1%)
Challenges Behaviour (B2)	Yes	N (%)	60(39.7%)	0(0%)	60(16.6%)
	Normal	N (%)	0(0%)	210(100%)	210(58.2%)
	Not Applicable	N (%)	91(60.3%)	0(0%)	91(25.2%)
Passivity Behaviour (B3)	Yes	N (%)	11(7.3%)	0(0%)	11(3%)
	Normal	N (%)	0(0%)	210(100%)	210(58.2%)
	Not Applicable	N (%)	140(92.7%)	0(0%)	140(38.8%)
Ilness belief (B4)	Yes	N (%)	27(17.9%)	0(0%)	27(7.5%)
	Normal	N (%)	0(0%)	210(100%)	210(58.2%)
	Not Applicable	N (%)	124(82.1%)	0(0%)	124(34.3%)

IQR Interquartile range: (3st quartile - 1rd quartile), IQR = Q3 – Q1

SD: Standard deviation

5.13. Distribution of Patient's characteristics by Existence of behaviour.

The Factors			The Existence of Behaviour		
			Difficult Behaviour	Normal	Total
Intensity of Behaviour	Mild	N (%)	28(18.5%)	0(0%)	28(7.8%)
	Moderate	N (%)	69(45.7%)	1(0.5%)	70(19.4%)
	Severe	N (%)	53(35.1%)	0(0%)	53(14.7%)
	Not Applicable	N (%)	1(0.7%)	209(99.5%)	210(58.2%)
The Reasons of Difficult Behaviour	Long Waiting Time	N (%)	60(39.7%)	0(0%)	60(16.6%)
	Leak Organisation	N (%)	47(31.1%)	0(0%)	47(13%)
	staff behaviour	N (%)	37(24.5%)	0(0%)	37(10.2%)
	no answer	N (%)	7(4.6%)	0(0%)	7(1.9%)
	Not Applicable	N (%)	0(0%)	210(100%)	210(58.2%)
Staff Behaviour	Positive Staff Interaction	N (%)	49(32.5%)	0(0%)	49(13.6%)
	Negative Staff Interaction	N (%)	65(43%)	0(0%)	65(18%)
	Neutral Staff Interaction	N (%)	37(24.5%)	0(0%)	37(10.2%)
	Not Applicable	N (%)	0(0%)	210(100%)	210(58.2%)
B1_Time	Median (IQR)		7 (11 - 6)	8 (12 - 4)	8 (12 - 6)
	Mean(SD)		11.6(8.5)	8.5(4.0)	9.1(5.4)
B2_Time	Median (IQR)		10.5 (15 -9)	8 (12 - 4)	9.5 (12 - 7)
	Mean(SD)		14.5(9.1)	8.6(4.0)	9.9 (6.1)
B3_Time	Median (IQR)		8 (18- 7)	8 (12 - 4)	8 (12 - 5)
	Mean(SD)		12.6(7.7)	8.6(4.0)	8.8(4,3)
B4_Time	Median (IQR)		17 (26 - 10)	8 (12 - 4)	9 (12 - 6)
	Mean(SD)		18.1(8.9)	8.6(4.0)	9.6(5.7)

IQR Interquartile range: (3st quartile - 1rd quartile), IQR = Q3 – Q1
SD: Standard deviation

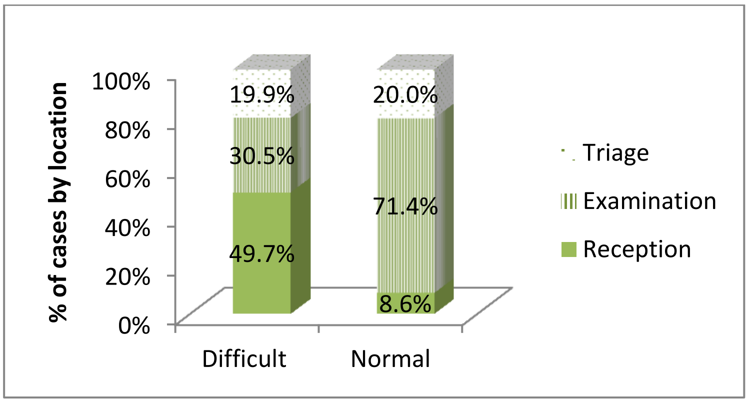


Figure 5.6 Distribution of cases by location and behaviour

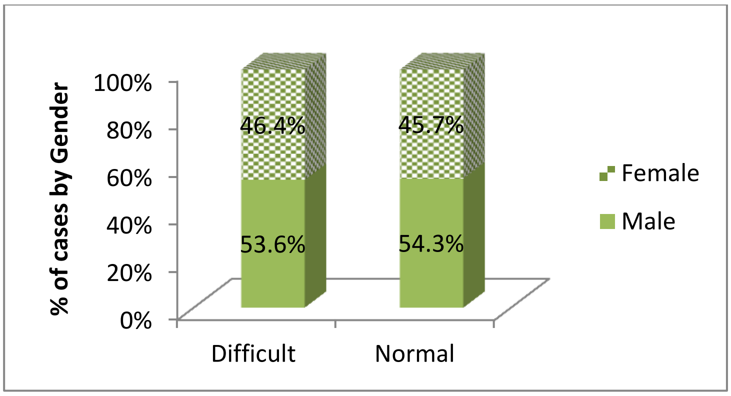


Figure 5.7 . Distribution of cases by Gender and behaviour

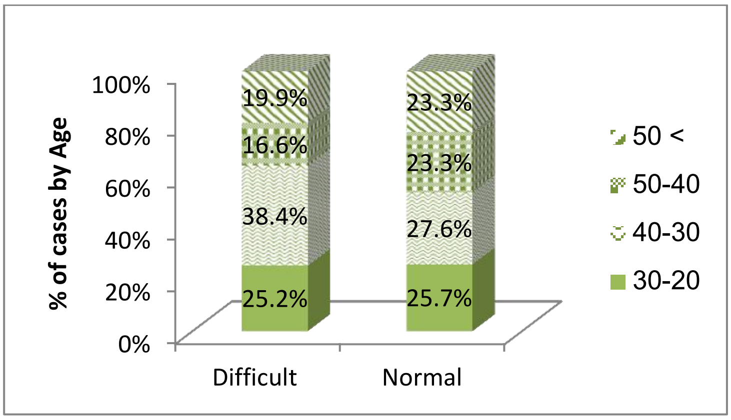


Figure 5.8 Distribution of cases by Age and behaviour

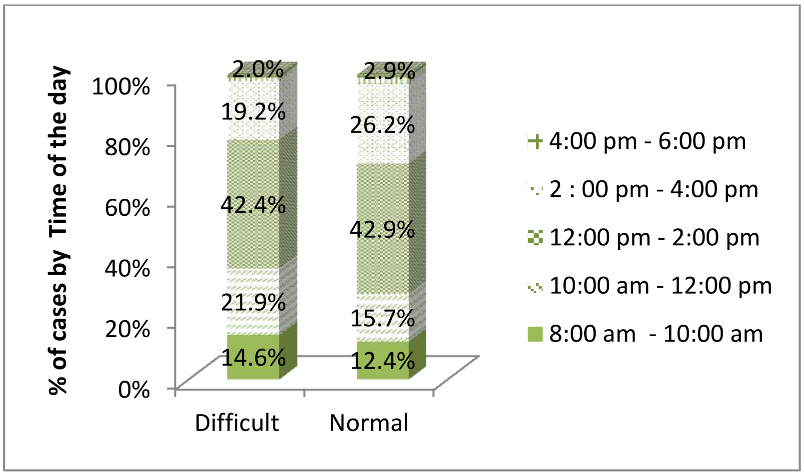


Figure 5.9 Distribution of cases by Time of observation and behaviour

Boxplot has been used to show the distribution of dataset (at a glance). Boxplot shows that the service times are longer in the presence of behaviour, Figure 5.10 represents the boxplot of the different service time by "behaviour".

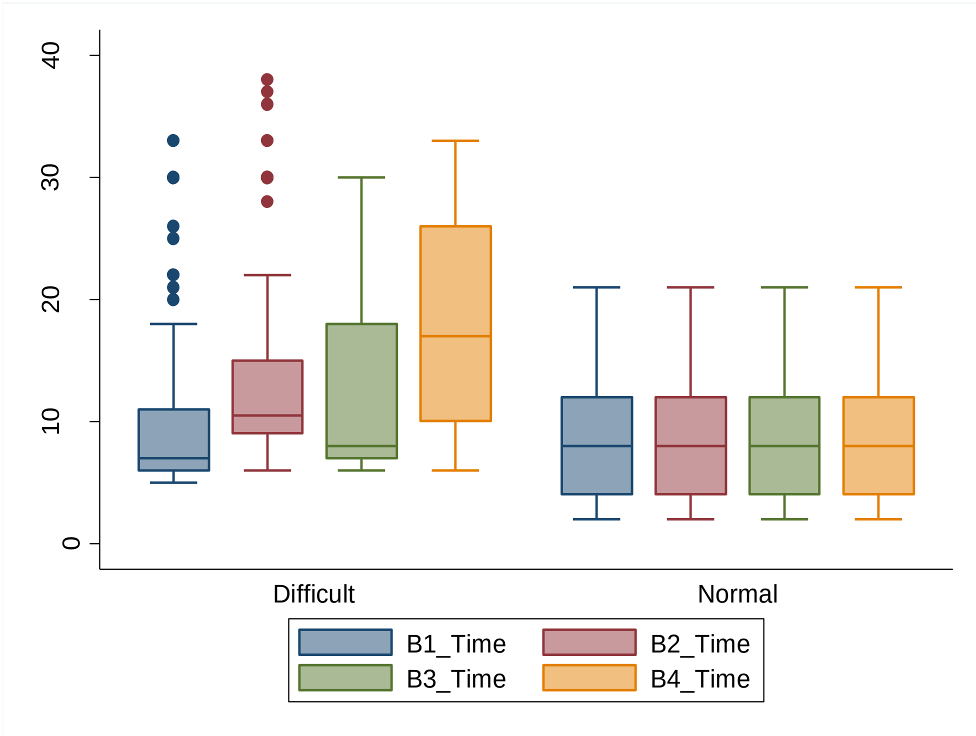


Figure 5.10 Service Times in minutes

In order to statistically check the hypothesis of any association between behaviour and the factors displayed in Table 5.12 and 5.13 the chi square test (χ^2) will be used for categorical variable, but when there is an ordinal variable the χ^2 test for proportion will be used to test for linear trend. For continuous variable such as service time, t-tests and analysis of variance (ANOVA) when necessary will be used. The justification of the use of the parametric tests (t-test and ANOVA) is because a graphical check on the normality of the data was carried out using Normal plots and it does not show an important departure from normality as displayed in Figures (5.11 to 5.14).

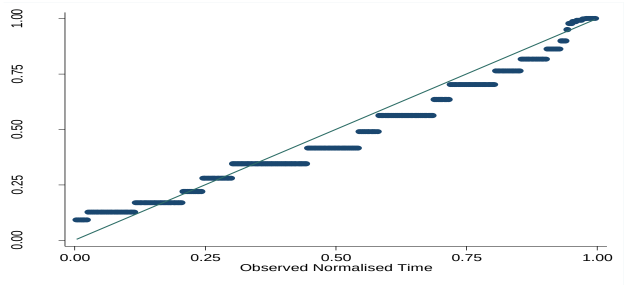


Figure 5.11 Normal plot for Confrontation Behaviour (B1) Time

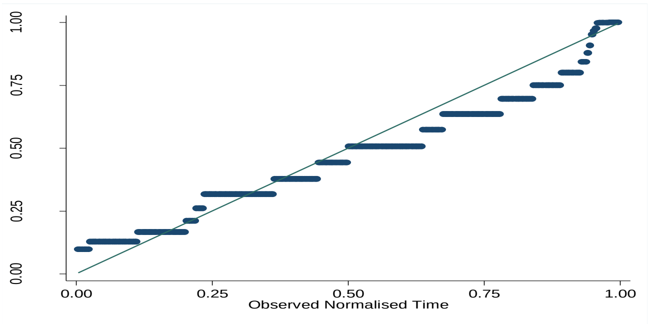


Figure 5.12 Normal plot for challenges behaviour (B2) Time

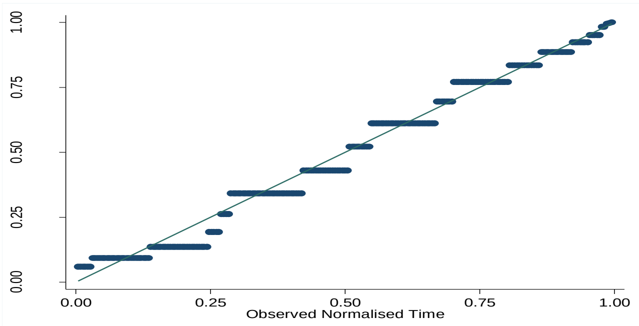


Figure 5.13 Normal plot for passivity (B3) Time

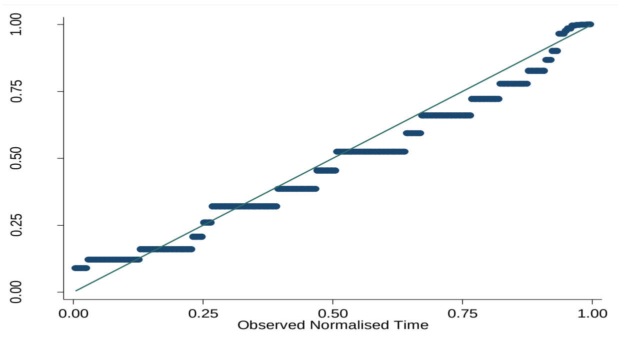


Figure 5.14 Normal plot for B4 Time

A chi-square test of independence is used to see if there is a potential association between the “Place” and behaviour. Here the aim is to determine if two variables; i.e place of services and behaviour, are related. It has been found that Pearson χ^2 (2 df) = 84.74, P-value < 0.001 (df: degree of freedom). From the result, it is very clear that there is highly statistically significant between place and behaviour. It means that behaviour existence is related to the place. Examining the pattern of numbers in table 5.12, it is noted that more difficult behaviour found in reception area than expected, and less difficult patient exist in triage. The normal behaviour is more existence in examination area.

To examine the relation between the time of observation and behaviour, a test on proportion is used. It is of interest to know if the behaviour exists is related to a different period of observation, and it shows that there is no significant trend or association between two factors. When, overall χ^2 (4 df) = 4.241, p-value = 0.3743. χ^2 (1 df) for trend = 3.191, P-value = 0.0741, χ^2 (3 df) for departure from linearity = 1.051, p-value = 0.7890. Therefore, it can be confidently stated that the behaviour exists similarly in any other period of observational time.

Gender is not statistically associated with behaviour, when Pearson χ^2 (1 df) = 0.0146 p-value = 0.904. This result is completely unexpected and it is actually on the contrary of staff response that is shown in table 5.11. They express that male patients usually show more difficult behaviour than females.

The interpretation that may come to mind that the statistical test that has been done studied the behaviour in general, without look deep inside each kind of behaviour. To illustrate, If the Pearson χ^2 text examine the association between each type of behaviour and patient's gender, it will probably be found that some of the behaviour, especially that shows aggressive, i.e. lack of respect, and interfering, significantly different between male and female.

Age is showing a significant association with behaviour and also a linear trend, when overall χ^2 (3 df) = 13.190, p-value = 0.0042.

T-tests for service times were carried out to check for any difference in time on average for the “behaviour” factor. T-test with unequal variances will be used as it shown in Tables 5.12 and 5.13 that the standard deviations of the times in the two groups are different.

For Confrontation Behaviour (B1), there was a significant difference between the two groups, (normal and difficult patients), when $p = 0.0128$. For Challenges Behaviour (B2), there was a significant difference between the two groups, when $p < 0.001$. For Illness belief (B4), there was a significant difference between the two groups, when $p < 0.001$. For Passivity Behaviour (B3), there was no evidence of any difference in time on average between the two groups when, It has been found that $p = 0.109$. The t-tests tables’ analyses are shown in AppendixE.

Service times are displayed in Table 5.14 and Figure 5.15. It can be observed that the times are longer in the presence of behaviour, in particular in the “examination” area.

Results shown in Table 5.14 highlight the difference between average time spent by two groups is highly significant. It means that the average time for service provided to two groups is not equal or similar. To gain a better understanding for these results, analysis based on the results in table 5.12, 5.13 and 5.14 has been done, and it can be easily noticed that the time consumed by patients who have difficult behaviour (any type of behaviour), is much longer than time spent by normal patients. For instance, the average time consumed by patients who are considered to have a B1 behaviour, regardless of the place of service, is approximately 12 minutes, it is about 3 minutes more than patients who do not show this behaviour. In addition, patients who show B2 behaviour need an average of 15 minutes to serve them, while normal patients only require about 9 minutes in average. B3 behaviour needs about 3 minutes more than normal group, and patient who have B4 behaviour need about an average of 10 minutes more than normal patient.

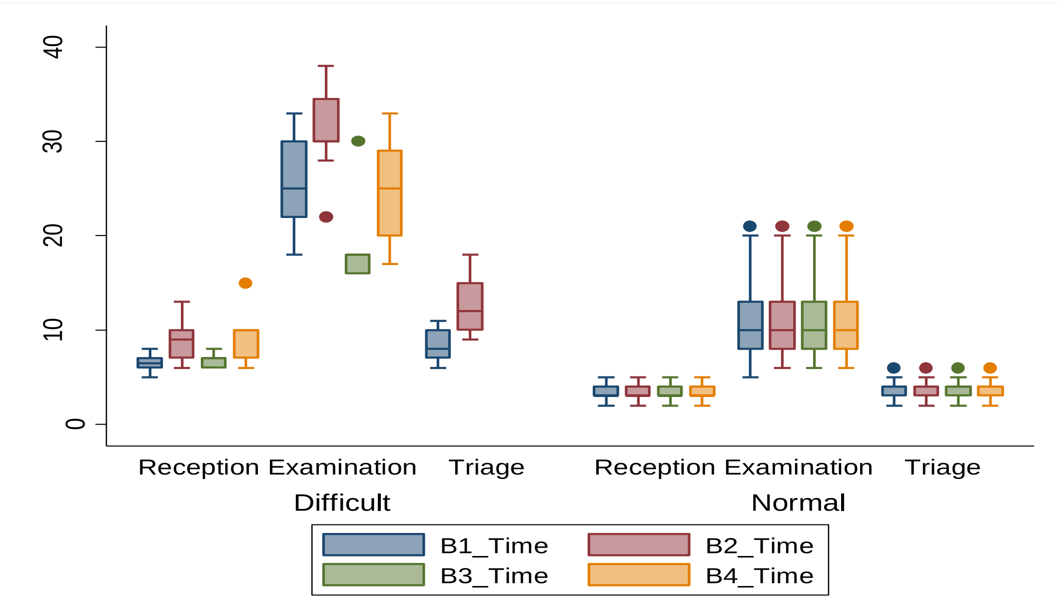


Figure 5.15 Boxplot of service times by Place and Behaviour

5.14. Summary statistic for service times by Place and Behaviour

		The Place							
		Reception		Examination		Triage		Total	
		The Existence of Behaviour		The Existence of Behaviour		The Existence of Behaviour		The Existence of Behaviour	
		Difficult	Normal	Difficult	Normal	Difficult	Normal	Difficult	Normal
B1_Time	Mean	6.57	3.22	25.54	10.53	8.25	3.64	11.60	8.52
	Standard Deviation	1.00	.88	5.14	2.92	1.71	.82	8.49	4.04
B2_Time	Mean	8.83	3.22	31.42	10.59	12.61	3.64	14.48	8.57
	Standard Deviation	1.91	.88	4.38	2.86	2.59	.82	9.11	4.03
B3_Time	Mean	6.83	3.22	19.60	10.59	N/A	3.64	12.64	8.57
	Standard Deviation	.75	.88	5.90	2.86	N/A	.82	7.66	4.03
B4_Time	Mean	8.91	3.22	24.38	10.59	N/A	3.64	18.07	8.57
	Standard Deviation	2.66	.88	5.34	2.86	N/A	.82	8.90	4.03

The service time naturally increases as the number of patients who carry difficult behaviour increase. This increase in time obviously can lead to increasing in WT and LOS of all patients. Based on the above results, there is clear evidence that patients' WT and LOS are seriously affected by the patient behaviour. This is further validated as experts within the TMC ED share the same concern which has been highlighted in the respondent questionnaire and interviews.

Two- way ANOVA were performed to test the difference in service time between the factors "Place" and "Behaviour". A test on interaction were also included in the analyses to see whether there is a difference in time at different levels of the factors. Figure 5.16 shows a clear difference in service time for "Behaviour" and "Place". Interaction is present but not as clear as the main effect. In the "Examination" area the service time is clearly significantly higher than the other two areas when "difficult behaviour" is observed. The same phenomenon is observed in Figures 5.17, 5.18 and 5.19.

It can be concluded that the service time is more affected in the examination area when difficult behaviour is observed.

The result achieved is complementary with the response of the participants in this study which shows a perfect correlation. ED staffs are more concerned from unacceptable behaviour within the examination area. Staff express that behaviour i.e. confrontation, challenges, passivity, and illness belief cause more problems and can easily consume long periods of time more than other areas. In table 5.10, it is clearly showed that patient with unacceptable behaviour spend a two fold increase in time when compared to estimated time of this service. While in other areas, even though, there is a delay and time is consumed by existing behaviour, it is not as much as time wasted in the examination area.

This is partly due to the high numbers of patients that attend examination and enable larger clusters of patients to gather and hence the chance of disruptions is greater. For example, the examination area has 6 patients attending every hour that equates to a patient every 10 minutes. Now, if a patient with difficult behaviour consumes 20 minutes due to disruption caused, this allows two patients to gather and makes the examination areas fall behind by two patients in terms of service time.

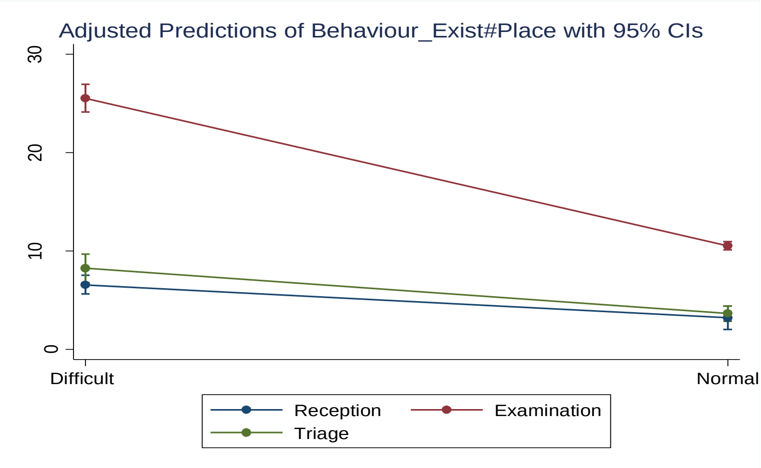


Figure 5.16 Two-way ANOVA for Time B1 by Behaviour and Place

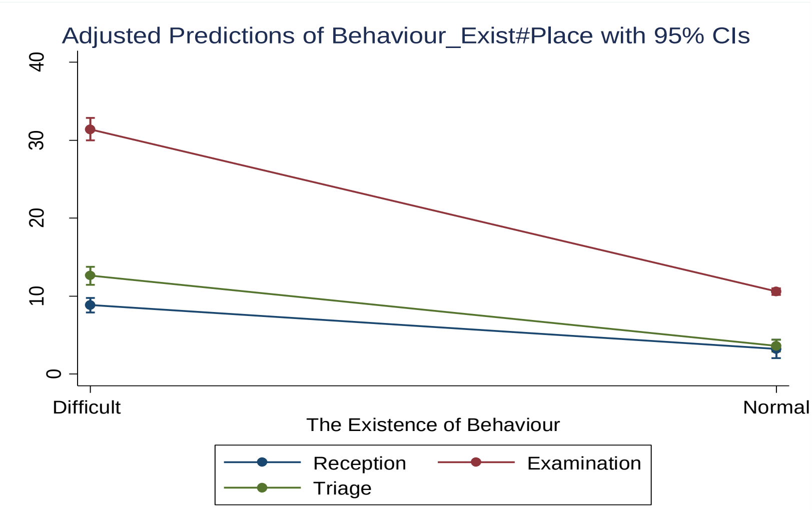


Figure 5.17 Two-way ANOVA for Time B2 by Behaviour and Place

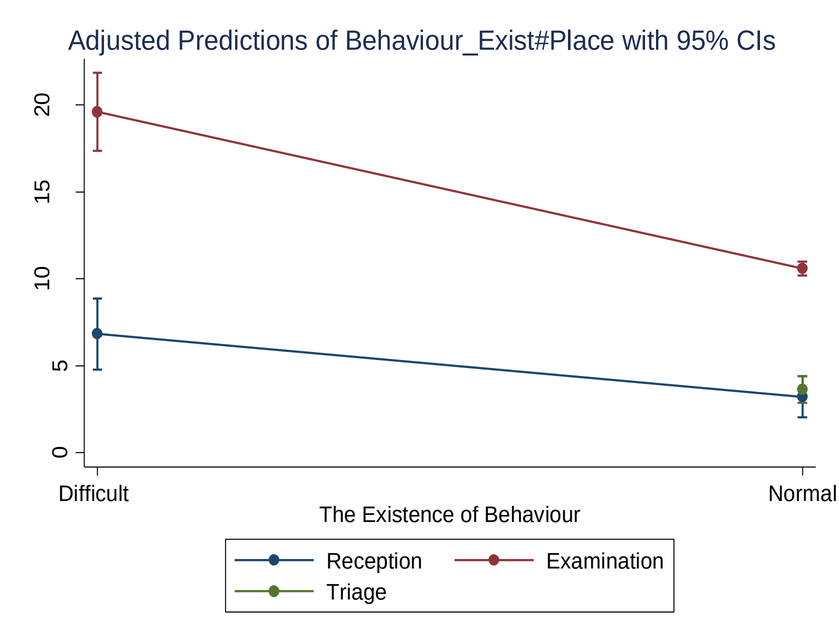


Figure 5.18 Two-way ANOVA for Time B3 by Behaviour and Place

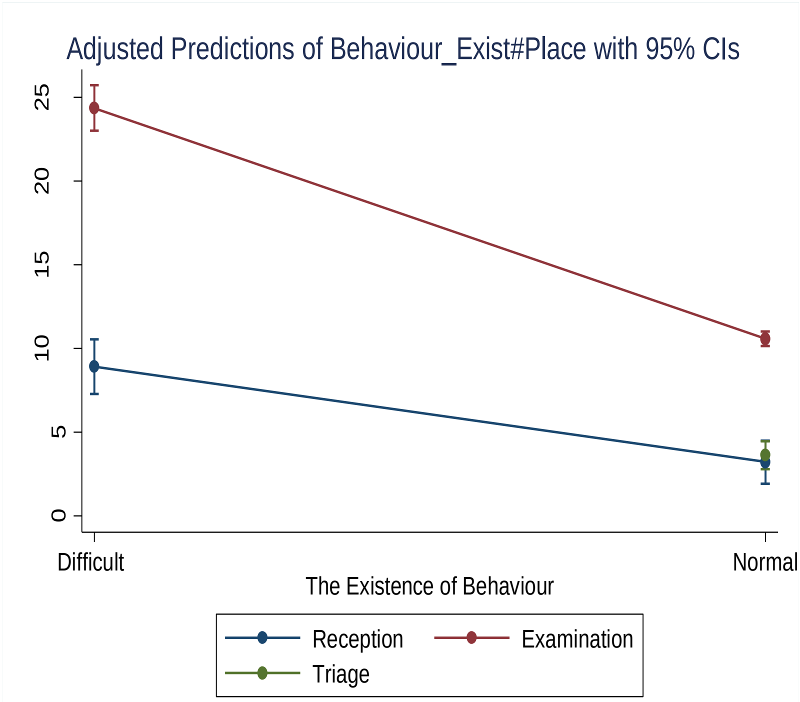


Figure 5.19 Two-way ANOVA for Time B4 by Behaviour and Place

5.5 Summary

This chapter examined historical data analysis to gain insights into ED TMC. The contents of this chapter can be summarized as follows

1. Description of the emergency department of the Tripoli Medical Centre (TMC) and the attending patients was explained in section one of this chapter. Data was collected by reviewing ED records and administrative records for May 2012. Additionally, the researcher used an innovative form that was designed to collect data about service times and patient waiting time. The results showed that the mean age of all ED visitors was 52 years, and the majority were Libyan. The study found that the average number of patients on a daily basis was 229. The results also showed that there was shortage of beds compared with other hospitals of similar size and type as the TMC. Most of the cases attended to at ED TMS were non-urgent and minor cases. Moreover, this section displayed and discussed the wait times and operation times of the service procedures using a number of tables and figures.

2. The factors that affect patient wait times at the ED TMC have been described in section two of this chapter. This was accomplished through the statistical analysis of the questionnaires and interviews with staff who were working in ED TMC during study period. The results show that overcrowding is considered to be a very exasperating and bothersome problem that they face daily. Majority of responders believe that difficult patients' behaviour had a negative impact on their work at ED. This section discussed extensively all behaviour factors, that disturb staff while they provide emergency services.

3. The third section of this chapter comprises elaborate discussion of the results that have been gathered using observation method.

   The results of this section gave an in-depth explanation of the problems affecting ED's service time in relation with patient's behaviour.

   The result included a descriptive analysis summarising the patient's characteristics and in addition, analytical statistics in order to statistically check the hypothesis of any association between behaviour and the various factors. All results have been discussed by using tables, figures and statistical tests.

Chapter 6: Models Analysis and Discussion

6.1 Introduction:

This chapter introduces all Five DES models and discusses each model in greater detail, the purpose of each DES model and the proposed representation and outcome. The first three DES model are based on the entire TMC ED whilst the remaining two DES models concentrate solely on minor and non-urgent patients that reside within the Examination area. This chapter sheds further light on patient behaviour and how this is represented within the DES models and the technique used to generate accurate representation. All DES models are analysed and discussed for a thorough understanding of the key developments. Throughout this chapter Key Performance Indicators (KPI) are used to compare and validate results with the research undertaken. The main concentration is the patient LOS and patient WT with reference to difficult behaviour.

6.2 TMC ED Models.

6.2.1 DES Model 1: Logical Representation

The Logical DES model is developed purely to observe an accurate representation that has been applied in terms of entity processing. Logical Model building, its validation and verification and its results will be displayed in the following sections.

6.2.1.1 DES Model 1 implementation:

The first and most important step was to develop a logical representation of the processes that exist within the chosen facility to its truest nature. Figure 6.1 shows the logical model representation. This model is based on the research undertaken via liaising and communicating with healthcare practitioners within the ED in TMC.

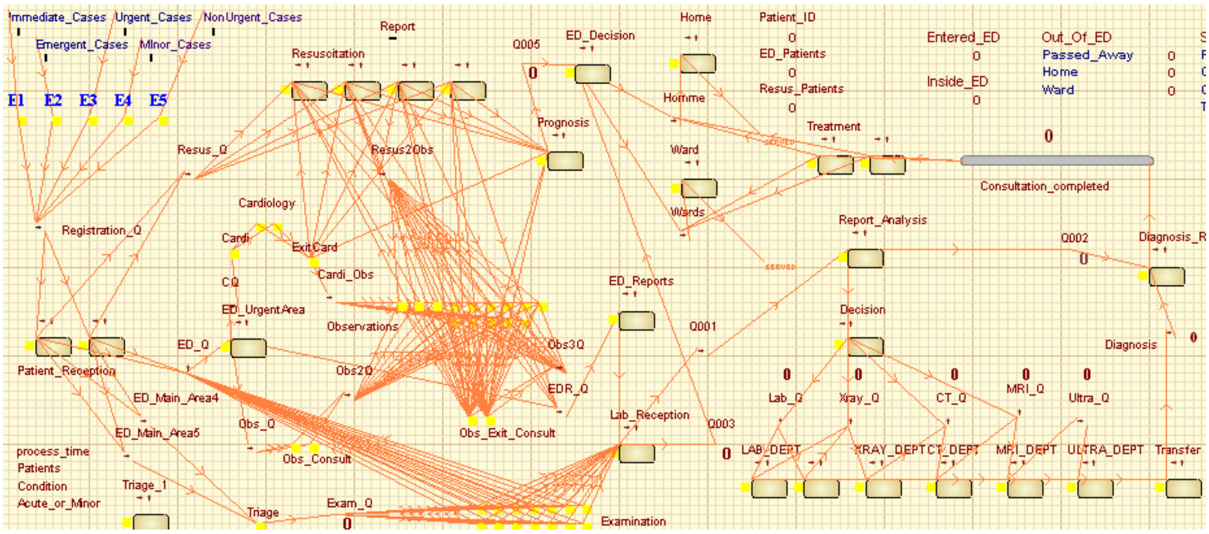


Figure 6.1 Logical model Representation of TMC ED, 2012

DES model 1 considers a certain number of patients arriving within the ED and observes the effects thereof. Five different types of patients are considered i.e. immediate cases, emergent cases, urgent cases, non-urgent cases and minor cases. The model has been run for one day (1440 minutes) continuously. Figure 6.2 shows how the model looks after one day of run time.

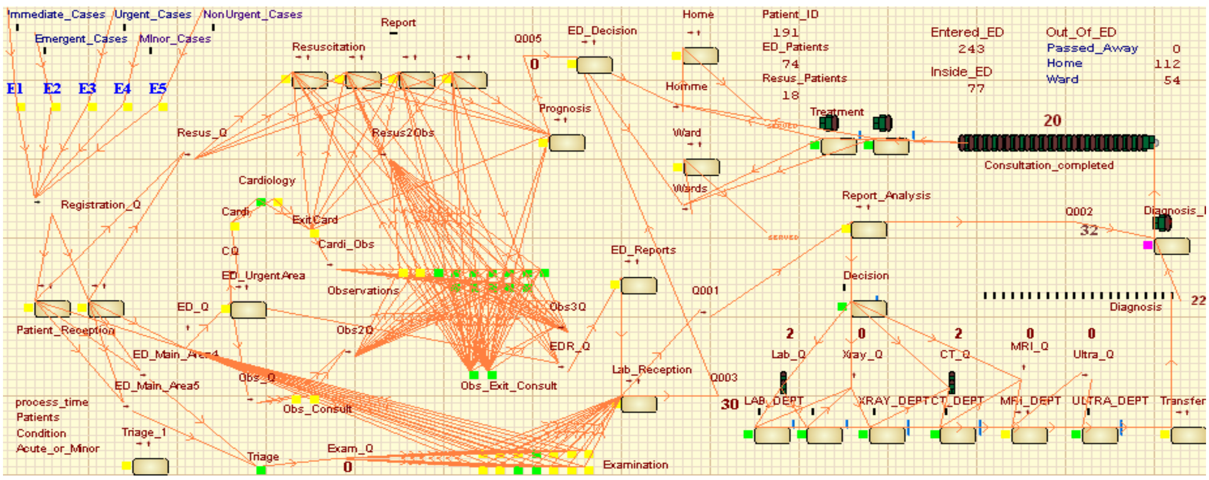


Figure 6.2 Logical Model, Hourly 10 patients visiting the TMC ED, 2012

6.2.1.2 Logical Model Verification:

Two verification methods which are; Checking of the code by a simulation expert and Visual checks by the modeller have been done to ensure that all patients that enter the system are able to move forward to designated areas accurately, from start to finish whether they exit the system in any of the three routes possible i.e. passed away, home, and ward. These have been implemented with dynamic counters as can be seen in Figure 6.3. Further counters show the number of entities that have entered, still remain in the ED and the four different sections of the departments that the patients were directed to according to their symptoms. It can be seen from figure 6.3 that in one day, a total of 338 patients have come to the ED, at the end of the 1440 minutes only 91 remain in the system and all the rest of the patients have exited.

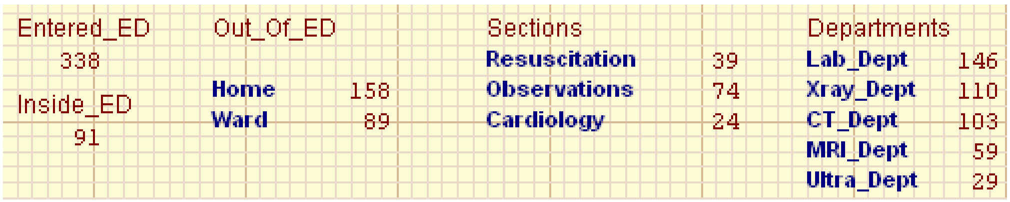


Figure 6.3 Logical Model Counters of TMC ED,2012

The coloured boxes in figure 6.4 indicate the status of every activity within the model. All activities have these coloured boxes to show the current condition or situation the activity is carrying out, whether it is busy, blocked or awaiting resources etc.

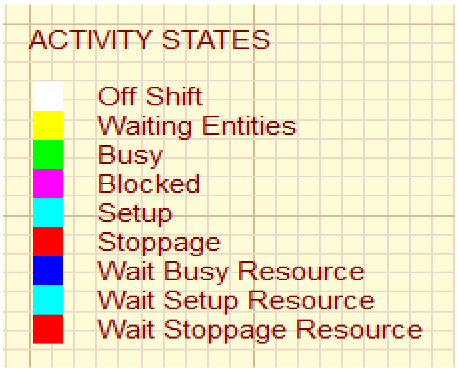


Figure 6.4 Logical Model Activity Status of TMC ED, 2012

Figure 6.5 shows the number of patients that are waiting in different departments. Based on figure 6.4, 2 patients are awaiting Laboratory and a further 2 patients awaiting for the CT service, 2 patients also happen to be waiting to register at the registration queue in figure 6.6.

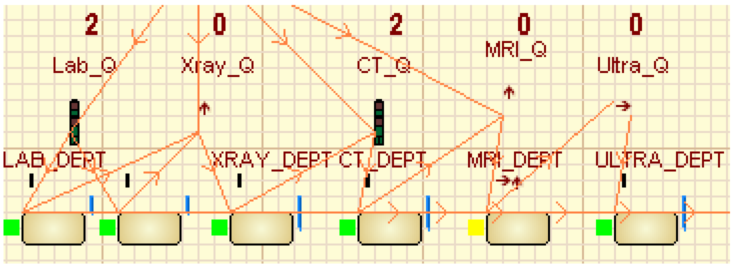


Figure 6.5 Logical Model Ancillary waiting queues of TMC ED, 2012

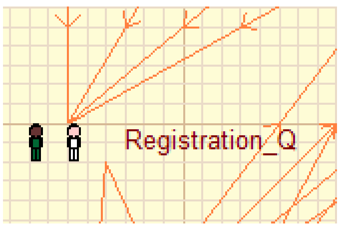


Figure 6.6 Logical Model Registration queue of TMC ED, 2012

All the above results only highlight the working order of all the existing processes as this is only a logical representation of which the purpose is to make all the patients move in a swift manner and proceed to designated areas throughout the entire model according to their conditions.

6.2.1.3 Logical model results:

This section displays the results that were extracted from the statistical data available by Witness. Table 6.1 shows how busy each existing activity is, whether it is blocked and if resource is available to undertake required tasks at hand. Table 6.1 shows that there are 4 activities, which have been highlighted in bold, indicate that at times tasks cannot be carried out due to the unavailability of required resources. The busy section in Table 6.1 indicates the percentage they are busy with regards to the amounts of patients they are required to treat.

6.1. Activity statistics of DES Model 1 (Logical Representation Model).

No.	Name	% Free	% Busy	% Blocked	% Task Wait Resource
1	Patient Reception	73.27	26.73	0	0
2	Observation	91.92	8.08	0	0
3	ENTRANCE	100	0	0	0
4	**Diagnosis_Review1**	**64.3**	**32.3**	**0.05**	**3.34**
5	Examination1	74.95	25.01	0.03	0
6	Treatment1	62.53	32.47	0	5
7	**Treatment2**	**55.49**	**37.94**	**0**	**6.56**
8	Ward	94.86	5.14	0	0
9	Home	93.75	6.25	0	0
10	Discharge	81.23	18.77	0	0
11	Discharge2	93.75	6.25	0	0
12	LAB_DEPT	87.1	12.9	0	0
13	XRAY_DEPT	13.84	86.16	0	0
14	CT_DEPT	38.6	61.4	0	0
15	MRI_DEPT	18.89	81.11	0	0
16	ULTRA_DEPT	44.04	55.96	0	0
17	Decision	90.76	9.24	0	0
18	Transfer	100	0	0	0
19	**Diagnosis_Review2**	**63.8**	**29.96**	**0.08**	**6.16**
20	Resuscitation	92.51	7.49	0	0
21	**Immediate Care**	**68.27**	**27.98**	**0**	**3.75**
22	Triage_1	83.18	16.82	0	0

Table 6.2. shows the Queue statistics that is very important as this indicates waiting time for patients in the different areas within the system. Important queues have been highlighted and the column average time is the area of concern. This column indicates the amount of time patients spend in the queues or have to wait in order to proceed. Table 6.2. shows that the main department for concern is the CT queue as the waiting time currently is 97 minutes based on DES model 1, thereafter the MRI and other indicated queues.

6.2. Queue statistics of DES model 1, (Logical Representation Model)

No.	Name	Total In	Total Out	Now In	Max	Avg Time (Minutes)
1	Diagnosis_1	50	49	1	2	1.93
2	Care _Waiting Room	46	46	0	1	0
3	Registration _Q	196	194	2	4	1.94
4	T1_WaitingRoom	66	66	0	1	0.01
5	Lab _Q	22	22	0	1	0
6	**X-ray _Q**	**70**	**66**	**4**	**5**	**24.38**
7	**CT_Q**	**38**	**38**	**0**	**10**	**97.09**
8	**MRI_Q**	**40**	**38**	**2**	**4**	**40.86**
9	**Ultra _Q**	**27**	**27**	**0**	**2**	**11.89**
10	T2_WaitingRoom	96	96	0	1	0.81
11	Passed Away(1)	11	11	0	1	2.16
12	Passed Away(2)	0	0	0	0	0
13	Diagnosis_2	74	74	0	2	1.21
14	Home	90	90	0	1	0.01
15	Wards	74	74	0	1	0.03
16	Obs _Q	57	57	0	1	0
17	Exam1_Q	57	57	0	1	0

Table 6.3 shows the resource statistics, this explains the utilisation of available doctors and nurses, how busy or free they are based on carrying out the designated work. This indicates where staffs are being used affectively or ineffectively, this indicates the requirement to increase or decrease staff.

6.3. Resource statistics of DES model 1, (Logical Representation Model)

No.	Name	% Busy	% Free
1	Immediate _Doc	27.98	72.02
2	Immediate _Nurse	55.95	44.05
3	Receptionists	26.73	73.27
4	Triage _Doc	41.38	58.62
5	Triage _Nurse	22.19	77.81
6	Resuscitation _Doc	18.74	81.26
7	Resuscitation _Nurse	14.98	85.02
8	Lab _Nurse	12.9	87.1
9	X-ray _Staff	86.16	13.84
10	CT _Staff	61.4	38.6
11	MRI _Staff	81.11	18.89
12	Ultra _Staff	55.96	44.04
13	Lab _Staff	12.9	87.1

Table 6.4 shows the entity statistics that will be used as the Key Performance Indicators (KPI's) i.e. the five types of emergencies and the average time each entity spends within the system. It can be seen in table 6.4; immediate cases take an average of 40 minutes, emergent cases take an average of 50 minutes, urgent and non-urgent take 191 minutes i.e. 3 hours and 11 minutes, minor cases take on average approximately 108 minutes i.e. 1 hour 48 minutes.

Table 6.4 will hold the most significance in terms of results currently as they will be used as the KPI's. This set of results shows how long patients spend within the ED depending on their case type. It will be used to reflect the difference in results, and compared to further developments of model enhancements to show the times consumed due to the changes applied. Currently table 6.4 only shows logical representation to ensure working order and flow. DES model 2 will highlight greater importance in terms of results.

6.4. Entity statistics of DES model 1, (Logical Representation Model)

No	Patient's condition	No. Entered	No. Served	No. In system	Avg Time (Minutes)
1	Immediate Cases	49	48	1	**40.74**
2	Emergent Cases	49	47	2	**50.47**
3	Urgent Cases	49	40	9	**191.78**
4	Non Urgent Cases	49	44	5	**191.84**
5	Minor Cases	49	44	5	**108.20**

6.2.2 DES Model 2: Basic Model

The Basic DES model takes into consideration the initial research to test the models capability and outcome. Basic Model building, its validation and verification and its results will be displayed in the following sections.

6.2.2.1 DES Model 2 implementation:

DES Model 2 considers and simulates the actual number of patients that enter the ED, gathered from the initial field research undertaken in order to understand and see how the model is affected. Implementing the actual number of resources was integral to the development of the model i.e. the number of doctors, nurses, physicians etc. This meant greater control and scrutiny of not just the patients, but also the available resources. The model was developed to aid greater understanding of how the ED is affected by actual number of patients and resources in comparison to the first model that only looked at the logical processes of the ED.

One of the key aspects of simulating any model, is finding accurate reliable data, especially with regards to the state of ED in order to allow real time control and operational planning. Many a times, only partial data is available, for example, the extent/number of patients waiting in queues in the different areas. However, due to the model being based on ED, it is reasonable to assume due to nature of any ED, some data will always be missing else unavailable as it may be too costly to acquire, not in terms of finance but rather costly to patients well-being as it is a ED.

Missing data is a common problem for simulation modelling, how to create simulation paths that are consistent with the ED, so consistency can be an issue. Inaccurate data may also cause further complexities throughout the system and lastly incomplete data which is available in order to establish the initial state for the simulation model.

Hence the initial research consisted of a through system log which took in to account the actual patients and resources numbers for an entire month on a daily basis, from which a average was derived and a distribution was assigned to give it the most accurate representation.

Based on the research, a Poisson distribution has been adhered to in accordance to patient arrivals, to represent patient flow and numbers in the most accurate manner. Initial literature review also highlights the poison distribution to be the most suitable distribution in order to calculate patient arrival times [Kuo *et al*., 2012; Marmor, 2010; Khare *et al*., 2008; Ahmed *et al*., 2009]. Further, in order to strengthen the results, a stochastic process has been adhered to in order to take into account any variance that may actually occur from the pseudo random number generation of the simulation model.

6.2.2.2 Basic Model Verification:

In order to validate and verify the results further to ensure validity, a stochastic process has been adhered to where replications are made by the partnering software named Witness Experimenter. This software enables pseudo random number generation that aid tests to be carried, this means, an array of different statistical ratios are developed based on the models programming.

Witness Experimenter enables time compressions and replications to be carried out in a very fast and affective manner as well enables the user to extract and develop an array of different results. Witness Experimenter was used to run replications of the model, an additional 100 times over with the implementation of pseudo random number generation to increase the chance of change which can be taken under consideration as logic dictates, every single replication will be different and in real life everything within this sector occurs almost at random.

This stochastic process takes into account and considers every single process within the model i.e. activities, entities, queues, resources, variables etc. However, the main concentration will be the patient entity as it represents the key performance indicator (KPI). The KPI will actually go through this stochastic process at every stage within the model i.e. pseudo random generation is made by the simulation program at every stage from the moment the entity enter the system, through all the activities and queues until the entity exits. Hence, the KPI is used as it goes through the entire system, which is full of stochastic processes and is actually undergoing a stochastic process itself.

Once all the replications are in place, Witness Experimenter will extract the average and Standard Deviation (SD), a confidence level will also be extracted which will display a minimum and maximum based on a 95% Confidence Interval (CI). The results will indicate the variance over 100 replications, and the average in essence should be between the minimum and maximum confidence intervals, this will indicate a very strong result where the validation and verification process can be viewed as completed.

This will bring together all the results of the replications and produce a stronger collective result, which can be used to understand and see the status of the patients which represent case types, See Table 6.5.

6.5. KPI results of stochastic analysis of DES Model 2, (Basic Model)

Statistical Measurements	Immediate Cases	Emergent Cases	Urgent Cases	Non Urgent Cases	Minor Cases
Average Time	176.56	350.86	318.44	208.10	209.14
Standard Deviation (SD)	24.11	37.65	15.65	37.15	16.16
Minimum 95% CI	149.18	318.05	301.23	187.93	194.91
Maximum 95% CI	199.36	385.55	346.76	241.47	223.33

Table 6.5 shows the stochastic analysis results of the 5 different patient types, the results show the average time the patients spend according to their case based on the 100 replications, the standard deviation with the minimum and maximum confidence interval (CI) . This shows the variance in results and how the average derived from the stochastic analysis is between the minimum and maximum 95% CI. The results shown in table 6.5 helps to develop greater understanding by addressing the difference and variation that may occur. How in a real life system due to the nature of the patients illness, no two time frames are the same. Hence the average is derived from 100 replications to represent an accurate time frame which is used as a KPI.

This take into consideration the variation that exist in the time frames that patients consume on a daily basis.

6.6. Comparing the Model 2 KPI Results to the Research KPI Results

Average Time	Immediate Cases	Emergent Cases	Urgent Cases	Non Urgent Cases	Minor Cases
Simulation Average Time	176.56	350.86	318.44	208.10	209.14
Research Average Time	185.58	324.43	307.90	240.45	219.21

Table 6.6 displays the research results in comparison to the stochastic analysis results, both the average times of patients else case types are considered, to understand how far the simulation model is to the actual real life system. The results shown in table 6.6 seem to be a very good fit, firstly because the average of both results are not far from one another for all case types and more importantly, the research average times although may seem to fluctuate a little is within the 95% CI of the stochastic analysis.

6.2.2.3 Basic Model Results.

After running the model for 100 replications, extracting the statistics for ED of TMC using Witness, it will make it more clear as to how big the problem is and if it is a sustainable problem or do changes need to be made in order to acquire a more efficient result. It will also show the current status of the ED and the difficulties it faces in providing the service on a day to day basis. The result of this model, Basic Model, is expected as DES Model 1, highlighted certain developments in progress. The increase in patients based on actual data will now allow the scrutiny of the results highlighting specific problem areas with more details, also will enable greater understanding to enable further changes to be applied to the model in order to carry out tasks more effectively and increase efficiency.

Figure 6.7 shows a high increase in queues for certain ancillary departments. Big queues exist now in the ancillary department, X-ray showing 32 patients, CT showing 16 patients and MRI shows 22, this will have a direct effect on the patient waiting time and increase staff usage. Patients also seem to be waiting for doctors for consultation before treatment that can be seen in figure 6.8.

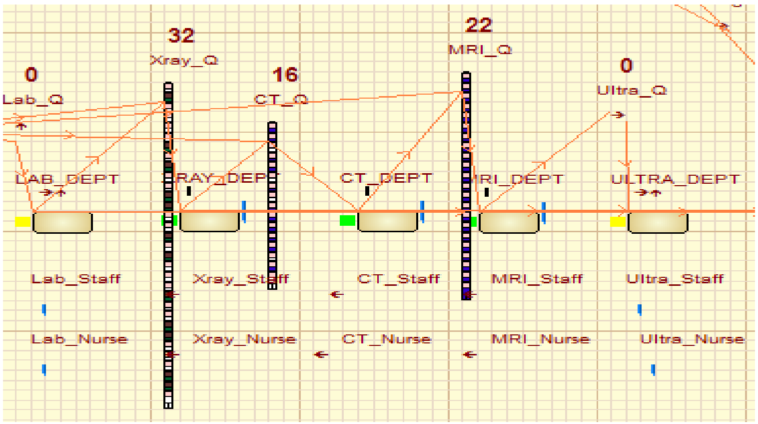


Figure 6.7 Basic Model Ancillary departments of TMC ED, 2012

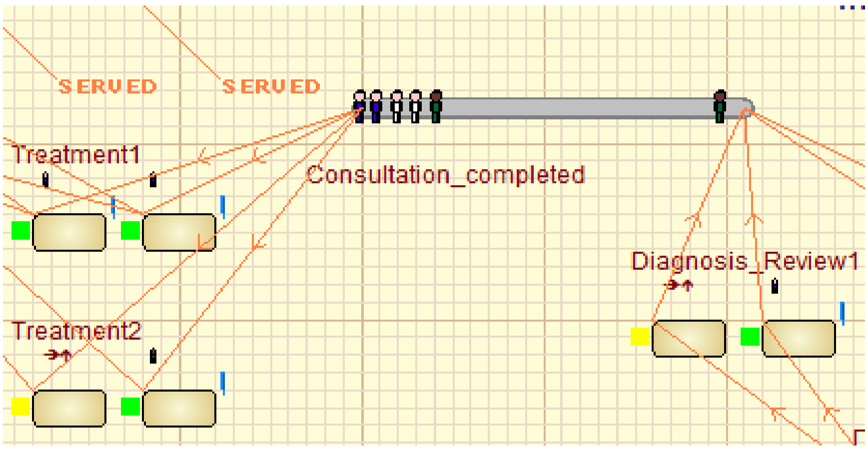


Figure 6.8 Basic Model Awaiting Treatment of TMC ED, 2012

Figure 6.9 shows the immediate care area, where two resources are busy at their stations whilst the other two station have turned into a dark blue status which indicates the resource needed to carry out the task, is currently busy and hence has to wait until the resource is free. i.e. patients are waiting in the room until doctors and nurses finish previous tasks. The Care Waiting Room also shows patients waiting to move forward but has to wait until stations or rooms are free.

Patients can only move forward if beds are free, hence patients have to wait in the waiting area where problems can develop i.e. patients become dissatisfied and cause disruption due to the duration of the wait and the lack of facilities [Umar *et al*., 2011; Bankauskaite *et al*., 2003]. Further, as time is consumed, it is reasonable to assume, the number of patients waiting will only increase due to the current status caused overcrowding. A single patient due to difficult behaviour can consume the time of two patients that will lead to a queue in processing and can develop a backlog of patients waiting.

Based on the immediate care area shown in figure 6.9, which caters for severe pain patients, the most important problem caused by overcrowding is poor quality of care and increased waiting times. Similar result were found in many studies carried out in EDs all around the world. Studies established that there is association between overcrowding with poor quality of care in patients with severe pain [Barrett *et al*., 2008; Hwang *et al*., 2006; Abbuhl *et al*., 2003; Pines *et al*., 2010; Blot *et al*., 2007].

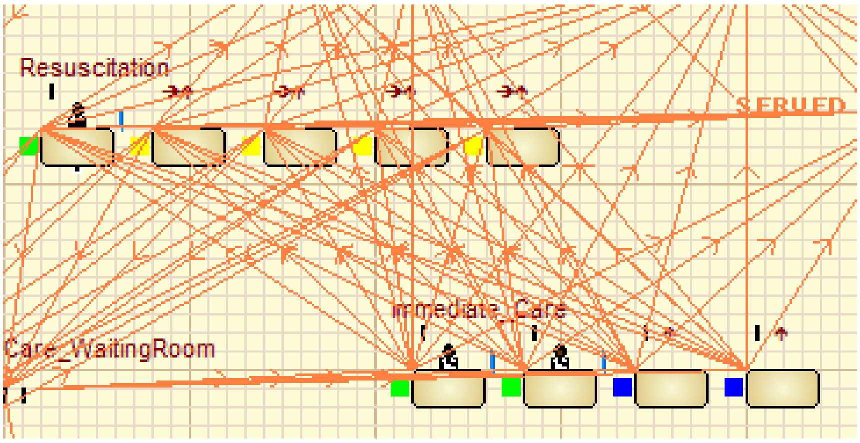


Figure 6.9 Basic Model Resuscitation and Immediate Care of TMC ED, 2012

Figure 6.10 shows the examination area is full. Majority of the activities are awaiting resources and busy, the examination queue has 59 patients waiting to be examined. This displays a definite problem from triage through to examination. This seems to be the single most important problem as this is where majority of the patients are sent to as the examination area takes care of all minor and non-urgent patients. This area will cause the bulk of problems in respect to waiting times, as the queue of 59 patients indicates a very long wait. The triage station also seems to be forwarding patients to examination without considering the current situation of the examination area and the queue. This result compares favourably with the finding from study has done in US that 59% of participants experienced delays in treatment from triage. In addition, 20% experienced delays from time of room placement that cause Increasing waiting room number and occupancy rate [Jesse *et al*., 2007].

The examination area has the same problems faced by the immediate care area, but to a greater extent. Firstly, all the stations are occupied and secondly, majority of the stations indicate the lack of resources as all the doctors are busy carrying out tasks.

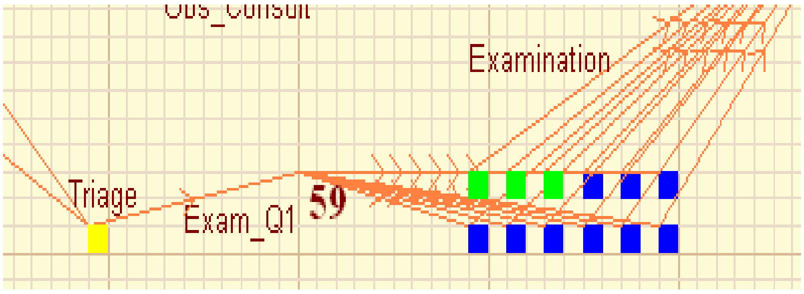


Figure 6.10 Triage and Examination

Table 6.7 shows the activity statistics as explained in ED model 1 (Logical Model). This shows how busy or free the activities are and the percentage of time an activity has to wait in order to complete a task due to the unavailability of resources and further if the station is or has come to a blockage at any point in time.

The ancillary departments that can be seen to be very busy for majority of the time, the X-ray department has a busy percentage rate of 98.98 which indicates a very efficient usage rate. This also indicates that currently staffing may not be a problem however space is, as the queues for the ancillary departments develop in the simulation model resulting in huge waiting times for patients. In fact, the ancillary departments is essential in the rapid diagnosis of patients, implementation of treatment, and ED's doctors cannot make decision before getting patient's results that are required and have to go through the ancillary department. Delay in this department leads to increase in waiting time and then increases overcrowding, this has also been established within this study. Comparing this result with other studies, found many previous researchers findings that blame the ancillary departments to be a cause for overcrowding in ED because of delay in services. For instance, Miele. V, et al found delays in getting imaging result and delayed assessments resulted in prolonged stays within the ED, especially in the case of trauma patients [Miele *et al.*, 2006]. Davis. et al also found that delays in ancillary departments is one of the causes of overcrowding and prolongs waiting time in ED [Davis *et al.*, 1995].

The ancillary department in ED TMC are very busy and can be explained as the ancillary department is not only used by ED patients, but also inpatients and all other departments in TMC who send patients to the ancillary department. This makes it very difficult for ED patient to move any faster. It is worth mentioning that there is a specific laboratory for emergent and urgent patients, but not minor and non-urgent patients. This situation leads to the creation of long queues and long waiting times for their result to compete their assessment and treatment in ED.

Table 6.7 also shows that the examination activity has the highest percentage at 15.02 for task awaiting resources which indicates, the resources here are being stretched and any busier will see these figures increase dramatically. This can easily cause bottlenecks which can develop problems elsewhere i.e. activities preceding the examination. This was also apparent in figure 6.10 (examination queue, triage and reception) where the screen shot shows all the examination activities to be engaged in carrying out tasks and patients waiting. This will definitely have a knock on effect on the examination queue which, as highlighted has a significant queue currently that will only carry on increasing as they have reached capacity and resources are fully engaged.

Patient reception is also blocked for a certain period which may be due to excessive number of patients coming in simultaneously and not being able to forward patients to triage for examination. This can also be connected to the triage and examination problems discussed which as highlighted can have an effect on tasks preceding the examination queue.

Other tasks also have slight blocked percentages and task wait resources but nothing as significant as those highlighted and discussed.

6.7. The Activities statistics for DES Model 2, (Basic Model)

No.	Name	% Free	% Busy	% Blocked	% Task Wait Resource
1	Patient _Reception	51.50	45.27	3.23	0
2	Observation	85.21	14.79	0	0
3	ENTRANCE	100	0	0	0
4	Diagnosis_Review1	50.22	45.87	0.05	3.86
5	Examination1	18.38	65.62	0.98	15.02
6	Treatment1	49.97	45.91	0	4.12
7	Treatment2	47.52	49.13	0	3.35
8	Ward	91.87	8.13	0	0
9	Home	92.43	7.57	0	0
10	Discharge	72.91	27.09	0	0
11	Discharge2	92.43	7.57	0	0
12	**LAB_DEPT**	**82.44**	**17.56**	**0**	**0**
13	**XRAY_DEPT**	**1.02**	**98.98**	**0**	**0**
14	**CT_DEPT**	**17.79**	**82.21**	**0**	**0**
15	**MRI_DEPT**	**2.63**	**97.37**	**0**	**0**
16	**ULTRA_DEPT**	**35.54**	**64.46**	**0**	**0**
17	Decision	83.45	15.28	0	1.27
18	Transfer	100	0	0	0
19	Diagnosis_Review3	53.58	43.73	0.04	2.65
20	Resuscitation	81.96	17.12	0	0.92
21	Immediate _Care	16.16	63.97	0	13.87
22	Triage_1	65.41	32.13	0	2.46

Table 6.8 shows the amount of time patients consume waiting in certain queues before proceeding to the actual task that needs to be carried out, this table shows time patients spend or wait to receive treatment. This table is based on all the queues within the DES model where patients await to move forward.

The ancillary departments (Lab, X-ray, CT, MRI and Ultra) have long waiting times as can be seen. This is partly due to the lengthy queues, but rather the duration the tasks take in order to carry out the task as patients do not join queue on an appointment basis as it is the ED.

However, the laboratory queue does not show any waiting time, as this queue is solely for receiving the sample from either patients or staff. This queue represents patients or staff simply handing in their paperwork or samples to be tested.

The urgent waiting area shown in table 6.8 that leads to the resuscitation, observation and the cardiology rooms. This area shows an average waiting time of approximately 45 minutes. The average combined time for all cases in that area i.e. immediate cases who should be seen in less than 1 minutes, emergent who should be seen in less than 1 to 14 minute and the urgent cases who should be seen in 60 to 120 minutes. The results shown in table 6.8 based on the urgent waiting room represents actual data gathered from research. Findings reveal immediate patients wait about 10 mints to see a doctor, emergent cases spent about 38 mints waiting for health provider and the average waiting time of urgent patients is about 53 mints.

Table 6.8 also considers the examination area, the simulation results show that waiting time in examination queue (Exam1_Q) is also very high. It is currently at 174 minutes, this queue has been previously highlighted to be a significant problem area as all the minor and non-urgent patients have to go through this process. The current waiting time validates this point as the examination area is very busy. The model is only based on 1440 minutes, it is very reasonable to assume that this number will carry on increasing. The examination queue currently does not have a fixed capacity; hence further assumptions can be made on the basis of capacity alone i.e. when capacity is reached firstly it may cause a bottleneck and get blocked and secondly patients may start to wait outside the waiting area within the ED causing further problems on corridors and unacceptable disruptions causing havoc.

6.8. The Queue statistics for DES Model 2, (Basic Model).

No.	Name	Total In	Total Out	Now In	Max	Avg Time (minutes)
1	Urgent _Waiting Room	87	85	2	9	44.51
2	Registration _Q	340	338	2	6	1.57
3	T1_WaitingRoom	121	121	0	2	7.55
4	Lab _Q	30	30	0	1	0.11
5	**X-ray _Q**	**110**	**78**	**32**	**33**	**189.54**
6	**CT_Q**	**64**	**48**	**16**	**20**	**196.05**
7	**MRI_Q**	**68**	**46**	**22**	**22**	**258.24**
8	**Ultra _Q**	**33**	**33**	**0**	**3**	**14.79**
9	T2_WaitingRoom	144	144	0	1	10.03
10	**Exam _Q**	**103**	**91**	**12**	**59**	**174.08**

- Lab _Q = Laboratory Queue, T1= Triage 1, T2 = Triage 2, Exam1_Q = Examination Queue.

DES Model 2 results were in line and in support of the results obtained by calculating the waiting time for patients visiting the ED during the research study time. The data recorded for patient waiting times to see a doctor after triage for both types of patients, minor and non-urgent exceeded two hours.

Table 6.9 shows how busy the resources (staff) are within the facility, the busiest activities shown in table 6.7 have the busiest staff i.e. the examination area and ancillary departments. The examination area staff (triage doctor and nurses) are busy for majority of the time, it is also noteworthy to mention, the triage is actually part of the examination area as they process all patients forward to examination, this is expected as all the previous tables highlighted problems within the examination area such as capacity issues and the shortage of staff. This will automatically have a direct effect on the usage rate of staff making it reasonably high as shown.

The X-ray, CT and MRI staffs and nurses are the busiest according to their activities, however they are free for a little percentage of time and more so the remaining two ancillary departments i.e. Lab and Ultra.

A certain percentage of the resource free percentage shown in table 6.9 is actually due to the model starting from the very beginning where no entities or tasks are carried out at the very start. The simulation model will take this into consideration and class the activities and resources as being free until the time entities come and join the activities. In the case of the examination area, all the staff have to be engaged to be classed as busy and hence will take a little longer until the point where all the doctors and nurses are busy simultaneously.

This also indicates that there is only enough staff to carry out single tasks at a time and that emergencies arrive faster than the tasks can be carried out, hence resulting in a backlog of patients that result in an increase in waiting time. The average task time in table 6.9 can validate this problem as a whole i.e. CT staffs and nurses average tasks time is almost 25 minutes. So if there are more than one every 25 minutes, this will result in queues being developed as can be seen in table 6.7 where the wait time has increased dramatically and figure 6.8 ancillary department shows the extent of the queues within the model as it increases. This happens to be a common problem in many areas within the ED of TMC as the facility struggles on a daily basis to cater to the needs of their patients partly because they arrive unscheduled as is the purpose of the EDs.

6.9. The Resource Statistics (The average task time) for DES Model 2 (Basic Model).

No.	Name	% Busy	% Free
1	Immediate _Doc	46.97	53.03
2	**Immediate _Nurse**	**93.95**	**6.05**
3	Receptionists	76.47	23.53
4	**Triage _Doc**	**93.59**	**6.41**
5	**Triage _Nurse**	**92.2**	**7.8**
6	Resuscitation _Doc	37.56	62.44
7	Resuscitation _Nurse	34.24	65.76
8	**Lab _Staff**	**17.56**	**82.44**
9	**X-Ray _Staff**	**98.98**	1.02
10	**CT _Staff**	**82.21**	17.79
11	**MRI _Staff**	**97.37**	2.63
12	**Ultra _Staff**	**64.46**	35.54
13	Consultant	78.32	21.68

The entity statistics (KPI's) in table 6.10 shows the average duration the different emergencies spend within the simulation model from start to finish. They have to follow the rightful route based on their condition that can take them through an array of different tasks resulting in different times. This also indicates how fast the ED can react to or take charge of the emergencies that arrive on a continuous basis daily. The statistics show that immediate cases take an average of 176.56 minutes that is a long period of time as these patients conditions can be very specific and precise that requires immediate action. Emergent cases take a considerable 350.86 minutes, consuming just slightly less than 6 hours, this is a very long duration for emergent cases and highlights the existence of problems in patient process. Non-urgent cases have the longest average time of 368.49 minutes, just over 6 hours which is a considerable amount of time as well as minor cases that take 343.87 minutes. Urgent emergencies have an average time 318.44 minutes, being less than non-urgent and minor, this is because urgent follow a shorter route with a specific problem.

6.10. Average time of Key Performance Indicators for Model 2, (Basic Model)

No.	Patients	Average Time
1	Immediate Cases	176.56
2	Emergent Cases	350.86
3	Urgent Cases	318.44
4	Non urgent Cases	368.49
5	Minor Cases	343.87

6.2.2.4 Finding

The current results indicate an array of problem areas which results in a definite increase in time, this is also clearly apparent by the results of the key performance indicators (KPI) where there has been dramatic changes from the logical model and basic model. However these results do not specify the cause, but rather identify a collective effect of many issues and concerns within the ED. Hence, this model represents only the gathered research data to display the current status of the ED without pin pointing or segregated any specific issues. Therefore, the cause and reason behind the current waiting times cannot be singled out to find the root cause. However the KPI results can be now used as guidance for further developments and further KPI's within certain areas can be developed to display stronger results aided by a stochastic process.

An important problem area happens to be the ancillary departments, these departments have the largest queues causing the biggest backlog of patients and resulting in a definite increase in waiting times. This is also because of the lack of facilities available, further if more than one task is to be carried out, more resources will be required. This department alone contributes to the increase in waiting times as the problems are interconnected i.e. staffing, lack of resources and queues.

However, the key problem area seems to be the Examination area that consists of the triage and examination queue. As firstly, this area seems to take care of majority of the patients on a daily basis (minor and non-urgent). The examination activities indicate areas of concern which intern have an effect on the examination queue as highlighted and the triage activity preceding it and can only develop major disruptions in the future that will cause more problems for other activities such as the reception.

6.2.3 DES Model 3: Ideal Model

The Ideal DES model is based on further research undertaken with regards to the ideal consumption times physicians propose to take in order to see the outcome where a comparison can be made with the Basic DES model to identify verification. Ideal Model building, its validation and verification and its results will be displayed in the following sections.

6.2.3.1 DES Model 3 Implementation:

DES model 3 is an actual representation of the ED within the TMC based on the ideal operational times, these process times were collected via thorough research undertaken with the ED staff and management. These times represent the allocated times doctors, nurses, physicians and duration tasks should take in reality without the existence of any disruptions. This model is based on all the processes being in perfect order and without the existence of any disruptions regardless of the situation. This is in fact how the management would like to see the ED run on a daily basis and hence can be used as a benchmark for all the KPI's.

This model will further enable enhancements to be made in order to see the effects of certain disruptions that do occur and cause problems on a daily basis. This model serves the purpose of further developments, to see the effects of different types of behaviour on an individual basis rather than a collective problem basis. By developing this actual model that represents a state of perfect order, this study will enable a strategic screening process, to see and calculate the effects of behaviour and the effects of such behaviour types throughout the ED.

This study considers how human behaviour affects the patient flow through the ED, and how much time is consumed by difficult patients. Hence, this study will only concentrate on a single issue named human behaviour which causes problems in order to see how behaviour affects patient flow, as highlighted in the initial research.

6.2.3.2 DES Model 3 Verification

To validate, verify and strengthen the results, a thorough stochastic analysis will take place in an array of different key areas, the same validation and verification process will be followed as discussed previously in the Verification and Validation sections.

6.2.3.3 DES Model 3 Result

The results displayed in table 6.11 have been extracted directly from the witness simulation statistics tool, which calculates an array of different averages based on the developed simulation model. The main concentration will be the average time entities i.e. case types/patients spend within the model that represents LOS. This is shown in table 6.11 under the Average Time column, which displays the average time of entities within the system. It shows that immediate cases spend an average of 143 minutes, emergent cases spend an average of 216 minutes, urgent cases spend the most amount of time consuming an average of 265 minutes, non-urgent cases consume an average of 205 minutes and minor cases take an average 193 minutes.

6.11. Patient Length of Stay (LOS) Results for Model 3, (Ideal model)

Patient Types	No. Served	No. in system	Average Time (min)
Immediate Cases	16	2	143.49
Emergent Cases	14	3	216.42
Urgent Cases	13	4	265.57
Non urgent Cases	16	23	206.11
Minor Cases	15	22	193.42

Table 6.12 shows the stochastic results of the entities, which will be used as a key performance indicator (KPI) that represents LOS in the witness simulation model. The results firstly indicate a variance in the results when compared to table 6.11 actual model which is expected due to the number of replications run and the averages derived from within. Immediate cases time has decreased, emergent cases time has increased, urgent cases time has decreased, non-urgent and minor cases has increased.

This shows the existence of variance within the same results when a stochastic analysis is carried out and thus fulfilling the purpose of increased understanding of model results and variances that may exist.

6.12. Stochastic Analysis Results of Case Types for DES Model 3, (Ideal Model)

	Immediate Cases	Emergent Cases	Urgent Cases	Non Urgent Cases	Minor Cases
Average Time	133.71	251.38	201.01	258.08	200.64
SD	24.11	37.65	15.65	37.15	16.16
Minimum 95% CI	125.17	238.04	195.46	244.92	194.91
Maximum 95% CI	142.26	264.73	206.56	271.25	206.37

Similarly, many key elements (Activities and Queues) within the simulation model had to be considered, many activities and queues have been taken under consideration that will be discussed.These activities relate to key areas within the

ED, table 6.13 shows the resuscitation activity that represents the resuscitation area, how busy the area is and the percentage of time a task awaits for a resource which in reality means how long a patient may have to wait before doctors and nurses are free to see to the patient's needs.

6.13. ED Resuscitation Area Task Statistics for DES Model 3, (Ideal Model)

Resuscitation area	Task Wait Resource%	Free %	Busy%
Average	2.14	11.63	86.24
Standard Deviation	1.48	1.37	2.62
Minimum 95% Confidence	1.61	11.14	85.31
Maximum 95% Confidence	2.66	12.11	87.17

The examination area results shown in table 6.14 has a further column listed blocked which indicates the percentage of time activities were blocked, which means activities were totally restricted from carrying out any task. This can be a result of reaching capacity to the extent no further patients can move forward, causing the development of bottlenecks that cause patients to create a backlog. This also can be as a result of the lack of facilities as increasing numbers of patients arrive and have to go through the general processes i.e. if the examination area has reached capacity, then the triage cannot not forward patients till there is space which means the queue to the triage will also increase.

6.14. ED Examination Area Task Statistics for DES Model 3, (Ideal Model)

Examination	Blocked %	Task Wait Resource%	Free%	Busy%
Average	0.17	0.34	16.54	82.95
Standard Deviation	0.03	0.08	0.16	0.22
Minimum 95% Confidence	0.15	0.31	16.48	82.88
Maximum 95% Confidence	0.18	0.37	16.60	83.03

The triage results in table 6.15 indicate how busy or free the activity is depending on the number of patients. This indicates efficient usage rates as it is not blocked for any duration nor does the task seem to be waiting for resources as shown in the previous table 6.13 and 6.14. Further, it shows the triage to be free for over 60% of the time, revealing the triage is capable of carrying out a further increased number of tasks if needed as well as the fact it is running below efficiency.

6.15. ED Triage Statistics for DES Model 3, (Ideal Model)

Triage	% Free	% Busy
Average	39.86	60.14
Standard Deviation	1.22	1.22
Minimum 95% Confidence	39.43	59.71
Maximum 95% Confidence	40.29	60.57

Table 6.16 shows the cardiology activity statistics, which is free for over 25% of time and also seems to be blocked for a very small amount of time. This can be a

result of lack of space after the activity or preceding activities as patients cannot move forward or cannot exit the cardiology.

6.16. ED Cardiology Statistics for DES Model 3, (Ideal Model)

Cardiology area	Blocked%	Free%	Busy%
Average	0.09	25.11	74.80
Standard Deviation	0.11	5.85	5.85
Minimum 95% Confidence	0.05	23.04	72.73
Maximum 95% Confidence	0.13	27.18	76.88

Table 6.17 represents where patients come and wait to see consultants before being admitted into the observation area. Hence, indicates amount of time patients wait to see consultant, and how busy or free the activity is.

6.17. Observation Consulting Activity Statistics of DES Model 3, (Ideal Model)

Observation Consult	Task Wait Resource %	Free %	Busy %
Average	0.36	11.62	88.02
Standard Deviation	0.26	1.17	1.33
Minimum 95% Confidence	0.27	11.20	87.55
Maximum 95% Confidence	0.45	12.03	88.50

Table 6.18 represents the actual observation area which is busy for more than 64% of the time and free for over 35%, however also appears to be blocked for a very small percentage. This is where patients are entered into for observational purposes after consultation with physicians.

6.18. Observation Activity Statistics of DES Model 3, (Ideal Model)

Observation	% Blocked	% Free	% Busy
Average	0.06	35.14	64.81
Standard Deviation	0.04	7.83	7.81
Minimum 95% Confidence	0.04	32.36	62.04
Maximum 95% Confidence	0.07	37.91	62.57

Table 6.19 represents patients leaving the observation area, upon which they have to be discharged by a doctor. The results indicate the percentage of wait in order for patients to be discharged from the observation area.

6.19. Observation Exit Activity Statistics for DES Model 3, (ideal Model)

Observation Exit Consult	Task Wait Resource %	Free %	Busy %
Average	0.52	17.27	82.01
Standard Deviation	0.28	2.04	2.22
Minimum 95% Confidence	0.42	16.54	81.43
Maximum 95% Confidence	0.62	17.99	83.00

6.2.3.4 Comparison of Basic Model (DES Model 2) KPI against Ideal Model (DES Model 3) KPI

Table 6.20 shows the statistics and variance in the KPI results from both models after a stochastic process. The actual model results seem to have decreased dramatically in most cases. An overall decrease is expected as the actual model only takes into account the ideal process times derived from the research undertaken and does not dictate reality where disruptions do occur and the resulting disruptions cause increase waiting times.

The KPI result indicates times that can be compared to actual research undertaken and shows how LOS is affected on a daily basis. The Basic Model times can be compared to the current status of the ED and the Actual Model times can be considered against the research for ideal process times. The difference between the Basic Model and Actual Model also indicates how much difference can actually exist due to disruptions; the percentage change column displays dramatic changes with LOS. It is also noteworthy, the times shown in table 6.20 represent individual patients, hence even a difference of a single minute can add value or cause tarnish to the process as a whole as the ED has more than 200 visitors daily. The results shown in table 6.20 display dramatic changes in time consumption between DES Model 2 and DES Model 3. The percentage change is from 32% to 77% that accounts for huge periods of time.

6.20. Comparing Between KPI Statistics in DES Model 2, (Basic Model) and DES Model 3, (Ideal Model)

Comparing the Averages	Immediate Cases	Emergent Cases	Urgent Cases	Non Urgent Cases	Minor Cases
DES 2 Basic Model Average Time	176.56	350.86	318.44	368.49	343.87
DES 3 Actual Model Average Time	133.71	251.38	201.01	208.10	200.64
Percentage % Change	32.05	39.57	58.42	77.07	71.39

6.2.3.5 Finding:

Previous section of the current chapter highlights an overview of the basic and actual model. i.e. the representation of results, their purpose and influence on the model, what the results represent in terms of reality and how the results will be utilised in order to understand the condition of the ED and processes within. KPI and LOS were developed to aid understanding so comparisons can be made affectively as model enhancements were made.

Firstly, the DES Model 2 model is shown to represent the basic model, the current status of the ED where disruptions are prevalent throughout all the processes involved. Thereafter, a stochastic analysis is carried out ensure greater scrutiny of results in order to strengthen via validation and verification.

Secondly, DES Model 3 represents the Actual Model based on the initial research undertaken of ideal process times stated by experts within the ED. This represents actual times tasks should take without the occurrence of disruptions, hence eliminating all additional time that would be considered if disruptions did exist.

KPI's were used to understand the difference it made to patient LOS in both DES models. The KPI results develops a understanding of how disruptions affect the actual system within the ED and how patients are affected in terms of waiting times and increased total average time of patients within the ED.

The results are only to be used for purpose of comparisons, and aid greater understanding in terms of processes and how these process simulations represent the existence of different tasks in reality. All the tables show how key processes work and what they represent, if the tasks carried out are operating smoothly, if blockages exist and how busy or free all the resources are. All these activities have been looked at from a stochastic approach as 100 replications have been made to assure variance is within the confidence intervals.

A stochastic approach enables greater validity and verification in terms of strengthening the results achieved by means of replications carried out and developing further statistical averages including the use of a 95% confidence interval. This also highlights the standard deviation as all the replications produce a different set of results where the average is extracted from rather than the average of one single replication.

The purpose of DES 3 model is to aid the integration and development of DES 4 where behaviour is considered where additional time is required due to patient behaviour. DES 3 enables results to be considered based on the ideal operational times and the difference that behaviour causes to this time.

6.2.4 DES Model 4: Behaviour Model

The Behaviour DES model concentrates on only the Examination area where the minor and non-urgent patients attend. A conditional Behaviour is attributed to every patient in order to represent patient behaviour and identify the difference in time. More explanation of Implementation and results that has been obtained from DES Model 4 will discuss in following sections.

6.2.4.1 DES Model 4 (Behaviour Model) Implementation:

Figure 6.11 shows the changes that have been applied to the model in order for behaviour to be considered. Patient behaviour is considered within the examination area of DES 4 alone, as modelling behaviour throughout the TMC ED is a very complex and time consuming process. Modelling the entire system would not be achievable within the given time and it is better to choose the most desirable or affected area in order to extract findings and develop solutions that can be transferred to other areas. The objective is to find a strategic solution using DES to reduce patient down time within the ED. Hence at this current stage, the examination area alone will suffice to reach the objectives of the study.

The behaviour model only concentrates on patients attending the examination area; this consists of minor and non-urgent patients that account for the majority of patients. Therefore, the model will only be based from the moment patients enter the reception, are screened through to triage, admitted into the examination and as they exit the examination area shown in figure 6.11.

The field research also showed that majority of the patients entered the ED are non-urgent and minor cases as highlighted in the data analysis chapter (Chapter 5). Hence, this has been done due to the research and the findings of the initial simulation model, which highlights consistent problem occurrences within the examination area that solely caters to non-urgent and minor patients.

However, the key difference in this model development will be the addition of behaviour to patients. Firstly, a basic model (DES Model 2) was constructed that took into account all types of problems that ED is facing every day , then the actual model (DES Model 3) considers the ideal operational time which represented no behaviour occurrences. The behaviour model i.e. DES Model 4, however will consider the existing four behaviour types identified in the research that collate to patient disruptions.

The KPI will remain the same, but over a smaller scale of processes within the model i.e. instead of considering the LOS of entities from the very start right through all the process to the very end, consideration will only be now made up to when entities exit the examination area. The length of stay in queue (LOSQ) will remain the same as reception queue, triage queue, and examination queue will be considered as normal as shown in figure 6.11.

A new LOS will be calculated using the actual model to find the ideal time. This will show the time patients should take in reality and according to the actual model but only to the point of exit after the examination process as shown in table 6.22.

Thereafter, behaviour will be added to the examination area, the triage area, and the reception to see the affects behaviour can have on the individual areas and how it affects the KPI's. This will enable a better scrutiny of the results and lead to better understanding, as the main concentration will be the minor and non-urgent patients.

Figure 6.11 shows the changes in terms of modelling, where the examination now comes to an end indicated by the use of arrows leading to served. Served in terms of simulation modelling means the patients have exited the system. Hence, length of stay (LOS) will now be the duration from arrival to when patients exit the examination area. The number of patients waiting in queue will also be considered as a KPI to increase understanding and to show in terms of patient numbers, how queues can fluctuate according to the changes applied and the affects thereof.

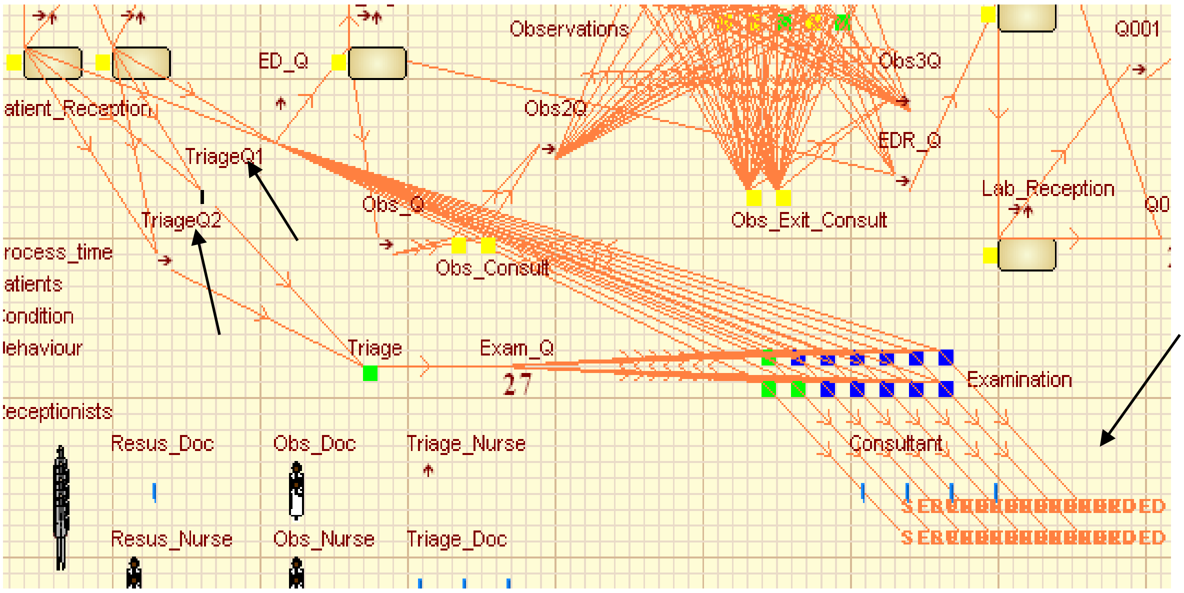


Figure 6.11 New Enhancement of Examination Area with Behaviour

In order to create an accurate representation of behaviour, the following details have been changed according to the research under taken. These changes are to make sure the correct time is consumed as different behaviours occurs within the examination area.

Figure 6.12 shows how time is programmed to be consumed by patients due to the behaviour applied in the simulation model which is explained in table 6.21.

Duration is now based on a random occurrence of a variable named Behave. Behave has been divided accordingly to the four behaviours under scrutiny and the chance of these behaviours is solely based on random. Depending on the random variable, a certain behaviour will be considered and a time will be consumed accordingly as shown in table 6.21.

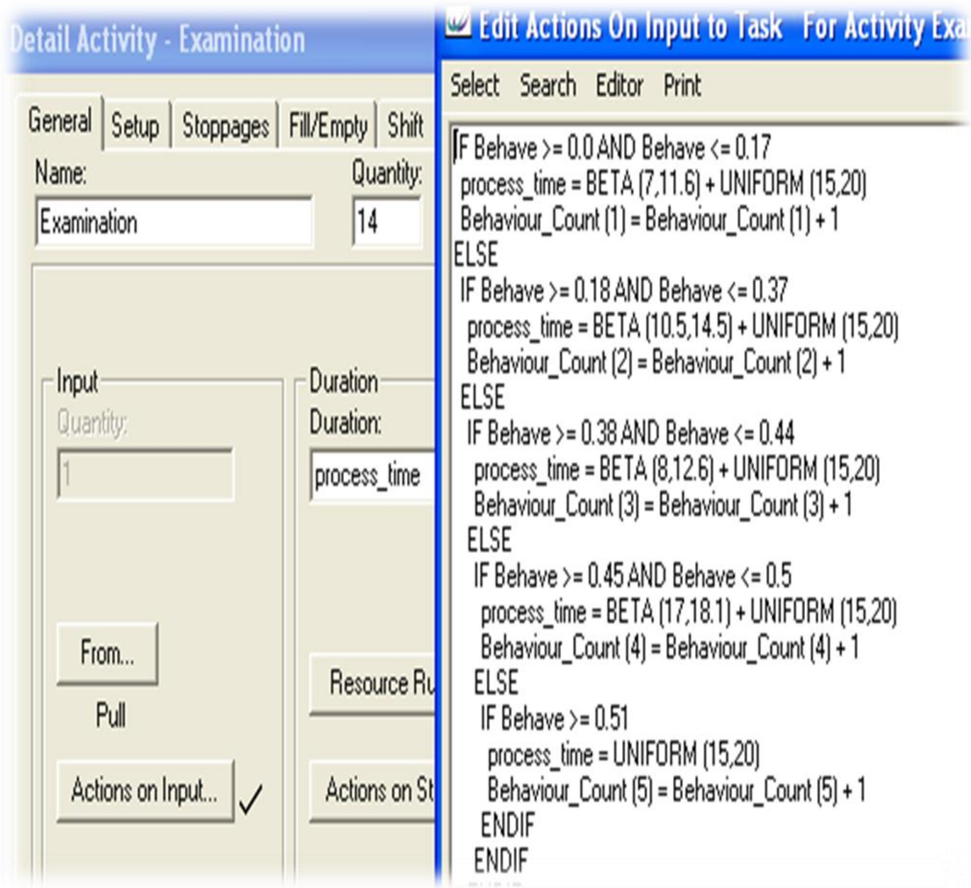


Figure 6.12 Behaviour Time Application

6.21. Formula Representation and Time Consumption for DES Model 4, (Behaviour Model)

Behave (Random)	Behaviour Type	Time Consumed (minutes)
0.0 – 0.17	Confrontation	Beta (7, 11.6) + uniform (15,20)
0.18 – 0.37	Challenge	Beta (10.5, 14.5) + uniform (15,20)
0.38 – 0.44	Passivity	Beta (8, 12.6) + uniform (15,20)
0.45 – 0.50	Illness Belief	Beta (17, 18.1) + uniform (15,20)
0.51 – 1.0	Normal	Uniform (15,20)

The probability of random is based on 0.0 to 1.0. The random value has to fall between 0.0 and 1, and hence the probability of random has been divided according to the research carried out based on behaviour. In the data collection chapter (chapter 3) it highlights the four types of behaviour and occurrence of them in terms of a percentage. This percentage has now been used to aid the random occurrence of behaviour. Therefore, based on table 6.21 which represents the research data, confrontation has a 17% chance which is represented by 0.0- 0.17, challenge has a 19% chance which is represented by 0.18 to 0.37, passivity has a 7% chance of 0.38 – 0.44 and illness belief has a 5% chance based on 0.46 – 0.50. The remainder of patients happen to be classed as normal according to the research where 50% of all patients did not cause any disruptions via the use difficult behaviour. Hence, the remainder of the random probability i.e. 0.51 – 1.0 is classed as normal. However, the chance or probability that the random falls within these given percentage is totally random.

Table 6.21 shows a clearer understanding of how the correct time is consumed according to the random occurrence of a behaviour type. If the random occurs within the designated behaviour type as shown in table 6.21, a certain time will be consumed according to the research undertaken. This is represented by the distribution Beta that was found to be the best fit after carrying out a fitting test against other distributions. The standard uniform process time will also be consumed.

6.2.4.2 DES Model 4 (Behaviour Model) Results

Table 6.22 shows the actual consumption time of minor and non-urgent patients within the ED up to the examination area as discussed and shown in figure 6.11. All the queues are taken under consideration displaying the maximum patients in the queue due to behaviour as well the length of stay in queue. All the results have also been put through a stochastic analysis to validate, verify and strengthen the results.

The main concentration will be the stochastic average times of minor and non-urgent patients, which represent length of stay, Further the number of patients waiting in the queue and patients length of stay in queues. The ideal times shown in table 6.22 seem to have some variance due to the stochastic approach. The minor and non-urgent now consume a very similar time with very similar results as they follow the exact same processes when they are admitted into the TMC and attend the examination area.

6.22. KPI Results of Ideal Simulation Without any Behaviour Disruptions

Ideal Simulation	Stochastic Average (Min)	Standard Deviation	Confidence Minimum	Confidence Maximum
Minor	75.11	11.79	72.77	77.45
Non Urgent	75.14	12.81	72.60	77.69
	Maximum In Queue	**Average Time (Min)**		
Reception Queue	5	0.12		
Triage queue1	7	3.31		
Triage queue2	8	4.35		
Exam queue	8	9.65		

The results from table 6.22 will be used as the primary KPI almost like a benchmarking process where all the model enhancements and results will be checked against to see the variance.

Now, behaviour will be added to the model as shown in figure 6.11 and table 6.21. Behaviour will be added from the very start being the reception, through to triage and then the examination area to see the effects of behaviour with reference to the KPI's highlighted. Once the effects of behaviour are added to the reception within the ED, table 6.23 shows the results which can be compared to table 6.22.

6.23. Key Performance Indicator results in Reception (minutes)

Reception	Stochastic Average	Standard Deviation	Confidence Minimum	Confidence Maximum
Minor	84.87	11.25	80.88	88.85
Non-Urgent	84.92	13.32	80.20	89.64
	Max In Queue	**Average Time**		
Reception Queue	7	3.02		

LOS time has increased for patients. This firstly highlights the fact that, patient behaviour does without a doubt affect the process of screening patients and how much time actually can be consumed by the disruptions caused. The average time patients now spend due to disruptions caused by behaviour has increased as every single patient is affected. This set of data represents an average time for individual patients. The stochastic results show an increase from 75 minutes to almost 85 minutes in the LOS based on the average time. The reception queue has increased by 2, from 5 to 7 patients waiting and has affected how much time is spent in the queue, spending an average of approximately 3 minutes waiting in the queue in comparison to table where only 0.12 minutes on average was consumed.

6.23. Key Performance Indicator results in Triage (minutes)

Triage	Stochastic Average	Standard Deviation	Confidence Minimum	Confidence Maximum
Minor	95.16	12.76	90.64	99.68
Non Urgent	96.14	14.19	91.11	101.17

	Max In Queue	Average Time
Triage Q1	8	10.67
Triage Q2	7	14.00

Now the same has been applied to the triage within the ED shown in table 6.24. This area seems to have had the largest and most significant increase in LOS, increasing from 75 minutes to over 95 minutes. This is where patients are sent after the reception in order to be screened for examination. Triage only has one single desk to process patients accordingly, so if any disruptions occur at this point due to behaviour, everything comes to a standstill. This is also apparent as the average time in the triage queues have increased although the number of patients in the queues remains almost the same. The average queue time has increased dramatically from a small duration of 3.31 minutes to approximate 10 to 14 minutes depending on patient type. This in reality displays the possibility of disruptions developing on an on-going basis and restricting the ED as a whole to be able to recover and proceed as normal. As a certain disruption where there is a lack of facilities can leave all processes stagnant and even draw resources from other areas simply to be able to move forward.

A backlog is developed and patients have to wait in the ED triage queue until the problem is resolved, the time consumed in resolving the situation only allows more patients to arrive from the reception and the queues get larger in number. This is a definite problem area, which indicates a lack of facility and resources in order to process patients faster when problems do occur.

Table 6.25 shows the examination results after behaviour has been applied accordingly, similar results are shown here where the average LOS has increased. The LOS has increased from 75 minutes to over 92 minutes depending on patient type causing examination to be fully capacitated and developing a queue for examination. The examination queue has increased to 30 patients as has the length of stay within the queue has increased dramatically from a few minutes to over an hour. The resulted indicated in the above tables represent individual patient case times.

6.25. Key Performance Indicators Results in Examination Area

Examination	Stochastic Average	Standard Deviation	Confidence Minimum	Confidence Maximum
Minor	92.93	18.72	86.30	99.57
Non -Urgent	94.44	15.16	89.07	99.81
	Max In Queue	**Average Time**		
Exam Q	30	65.27		

Table 6.26 shows a comparison of the minor and non-urgent cases when behaviour is applied to the DES model. The length of time consumed by minor and non-urgent patients is displayed, due to patient disruptions as a result of difficult patient behaviour. Significant time increases has occurred and when taken into a percentage consideration of the ideal operational times, time had increased by more than 25%

for the triage and examination processes. Overall, the sole disruptions caused by patient behaviours can have devastating effects on the ED as a whole. As LOS increases, so do the patient queues, which only aids the developments of further disruptions that will cause further bottlenecks and backlogs and patients.

6.24. Comparison of Minor and Non-urgent Patients in DES Model4, (Behaviour Model) and DES Model 3, (Ideal Model)

Factors	Ideal Time LOS DES 3	DES 4 LOS with Behaviour		
		Reception	Triage	Examination
Minor	75.11	84.87	95.16	92.93
Non-Urgent	75.14	84.92	96.14	94.44
Time Increase (mins)	Minor	9.76	20.05	17.82
	Non-Urgent	9.78	21.00	19.30
Percentage Increase (%)	Minor	13 %	26.7 %	23.7 %
	Non-Urgent	13.02 %	27.9 %	25.7 %

The results shown in table 6.26 clearly shows how much difference patient behaviour can have on processes and the difference it can make to the service time within the ED.

6.2.4.3 Finding

The results firstly expose the development of an unequivocal problem that is faced by the ED on a daily basis and how these problems are interconnected, affecting the entire department from an array of different possible routes.

The examination area, triage and reception, for which results have been shown and a stochastic process has been followed indicate a very big problem as time increases due to the disruptions caused by the effects of patient behaviour which only accounts for a single case of disruption within the ED. All the activities are interconnected and have an adverse effect that only seems to be developing further, as time increases within activities and queues for waiting. This can only increase the chance of further patient behaviour disruptions. Behaviour causes disruptions and predominantly increases LOS as shown by the KPI's and when compared to the ideal LOS, the increase is very significant as it only represents a single problem within the ED and hence can have drastic effect on the ED as a whole. Similarly, the number of patients in queues and the length of stay in queues develop significant problems due to the disruptions caused by patient behaviour. A solution or strategy is required so that the ED staff can recover effectively and efficiently from disruptions caused so that the processing can carry on as normal in order to be able to cope within the ED on a daily basis.

The results clearly indicate an increase of time due to difficult behaviour that causes the KPI to increase considerably. This model allows the time consumed by difficult behaviour to be recognised for the first time, it shows how much times is consumed and wasted due to behaviour alone.

6.2.5 DES Model 5: Bayesian model

The Bayesian DES model uses the Bayes theory of probability to generate a more accurate representation of the occurrence of difficult patient behaviour based on the influencing nodes. Bayesian model building, its validation and verification and its results will be displayed in the following sections.

6.2.5.1 DES Model 5 Implementation

The Bayesian model continues from the behaviour model with changes in how the behaviour is developed and calculated. In the previous model i.e. behaviour model, the chance of behaviour is generated totally at random and a behaviour type is designated according to the random occurrence.

In this model, the Bayesian approach will be added within the simulation model enabling it to be a dynamic tool that can calculate probabilities for all patients continuously. Bayesian as highlighted in previous chapters (chapter 4) normally requires manual data entry to be made in order to develop probabilities. Applying Bayesian to Witness simulation has eradicated this necessity and probabilities can be developed and calculated on a dynamic basis based on the condition of patients and behaviour types.

The Bayesian model will show the Bayesian process based on the Bayes theorem of probability, and the probability of behaviour will be calculated accordingly. In order for the Bayesian process to be applied, many model enhancements had to be adhered to and will be discussed in further detail.

The Bayesian model takes into consideration all four types of behaviour occurrences that can be seen in figure 6.13 in order to develop the final probability.

The Bayesian approach within simulation will serve to show an alternative in calculating the occurrence of behaviour and therefore will change the outcome of the results of the model in terms of the KPI. This alternative approach will be compared to the behaviour model to see the variance and will also go through the stochastic analysis to derive the best possible outcome. This will give insight into how close to reality the results are as processes change and behaviour is dependent on the Bayes theorem. Therefore it will also serve as a partial validation and verification of the results which will be discussed further with experts within the ED to gain greater understanding.

6.2.5.2 Model Enhancements

Figure 6.13 shows a screen shot of the existing model with all the applicable changes, the 4 types of behaviour can be seen along with the probability as well as the 16 sums that equate to the final probability shown. A further counter named behaviour count, displaying the number of behaviour type occurrences has also been added to aid understanding. This figure shows how many types of behaviours have been considered according to the random occurrence. Figure 6.14, in addition, shows the programming implications with reference to the Bayesian approach to probability.

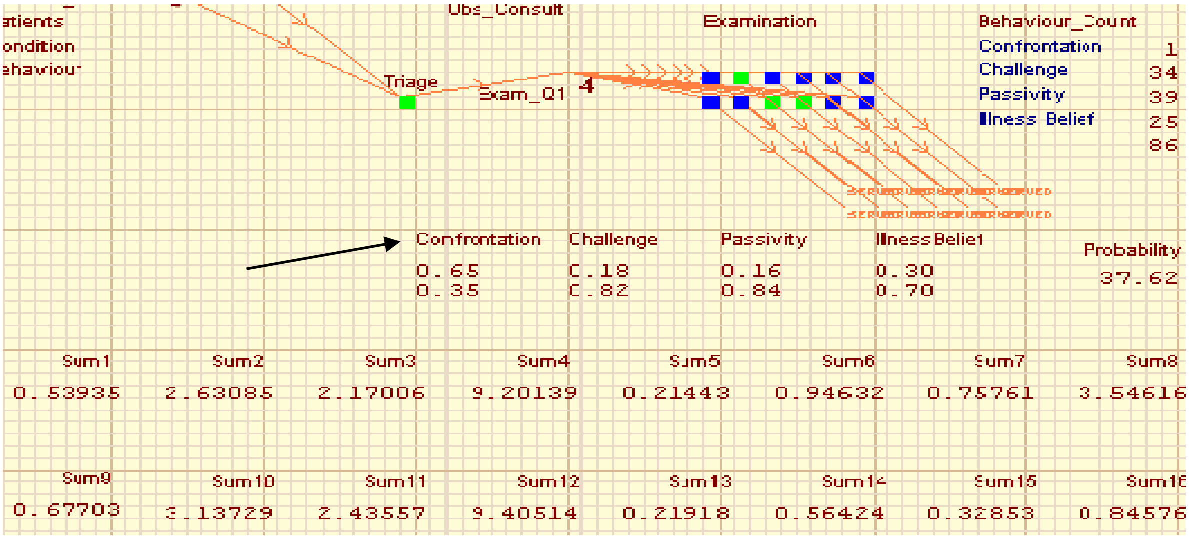


Figure 6.13 Development of random behaviour and probability equation

Figure 6.13 shows the 4 behaviour types that have two distinct numbers below them all which add to exactly 1.0. Figure 6.14 shows how these behaviours have been applied with a random occurrence. All 4 behaviour develop a random value shown by the programming in figure 6.14, the random value can fall within 0.0 to 1.0 as shown in figure 6.13. Once the random value has occurred, it is subtracted from 1 as shown in figure 6.14 for example, confrontation = 1 – confrontation, this develops the remaining value. This is required in order to calculate the Bayesian probability as both figures are required and as discussed previously in chapter 4.

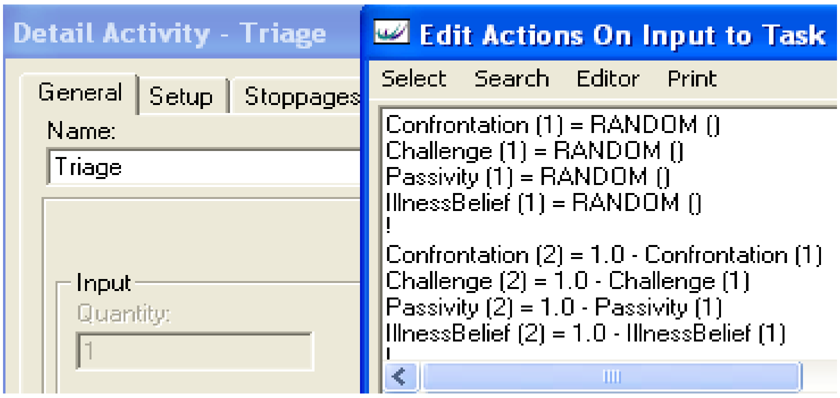


Figure 6.14 Random behaviour programming in triage

Once the random value is developed as shown in figure 6.14, figure 6.15 shows the probability of those behaviour types being developed according to the equation using the 16 sums where it considers the random probability values of all 4 behaviour types in order to generate a single probability for the occurrence of behaviour. Bayesian equation [Equation 3, chapter 4].

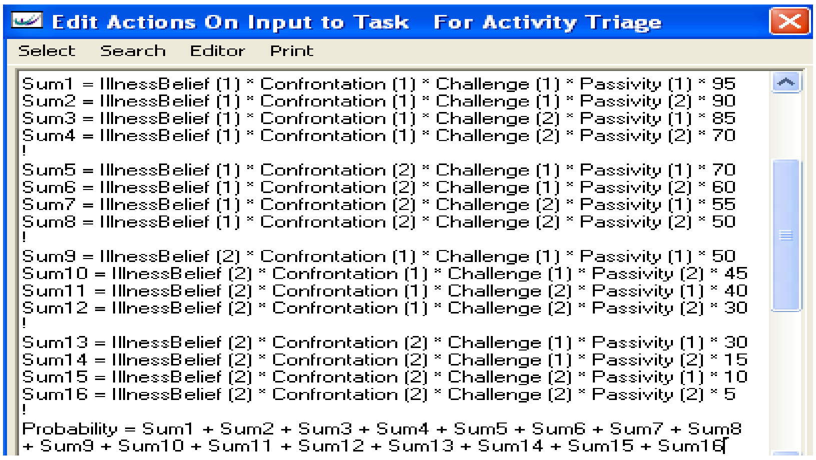
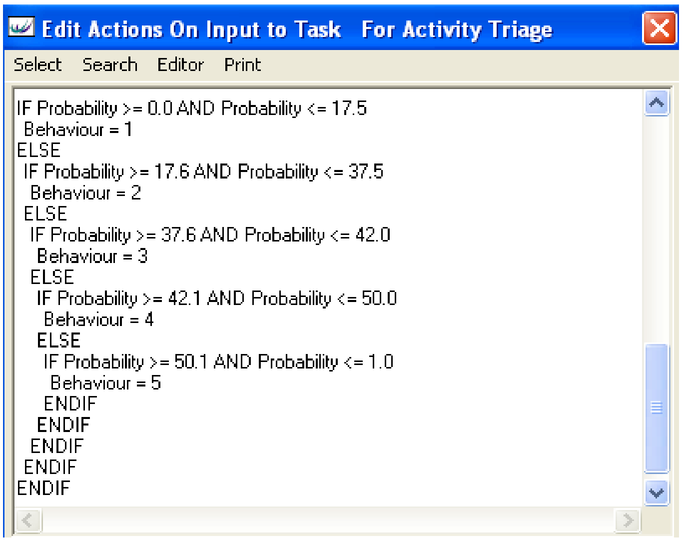


Figure 6.15 Programming of the Bayesian equation (Equation 3)

Once the final probability is developed, figure 6.16 shows how the probability is designated to behaviour type according to the probability. Figure 6.16 shows, if the probability is within a certain fraction then a behaviour is assigned to that fraction from 1-4 as can be seen in figure 6.16. The 4 behaviour represents the 4 behaviour types and helps simplify the programming for witness to recognise effectively.




```
IF Probability >= 0.0 AND Probability <= 17.5
 Behaviour = 1
ELSE
 IF Probability >= 17.6 AND Probability <= 37.5
  Behaviour = 2
 ELSE
  IF Probability >= 37.6 AND Probability <= 42.0
   Behaviour = 3
  ELSE
   IF Probability >= 42.1 AND Probability <= 50.0
    Behaviour = 4
   ELSE
    IF Probability >= 50.1 AND Probability <= 1.0
     Behaviour = 5
    ENDIF
   ENDIF
  ENDIF
 ENDIF
ENDIF
```

Figure 6.16 The probability representation according to behaviour type

Once the correct behaviour is assigned to the patients with the use of the behaviour attribute, when this patient or all patients enter their designated places within the ED, the correct time can be consumed accordingly as shown in figure 6.17, where different behaviour types equate to a consumption of different times, very similar to the behaviour model.

Figure 6.17 shows the application of a counter after all behaviour types, so the behaviour type can be noted as shown in figure 6.13.

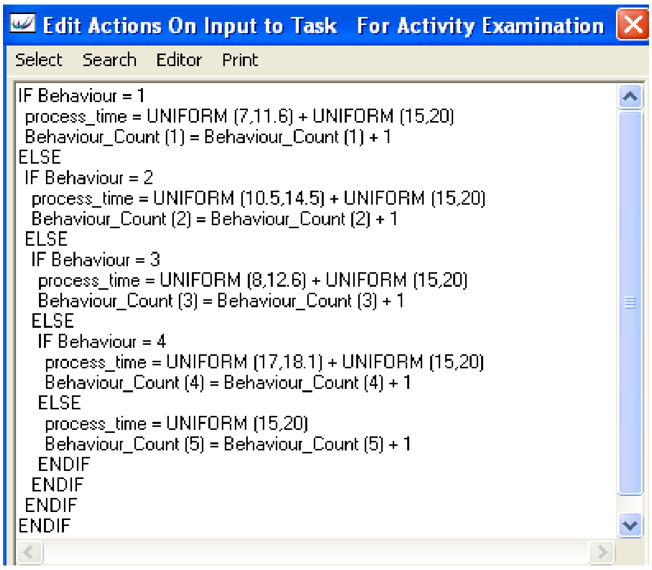


Figure 6.17 Classification of behaviour and the time consumption with counters

The model enhancements highlighted enable the affective application of the Bayesian approach within the simulation to produce a dynamic platform where patients and their random occurrence of behaviour can be considered to the best of knowledge gained from the research undertaken with professional guidance from ED experts.

6.2.5.3 DES Model 5 (The Bayesian model) Results

The Bayesian model run for the same amount of time, and the same KPI will be considered for means of comparisons. Additionally, further implication will be discussed in following.

Table 6.27 shows the LOS results of all 3 simulation models after a stochastic analysis with a time variance between the behaviour model and Bayesian model.

6.25. Comparison of LOS for Ideal, Behaviour and Bayesian behaviour Models

Patient's Condition	Ideal Time LOS	DES 4 Model LOS with Behaviour		
		Reception	Triage	Examination
Minor	75.11	84.87	95.16	92.93
Non-Urgent	75.14	84.92	96.14	94.44
		DES 5 Model LOS with Bayesian Behaviour		
Minor		90.53	104.45	93.79
Non-Urgent		89.09	103.24	94.86
		Time Variance		
Minor		5.66	9.29	0.87
Non-Urgent		4.17	7.10	0.42

Table 6.27 shows the Bayesian results to have increased the LOS further for both minor and non-urgent patients in the ED, the results indicate an increase in all the keys areas i.e. reception, triage and examination. The Bayesian approach in the reception has increased LOS by approximately 4 – 5 minutes and the triage has seen the highest increase in time by 7-9 minutes, whereas the examination has seen to be affected the least at less than a minute.

The change in results is due to the Bayesian method of calculating behaviour which has in essence enabled a different number of behaviour types to be considered. table 6.28 show an account for the types on behaviour for patients. It shows confrontation has decreased by 16 patients, challenge has increased by 9 patients, passivity has increased by 18 patients and illness belief has increased by 6. The number of normal behaviour has also decreased by 6 patients however as highlighted in table 6.27, the LOS has increased regardless of the number of patients. This is partly due to different behaviours consuming different amounts of time at different points. The total number of patients has only changed by a single patient, who shows although more time is consumed, the total processing of patients remains very similar.

6.26. The Number of Patient with Behaviours Considered by the Behaviour Model and Bayesian model.

Behaviours	**Behaviour Model**	**Bayesian Model**
Confrontation	30	14
Challenge	20	29
Passivity	13	31
Illness Belief	19	25
Normal	102	86
Total	184	185

Table 6.29 shows the results of the queues in all three models, the maximum patients in the queues and the average time spent in the queues by patients in order to proceed to the actual task that needs to be carried out. The time variance shows how much change in time has occurred between model developments and difference caused in approach, it shows a continuous increase in the time consumed and the maximum number of patients that have developed due to the changes. It is reasonable to assume, as the number of patients in queues increases, so should the average waiting time in the queues increase.

6.27. Results of Stochastic Analysis of Queues for The 3 Model Types (Ideal, Behaviour and Bayesian)

Queues	Max in Queue	Average Time	Time Variance
Reception Queue			
Ideal Time	5	1.52	
Behaviour	7	3.02	1.50
Bayesian	10	7.36	4.34
Triage Q 1			
Ideal Time	7	1.31	
Behaviour	9	8.67	7.36
Bayesian	11	14.57	5.90
Triage Q 2			
Ideal Time	8	2.35	
Behaviour	10	9.50	7.15
Bayesian	11	15.12	5.62
Examination Queue			
Ideal Time	5	3.93	
Behaviour	9	5.82	1.89
Bayesian	12	8.64	2.82

Table 6.30 show displays how efficient the activities are in terms of processing patients, it shows how free, busy and whether or not patients are waiting for resources within designated areas. The examination area within the ED takes into consideration all the columns displayed in table 6.30. Firstly it is noteworthy to state; as the examination area is represented by 12 activities which represent beds that can be seen in figure 6.13, patients are able to move to these activities without the need of an immediate aid from a professional within the ED. this is to represent reality where patients are admitted into beds after which doctors and nurses may come and see the patients. This waiting period of patients for doctors within the activities is considered by task waiting resources as displayed in table 6.30. The remainder activities i.e. triage and examination, have enough resources to cover the number of activities, for example, triage only has a single desk which is looked after by a single

resource hence patients cannot be waiting for resources but need to remain in the triage queue as displayed in queue statistics in table 6.29. This is also a reason why the examination area queue waiting time is actually less than the triage queue.

6.30. Activity Statistics for Behaviour and Bayesian Models

Model Type	Activity	Free	Busy	Task Waiting Resource
Behaviour	Examination	66.73	20.32	12.96
Bayesian	Examination	39.61	24.60	35.79
Behaviour	Triage	20.32	69.04	10.64
Bayesian	Triage	2.28	93.12	4.60
Behaviour	Reception	31.45	66.25	2.40
Bayesian	reception	2.19	90.81	2.00

The activity statistics and results in table 6.30 actually shows the Bayesian approach to consume an increased lengths of resource and activity time and usage although the end results shown in table 6.28 displaying the number of patients remains very similar. The Bayesian approach in essence represents the same research data but under further scrutiny using the Bayesian approach. This has increased the percentage of time all 3 activities are busy as they are engaged with patients for longer than usual periods.

This data can also be further validated to be a more of an accurate representation of reality when discussed with experts in the field. Who highlight the constant problems caused by patient behaviour within the ED and the unaccountable time consumed by resources combating troublesome patients.

The queue statistics displayed in table 6.29 and LOS statistics shown in table 6.27, when presented to experts within the ED seem to be less than expected in the behaviour model whereas the Bayesian approach seems to be more reasonable in their eyes as the waiting times for patients is currently small when compared to reality and as highlighted above, increased usage of resources are made due to the Bayesian approach in considering behaviour.

6.2.5.4 Finding

The Bayesian enhancements are explained in terms of programming and representation. The difference in LOS is discussed and further scrutiny is made of all the elements within the system that represent key tasks and activities in reality. A stochastic approach is taken and the results are discussed with experts in the ED for further elaboration and to gain a deeper understanding so a comparison can be made as to which model approach is best suited and represented reality in the most accurate manner.

The Bayesian approach happens to increase time throughout the model and all processes due to the system used in calculating the behaviour. Although the behaviour model represents a true reflection of the system and the affects behaviour can have within processes. The Bayesian system is seen to be a better fit outlined by experts in the ED. This is mostly because it displays a greater usage of all resources as well as the increase in time consumed that reveal the extent of disruptions caused by behaviour. This will also serve as a partial validation and verification in terms of representation to a true to life system.

6.3 Summary

DES model 1 serves as logical representation of the entire ED of TMC, it is used to observe and make sure all the processes are in working order, it also serves as a partial validation and verification of the development of DES model 1.

DES model 2 is the basic representation of ED system that takes into account the average number of patients attending the ED derived from historical data. This model allows scrutiny of all the processes as the entire ED is challenged by the number of patients visiting the ED. DES model 2 is used to derive all the results of key performance indicators to see how they compare to historical data based on length of stay (LOS) and waiting times (WT).

DES model 3 is categorised at the actual representation as it represents the ideal operational times that physicians have highlighted. DES 3 represents the ED where there are no disruptions in the processing of patients and how the physicians would like to see the ED run on a daily basis almost representing a perfect state. This model and the results derived from within will be used as a bench mark for future developments and strategies. The results have also been compared to that of DES 3 to see the time variance, this indicated huge time variance between DES 3 and DES 4. The difference highlighted the additional time consumed on a daily basis by patients. This enabled strategies to be developed in order to decrease patients LOS and WT.

One of the main developments of this study was to divert concentration to a single area within the ED i.e. examination, rather than the ED as a whole as this would prove to be a very complex and lengthy process. Hence based on the historical data, expert opinion and the results derived from DES 2 and 3, the decision was made to divert concentration to the examination area alone. This was done firstly, because this area catered for the minor and non-urgent patients that accounted for majority of the patients that attended the ED. Secondly, research highlighted the fact that, the main disruptions caused by difficult patients took place within this area by patients with minor and non-urgent patients. Lastly, the resulted acquired from DES 2 and 3 showed very similar results and experts agreed a reduction in patient times within this area would surely mean a devised strategy that can be applied to other areas in a very similar manner.

Hence, DES model 4 only concentrates on the examination area, however, DES 4 is where the novelty of patient behaviour is implemented within the system based on a random occurrence. Firstly, a new LOS has to be derived from DES 3 but only to the extent where patients leave examination rather the ED as a whole. Therefore, patients will now be considered from the point of entry to the ED till they leave the examination area. Secondly, behaviour will be applied to the model changing it to DES model 4. This will show the variance in time, how much time is spent additionally due to patient difficult behaviour and the disruptions caused from therein.

DES model 5 is where the Bayesian Network modelling is applied to the DES model to enable a superior set of results to be achieved in order to represent patient behaviour to the truest of nature. This model will also show the additional time consumed by patients in order to devise a strategy to decrease patient LOS.

Chapter 7: Patient Behaviour Control (PBC)

7.1 Introduction

The hospital under study (TMC) sought insight into strategies that would reduce prolonged patient length of stay (LOS) and patient waiting time (WT), as caused by difficult patients, for the ED. This chapter will focus on these two effectiveness measures, i.e. LOS and WT.

The purpose of this chapter is to consider the way in which key features of the Fast Tracking Strategy (FTS) and Lean Thinking Theory can be implemented within the ED on an operational level in order to control patients with difficult behavioural problems, thus devising a strategy known as Patient Behaviour Control (PBC). The way in which these patients can be alienated from normal patients and processes, to go through a behavioural control system, are very similar to the widely used FTS. This chapter explains, discusses and concentrates on how the successful FTS, based on patient acuity levels, can be manipulated and simulated for use based on patient behaviour in an effort to further reduce LOS and WT, i.e. PBC.

The study within TMC sought means by which prolonged LOS and WT, as caused by difficult patients, could be reduced without affecting the quality of service provided and impacting patients in other departments. The patient flow and processes were studied, and a model was developed replicating the existing facilities within the ED, after which changes were made to the DES models to facilitate a PBC system for implementation. This gives the study a 'before and after PBC' analysis, where comparisons can be made and the effects thereof analysed. In the present research, emphasis is directed towards a simulation-based solution centred on reducing LOS and WT by implementing a patient behaviour control (PBC) system.

7.2 Background of PBC

Emergency departments are placed with the highest demands on hospital services due to the on-going pressure to improve with the same amount of resources, whilst sometimes achieving a reduction in the resources available. Further pressure is also applied in seeing an increasing number of patients efficiently and safely. As a result, EDs within the most developed and Western countries are struggling to cope with the increasing demands for services. This has motivated the focus to be directed towards optimising patient processes, i.e. pathways and flow, where EDs are taking lessons in Lean Thinking Theory and system analysis to look for more efficient strategies of working [Holden., 2011; Mazzocato *et al*., 2012; King *et al*., 2006].

Research into previous studies demonstrated Fast Track (FT) to be the most results-driven and best solution in decreasing LOS and WT, which leads to the decrease in overcrowded EDs. Moreover, An FT programme is assumed to increase throughput for non-emergent patients. Hence many hospitals' EDs have resorted to an 'FT', which aims to achieve these goals.. [Fernandes *et al*., 1997; Meislin *et al*., 1988; Cooke *et al*., 2002; Considine *et al*., 2008]. Similar research has also demonstrated and shown improvements in patient flow and processing with the use of Fast Track [Simon *et al*., 1997; King *et al*., 2006].

Studies carried out around the world have used FT in relation to both groups of minor and non-urgent patients with the aim of managing their flow throughout EDs in order to solve the overcrowding issue, namely through reducing LOS and WTs.

Moreover, also as a result of using this strategy, enhancement will be achieved in different areas of EDs, with good impacts achieved for all types of patient. Furthermore, previous studies centre on many factors when implementing FT. To illustrate this point, the following includes examples of studies that have been carried out in different countries, all of which seek to explain how FT has been implemented, in addition to the aim of this strategy and the significant benefits to be derived.

Doyle *et al*. [2012] carried out a study in Kansas, USA, which implemented FT to improve patient throughput and department efficiency. They also aimed to examine whether FT strategy would have a significant influence on the Left Without Being Seen (LWBS) rate. They found that, after using the FT system, patients experienced a decrease in LOS and WTs when compared with before the use of FT; however, overall, the LWBS rate did not decrease with the adoption of the new strategy [Doyle *et al*., 2012].

The study carried out in Canada sought to implement FT in an effort to reduce patient LOS and Queuing Wait Time (QWT) with focus centred on examining the effects of increased physician presence within the FT system, followed by an additional emergency nurse practitioner (ENP) in the system, who was assigned the role of improving performance measures, i.e. LOS and WTs. It was found that the FT system led to a reduction in the LOS and queue length (QL). Furthermore, the study detailed that the most significant reduction of LOS and QL were when there was increased physician presence in the FT, followed by ENP in the system [La *et al*., 2013].

Another study has been carried out in the UAE by Devkaran *et al*. [2009], which sought to establish the effect of using FTS on WTs and LOS. Moreover, the study focused on how FT would affect ED quality measures, namely LWBS rate and mortality rate. The results of this study showed that FT is a very useful strategy, leading to reductions in WTs and LOS. The results also show that LWBS rate can be significantly improved through the use of FT, although mortality rate was seen to remain unchanged [Devkaran *et al*., 2009].

An Australian study, conducted in 2006, demonstrates that separate use of a dedicated treating team in the FT system can result in a significant reduction of WTs for all discharged patients, without the occurrence of adverse effects on WTs for patients requiring admission. In the same vein, implementing FT helped to reduce the number of patients who chose not to wait for treatment [O'Brien *et al*., 2006].

As can be seen from prior sections, it is clear that the majority of previous studies are similar in terms of the use of FT in EDs: they all implement FTS in mind of managing the flow of a certain type of patient (minor and non-urgent, for example). The literature supports the belief that managing this type of patient flow leads to a reduction in the extra WTs and LOS that result from the presence of non-urgent cases in EDs. By the same token, through the implementation of FTS, previous studies have demonstrated improvements in the health services provided in all parts of EDs, as well as improvements of WTs and LOS amongst other types of patient, such as emergent and urgent patients.

This strategy has proven successful through the results, as well as through the acceptance of patients and staff in emergency departments. Moreover, the approach is recognised as being the best solution when seeking to improve services. This is shown by the high rate of satisfaction amongst doctors and nurses, on the one hand, and patients on the other. Furthermore, it is well-known in all scientific studies centred on management services that customer satisfaction is an indicator of service quality.

This strategy has proven successful, which can be seen through its useful results, as discussed earlier, as well as through the acceptance of this strategy amongst ED patients and staff; they consider FTS as the best solution in terms of improving the services across EDs. Importantly, previous research have shown this by demonstrating an increasing level of satisfaction amongst doctors and nurses who work in EDs. Moreover, patients' satisfaction has been highly increased with the use of FT, including—but not limited to—an Australian study, which evaluated the quality of care delivered by an ED after implementing FT. This went on to state that the satisfaction scores of approximately 70% of all patients involved in the study were 'excellent' or 'very good' [Dinh *et al*., 2012]. A similar study was conducted in Texas, USA, which established that the majority of respondents who completed a patient satisfaction survey in the FT area were welcome to implement FT in EDs, and that patients expressed their agreement with this strategy, stating that it saved their time and increased the quality of the health services delivered and received [Nash *et al*., 2007].

It is well known in the literatures of various arenas, including healthcare provision, that customer satisfaction is considered an indicator of service quality, with such literature indicating that two factors—notably customer satisfaction and quality of service—are closely related, thus suggesting that improvement in one is likely to lead to improvement in another; in other words, customers perceive quality before building up their satisfaction levels, and accordingly generate their behavioural intentions [Wang *et al*., 2006; Sureshchandar *et al*., 2002; Mosahab *et al*., 2010].

As shown from the above, it may be concluded that the FT approach has contributed to increasing the levels of quality of healthcare services delivered across EDs.

Despite such successes, however, to the best of the writer's knowledge, thus far, there has been no attempt to use FT in a different way, meaning that FT usually manages patient flow based on the severity or acuity of patients. They consider this factor as key to improving ED efficiency and effectiveness; however, they ignore its use in combination with other factors, which may be considered an additional reason for the presence of overcrowding.

Through reference to preliminary research, proposed by this study and as described in the previous chapters, it can be stated that the study highlighted two important findings. Firstly, it demonstrated that minor and non-urgent patients within the ED TMC are the highest attending, with these two types of patient recognised as the root cause of overcrowding. The second interesting finding, which is considered a novelty factor of this study, is that overcrowding increases in LOS and WT were partly due to difficult patients' behavioural issues impacting the patient processes, flow and service time.

Patient behaviour is held as being a cryptic factor that has been ignored by researchers who are interested in studying the causes of overcrowding in ED and who, despite their previous researches, highlighted this factor as being a reason of increased customer waiting times, whether in hospital or any other services facilities.

However, earlier studies did not assign much importance or relevance to this factor in terms of its influence on WTs, although there are many studies that have been carried out to study the way in which waiting times increase the probability of witnessing difficult behaviours in patients (as fully discussed in Chapter 2). The scarcity of previous studies led to a lack of clarity concerning the impact of this factor on the LOS and WT. Additionally, it cannot be sure about the exact duration of time consumed by this factor alone. Furthermore, there is no clue concerning the specific areas of ED that mostly face such behavioural issues. The reasons behind increasing behavioural issues are also not clarified; these questions, and others, have been touched by the current study for first time, as discussed in prior chapters.

The current study provides a new idea designed with the aim of reducing wait times, which is caused by behavioural issues, which will lead, as previous studies have stated, to improvements in the efficiency and effectiveness indicators of TMC ED. This new strategy is built based on the idea of FT, with some modifications taking into account the behaviour factor as a reason behind increasing WT and LOS, as opposed to patient severity. The actual aim of implementing PBC is making waiting times more agreeable for patients and staff by re-managing minor and non-urgent patient flow according to patient behaviour. This will lead to alleviating the situation and comforting impatient users, which certainly helps in terms of avoiding more difficult behaviours. It is worth mentioning that DES will be used to develop PBC, as being a very good tool in demonstrating the current framework, and is considered requisite due to its suitability to this kind of research. The following sections fully explain PBC.

7.3 Lean Thinking of Patient Behaviour Control (PBC)

The principles of 'Lean Thinking' were adhered to throughout the research, and applied with the consent of expert opinions in patient flow and processes. This involved eradicating duplicate work, minimising queuing, and focusing on value-adding processes [Womack *et al*., 2005]. A distinctive set of features aiding the Fast Tracking system is the use of stream lining patients according to acuity levels. Notably, similar features will be followed in order to apply the new strategy PBC; however, the novelty of patient behaviours will be considered, and will be assigned the highest priority.

At the present time, TMC uses the Fast Tracking system and, in so doing, forwards all non- urgent and minor patients to the triage, based on acuity levels where they are all forwarded to the examination area. Therefore, at this current stage, it is reasonable to assume that all patients attending the examination area of the ED have a low risk in terms of illness. Accordingly, the new PBC strategy will be applied within the triage, prior to examination, meaning patients can be controlled according to behaviour before being admitted into the examination area.

The PBC strategy will mean patients that are designated to go to examination will go through a PBC process without prior knowledge to facilitate in separating patients; therefore, patients will be tracked to the triage, at which stage they will go through to a PBC system to segregate patients further into two separate queues. Patients will be isolated as normal, who show no significant behaviours, and those who seem to demonstrate behavioural issues, who will be classed as difficult within the existing processes. Hence, rather than acuity levels or diagnosis requirements, the new streams are designed based on patient behaviour. It is believed that this adds value for normal patients as they can continue on with the normal processes in an efficient manner and time, with normal patients segregated from other patients to stop behavioural problems being passed down or through to other patients, reducing the chances of escalating behaviours. ED resources, such as doctors and nurses, then do not waste time dealing with patients with behavioural issues; this means optimal use of the resources available so as to keep the patient flow progressing in a timely method.

Another distinctive feature is the application of the Bayesian Theory. This theory of probability has been implemented within the simulation model, with the approach developing the random probability of the occurrence of difficult behaviour based on Bayes Theorem of Inference. Hence, patient behaviour would be represented by a random distribution, which would identify the patient's behaviour; the behaviour will be attributed to the patient. This enables ED staff to select patients with difficult behaviours and control patients accordingly from within the triage prior to processing them further. This represents resources/staff being proactive in selecting patients who have behavioural issues and segregating them into a different queue.

Importantly, however, patients still have to see staff and cannot be directly withdrawn from the queuing system; they still need to wait in the queue and spend their designated time before they can be controlled. This a very important aspect of Lean Theory, which considers the simple fact that, although patients may be seen to have behavioural issues, they still have to be seen to by a resource and examined minimally before they can be segregated, only to check their condition is not life-threatening. Accordingly, the simulation model represents this factor by means of ensuring that all patients see a resource before they are selected and designated accordingly.

7.4 Patient Behaviour Control (PBC)

7.4.1 PBC Implementation in ED TMC

A thorough review of the existing ED was undertaken by means of observations and consultation with staff within the facility and expert opinions (data collection was explained in details in Chapter 3). Moreover, as explained in previous chapters of this thesis, this initial stage can also be considered as the assessment requisite for the primary research, needed to develop a simulation model that replicates the existing facility to the truest of nature.

Research has established that TMC currently fast tracks patients directly from reception to their designated areas according to acuity level. Hence, based on this premise, it can be assumed that existing staff were aware of the benefits of fast tracking, although based on an acuity level, which seems to be a very logical approach as ED staff understand the need to send patients to the correct places according to their condition.

The existing FT system will not be abolished and will remain the same: it serves as a prerequisite to the newly developed patient control system according to behaviour; therefore, rather than using the FT strategy based on patients acuity levels, condition and needs—where patients are divided into separate streams accordingly—the newly proposed ED simulation model considers the behaviour of minor and non-urgent patients, aided by the Bayesian network modelling method, and streams patients from triage through to two separate queues, namely the examination queue and the PBC queue.

Patients of minor and non-urgent requisite conditions are currently forwarded directly from the reception to the triage where the further scrutiny of patients is performed before forwarding into examination for the right care. The examination area alone takes care of minor and non-urgent patients as the variables between the two types of patients are very small in terms of professional care, i.e. the practising nurse is very capable of taking care of or looking after non-urgent and minor patients within examination. With this in mind, the assumption is that all patients—minor and non-urgent—can be controlled, regardless of acuity level, as the conditions presented be deemed non-complex and low-risk. This was also agreed by experts within the ED of TMC.

Patient control from the triage point was highlighted as the most beneficial point as the initial fast tracking, according to acuity level, had already been considered by reception, where minor and non-urgent patients were segregated from those requiring urgent and higher acuity levels of care. This was also agreed by experts in the field as being the best starting point to consider behaviour as these two patient types accounted for the highest number of patients and were the overall concentration of the study (See Chapter 5)

7.4.2 Validation and Verification

It is worth mentioning that the same methods used with all previous models in this study have been used to verify and validate the PBC model.

In the following, there is a reminder of the most important methods used for the PBC model's validation and verification:

- Visual validation
- Stochastic validation and verification = 100 replications to reassure variance in results
- Expert discussion of model and results achieved.

7.4.3 Changes Applied Explanation

The most suitable area in which to implement PBC is within the actual triage area prior to examination. As the patients are separated at reception according to acuity levels, only the minor and non-urgent cases are forwarded to triage for further scrutiny, according to needs, although they are very similar as both types of patients reside within the examination area.

Triage will run the PBC strategy based on patient behaviour. They will be responsible for separating the normal patients from those who seem to have behavioural conditions that could cause further delays for no significant reasons other than behavioural issues and distractions. The behaviour will be recognised by the existing random behaviour occurrence. Patients will spend their designated uniform time of 1–5 minutes, after which the triage staff will forward patients to either the normal process for examination or the PBC system, where they will join the queue with other patients identified as having similar problematic issues. This is a very similar process used across all FTS, where triage has the responsibility of forwarding patients according to their acuity levels. Patients with difficult behaviours similarly will be recognised and forwarded accordingly. It is held that this will guarantee normal patients' ability to carry on as normal, given the highest of priorities by doctors and nurses, to make the process run as quickly and efficiently as possible; patients with difficult behaviours, on the other hand, will go through the PBC process with less priority, enabling normal patients and processes to carry on as normal.

7.4.4 PBC Analysis and Strategic Planning

Design changes are planned for the TMC ED examination area. This chapter considers separating the examination beds. Currently, there are twelve beds in examination; eight will remain in the existing location, whilst the remaining and four will be moved to a PBC location. The examination area will have two rooms or areas separating the patients according to normal patients and those with behavioural issues. Accordingly, triage will forward patients into two queues instead of one, notably a queue for examination and a queue for the PBC, which actually represents patients with behavioural impacts. The same numbers of doctors and nurses will be present; however. This has also been represented within the simulation model. current and the new design of patient flow will be explained in figures 7.1, 7.2 and 7.3.

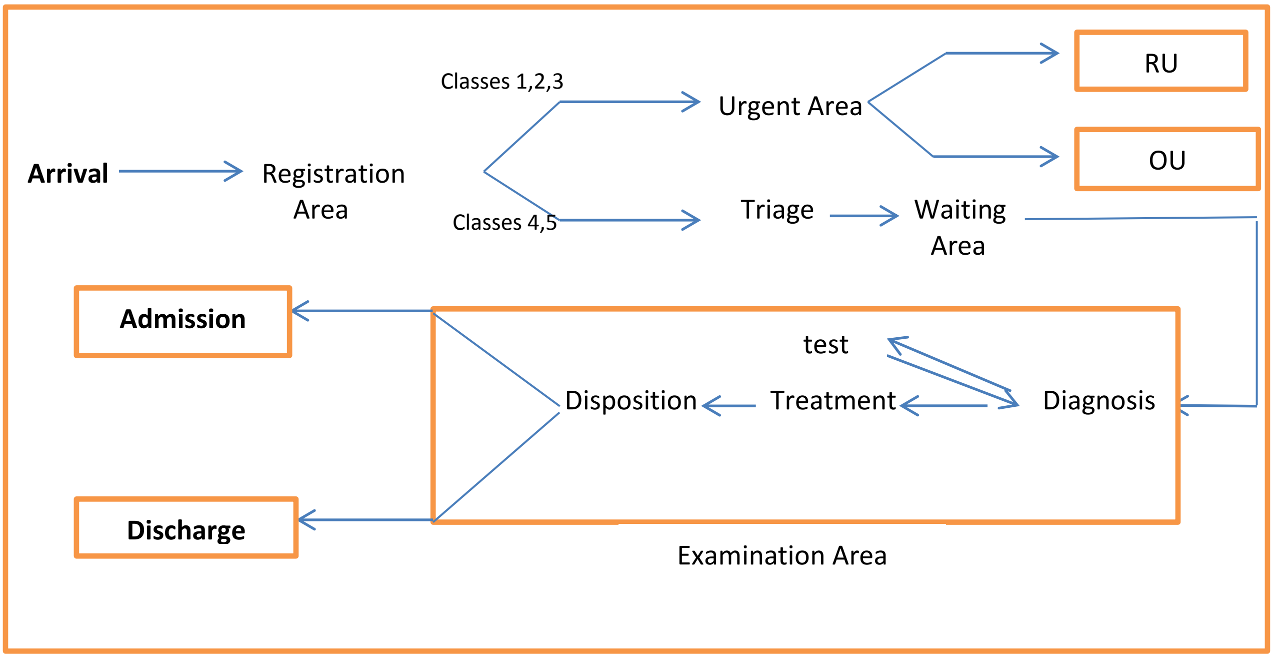


Figure 7.1 current ED TMC Patient Flow Design

Figure 7.1 displays the general current status from the point of arrival when patients register in registration area, then Class 1, 2 and 3, which are directed to urgent area including Resuscitation Unit (RU) and Observation Unit (OU); these are allocated for classes 1, 2 and 3 (i.e. immediate, emergent and urgent). These classes use RU and OU according to needs. The figure also shows that classes 4 and 5 (i.e. minor and non-urgent). Minor and non-urgent patients simply come to triage where they are screened before joining the examination queue (one queue), after which they are examined accordingly as soon as there is available space.

In this work, the focus is assigned to the triage area. Figure 7.2 illustrates the way in which examination areas work in the current patient flow. Class 4 and 5 patients push from triage to waiting in a single queue in the examination area in order to enter treatment room. This step is important as it allows the reader to understand all changes to be made in this area.

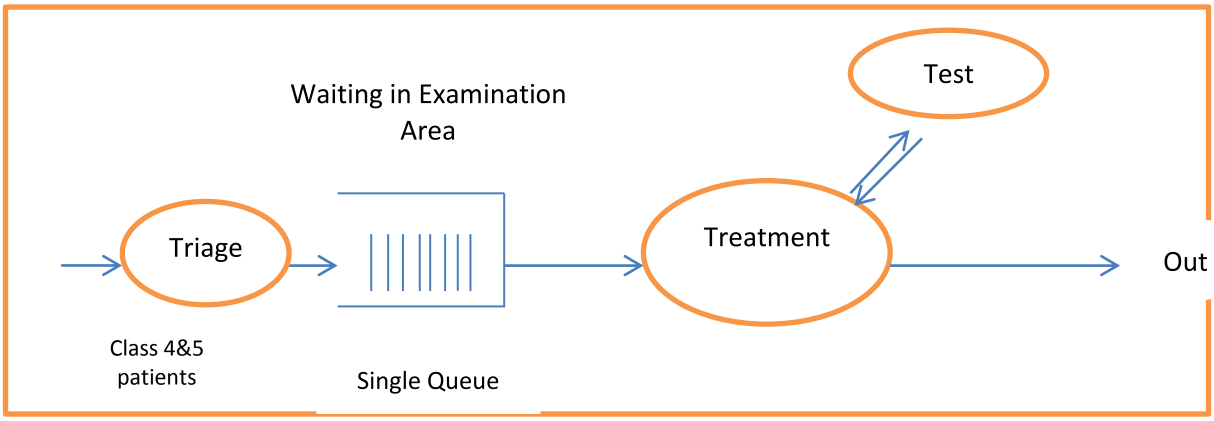
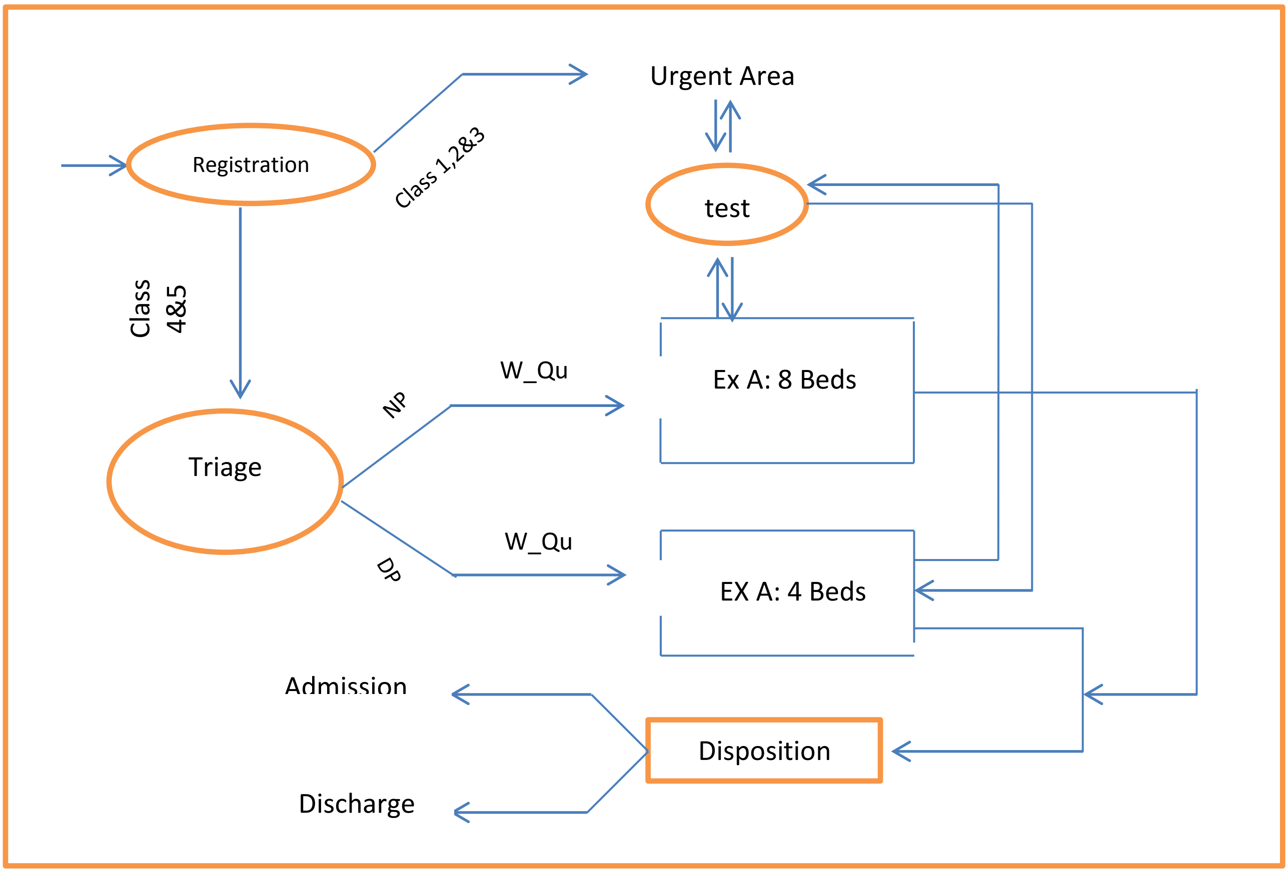


Figure 7.2 current of Examination Area ED TMC Patient Flow Design _ One Queue

Figure 7.3 shows the new PBC system in place, with triage segregating patients into two queues according to patients' behaviour, as developed by the Bayesian approach. Triage now forwards to two separate queues, and patients will move to their selected queues according to behaviour. Thereafter, patients will proceed to PBC or examination. The number of beds in examination has been reduced from 12 to 8, with 4 beds designated to the PBC system to cater for those patients displaying difficult behaviours. Figure 7.3 explains the new strategy in detail.



NP = Normal Patients, DP= Difficult Patients, EX A= Examination Area, W_Qu= Queue

Figure 7.3 Design of PBC Strategy of ED TMC _ Two Queue

If this aspect of the strategy is to be represented in real life, additional space, for queuing and a separate allocated space for beds, would need to be available in order to keep patients separated.

7.5 PBC results and discussion

7.5.1 Comparing the Patient Behaviour Control Model Results to DES 5

This section displays the value of applying the new strategy in ED TMC, which has redesigned patient flow, taking into account the behaviour factor. This value will be presented by comparing the results of PBC with the results obtained after implementing models 1–5 (the models were fully discussed in Chapter 6). The goal of this comparison is to prove that the new strategy, applied to control behaviour, improves the efficiency of ED by reducing LOS and WTs.

A thorough stochastic analysis was carried out, comprising 100 replications. The results can be found follows. Table 7.1 shows the LOS in examination for minor and non-urgent patients, where the changes were concentrated on and the PBC strategy applied. The results that have been extracted from the PBC model clearly show that, after applying the PBC strategy with reference to behaviour rather than acuity levels, a certain reduction of LOS was achieved in minor and non-urgent patients. Minor patients LOS time reduced from (92.93) minutes to (68.27) minutes, and non-urgent LOS time reduced from (94.44) minutes to (67.79) minutes. An average reduction of LOS by 24% is achieved by implementing the defined PBC based on patient behaviour.

This strategy has also taken into consideration the Lean Thinking Theory and the findings of the preliminary research, which highlights the impact of difficult patients and how they can be the cause and effect of overcrowding in the EDs of hospitals.

The independent sample t-test was used to calculate the differences in the mean LOS between the two study periods (i.e. pre- and post-PBC), with the differences expressed as 95% confidence intervals. All hypotheses-testing were two-tailed. A P value of < 0.05 was considered to be statistically significant. The results were achieved by Minitab, Version 16 (Statistical Software).

Table 7.1 displays the first major discovering of this study, which was approximately (25) minutes' reduction in ED LOS for minor patient (class 4), and approximately

(27) minutes for non-urgent patients (Class 5) after applying the PBC. This represented a 26% improvement in the LOS of Class 4 patients and 28% in Class 5.

7.1. Mean patient LOS (minutes) in Examination area Compared Before and After the Implementation of Patient Behaviour Control (PBC)

Outcome measure LOS in Examination (Minutes)				**Independent sample t-test**		
				Test statistic t value	Difference (95% CI of difference)	P Value Two Tailed
	Pre-PBC Mean/SD	Post-PBC Mean/SD	Difference Time Reduced			
Minor	92.93/12.13	68.27/ 10.25	24.66	-24.53	(-41.4 to -20.7)	<0.001
Non-Urgent	94.44/12.67	67.79/10.03	26.65	14.92	(30.2 to 13.5)	<0.001

- $\hat{P} < 0.05$

Such decreases are statistically significant for both minor and non-urgent patients, as shown in table above. The table shows that the mean LOS in the examination area alone, for Class 4, was longer in the pre-PBC (93 minutes) than the post-PBC (68 minutes, 95% CI = -20.7 to – 41.4, SD = 12.1) and ($\hat{P}$ < .001). Similarly, the study showed that the mean LOS in the examination area for Class 5 decreased by 27 minutes (95% CI =13.5 to 30.2, SD = 10), where the $\hat{P}$< .001). The results provide very clear proof that there is a significant difference between the time before and after PBC, which indicates the benefit of the PBC; in other words, it can be stated that the examination area LOS has shown a reduction of almost 26% and 27% for Class 4 and Class 5, respectively. This, in reality, represents an individual case (for every single patient), which absolutely displays the significant reduction that can be achieved.

The reductions in ED LOS, as achieved through implementing FTS, have been stated in previous studies from the USA, the UK, Canada, Australia and Europe [Welch, 2012; Murrel *et al*., 2011; Considine *et al*., 2008; Kelly *et al*., 2007; King *et al*., 2006; Fernandes *et al*., 1996]. However, this study's findings are in contrast with other studies, where the reduction of LOS was wider. For example, the study has been carried out in the UAE [2009], which showed that LOS in cases 4 and 5 decreased by 30 minutes after opening the FT area, which represented 40% improvement in the LOS [Devkaran *et al*., 2009]. Sanchez *et al*. [2006] in their study, which was carried out in in Spain, demonstrated that opening a Fast Track Area (FTA) was able to reduce the LOS for all types of patient by 50% [Sanchez *et al*., 2006]. Another study carried out in the US in 2008 showed that the LOS for Class 4 patients decreased by 44%, whilst the length of stay for Class 5 patients was reduced by 76% [Medeiros *et al*., 2008]. A possible explanation for this is that this study is different from most studies in a number of ways. Firstly, the unique feature of the PBC strategy is that it is different from FTS where the PBC strategy took into account the patient behaviour factor to deal with a reduction in LOS for patients. This made the study distinct from others owing to the fact that the time spent by behaviours differed from the time spent by other factors examined in previous studies. The second difference that could cause this difference in results from others works is the fact that this study used PBC to examine the LOS of the examination area alone. This means that the result does not show ED LOS in total; rather, it shows only the LOS for the examination area in an effort to reduce time there. The examination area, as explained in previous chapters, is used by minor and non-urgent patients, where behaviour issues take place; therefore, the time shown in Table 7.1 refers to the LOS of both minor and non-urgent cases in the examination area, taking into account the controlling behaviour factor. Another unique feature distinguishing this study is that PBC achieved its goal by repositioning staff and beds.

Table 7.2 shows how the number of patients processed has been impacted, with the PBC increasing patient processing efficiency and increasing the number of patients by 14. This clearly shows the positive impact of implementing a PBC strategy based on behaviour rather than acuity level, as it diverts and segregates patients with behavioural issues that can easily spread negativity and waste valuable resource time from those who do not display such characteristics.

7.2. Number of Patients Processed, (Before and After PBC Implementation)

Number of Patients Processed			
PBC Process	**Minor**	**Non-Urgent**	**Total**
Pre-PBC	102	78	180
Post-PBC	105	89	194

Tables 7.1 and 7.2 details the findings recognised as being most fundamental. In specific regard to time-sensitive diagnosis and subsequent treatment, a hugely different outcome could be witnessed as a result of a few minutes—notably the difference between life and death. Through the ED, improved flow was recognised, which will help to provide patients with better service and will help to save patients' lives. This impact on minor and non-urgent patients should be considered valuable as two-thirds of the population were seen to fall into the minor and non-urgent triage group.

Table 7.3 shows how the examination waiting area has been affected, which is currently a single queue where both minor and non-urgent patients reside and wait a response from the examination room. For example, patients wait in the queue and for a bed to be free in order to move into examination. The maximum number of patients within the queue is also recognised as helping to develop an idea surrounding the current situation within the waiting area, which can then lead to overcrowded areas within the ED; therefore, both minor and non-urgent patients have the same average waiting time of (70.08) minutes, which can be seen in Table 7.3, and a patient queue of 30. This clearly represents a very long queue and long waiting times for patients before being admitted into the examination area. Moreover, this also represents patients with bad behaviour: once they cause a disruption, regardless of patient type, this means everyone is at standstill and cannot move forward until the problem is solved.

The newly implemented PBC system does not consider normal and difficult patients separately; rather, it allows triage staff to strategically choose and direct patients into two different categories, namely normal patients that can move forward to examination as normal, and difficult patients showing behavioural issues, who are moved into a totally new queue, where all patients with behavioural issues have to wait to be seen by the same staff of examination. However, those patients that are classed as difficult have a lower level priority solely based on their behaviour, as these actions are recognised as causing further escalating problems and reducing process efficiency levels. Difficult patients require a separate queue (waiting area) and separate beds for examination. The same number of bed remains within the ED; however, 4 beds have been designated for difficult patients alone.

7.3. Examination Waiting Time of Minor and Non-urgent Patients (Before and After PBC)

Examination Waiting Time (minutes)			
PBC Process	**Minor**	**Non-Urgent**	**Max Number in Queue**
Pre _PBC: (One single queue for both types of patients)	70.08		30
	Normal (8 beds)	Difficult (4 beds)	
Post _PBC: (Patients segregated into two queues due to behaviour type)	30.40	40.67	11

Table 7.3 shows the waiting times extracted from the additional queues of the examination area due to the changes applied. Normal patients now have 8 beds designated to them but receive overall priority from resources in order to maintain an efficient process. Importantly, their waiting time is a mere (30.40) minutes, which shows a significant reduction in processing time as they are not colluded with patients with behavioural issues. Difficult patients now have four beds designated to their examination purposes, with their waiting time also seen to have decreased significantly, although this is higher than for normal patients. At this stage, it is important to remember that we can assume, as the number of patients within a queue increases, the waiting time within that queue will also increase. Hence, such variable results in waiting time, which is directly related to the number of patients within the queues. By applying the PBC strategy, the queue for being admitted into the

examination area for both patients types has decreased. This strategy shows a reduction of 61.94% in patient waiting times, meaning the queue for examination has been reduced by two-fold.

From the results, it is very clear that, once normal patients are segregated, the examination is able to move forward with all normal patients in a very efficient manner, with the waiting time for examination decreasing significantly. Furthermore, the results shed light on the fact that the waiting time for the behavioural PBC seems to be higher than the initial waiting time. This has decreased significantly; this is due to all the behavioural patients being collated together, as well as the fact that those patients recognised as being difficult are assigned a lower priority. This is simulated within the model as priority is given to normal patients by doctors and nurses. Due to the nature of patients' behaviour, their importance has been diverted to the fast tracking route in order to enable a constant flow of efficient processes.

The initiation of the PBC system for minor and non-urgent patients, based on behaviour, has not had a negative impact on patients with high levels of acuity. The LOS for such patients remained very similar; this is owing to the initial fast tracking that separates patients according to acuity level and condition. This is done within the reception, upon patients registering, at which point they are separated accordingly. This demonstrates that patients cannot interrupt other departments or at least the chance of disruption following through to other departments is decreased in order to result in positive influences.

Table 7.4 shows an overview of all LOS times across the four different models developed, represented by the five case types. The actual model results represents the ideal time within which the ED would like to within. The behaviour model represents the impact difficult patient behaviour can have on the processes within the ED as all the case type times increase significantly. Lastly, the PBC model is recognised in line with its changes applied to the examination. This result also indicates whether the change has any adverse or positive effects on the other case types. As the FT concentrates on only the examination area—where only minor and non-urgent patients are considered—the results indicate very little change in the remaining cases, i.e. immediate, Emergent and Urgent. These results remain very much the same as noted previously, with the responsibility of the reception just like a triage system where they segregate patients according to acuity levels. After this point there, is no reason for patients to concoctor with other patient types. This is also based on the assumption that, once patients are forwarded to examination, they do not have a requisite to be forwarded to any other area of higher acuity. This is not the case in real life: patients' acuity levels can change at any juncture whilst within the ED; however, the results clearly indicate a positive decrease in LOS for minor and non-urgent patients due to the changes applied where patients are strategically diverted according to their behaviour.

7.4. Average Length of Stay (LOS) of Case Type According to Developed Models

Models	Immediate Cases	Emergent Cases	Urgent Cases	Non Urgent Cases	Minor Cases
Basic Model Average Time	176.56	350.86	318.44	208.10	209.14
Actual Model Average Time	133.71	251.38	201.01	258.08	200.64
Behaviour Model Average Time	142.53	347.23	269.14	368.04	368.59
PBC Model Average Time	143.00	344.33	265.28	294.96	295.87

The above table details that the utilisation of a PBC does not negatively impact patients' LOS in the case of patients with urgent illnesses and injuries. The LOS of class 2 and class 3 patients were seen to decrease following intervention. Such developments were unpredicted owing to the fact that the PBC was designed in such a way to provide quicker care in the cases of both minor and non-urgent patient groups. Such improvements could have arisen as a result of various factors. Primarily, owing to the fact that the PBC decrease ED waiting room overcrowding through separating non-urgent patients to a different treatment area, it may be that staff had a larger physical space in which to work, in addition to a less distracting environment. Moreover, the ED, when overcrowded, can be very hectic and frantic, which negatively impacts the productivity of the physician, meaning levels decline and there is a compromised in patient care, which could have been circumvented without such overcrowding.

Following the completion of a number of analyses, the conclusion can be drawn that, when adopted within the ED, the PBC approach is promising. This research emphasises the many changes in the processes of the ED in terms of the use of Lean Thinking, the presence of behavioural issues, and how resources can be used more efficiently. In this particular Teaching Hospital ED, patients' LOS and WTs were decreased with the application of the PBC strategy.

7.6 Summary

This chapter sought to provide a discussion on the way in which the FT Strategy, in combination with Lean Thinking Theory, could be adopted in a hospital's ED, at an operational level, with the aim of achieving patient control in the case of those patients displaying behavioural issues. Accordingly, the strategy was centred on the control of such patients, and has been named the Patient Behaviour Control (PBC) strategy.

Within TMC, the study aimed to establish methods of decreasing patients' LOS and WTs without service provision quality being impacted and also without impacted other patients.

The chapter described the way in which PBC was applied in ED TMC, highlighting the effects of how this approach could impact the effectiveness measures of ED TMC, namely LOS and WTs. Furthermore, the chapter detailed the fact that a decline in WTs and LOS was both clinically fundamental and statistically significant for those patients attending a hospital's ED.

Chapter 8: Conclusions and Future Work

8.1 Conclusion

A Hospital Emergency Department (ED) is a medical treatment facility, specialising in the care of patients who attend without a prior appointment either by their own means or via the ambulance service. Due to the lack of predictability in regards to patient attendance, it is imperative that the department deliver a range of treatments covering a vast arena of different injuries and illnesses. EDs throughout the globe are experiencing many different obstacles and challenges on a daily basis owing to the fact that there has been a significant surge in patient demand. The most excruciating challenge that EDs face today around the world is the overcrowding of areas within the department. This problem of over crowdedness alone can easily lead to the demise of a healthcare service. Over crowdedness affects EDs from an array of different avenues that only lead to a deficiency in activity and processes reducing the quality of service dramatically.

Overcrowding within the ED can be looked upon like a disease, once it is apparent, it is very difficult to control. Almost contagious as the effects are firstly, visible in nature and thereafter can affect patients as well as ED staff mentally and emotionally which in some cases can result in a physical uproar.

Therefore, it is of extreme importance and above all priorities in majority of the EDs where possible to put effective measures in place to make sure departments do not get over crowded and to reduce the effects of over crowdedness. This is the reason why hospital EDs invest heavily into research and developments continuously to understand and develop the best possible management strategy for health care providers namely to reduce down time, increase productivity, reduce waiting times and queues but not limited to. New research is being carried out continuously to enhance the service and care within hospital EDs around the world.

The problem of over crowdedness is unfortunately prevalent within the ED of Tripoli medical centre (TMC), where this research was undertaken. The aim of the research was firstly to understand the cause and effects of over crowdedness within the ED of TMC. The idea of this process was to develop greater understanding and reasoning of how over crowdedness occurs in order to be able to combat the problems faced by the ED effectively. The research highlighted many causes of over crowdedness, i.e. long waiting times, long queues, lack of space, lack of facilities, etc. However, the research undertaken concluded these causes to be influencing factors that aid the development of overcrowded EDs. The focus thereafter turned to finding the root cause of problems. The underlying root cause of all the causes that lead to an overcrowded facility concluded to be human behaviour. This problem of inadequate human behaviour happens to be attached to all the causes of disruptions that when combined together develop over crowded situations.

In order to gather greater understanding of the influencing factors, a descriptive method has been followed and a pilot study has been carried out to understand the environment of the ED by using questionnaires, record analysis, interviews with staff, and observational data analysis.

Research further highlighted the main problem area being the examination area as it accounts for majority of the patients and patients of lower levels of acuity that cause the brunt of the disruptions.

The study shows the ED of TMC operating in a slight different manner in terms of processing patients and patient flow compared to other hospital EDs. The ED of TMC stream lines patients (5 patient types according to acuity levels) straight away from the reception as soon as they enter into two groups. Acuity levels 1,2 and 3 are referred to care straight away, and acuity levels 4 and 5 are sent to examination area. The examination area, where all the concentration will be given, consists of triage, diagnosis and treatment.

This study makes use of discrete event simulation (DES) to represent the current status of the ED in TMC and shows further developments in terms of model enhancements. Recent technological advances in DES modelling and on-going ED data tracking allow a more comprehensive patient data driven computer simulation to be achieved. The DES model demonstrates prospective DES usage for ED operations and management research. It is currently used in all industries including healthcare facilities for different purposes to investigate answers to a variety of questions accordingly. DES models seem to be particularly suited for advancing the quantitative study of overcrowding. The predictive capability of the DES models achieves best when applied to a group average patient times where confidence interval can be extracted based on any number of replications to ensure strong results.

In this study, five DES models were developed as follows: DES 1 is a simple logical representation, DES 2 represented the current status of the ED of TMC, DES 3 represents actual times that should be adhered to in providing the service, DES 4 represents the ED with behavioural problems and DES 5 is where the Bayesian network modelling (BNM) is applied to generate a more accurate occurrence of human behaviour.

This study is the first of its kind within Libya for the ED of TMC, and for the first time, the hospital records have been assessed, observational data has been collated and further research data has been gathered and implemented within a DES model that has an integrated Bayesian approach. This has enabled results to be extracted that show the ED of TMC, their current status in terms of patient processing and flow. For example, patient length of stay (LOS) can now be accounted for, patient waiting times (WT) can be assessed according to area, this will enable the ED of TMC to make comparisons in terms their current status and target where they would like to be in the foreseeable future. The DES models have aided in developing a dynamic visual aid that helps to visualise cause and effects. The thorough research within this study has shed light upon the novelty of how patients behaviour is the overall additive to all disruptions and the root cause for developing over crowded facilities. The problem of behaviour seems to be prevalent in developing countries such as Libya where processes are not governed extensively. An additional innovative discover in this study is the group of behaviours that are responsible for increasing waits time and LOS, and lead to disruptions in patient processing and flow. The key behavioural factors are confrontation, challenges, passivity, and illness belief. These factors have been discovered by carrying out a thorough literature review, extensive discussions and consultations with doctors and nurses within the ED.

Every patient that enters the ED is different, no two patient reactions to a situation is the same regardless of the condition the patients may arrive in. Even more so, every single human being is different, i.e. emotionally and mentally, for example, how an individual person reacts, understands, listens, cares, etc. This can be classed as human behaviour. This study takes into consideration the existence of human behaviour that effects every single process throughout the ED.

Research highlighted the most commonly used and most effective strategy throughout the globe is the fast track system used to route patients according to their acuity levels. Similar principals of fast tracking was used to develop the new strategy of Patient Behaviour Control (PBC), where acuity levels are replaced by human behaviour. This would mean all the patients will now also be screened for attributes of difficult behaviour.

The new strategy named PBC that was introduced in chapter 7 in this study, aimed to aid the prevention of overcrowded departments and reduce patient LOS and WTs.

The PBC Model has been developed using Witness simulation, which provided a platform where real data could be represented, evaluated and analysed. The effectiveness of PBC within the ED were evaluated, which have practical implications for reducing patient LOS and WTs in the ED of TMC.

This study demonstrates that by managing patients behaviour, leads to a significant decrease in LOS and WTs. Therefore increasing efficiency by making optimum use of the available resources.

This research would be most valuable to operational managers, practitioners in areas such as health service research and health service delivery. It demonstrates a new strategy based on human behaviour being the root cause in order to achieve greater efficiency throughout all the activities and processes of the healthcare service. Further, this new strategy is not limited to the healthcare service but can be applied to numerous other industries to manage human behaviour.

Future Work

This final section displays recommendations for future work in an effort to address the limitations of this study. In actual fact, the results of this study alter the researcher's vision of the phenomenon, thus leading to new directions for further practical or theoretical investigations. This includes the following ideas:

- Investigate the performance of DES in further real-life case studies of healthcare services.
- Investigate the performance of DES by combining DES with other types of simulation, as recommended in the literature review as a good choice for simulating human behaviour, i.e. Agent Based Simulation (ABS).
- Investigate the performance of DES in a large sample with more complex patient behaviours.
- Reintegrate other factors that are known to impact patient flow with behaviour factors in the study of overcrowding within EDs.
- Enhance the simulation models by means of implementing a warm period in order to improve and strengthen the results.
- Add more comparison measures, such as model-building or model use.
- Develop a model simulating patient behaviour and staff behaviour in order to determine the impact of the interfere of these two factors on services time.
- Determine whether using PBC will impact the quality of care provided, measured by rates of mortality and/or re-visits, for example.

References

Abbuhl, F. B., Reed, D. B. Time to Analgesia for Patients with Painful Extremity Injuries Transported to the Emergency Department by Ambulance. Prehospital Emergency Care, 2003. Vol. 7(4): 445–447.

Affleck, A., Parks, P., Drummond, A., Rowe, B. H. & Ovens, H. J. Emergency Department Overcrowding and Access Block. CJEM, 2013;15(6): 359–370.

Ahlstrom, P. “Lean Service Operations: Translating lean production principles to service operations”, International Journal of Services Technology and Management, 2004. Vol. 5(6): 545–564.

Ahmed, M. and Alkhamis, T. Simulation Optimization for an Emergency Department Healthcare Unit in Kuwait. European Journal of Operational Research, 2009. Vol.198 (3): 936–942.

Ahmed. M and Alkhamis, T. Simulation Optimization for an Emergency Department Healthcare Unit in Kuwait. European Journal of Operational Research, 2009. Vol. 198: 936–942.

Altiok, T. and Melamed, B. Simulation Modeling and Analysis with Arena. Elsevier Inc. 2007; ISBN 9780123705235.

Andersson, G. and Karlberg, I. Lack of Integration, and Seasonal Variations in Demand Explained Performance Problems and Waiting Times for Patients at Emergency Departments: A 3-years evaluation of the shift of responsibility between primary and secondary care by closure of two acute hospitals. Health Policy, 2001. Vol. 55: 187–207.

Andrulis, D. P., Kellermann, A., Hintz, E. A., Hackman, B. B. and Weslowski, V. B. Emergency Departments and Crowding in United States Teaching Hospitals. Ann Emerg Med 1991, 20: 980–986.

Anneveld, M., van der Linden, C., Grootendorst, D. and Galli-Leslie. M. Measuring Emergency Department Crowding in an Inner City Hospital in the Netherlands. Int J Emerg Med, 2013. Vol. 6: 21–28.

Arnold, JAnd Randall, R. Work Psychology: Understanding Human Behaviour in the Work Place. Rotolito Lombarda; Italy, 5 ed; 2010. ISBN: 9780273711216.

Baer, R. B., Pasternack, J. S. and Zwemer, F. L. Recently Discharged Inpatients as a Source of Emergency Department Overcrowding. Acad Emerg Med, 2001. Vol. 8: 1091–1094.

Bankauskaite, V. and Saareima, O. Why are People Dissatisfied with Medical Care Services in Lithuania? A qualitative study using responses to open-ended questions. International journal for Quality in Health care, 2003. Vol. 15: 23–29.

Banks, J. Introduction to Simulation. WSC '99 Proceedings of the 31st conference on Winter simulation: a bridge to the future - Volume 1, 2000

Banks, J., Carson, II. J. S, Nelson, B. L & Nicol, D. M. Discrete-Event System Simulation. United States of America, Prentice Hall, 2005 (4th Edition). ISBN: 978-7111171942.

Banks, J., Carson, II. J. S., Nelson, B. L. & Nicol, D. M. Discrete-event System Simulation. 4th ed. Prentice-Hall, 2005. ISBN: 0131446797.

Banks, J., Carson, II. J. S., Nelson. B. L. & Nicol, D. M. Discrete-Event System Simulation. 5nd ed. Upper Saddle River, Pearson Education, Inc. 2010: ISBN 0136062121.

Barfod, C., Lundstrom, L. H., Lange, K. H. W. & Barfod, K. A Biological Bayesian Network for Prediction of Adverse Outcome in a Population of Acutely Ill Patients Triaged in the Emergency Department. Scand J Trauma Resusc Emerg Med. 2013; 21(2): 111–119.

Barrett, T. W. & Schriger, D. L. Annals of Emergency Medicine Journal Club. Emergency department crowding is associated with poor care for patients with severe pain. Annals of Emergency Medicine, 2008. Vol. 51: 6–7.

Bartlett, J. E., Kotrlik. J. W. & Higgins. C. C. Organizational Research: Determining Appropriate Sample Size in Survey Research. Information Technology, Learning and performance Journal. 2001, Vol.19: 43–50.

Baysan, S. Modeling People Flow: A Real Life Case Study in ITU Science Center, 2009.

Blot, S. I., Rodriguez, A., Sole-Violan, J., Blanquer, J., Almirall, J. & Rello, J. Effects of Delayed Oxygenation Assessment on Time to Antibiotic Delivery and Mortality in Patients with Severe Community-acquired Pneumonia. Critical Care Medicine, 2007. Vol. 35(11): 2509–2514.

Bolstad. W. M. Introduction to Bayesian Statistics. 2th ed. John Wiley and Sons, 2007. ISBN: 9780470141151.

Bolton, F. P. & Johnson, K. D. The Effect of Emergency Department Crowding on Patient Outcome: A Literature Review. Advanced Emergency Nursing Journal; Vol. 33 2011: 39–54.

Borshchev, A. & Filippov. A. From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools. Proceedings of the

22nd International Conference of the System Dynamics Society Oxford, England, 2005.

Brailsford, S. & Katsaliaki, K. Using Simulation to Improve the Blood Supply Chain. Journal of the Operational Research Society, 2007. Vol. 58: 219–227.

Brailsford, S. C., Sykes. J & Harper, P. R. Incorporating Human Behaviour in Healthcare Simulation Models. Proceeding of the 38th Winter simulation Conference, Monterey, California, 2006.

Brenner, S., Zeng, Z., Liu, Y., Wang, J., Li, J. & Howard, P. K. Modelling and Analysis of Emergency Department at University of Kentucky Chandler Hospital using simulations. J. Emerg Nurs 2010. vol. 36(4): 303–310.

Care Quality Commission. National Summary of the national results for the 2012 Accident and Emergency survey. Available www.cqc.org.uk/accidentandemergency.

Carson, D., Clay, H. & Stern, R. Primary Care and Emergency Departments. Report from the Primary Foundation; March 2010. Available on http://www.primarycarefoundation.co.uk/images/PrimaryCareFoundation/Downloading_Reports/Reports_and_Articles/Primary_Care_and_Emergency_Departments/Primary_Care_and_Emergency_Departments_RELEASE.pdf

Carson, J. S. Introduction to Modeling and Simulation. WSC '04 Proceedings of the 36th conference on Winter simulation, 2004.

Chan, L., Reilly, K. M., Salluzzo, R. F. Variables that Affect Patient Throughput Times in an Academic Emergency Department. *Am J Med Qual*. 1997;12: 183–186.

Cheng, L. & Duran, M. A. Logistics for Worldwide Crude Oil Transportation using Discrete Event Simulation and Optimal Control. Computers & Chemical Engineering, 2004. Vol. 28(6-7): 897–911.

Cochran, W. G. Sampling Techniques. 3rd ed. John Wiley & Sons, New Yourk. 1977: ISBN 0-471-16240.

Connelly, L. G. & Bair, A. E. Discrete Event Simulation of Emergency Department Activity: A Platform for System-level Operations Research. ACAD Emerg Med d, 2004. Vol. 11 (11): 1177–1185.

Connelly, L. G. & Bair, A. E. Discrete Event Simulation of Emergency Department Activity: A platform for System-level Operations Research." Academic Emergency Medicine, 2004; vol. 11(11): 1177–1185.

Considine, J., Kropman, M. & Kelly, E. Effect of Emergency Department Fast Track on Emergency Department Length of Stay: A case-control study. Emerg Med J, 2008. Vol. 25(12) :815–819.

Cooke, M. W., Wilson, S. & Pearson, S. The Effect of a Separate Stream for Minor Injuries on Accident and Emergency Department Waiting Times. Emerg Med J, 2002. Vol. 19: 28–30.

Cunningham, P. J., Clancy, C. M., Cohen, J. W. & Wilets, M. the Use of Hospital Emergency Department of Non-urgent Health Problems: A national Perspective. Medical Care research and review, 1995. Vol. 52(4): 453–474.

Darley, V. & Sanders, D. An Agent-based Model of a Corrugated-box Factory: The trade-off between finished goods stock and on-time-in-full delivery. Proceedings of the 5th Workshop on Agent-Based Simulation. Lisbon, Portugal 2004.

Darwiche. A. Modeling and Reasoning with Bayesian Networks. Cambridge University Press, 2009. ISBN: 9780521884389.

Davis, B., Sullivan, S., Levine, A. & Dallara, J. Factors Affecting ED Length-of-stay in Surgical Critical Care Patients. Am J Emerg Med, 1995. Vol. 13(5): 495–500.

Day, T. E., Al-Roubaie, A. & Goldlus, E. J. Decreased Length of Stay After Addition of Healthcare Provider in Emergency Department Triage: A comparison between computer-simulated and real-world interventions. Emerg Med J, 2013. Vol. 30: 134–138.

De Koning, H., Verver, J. P. S., Heuvel, J. v. D., Bisgaard, S. & Does, R. J. Lean Six Sigma in Healthcare. Journal for Healthcare Quality 2006, 28(2): 4–11.

De Silva, D. Improving Patient Flow Across Organisation and Pathways. The Health Foundation Inspiring Improvement. No. 19, Nov 2013. Available on http://www.health.org.uk/public/cms/75/76/313/4519/Improving%20patient%20flow%20across%20organisations%20and%20pathways.pdf?realName=2QYl8X.pdf

Delia, D. Hospital Capacity, Patient Flow and Emergency Department of Health and Senior Services. The institute for Health, Healthcare Policy and Aging Research. A report of new Jersey Department of health and Senior Services. 2007. Available on http://www.nj.gov/health/rhc/documents/ed_report.pdf.

Denzin, K. & Lincoln, Y. S. Handbook of Qualitative Research. SAGE Publications, Calif. CA,. 1994; ISBN: 0803946791:105-117.

Der Linden, C. V., Reijnen, R., Derlet, R. W., Lindeboom, R., der Linden, N. V., Lucas, C. & Richards, J. R. Emergency Department Crowding in the Netherlands: Managers' experiences. International Journal of Emergency Medicine. 2013; 6 (41). Available on http://www.intjem.com/content/6/1/41.

Derlet, R. W, Richards, J. R. & Kravitz, R. L. Frequent Overcrowding in US Emergency Departments. Academy of Emergency Medicine, 2001, Vol. 8: 151–155.

Derlet, R. W. & Richards, J. R. Overcrowding in the Nation's Emergency Departments: Complex causes and disturbing effects. Annals of Emergency Medicine, 2000. Vol. 35: 38–63.

Devkaran, S., Parsons, H., Van Dyke, M., Drennan, J. & Rajah, J. The Impact of a Fast Track Area on Quality and Effectiveness Outcomes: A Middle Eastern emergency department perspective. BMC Emergency Medicine, 2009. Vol. 9: 11–19.

Dinh, M., Walker, A., Parameswaran, A. & Enright, N. Evaluating the Quality of Care Delivered by an Emergency Department Fast Track Unit with Both Nurse Practitioners and Doctors. Australasian Emergency Nursing Journal, 2012. Vol. 15(4): 188–194.

Doyle, S. L., Kingsnorth, J., Guzzetta, C. E., Jahnke, S. A., McKenna, J. C. & Brown, K. Outcomes of Implementing Rapid Triage in the Pediatric Emergency Department. J Emerg Nurs, 2012. Vol. 38: 30–35.

Dubiel, B. & Tsimhoni, O. Integrating Agent Based Modelling Into Discrete Event Simulation. Proceedings of the 2005 Winter Simulation Conference.

Duguay. C & Chetouane, F. Modeling and Improving Emergency Department Systems using Discrete Event Simulation. SIMULATION, 2007. Vol. 83 (4): 311–320.

Durand, A. C., Gentile, S., Devictor, B., Palazzolo, S., Vignally, P., Gerbeaux, P. & Sambuc, R. ED Patients: How non-urgent are they? Systematic review of the emergency medicine literature. *Am J Emerg Med*, 2011. Vol. 29: 333–345.

Durand, A. C., Palazzolo, S., Tanti-Hardouin, N., Gerbeaux, P., Sambuc, R. & Gentile, S. Nonurgent Patients in Emergency Departments: Rational or irresponsible consumers? Perceptions of professionals and patients. BMC Research Notes, 2012. Vol. 5: 525–532.

Duxbury, J. Difficult Patients. Butterworth-Heinemann, London. 2000. ISBN: 0750638389.

Edward, J. & Rykiel, J. Testing Ecological Models: The meaning of validation. Ecological Modelling , 1996. Vol. 90: 229–244.

Elmer, J., Pallin, D. J., Liu, S., Pearson, C., Chang, Y., Camargo, C. A., Greenberg. S. M., Rosand, J. N. & Goldstein. J. N. Prolonged Emergency Department Length of Stay is not Associated with Worse Outcomes in Patients with Intracerebral Hemorrhage. Neurocrit Care, 2012. Vol. 17(3): 334–342.

Elshove-Bolk, J., Mencl, F., van Rijswijck, B. T., Weiss, I. M., Simons, M. P. & van Vugt A. B. Emergency Department Patient Characteristics: Potential impact on emergency medicine residency program in the Netherlands. Eur J Emerg Med, 2006. Vol. 13 (6): 325–329.

Emergency Care Intensive Support Team. Effective Approaches in Urgent and Emergency Care: Rapid Assessment and Treatment (RAT) models in Emergency Departments, NHS Emergency Care Intensive Support Team (ECIST), 2012. nhs.imas@nhs.net.

Eng, S. J. Parallel Simulation Techniques for Large-Scale Discrete-Event Models. Thesis submitted to Electronic and Computer Engineering (OCIECE). Ottawa, Ontario, Canada, 2011.

Fallowfield, L. & Jenkins, V. Communicating Sad, Bad and Difficult News in medicine. Lancet 2004. Vol. 363: 312–319.

Fatovich, D., Nagree, Y. & Sprivalis, P. Access Block Causes Emergency Department Overcrowding and Ambulance Diversion in Perth Western Australia. Emerg Med J, 2005. Vol. 22(5): 351–354.

Fernandes, C. M., Christenson, J. M. & Price, A. Continuous Quality Improvement Reduces Length of Stay for Fast-track Patients in an Emergency Department. Acad Emerg Med, 1996. Vol. 3(3): 258–263.

Fernandes, C. M., Price, A. & Christenson, J. M. Does Reduced Length of Stay Decrease the Number of Emergency Department Patients who Leave without Seeing a Physician?. J Emerg Med, 1997. Vol. 15(3): 397–399.

FitzGerald, G., Jelinek, G. A., Scott, D. & Gerdtz, M. F. Emergency Department Triage Revisited. Emergency Medicine Journal, 2010 Vol. 27(2): 86–92.

Flick, U. Introducing Research Methodology: A Beginner's Guide to Doing a Research Project. SAGE Publication Ltd, London. 2011. ISBN 978-1-84920-780–785.

Friedman, Nir, Michal Linial, Iftach Nachman, and Dana Pe'er. Using Bayesian networks to analyze expression data. Journal of computational, 2000. Vol.7(3-4): 601-620.

Fromm, R. E. Jr., Gibbs, L. R., McCallum, W. G., Niziol, C., Babcock, J. C., Gueler, A. C. & Levine, R. L.: Critical Care in the Emergency Department: A time-based study. Crit Care Med 1993, 21: 970–976.

Gacki-Smith, J., Juarez, A. M. & Boyett, L. (). Violence against Nurses Working in US Emergency Departments. *Journal of Nursing Administration*, 2009. *Vol.39*(7–8): 340–349.

Gates, D., Gillespie, G., Smith, C., Rhode, J., Kowalenko, T. & Smith, B. Using Action Research to Plan a Violence Prevention Program for Emergency Departments. Journal of Emergency Nursing, 2011. Vol. 37: 32–39.

Gorelick, M. H, Yen, K. & Yun, H. J. The Effect of In-room Registration on Emergency Department Length of Stay. Ann Emerg Med. 2005 ;45(2): 128–33.

Gunal, M. & Pidd, M. Discrete Event Simulation for Performance Modelling in Health care: A review of the literature. Journal of Simulation, 2010. Vol. 4: 42–51.

Hall. R. W. Patient Flow: Reducing Delay in Healthcare Delivery. New York; Springer. 2006; ISBN: 0387336354.

Hancock, B. An Introduction to Qualitative Research. Trent Focus for Research and Development in Primary Health Care; 2002. Available on http://faculty.cbu.ca/pmacintyre/course_pages/MBA603/MBA603_files/IntroQualitativeResearch.pdf.

Harper, P. R. A Framework for Operational Modelling of Hospital Resources. Health care Management Science, 2002; Vol. 5: 165–173.

Haruno, L., Geling, O. & Kakuda, J. Re-engineering an American Emergency Department with Team Triage—Adapting to increasing patient volume in emergency services. BMC Proceedings 2012, 6(4): 52–58.

Hlupic, V. & Vreede, G.-J. D. Business Process Modelling using Discrete-event Simulation: Current opportunities and future challenges. International Journal of Simulation and Process Modelling, 2005. Vol. 1(1–2): 72–81.

Holden, R. J. Lean Thinking in Emergency Departments: A critical review. Ann Emerg Med. 2011. Vol. 57(3): 265–278.

Holroyd, B. R., Bullard, M. J., Latoszek, K., Gordon, D., Allen, S., Tam, S., Blitz, S., Yoon, P., Rowe, B. H. Impact of a Triage Liaison Physician on Emergency Department Overcrowding and Throughput: A randomized controlled trial. Acad Emerg Med 2007, 14:702–708.

Hoot, N. R. & Aronsky, D. An Early Warning System for Overcrowding in the Emergency Department. AMTA Annu symp proc, 2006: 339–343.

Hoot, N. R. & Aronsky, D. Systematic Review of Emergency Department Crowding: Cause, Effects, and Solution. Annals of Emergency Medicine. Vol.52(2). 2008: 126 –136.

Horwitz, L. I., Green, J. & Bradley, E. H. US Emergency Department Performance on Wait Time and Length of Visit. Annals of Emergency Medicine, 2010. Vol. 55(2): 133–141.

Hwang, U., Richardson, L. D., Sonuyi, T. O. & Morrison, R. S. The Effect of Emergency Department Crowding on the Management of Pain in Older Adults with Hip Fracture. Journal of American Geriatric Society, 2006. Vol. 54(2): 270–275.

Hwang, U., Richardson, L., Livote, E., Harris, B., Spencer, N. and Morrison, R. S. Emergency Department Crowding and Decreased Quality of Pain Care. Acad Emerg Med, 2008. Vol.15(12): 1248–1255.

Ibrahim Mahmoud, I. & Hou, X. Immigrants and the Utilization of Hospital Emergency Departments. World J Emerg Med, 2012. Vol. 3(4): 245–250.

Ingalls, R. G. Introduction to Simulation. Proceedings of the 33nd conference on winter simulation; 2008.

Jackson. J. L. & Kroenke, K. Difficult Patient Encounters in the Ambulatory Clinic: Clinical predictors and outcomes. Arch Intern Med 1999. Vol. 159: 1069–1075.

Jacobson, S. H., Hall, S. N. & Swisher, J. R. Discrete-event Simulation of Health care Systems, Patient Flow: Reducing Delay Healthcare Delivery, International Series in Operations Research & Management Science ,2006. Vol. 91: 211–252.

Jensen, K. & Kirkpatrick, D. G. The Hospital Executive's Guide to Emergency Department Management. HCPro, Inc., Marblehead, MA; 2010. ISBN: 978-1-60146-742-3.

Jensen, K., Mayer, T. A., Welch, S. & Haraden. C. Leadership for Smooth Patient Flow: Improved outcomes, improved service, improved bottom line. Health Administration Press, Chicago 2006, ISBN: 1-56793-265-7.

Jessem, M. & Hollander, J. E. Emergency Department Crowding is Associated with Poor care for Patients with severe pain. Annals of Emergency Medicine, 2008. Vol. 51: 10–15.

Kamali, M. F., Jain, M., Jain, A. R. & Schneider, S. M. Emergency Department Waiting Room: Many requests, many insured and many primary care physician referrals. Int J Emerg Med, 2013. Vol. 6: 35–42.

Kelly, A. M., Bryant, M., Cox, L. & Jolley, D. Improving Emergency Department Efficiency by Patient Streaming to Outcomes-based Teams. Aust Health Rev, 2007. Vol. 31: 16–21.

Kendally, J., Reeves, B. & Clancy, M. Point of Care Testing: randomized, Controlled Trial of Clinical Outcome. BMJ, 1998. Vol.316: 1052–1057.

Khare, K. R. & Powell, S. E. Adding more Beds to the Emergency Department or Reducing Admitted Patient Boarding Time: Which Has a More Significant Influence on Emergency Department congestions?. Annals of Emergency Medicine, 2008. Vol. 12: 1–8.

Khare, R. K., Powell, E. S., Reinhardt, G.& Lucenti, M. 2008. Adding More Beds to the Emergency Department or Reducing Admitted Patient Boarding Times: Which Has a More Significant Influence on Emergency Department Congestion?. Annals of Emergency Medicine; Vol. 23 (6): 355–343.

King, D. L., Ben-Tovim, D. & Bassham. J. Redesigning Emergency Department Patient Flow: Application of lean thinking to healthcare. Emerg Med Australasia, 2006. Vol. 18 (4): 391–397.

Komashie, A. & Mousavi, A. Modeling Emergency Departments using Discrete Event Simulation Techniques. Proceedings of the 37th conference on Winter simulation, 2005.

Kuo, Y-Hong, Leung, J. M. & Graham, C. M. Simulation with Data Scarcity: Developing a simulation model of a hospital emergency department. Proceedings of the 2012 Winter Simulation Conference: 979–990.

La, J. & Jewkes, E. M. Defining an Optimal ED Fast Track Strategy Using Simulation. Journal of Enterprise Information Management, 2013. Vol.26(1-2): 109–118.

Lambe, S., Washington, D. L., Fink, A., Herbst, K., Liu, H., Fosse, J. S. & Asch, S. M. Trends in the Use and Capacity of California's Emergency Departments, 1990–1999. Ann Emerg Med 2002, 39: 389–396.

Lambe, S., Washington, D. L., Fink, A., Laouri, M., Liu, H., Fosse, J. S., Brook, R. H. & Asch, S. M. Waiting Times in California's Emergency Departments. Ann Emerg Med, 2003. Vol. 41: 35–44.

Latif, M. Operations Modelling and Simulation. Lecture Notes; school of engineering. MMU, 2011.

Laurie, A. & Stevens, M. D. Responding to the Difficult Patient. Bulletin of the American College of Surgeons, 2010. Vol. 95(5): 12–15.

Lauritzen, S. L. & Spiegelhalter, D. J. Local Computations with Probabilities on Graphical Structures and their Application to Expert Systems (with discussion). Journal of the Royal Statistical Society, 1988. Series B (50): 157–224.

Lauritzen, S. L. & Wermuth, N. Graphical Models for Associations between Variables, Some of which are Qualitative and Some Quantitative. The Annals of Statistics, 1989. Vol.17: 31–57.

Law, A. M & Kelton, W. D. Simulation Modeling and Analysis. McGraw-Hill. 3ed; 2000. ISBN: 0070592926.

Law, A. M. Simulation Modeling and Analysis. 4th ed. New York: McGraw-Hill, 2007. ISBN: 978-0073294414.

Lee-Lewandrowski, E., Corboy, D., Lewandrowski, K., Sinclair, J., McDermot, S. & Benzer, T. I. Implementation of a Point-of-care Satellite Laboratory in the Emergency Department of an Academic Medical Center. Impact on test turnaround time and patient emergency department length of stay. Arch Pathol Lab Med 2003, 127: 456–460.

Liang, R. V., Paredis, C. J. & Khosla, P. Modeling and Simulation Methods for Design of Engineering. Journal of Computing and Information Science in Engineering, 2001.Vol.1: 84–91.

Lim, M., Nye, T., Bowen, J., Hurley, J., Goeree, R. & Tarride, J. E. Mathematical Modelling: The case of emergency department waiting times. Int J Technol Assess Health Care 2012, 28(2): 93–109.

Linden, C. V., Reijnen, R., Derlet, R. W., Lindeboom, R., Linden, N. V., Lucas, C. & Richards. J. R. Emergency Department Crowding in the Netherlands: Managers' experiences. International Journal of Emergency Medicine 2013, Vol. 6: 41–48.

Lindlof, T. R. & Taylor, B. C. Qualitative Communication Research Methods. Sage, 2002. ISBN: 9780761924944.

Litvak. E. Managing Patient Flow in Hospital: Strategies and Solutions. Joint Commission Resources; 2ed.2010; ISBN: 9781599403724.

Lyons, M., Brown, R. & Wears, R. Factors that Affect the Flow of Patients through Triage. Emerg Med J, 2007; Vol. 24: 78–85.

Mahmoud, Ibrahim, and Xiang-yu Hou. .Immigrants and the utilization of hospital emergency departments..2012*; Vol.3(4)*: 245-250.

Mahoney, E. J., Harrington, D. T., Biffl, W. L., Metzger. J., Oka, T. & Cioffi, W. G. Lessons Learned from a Nightclub Fire: Institutional Disaster Preparedness. Journal of Trauma-Injury Infection & Critical Care, 2005. Vol. 58(3): 487–491.

Marmor, Y. Emergency-Departments Simulation in Support of Service-Engineering: Staffing, Design, and Real-Time Tracking. Research Thesis, Submitted to the Senate of the Technion—Israel Institute of Technology, 5770 Haifa February 2010.

May, D. D. & Grubbs, L. M. The Extent, Nature and Precipitating Factors of Nurse Assault among Three Groups of Registered Nurses in a Regional Medical Center. Journal of Emergency Nursing, 2002. Vol. 28: 11–17.

Mazzocato, P., Holden, R. J., Brommels, M., Aronsson, H., Backman, U., Elg, M. & Thor, J. How Does Lean Work in Emergency Care? A case study of a lean-inspired intervention at the Astrid Lindgren Children's hospital, Stockholm, Sweden. BMC Health Serv Res, 2012 Vol. 12: 28–34.

McCarty, T., Roberts, L. W. The Difficult Patient, in Medicine: A Primary Care Approach. Edited by Rubin R. H, Voss. C, Derksen. D. J, Gateley. A, Quenzer. R. W, Coss. C. Philadelphia, P. A, WB Saunders, 1996: 395–399.

McGuire, F. Using Simulation to Reduce Length of Stay in Emergency Departments. in *Proc. Winter Simul. Conf.*, 1994: 861–867.

McHugh, M., Dyke, K. V., McClelland, M. & Moss, D. Improving Patient Flow and Reducing Emergency Department Crowding: A Guide for Hospitals. AHRQ; Oct 2011, No. 11(12)-0094. Available on http://www.aha-solutions.org/resources/AHRQ-report-ImprovingPatientFlow-100111.pdf

Medeiros, D. J., Deflitch, C. & Swenson, E. Improving Patient Flow in a Hospital Emergency Department. Proceeding of the 2008 winter simulation conference.

Meislin, H. W., Coates, S. A., Cyr, J. & Valenzuela, T. Fast Track: Urgent care within a teaching hospital emergency department: can it work?. Ann Emerg Med., 1988. Vol. 17(5): 453–456.

Miele, V., Andreoli, C. & Grassi, R. The Management of Emergency Radiology: Key facts. Eur J Radiol, 2006. Vol. 59: 311–314.

Miller, M. J., Ferrin, D. M. & Szymanski, J. R. Simulating Six Sigma Improvement Ideas for a Hospital Emergency Department, in *Proc. Winter Simul. Conf.*, 2003: 1926–1929.

Milliken, E. M. Understanding Human Behaviour: A Guide for Healthcare Providers. Delmar. 1987. ISBN 0-8273-2798-6.

Mosahab, R., Mahamad, O. & Ramayah, T. Service Quality, Customer Satisfaction and Loyalty: A test of mediation. International Business Research, 2010. Vol. 3(4): 13–18.

Moser, M. S., Abu-Laban, R. & Van Beek. C. Attitude of Emergency Department Patients with Minor Problems to being Treated by a Nurse Practitioner. CJEM, 2004. Vol. 6(4): 246–252.

Moskop, J. C. Non-urgent Care in Emergency Department- Bane or Boon?. Virtual Mentor, 2010. Vol. 12(6): 476–482.

Moskop, J. C., Ierson, K. V. Triage in Medicine, Part II: Underlying Values and Principles. Annals of Emreg. Med, 2007. Vol. 49(3): 282–287.

Moskop, J. C., Sklar, D. & Geiderman, J. *et al*. Emergency Department Crowding Part 1—Concept, Causes, and Moral Consequences. Annals of Emergency Medicine, 2009. Vol. 53(5): 605–611.

Murrell, K. L., Offerman, S. R & Kauffman, M. Applying Lean: Implementation of a Rapid Triage and Treatment System. West J Emerg Med, 2011. Vol. 12(2): 184–191.

Nadathur, S. G. & Warren. J. R. Emergency Department Triaging of admitted stroke patients-A Bayesian Network and analysis. Health Informatics Journal, 2011. Vol.17(4): 294–312.

Nash, K., Zachariah, B., Nitschmann, J. & Psencik, B. Evaluation of the Fast Track Unit of a University Emergency Department. J Emerg Nurs, 2007. Vol. 33: 14–20.

Nehme, C., Crandall, J. W. & Cummings, M. L. Using Discrete-Event Simulation to Model Situational Awareness of Unmanned-Vehicle Operators. Proceedings of the ODU/VMASC Capstone Conference, 2008.

Nelson, M., Waldrop, R. D., Jones, J. & Randall, Z. Critical Care Provided in an Urban Emergency Department. Am J Emerg Med 1998, 16:56–59.

Newstron, J. & Newstron, J. W. Human Behaviour at Work: Organizational Behaviour. McGraw-Hill/Irwin, 13ed; 2010. ISBN: 9780073381497.

Ng, J. Y., Fatovich, D. M., Turner, V. F., Wurmel, J. A., Skevington. S. A. & Phillips, M. R. Appropriateness of Health Direct Referrals to the Emergency Department Compared with Self-referrals and GP Referrals. Med J Aust, 2012. Vol. 197 (9): 498–502.

O'Brien, D., Williams, A., Blondell, K. & Jelinek, G. Impact of Streaming 'Fast Track' Emergency Department Patients. Aust Health Rev, 2006. Vol. 30(4): 525–532.

Olsen, W. Data Collection: key Debates and Methods in Social Research. SAGE Publication Ltd, London. 2012. ISBN 978-1-84787-255-5.

Oredsson, S., Jonsson, H., Rognes, J., Lind, L., Goransson, K. E., Ehrenberg, A., Asplund, K., Castren, M. & Farrohknia, N. A Systematic Review of Triage-related Interventions to Improve Patient Flow in Emergency Departments. Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine 2011. Vol. 19: 43–51.

Parliamentary Office of Science and Technology; postnote. Managing Human Error; June 2001. No. (156). http://www.parliament.uk/documents/post/pn156.pdf.

Partovi. S. N., Nelson, B. K., Bryan, E. D., Walsh, M. J. Faculty Triage Shortens Emergency Department Length of Stay. Acad Emerg Med 2001, 8:990–995.

Parunak, H. V. D., Savit, R. & Riolo, R. L. Agent-Based Modeling vs. Equation-Based Modeling: A Case Study and Users' Guide. Multi-Agent Systems and Agent-Based Simulation, Lecture Notes in Computer Science Volume 1534, 1998: 10–25.

Parvin, C. A., Lo, S. F., Deuser, S. M., Weaver, L. G., Lewis, L. M., Scott, M. G. Impact of Point-of-care Testing on Patients' Length of Stay in a Large Emergency Department. Clin Chem 1996, 42:711–717.

Patton, M. Q. Qualitative Research & Evaluation Methods. SAGE Publications. London. 3rd ed, 2002. ISBN: 0-7619-1971-6.

Pearce. B., Huynh, N. & Harris. S. Modeling Interruptions and Patient Flow in a preoperative Hospital Environment. *Proceedings of the 2010 Winter Simulation Conference*: 2261–2270.

Peck, J. & Kim. S. Improving Patient Flow through Axiomatic Design of Hospital Emergency Departments. CIRP Journal of Manufacturing Science and Technology, 2010. Vol. 2(4): 255–260.

Pew, R. W. & Mavor. A. S. Modeling Human and Organizational Behaviour: Application to Military Simulations. National Academy Press. A. S. (Eds.). Washington DC, National Research Council. 1998.

Pidd, M. Computer Simulation in Management Science. John Wiley & Sons Ltd. 4 rd; 2002. ISBN: 0-471-97931-7.

Pines, J. M., Shofer, F. S., Isserman, J. A., Abbuhl, F. B. & Mills, A. M. The Effect of Emergency Department Crowding on Analgesia in Patients with Back Pain in Two Hospitals. Academic Emergency Medicine, 2010. Vol. 17(3): 276–283.

Pitts, S. R., Niska, R. W, Xu, J. & Burt. C. W. National Hospital Ambulatory Medical Care Survey: 2006 Emergency Department Summary. U.S. Department of Health and human Services. No.7, August 2008. Available on http://www.cdc.gov/nchs/data/nhsr/nhsr007.pdf.

Pomm, H. A., Shahady, E. & Pomm, R. M. The CALMER Approach: Teaching learners six steps to serenity when dealing with difficult patients. Fam Med, 2004. Vol. 36: 467–469.

Price. C. P. Point of Care Testing. MBJ, 2001. Vol. 322(7297): 1285–1288.

Rathlev, N. K., Obendorfer, D., White, L. F., Rebholz, C., Magauran, B., Baker, W., Ulrich, A., Fisher, L. & Olshaker, J. Time Series Analysis of Emergency Department Length of Stay per 8-Hour Shift. West J Emerg Med. May 2012; 13(2): 163–168.

Raunak, M., Osterweil, L., Wise, A. & Henneman, P. Simulating Patient Flow through an Emergency Department using Process-driven Discrete Event Simulation. Proceedings of the 2009 ICSE Workshop on Software Engineering in Health Care, Vancouver, BC: 73–83.

Richards, J. R., Navarro, M. L. & Derlet, R. W. Survey of Directors of Emergency Departments in California on Overcrowding. West J Med, 2000. Vol. 172(6): 385–388.

Roberts, L. W. & Dyer, A. R. Caring for Difficult Patients. The Journal of Lifelong Learning In Psychia, 2003, Vol. 1(4):453–458.

Robinson. S. Successful Simulation: A Practical Approach to Simulation Projects., McGraw-Hill 1996, ISBN: 0077076222.

Ross, S. M. Simulation. Elsevier Inc, 4 ed; 2006. ISBN: 9780125980630.

Russell, S., Daly, J., Itughes, E. *et al*. Nurses and Difficult Patients: Negotiating non-compliance. Journal of Advanced Nursing,2003. Vol. 43(3): 281–287.

Sanchez, M., Smally, A. J., Grant, R. J. & Jacobs, L. M. Effects of a Fast Track Area on Emergency Department Performance. The journal of Emergency Medicine, 2006. Vol. 31: 117–120.

Sargent, R. G. Verification and Validation of Simulation Models. Proceedings of the 2011 Winter Simulation Conference. http://www.informs-sim.org/wsc11papers/016.pdf

Sargent. R. G. Verification and Validation of Simulation Models. Proceedings of the 2009 Winter Simulation Conference. M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin and R. G. Ingalls, eds.

Schneider, S. M., Gallery, M. E., Schafermeyer, R. & Zwemer, F. Emergency Department Crowding: A point in time. Ann Emerg Med, 2003. Vol. 42(2): 167–172.

Semini, M., Fauske, H. & Strandhagen, J. O. Applications of Discrete-event Simulation to Support Manufacturing Logistics Decision-making: A survey. Proceedings of the 38th conference on Winter simulation, 2006.

Shannon, R. E. Systems Simulation-the Art and Science. Prentice-Hall. 1975. ISBN:0138818398.

Sharon, K. & Broquet, K. How to Manage Difficult patient. Family practice management, 2007. www.aafp.org/fpm.

Siebers. P. O., Aickelin, U., Celia, H., Clegg, C. “Towards the Development of a Simulator for Investigating the Impact of People Management Practices on Retail Performance”, Proceedings of Journal of Simulation, 2010.

Simon, H. K., Ledbetter, D. A. & Wright, J. Societal Savings by 'Fast Tracking' Lower Acuity Patients in an Urban Pediatric Emergency Department. Am J Emerg Med, 1997. Vol. 15(6): 551–554.

Singer, A. J., Thode, H. C. Jr., Viccellio, P., Pines, J. M. The Association between Length of Emergency Department Boarding and Mortality. Acad Emerg Med, 2011. Vol. 18(12): 1324–1329.

Singer. A. J., Viccellio, P., Thode, H. C., Bock, J. L., Henry, M. C. Introduction of a Stat Laboratory Reduces Emergency Department Length of Stay. Acad Emerg Med, 2008. 15: 324–328.

Smith, S. Dealing with the Difficult Patient. Postgrad Med J 1995; Vol. 71: 653–657.

Sobolev, B. & Kuramoto, L. Analysis of Waiting—Time Data in health services Research. Springer Science, 2008. ISBN: 9780387764214.

Sohr, E. The Difficult Patient. Med Master, Inc. 1996. ISBN: 0940780275.

Sokolowski, J. & Banks, C. M. Principles of Modeling and Simulation: A Multidisciplinary Approach. A John Wiley and Sons, INC, 2009. ISBN: 978-0-470-28943-3.

Stewart, M. Reflection on the Doctor–patient Relationship: From evidence and experience. Br J Gen Pract, 2005. Vol. 55(519): 793–801.

Subash, F., Dunn, F., McNicholl, B. & Marlow, J. Team Triage Improves Emergency Department Efficiency. Emerg Med J 2004, 21: 542–544.

Subash, F., Dunn, F., McNicholl, B. & Marlow, J. Team Triage Improves Emergency Department Efficiency. Emerg Med J, 2004. Vol. 21: 542–544.

Sun, B. C., Hsia, R. Y., Weiss, R. E., Zingmond, D., Liang, L. J., Han, W., McCreath, H. & Asch, S. M. Effect of Emergency Department Crowding on Outcomes of Admitted Patients. Ann Emerg Med, 2013. Vol. 61(6): 605–611.

Sureshchandar, G. S., Rajendran, C. & Anantharaman, R. N. The Relationship between Service Quality and Customer Satisfaction—A factor specific approach. Journal of Services Marketing, 2002. Vol. 16(4): 363–379.

Tan, B. A, Gubaras, A. & Phojanamongkolkij, N. Schedule Evaluation: Simulation study of Dreyer Urgent Care Facility. Proceedings the 34th Conference on Winter Simulation, 2002: 1922–1927.

Thorwarth, M. & Arisha, A. Application of Discrete-event Simulation in Health care: A review. Dublin Institute of Technology. Report 2009. Health care sciences and services, Business and Management. Cited on; http://arrow.dit.ie/buschmanrep/3

Trazeciak, S & Rivers, E. P. Emergency Department Overcrowding in the United States: An emergency threat to patient safety and public health. Emerg Med J, 2003. 20(5): 202–205.

Tulsian, P. C. & Pandey, V. Quantitative Tehniques: Theory and problems. Pearson Education India, 2006. ISBN: 81-317-0186-7.

Umar, I, Oche, M. O. & Umae, A. S. Patient Waiting Time in a Tertiary Health Institution in Northern Nigeria. Journal of Public Health and Epidemiology, 2011, Vol. 3 (2); 78–82.

Varon, J., Fromm, R. E. Jr. & Levine, R. L. Emergency Department Procedures and Length of Stay for Critically Ill Medical Patients. Ann Emerg Med 1994, 23: 546–549.

Vissers, J. M., Adan, I. J. & Dellaert, N. Developing a Platform for Comparison of Hospital Admission System: An illustration. European Journal of Operational Research, 2007; Vol. 180(3): pp. 1290–1301.

Walsh, K. & Zander, K. Emergency Department Case Management: Strategies for Creating and Sustaining a Successful Program. HCPro, 2007; ISBN: 978-1-60146-046-2.

Walshe, K & Smith, J. Healthcare Management. Open University press, 2006. ISBN: 033522119.

Wang, J, Li, J., Tussey, K. & Ross, K. Reducing Length of Stay in Emergency Department: A Simulation Study at a Community Hospital . IEEE, 2012. Vol. 42(6): 1314–1322.

Wang, M. & Shieh, C. J. The Relationship between Service Quality and Customer Satisfaction: The example of CJCU Library. Journal of Information and optimization Sciences, 2006. Vol. 27: 193–209.

Wasan, A. D, Wootton, J. & Jamison, R. N. Dealing with Difficult Patients in Your Pain Practice. Reg Anesth Pain Med, 2005. Vol.30: 184–192.

Welch, S. J. & Davidson, S. D. Exploring New Intake Models into the Emergency Department. Am J Med Qual.2010; Vol. 25: 172–180.

Welch, S. J. & Savitz, L. Exploring Strategies to Improve Emergency Department Intake. The Journal of Emergency Medicine, 2012; Vol. 43: 149–158.

Welch, S. J. Using Data to Drive Emergency Department Design: A Meta-synthesis. Health Environments Research and Design Journal, 2012. Vol. 5(3): 26–45.

Weng, S. J., Cheng, B. C., Kwong, S. T., Wang, L. M. & Chang, C. Y. Simulation Optimization for Emergency Department Resourced Allocation. Proceeding of the 2011 Winter Simulation Conference.

Werker, G. & Shechter, A. S. S. The Use of Discrete-event Simulation Modelling to Improve Radiation Therapy Planning Processes. Radiotherapy and Oncology, 2009. Vol. 92: 76–82.

Womack, J. P., Byrne, A. P., Fiume, O. J., Kaplan, G. S. & Toussaint, J. Going Lean in Healthcare. Institution for healthcare Improvement, Cambridge. Innovation series, 2005.https://www.entnet.org/sites/default/files/GoingLeaninHealthCareWhitePaper-3.pdf.

Ye. Y., Tsui, F., Wagner, M., Espino, J. U. & Li, Q. Influenza Detection from Emergency Department reports using National Language Processing and Bayesian Network Classifiers. J Am Med Inform Assoc, 2014. Vol. 21: 34–41.

Yoon, P., Steiner, I. & Reinhardt, G. Analysis of Factors Influencing Length of Stay in the Emergency Department. CJEM 2003;5(3): 155–161.

Zaigler, B. P., Praehofer, H. & Kim, T. G. Theory of Modelling and Simulation. United States of America, Academic Press, 2000 (2th edition). ISBN: 0-12-778455-1.

Zeng, Z., Ma, X., Hu, Y., Li, J. & Bryant. D. A Simulation Study to Improve Quality of Care in the Emergency Department of a Community Hospital. J Emerg Nurs, 2012. Vol. 38(4): 322–328.

Zhao, L. & Lie, B. Modelling and Simulation of Patient Flow in Hospitals for Resource Utilization. 49th Scandinavian Conference on simulation and modelling; 2008.

Appendix A

Time Form

(Service Time of ED TMC)

Patient No: ( ) Patient Age : ( )
Gender : Male ( ) Female ( )
Patient Condition : 1- Immediate case ( ) 2- Emergent case ( ) 3- Urgent case ( ) 4- Minor case ( ) 5- Non-urgent case ( )
Time of arrival at the reception desk :( ) hrs. Time of Finishing Giving Information ( ) hrs.
First contact with doctor/nurse: Time: --------------------- hrs. , Time of finish: --------------------------hrs.
Presence in the treatment room for the first time: --------------------------------- hrs. Finishing time: -------------------------------------- hrs.
Presence in the treatment room after finishing required test/ X-ray : ------------------------------------- hrs. Finishing Time: --- hrs.
Discharging a patient from ED: -- hrs.
Patient Length of Stay (LOS): ------------------------------------ Minutes/hrs.

Appendix B

Tripoli Medical Centre – Emergency Department

The Questionnaire

This questionnaire is data gathering tool of PhD project which will be done at MMU University. The research is about making significant improvements in the Emergency Department services in one of the Libyan hospitals.

In this project researcher keens to capture the views of medical staff and emergency nurse working in Emergency Departments to inform the researcher about some important issue that help in emergency department improvements. This research will be done in summer 2012.

Researcher would appreciate you taking the time to complete this short questionnaire. All questionnaires returned will be treated as confidential.

Thank you for your help.
Entisar. K. Aboukanda
The Researcher

✓ ***Section (A):***

Q1- Please show the unit in which you work ________________________________

Q2 - Please show your position within the Emergency Department:-

1- Consultant ☐
2- Specialist ☐
3- Physician ☐
4- Emergency Nurse ☐
5- Other medical position ☐

Q3. Please indicate how long have you been in your current work

1- Under 5 years ☐ 2- 5- <10 years ☐ 3- 10- < 15 years ☐

4- 15- < 20 years ☐ 5- 20 years or more ☐

Q4. Has the patient's volume within your ED increased in the last 5 years?

1- Yes ☐

2- No ☐
3- Do not know ☐

Q5. From your experience, do you think that your ED is suffering from overcrowding?

1- Yes ☐
2- No ☐
3- Do not know ☐

If Yes: answer the following question please.

Q6. From your experience, Please indicate, by ticking the appropriate box, if the following issues have effect on increasing ED overcrowding. If you feel the issue is not relevant for your department, please indicate this.

The Issues under consideration	Major effect	Minor effect	No effect	Not relevant
1- Lack of management staff	☐	☐	☐	☐
2- Not enough available beds	☐	☐	☐	☐
3- Delayed in discharges process from wards	☐	☐	☐	☐
4- Delays in admitting patients process	☐	☐	☐	☐
5- Patient Behaviour	☐	☐	☐	☐
6- Other, please specify				

Q7. From your experience, Please indicate, by ticking the appropriate box, if the following issues have effect on patients prolonged waiting time?

The Issues under consideration	Major effect	Minor effect	No effect	Not relevant
1- Shortage in beds and capacity	☐	☐	☐	☐
2- Staff arrived late	☐	☐	☐	☐
3- Long time to assess patient	☐	☐	☐	☐
4- Large number of minor& non-urgent patients.	☐	☐	☐	☐
5- Difficulties to find ED services' place	☐	☐	☐	☐
6- Other, please specify				

✓ ***Section (B):***

Q1. From your experience, do you think that difficult patients' behaviour issues have a negative impact on the work of your ED?

1- Yes ☐
2- No ☐
3- Do not know ☐

If yes, please complete the following section. If your answer is <u>No</u> or <u>You Do Not Know</u>, please go direct to section (c).

Q2. Please indicate, by ticking the appropriate box, your level of agreement or disagreement with the following patient behaviour in terms of their negative effect on service delivery in your department.

	Strongly Agree	Slightly Agree	Neither agree nor disagree	Slightly Disagree	Strongly Disagree
1- Arguing behaviour	☐	☐	☐	☐	☐
2- Illness Belief	☐	☐	☐	☐	☐
3- cultural influences	☐	☐	☐	☐	☐
4- Anger behaviour	☐	☐	☐	☐	☐
5- Interfering behaviour	☐	☐	☐	☐	☐
6- Lack of respect behaviour	☐	☐	☐	☐	☐
7- Demanding behaviour	☐	☐	☐	☐	☐
8- Communication difficulties	☐	☐	☐	☐	☐
9- Over-involvement behaviour	☐	☐	☐	☐	☐

Q3. Please indicate by ticking the appropriate box, the most serious difficult patient's behaviour, in your opinion, that effect your ED services.

Behaviour	Major Effect	No effect	Minor Effect
1- Arguing behaviour	☐	☐	☐
2- Illness Belief	☐	☐	☐
3- cultural influences	☐	☐	☐
4- Anger behaviour	☐	☐	☐
5- Interfering behaviour	☐	☐	☐
6- Lack of respect behaviour	☐	☐	☐
7- Demanding behaviour	☐	☐	☐
8- Communication difficulties	☐	☐	☐
9- Over-involvement behaviour	☐	☐	☐

Q4. Please select the most important service areas that face unacceptable behaviour, and set the real time for each service, the same as your estimation of the extra time taken by difficult patients. (You can select more than one area and behaviour).

Service areas	Most repeated behaviour (select one or more behaviours (1-9)that shown in table above)	Real Time for this service	Estimated extra time after existing of behaviour
Resuscitation			
Cardiology			
Reception			
Triage			
Examination			

Q5. Please indicate your level of agreement or disagreement with the following statements

Statements	**Strongly Agree**	**Slightly Agree**	**Neither agree nor disagree**	**Slightly Disagree**	**Strongly Disagree**
Overcrowding at ED TMC needs a serious attention.	☐	☐	☐	☐	☐
Difficult patient behaviour Contribute to increase patient waiting time.	☐	☐	☐	☐	☐
Direct transfer of patients to primary healthcare centres will help reduce demand for ED services.	☐	☐	☐	☐	☐
Difficult Patient behaviour Contribute to disturb the patient flow system.	☐	☐	☐	☐	☐
Difficult Patient behaviour Contribute to increase staff dissatisfaction.	☐	☐	☐	☐	☐
Redesign of patient flow is important to improve services	☐	☐	☐	☐	☐
Staff dissatisfaction effects the quality of ED services	☐	☐	☐	☐	☐
Difficult patients are mostly Libyan men	☐	☐	☐	☐	☐
Difficult patients are mostly Libyan women	☐	☐	☐	☐	☐
There are no long waiting time in this ED	☐	☐	☐	☐	☐
Difficult patients are mostly young	☐	☐	☐	☐	☐
Difficult patients are mostly old	☐	☐	☐	☐	☐
Difficult behaviour usually occurs during early morning.	☐	☐	☐	☐	☐
Difficult behaviour usually occurs during afternoon.	☐	☐	☐	☐	☐
Difficult behaviour usually occurs during night time.	☐	☐	☐	☐	☐
Urgent area faces serious interruptions due to patient behaviour.	☐	☐	☐	☐	☐
Examination area faces serious interruptions due to patient behaviour.	☐	☐	☐	☐	☐

✓ ***Section (C):***

Q9. Please use the following box to indicate any further comments you wish to make.

Your Comments:

Thank You for Your Time,

Appendix C

Tripoli Medical Centre – Emergency Department

SEMI-STRUCTURED INTERVIEW

Name: ___________________ position Type ________________ Years of Experience (   )

Date: ____________________ Time: _______________

Part (1): General questions

Q1: Can you explain the patient flow system in your Emergency Department?

Q2: what is the procedures and rules that have to be considered in your work?

Q3: What does “Overcrowding" mean to you?

Q4: Do you think that Overcrowding is a problem in your workplace?

If yes : Why overcrowding? ***(hints)*….. Shortage in resources, number of patients,,, capacity ,,, unqualified staff,,,, assessment time,,,, patients and/or staff behaviour.**

Q5: Which services are most affected by overcrowding? Why?

Q6: Where these bottlenecks occur more? Why?

Q7: from your experience, can you indicate what are the negative effects of overcrowding? More details (if need) :

Q8: Can you explain (in details) your contribution to decrease overcrowding?

Q8: Can you explain (in details) how does overcrowding effect your work personally?

Q10: Do you think that the department needs to take serious steps in order to reduce overcrowding ?

Q11: According to your information, is there any previous studies about the ED overcrowding, and how to solve it?

Part (2): specific Issues

Q12: From your point of view, how does behaviour affect patient flow system ?

Q13: which kind of behaviour has the significant impact on service ? (discuss different kind with the respondent) .

Q14: In your opinion, what type of patient (patient condition) who shows undesirable behaviour

Q15: discussion the additional time that caused by behaviour.

Appendix D

Tripoli Medical Centre – Emergency Department

OBSERVED BEHAVIOUR CHECKLIST

Observer name: ___________________________ Observer ID:__________________

Date of observation: ____________________ Time of observation: From _________AM ( ) PM ( ) (check one)

Location of incident: ______________________________________ To ___________ AM ( ) PM ( ) (check one)

Please Check All Observations that applies:

1- Are alcohol and/or drugs present? ☐ Yes ☐ No (check one)

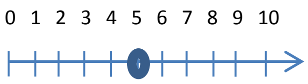
2- Is Mental Problem Present? ☐ Yes ☐ No (check one)

3- Characteristics :

Gender:		☐ Male	☐ Female	
Age:	☐ 16- 30	☐ 31- 45	☐ 46- 60	☐ 60 +
Nationality:		☐ Libyan	☐ non Libyan	
Condition:		☐ Minor case	☐ Non-urgent case	

4- Behaviour:

Behaviour scale;



☐ Normal, scale _______; Time: ------------ (Minutes).

☐ Challenge Behaviour, scale ________; Time: ------------ (Mints)

Includes; (Interfering, Over involvement, Demanding)

☐ Confrontation Behaviour, scale _______; Time: ------------ (Mints).

Includes; (Anger, Arguing, Lack of Respect)

☐ Passivity Behaviour, scale __________; Time: -------------(Mints).

Includes; (communication difficulties, lack of respect the rules)

☐ Illness belief Behaviour, scale ________; Time: ------------ (Mints)

5- Behaviour Reason:

- ☐ Long waiting time ☐ confused services ☐ staff reaction
- ☐ Unexplained waiting time ☐ Lack of coordination

Other (specify): --

6- Staff Reaction Behaviour:

- ☐ Positive Staff Interaction
- ☐ Neutral Staff Interaction
- ☐ Negative Staff Interaction

Completed by: ____ Date: ___________
(Name) (Signature)

Witnessed by: ____ Date: ___________
(Name) (Signature)

This checklist must be completed and signed, and must be returned to the reception in the end of the observation time.

This form received and reviewed by: _________________________ _________________
(Name) Date

Appendix E

T- test and ANOVA

Two-sample t test with unequal variances for B1

Group	Obs	Mean	Std. Err.	Std. Dev.	95% Conf.	Interval
Difficult behaviour	53	11.60	1.17	8.49	9.26	13.94
Normal	210	8.52	0.28	4.04	7.97	9.07
combined	263	9.14	0.33	5.37	8.49	9.80
diff		3.08	1.20		0.68	5.48

diff = mean(Difficul) - mean(Normal) t = 2.5697

Ho: diff = 0 Satterthwaite's degrees of freedom = 58.0812

Pr(|T| > |t|) = 0.0128

Two-sample t test with unequal variances for B2

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Difficult behaviour	60	14.48	1.18	9.11	12.13	16.84
Normal	210	8.57	0.28	4.03	8.02	9.12
combined	270	9.88	0.37	6.08	9.15	10.61
diff		5.92	1.21		3.50	8.33

diff = mean(Difficul) - mean(Normal) t = 4.8972

Ho: diff = 0 Satterthwaite's degrees of freedom = 65.7436

Pr(|T| > |t|) <0.001

Two-sample t test with unequal variances for B3

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Difficult behaviour	11	12.64	2.31	7.66	7.49	17.78
Normal	210	8.57	0.28	4.03	8.02	9.12
combined	221	8.77	0.29	4.35	8.19	9.35
diff		4.07	2.33		-1.09	9.23

diff = mean(Difficul) - mean(Normal) t = 1.7497

Ho: diff = 0 Satterthwaite's degrees of freedom = 10.2927

Pr(|T| > |t|) = 0.1099

Two-sample t test with unequal variances for B4

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Difficult behaviour	27	18.07	1.71	8.90	14.55	21.59
Normal	210	8.57	0.28	4.03	8.02	9.12
combined	237	9.65	0.37	5.68	8.92	10.38
diff		9.51	1.73		5.95	13.06

diff = mean(Difficul) - mean(Normal)   t = 5.4810

Ho: diff = 0   Satterthwaite's degrees of freedom = 27.3906

Pr(|T| > |t|) <0.001

For Time B1

Number of obs = 263   R-squared = 0.7773

Root MSE = 2.56016   Adj R-squared = 0.7729

Source	Partial SS	df	MS	F	Prob > F
Model	5878.0243	5	1175.6049	179.36	<0.001
Place	4841.6524	2	2420.8262	369.34	<0.001
Behaviour	1870.6776	1	1870.6776	285.41	<0.001
Behaviour by Place interaction	932.55295	2	466.27647	71.14	<0.001
Residual	1684.4852	257	6.5544172		
Total	7562.5095	262	28.86454		

For Time B2

Number of obs = 270   R-squared = 0.8299

Root MSE = 2.52899   Adj R-squared = 0.8267

Source	Partial SS	df	MS	F	Prob > F
Model	8239.719	5	1647.9438	257.66	<0.001
Place	5933.2047	2	2966.6023	463.84	<0.001
Behaviour	4855.0005	1	4855.0005	759.09	<0.001
Behaviour by Place interaction	1437.2411	2	718.62054	112.36	<0.001
Residual	1688.4884	264	6.3957894		
Total	9928.2074	269	36.907834		

For Time B3

Number of obs = 221 R-squared = 0.6638

Root MSE = 2.54511 Adj R-squared = 0.6575

Source	Partial SS	df	MS	F	Prob > F
Model	2762.0701	4	690.51753	106.6	<0.001
Place	1456.8394	2	728.41968	112.45	<0.001
Behaviour	371.60347	1	371.60347	57.37	<0.001
Behaviour by Place interaction	68.045607	1	68.045607	10.5	0.0014
Residual	1399.1606	216	6.4775955		
Total	4161.2308	220	18.914685		

For Time B4

Number of obs = 237 R-squared = 0.7696

Root MSE = 2.75101 Adj R-squared = 0.7657

Source	Partial SS	df	MS	F	Prob > F
Model	5866.1461	4	1466.5365	193.78	<0.001
Place	3352.2989	2	1676.1495	221.48	<0.001
Behaviour	1758.9444	1	1758.9444	232.42	<0.001
Behaviour by Place interaction	304.3794	1	304.3794	40.22	<0.001
Residual	1755.7864	232	7.5680448		
Total	7621.9325	236	32.296324		