INFORMATION-THEORETIC AND STOCHASTIC METHODS FOR MANAGING THE QUALITY OF SERVICE AND SATISFACTION IN HEALTHCARE SYSTEMS

A thesis submitted for the degree of Doctor of Philosophy

By

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AWARDS, PUBLICATIONS AND SEMINAR PRESENTATIONS RESULTING FROM THIS RESEARCH

AWARDS

1. Best PhD paper Award at the 10th International Quality Management and Organisational Development (QMOD) 2007 conference, Sweden.
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PUBLICATIONS

Journals

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4. Alexander Komashie, Ali Mousavi and Justin Gore (2007) *Quality management in healthcare and industry: A comparative review and emerging themes*, **Journal of Management History**, vol. 13, no. 4, pp. 359-370.

Conferences

1. Alexander Komashie , Ali Mousavi and Justin Gore (2008), *Using Discrete Event Simulation to Manage Theatre Operations in Healthcare: An Audit-Based Case Study,* in Proc. 10th EUROSim/UKSim Int. Conf. Modelling and Simulation, Cambridge, UK, April 1-3, 2008.
2. Alexander Komashie, Ali Mousavi and Justin Gore (2007) *A review of historical developments of quality assessment in industry and in healthcare*, in Proc. 10th Int. Conf. Quality Management and Organisational Development, 2007, Helsingborg, Sweden.
3. Alexander Komashie, Ali Mousavi (2005) *Modelling emergency departments using discrete event simulation techniques,* in Proc. 37th Winter Simulation Conference, 2005, pp. 2681-2685.
4. Siamak Tavakoli, Ali Mousavi and Alexander Komashie (2008), *A generic platform for real-time discrete event simulation modelling,* in Proc. 40th Winter Simulation Conference, 2008, Miami, FL, USA (accepted).

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4. Alexander Komashie, Ali Mousavi, Mustafa Özbayrak (2005) *A real-time knowledge-based decision support system for health care quality improvement using discrete event simulation techniques*. Winter Simulation Conference 2005: (an abstract presented at the WSC'05 PhD Colloquium in Florida, USA)
5. Alexander Komashie, Ali Mousavi and Justin Gore (2006), *Simulation modelling for healthcare quality and patient satisfaction improvement (Poster).* Health care informatics alliance seminar, 31st May and 27th June 2006, Royal Institute of Public Health, London. (available at http://.www.westfocus.org.uk/p54h39_home.aspx)
6. Alexander Komashie, (2005/6) *"Modelling operating theatre case mix using Discrete Event Simulation."* A number of presentations given to nurses and managers at the Northwick Park Hospital, 2005/06.
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ABSTRACT

This research investigates and develops a new approach to the management of service quality with the emphasis on patient and staff satisfaction in the healthcare sector. The challenge of measuring the quality of service in healthcare requires us to view the problem from multiple perspectives. At the philosophical level, the true nature of quality is still debated; at the psychological level, an accurate conceptual representation is problematic; whilst at the physical level, an accurate measurement of the concept still remains elusive to practitioners and academics. This research focuses on the problem of quality measurement in the healthcare sector. The contributions of this research are fourfold:

Firstly, it argues that from the technological point of view the research to date into quality of service in healthcare has not considered methods of real-time measurement and monitoring. This research identifies the key elements that are necessary for developing a real-time quality monitoring system for the healthcare environment.

Secondly, a unique index is proposed for the monitoring and improvement of healthcare performance using information-theoretic entropy formalism. The index is formulated based on five key performance indicators and was tested as a Healthcare Quality Index (HQI) based on three key quality indicators of dignity, confidence and communication in an Accident and Emergency department.

Thirdly, using an M/G/1 queuing model and its underlying Little's Law, the concept of Effective Satisfaction in healthcare has been proposed. The concept is based on a Staff-Patient Satisfaction Relation Model (S-PSRM) developed using a patient satisfaction model and an empirically tested model developed for measuring staff satisfaction with workload (service time). The argument is presented that a synergy between patient satisfaction and staff satisfaction is the key to sustainable improvement in healthcare quality.

The final contribution is the proposal of a Discrete Event Simulation (DES) modelling platform as a descriptive model that captures the random and stochastic nature of healthcare service provision process to prove the applicability of the proposed quality measurement models.

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DEDICATION

To the memory of my late mother Margaret Liggison

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1. The research context

"If the challenge 10 years ago was capacity, the challenge today is to drive improvements in the quality of care".

Prime Minister Gordon Brown, in Lord Darzi's report, (2008, p. 2)

This research involves the application of information-theoretic methods, stochastic methods and Discrete Event Simulation (DES) for developing a novel approach to the management of quality of care and effective satisfaction (satisfaction of both staff and patient) in healthcare systems.

This chapter sets out the research context by stating the aim and objectives of the research and explaining its relevance and timeliness.

1.1. Aim and objectives

1.1.1. Aim

The aim of this research is to investigate and develop a new approach to the measurement and monitoring of service quality and satisfaction in healthcare using analytical methods and real-time Discrete Event Simulation (DES) modelling.

1.1.2. Objectives

- To develop a good understanding of the major problems in quality research.
- To develop a good understanding of the concepts of quality and satisfaction in industry and healthcare.
- To investigate the weaknesses of the present healthcare quality management system in the NHS and identify the gaps to justify the current research.
- To investigate appropriate information-theoretic and stochastic methods for modelling quality and satisfaction in a healthcare environment.

- Identify key indicators of quality and integrate these into a unique Healthcare Quality Index (HQI) for the measurement and monitoring of healthcare quality.

- Develop a mathematical model for measuring staff satisfaction with service time (workload).

- Develop a mathematical relation between the satisfaction of patients with waiting time and staff satisfaction with service time (workload).

- Provide an exemplar programme for the continuous monitoring of the results of the above models in a typical healthcare environment using Discrete Event Simulation, Visual Basic .NET and a Radio Frequency IDentification (RFID) package.

1.2. Research relevance and timeliness

The quality of healthcare is increasingly becoming a critical issue in the United Kingdom and in many developed Countries (Campbell, Roland & Buetow, 2000). Quality and effective health care plays a fundamental role in improving a person's overall health and wellbeing, which leads to a good quality of life (WHO, 2000; Healthcare commission, 2005).

According to Sajid & Baig (2007), to provide a high quality of care in any healthcare system, the key requirement is the ability of the healthcare provider to continuously improve patient satisfaction. However, the pre-requisite for sustainable improvement, is accurate measurement of the quality of care and patient satisfaction. The popular quote from Lord Kelvin fits perfectly here:

"If you can't measure it, you can't improve it."

To speed up improvements, it is important that the results of measurements are made available in a timely manner. However, the time gap between measurement and improvement depends on the measurement system. Additionally, the impact of the results of a measurement process will depend on the way in which the results are presented or communicated to the stakeholders. Boyer et al. (2006) in a survey of 261 care providers concluded that despite a declared interest in satisfaction surveys, the results remain underused by hospital staff and insufficiently discussed within the teams that are responsible for taking necessary action. This finding may be attributed to the fact that information is most useful when it is most needed.

The provision of useful, easy to understand real-time (continuous) information on quality of care and staff and patient satisfaction is fundamentally the goal of this research. It is believed that this approach to monitoring and managing quality in healthcare has potential for driving continuous improvement in the quality of service in the NHS.

The relevance and timeliness of this subject is underscored by the current political landscape, as exemplified by Prime Minister Gordon Brown's statement that:

"If the challenge 10 years ago was capacity, the challenge today is to drive improvements in the quality of care" (Lord Darzi's report, 2008, p. 2).

The quality and efficacy of healthcare in the UK has seen great improvements over the past years, however, there still remains some room for improvement as reported in surveys conducted on patients' experience (Healthcare Commission, 2007; Lord Darzi, 2008). With a current annual budget of £100 billion (Carvel, 2009), the NHS receives considerable investment and would continue to face the need to improve for perhaps decades to come.

For the past 10 years, several documents such as the NHS plan 2000, the National Service Frameworks (NSFs), and many more have been released by the Department of Health (DoH) that set standards and targets for the NHS. The NHS Modernisation Agency (DoH, 2003) was set up in 2001 (Clemow & Seah, 2006) but since July 2005 has been replaced by the NHS Institute for Innovation and Improvement (NHS Institute). The mission of the NHS Institute was to support the NHS and its work-force in accelerating the delivery of a world-class health and healthcare for patients and the public. For this purpose, the NHS Institute received about £80 million to disburse (Community Care, 2007). The Healthcare Commission has also been given the mandate to monitor the deployment of these resources, assess the performance of all NHS Trusts and annually report the state of healthcare to both government and the public. The

Audit Commission also investigates the extent to which the Healthcare Commission's performance assessments of NHS Trusts reflect the reality.

In a general sense, the current approach to quality measurement and improvement in the NHS is an annual cycle of events involving the National Institute for Clinical Excellence (NICE), clinical governance teams in the NHS Trusts and the Healthcare Commission. The exercise is time consuming, costly, resource demanding and has a long time lag for any response needed to improve the quality of care and patient experience in a timely manner.

This research first examines the gap in the service quality literature and identifies the weaknesses of the existing measurement and improvement methods employed by the Healthcare Commission (HC). The service quality literature shows a particular focus on the development of conceptual models without an integrated view of the entire process from data collection to the presentation of results. The HC for instance relies on postal surveys of patients as part of its methodology for the annual survey of NHS Trusts. This approach is slow and does not help staff respond quickly to the concerns of patients. Of particular interest in this research is a real-time measure of quality at the operational level (at the point of care). In this way, staff may be able to respond more quickly than having to wait for an annual report to be published.

These issues justified the development of a unique index for measuring healthcare quality and a model for estimating system satisfaction based on a synergy between patient and staff satisfaction as developed in chapters 5 and 6 respectively. Whilst the major contributions in this research are the development of the Healthcare Performance Index (HPI) and the Staff-Patient Satisfaction Relation Model (S-PSRM), it is important to see these models in their bigger context. The fundamental idea is the development of a complete system for healthcare quality management referred to subsequently as E-Track NHS. This is not intended to be a replacement but a complement to existing methods of quality improvement such as provided by the HC.

E-Track NHS has two conceptual and three technological features that make it unique. The conceptual features in E-Track NHS are the Healthcare Performance Index (HPI) and the Staff-Patient Satisfaction Relation Model (S-PSRM). The HPI is developed to specifically address the problem of continuously improving quality of care. It is designed to be a robust index for monitoring healthcare performance in real-time and may be applied as an index of quality, satisfaction or cost. This is discussed in detail in chapter 5. The S-PSRM model is developed to address the second problem of improving patient satisfaction. This is the focus of chapter 6.

Technologically, E-Track NHS is developed as a platform for real-time Discrete-Event Simulation of the healthcare system. Its main features include automatic model development capabilities, predictive capabilities, and scenario generation and testing modes. In real-time, it will display current values of the HPI and S-PSRM by tracking patient arrivals and the acquisition of patient response to quality and satisfaction related questions. This is discussed in detail in chapter 7.

As a system, E-Track NHS intends to complement the annual patient surveys of the Healthcare Commission, with an attempt to capture the daily realities at the operational level of care. In this way, staff and managers will not ideally have to wait for an annual performance rating to be published to know how patients rate the quality of their services.

A key part of the proposed system is the shift of focus from strategic quality to operational quality. The ratings of the Healthcare Commission may be helpful at the strategic level for justifying investments but their impact at the interface between staff and patients on a continuous basis may be doubtful.

Primarily, this PhD is suggesting an entirely new way of managing service quality in healthcare – a real-time simulation based approach that involves real-time data acquisition, real-time data analysis and real-time presentation of relevant quality and satisfaction information to both staff and managers. The bigger picture is described and the main work in this thesis is a contribution to this anticipated shift in paradigm.

This paradigm shift is already beginning to emerge in the service quality literature, especially Oliva & Sterman (2001) and Oliva & Bean (2008) who used Systems Dynamics (SD) simulation technique to model service quality. These studies are discussed in more detail in section 2.4.2. As a further justification for the current research, the Centre for Medicare and Medicaid Services (CMS) in

America is currently posting the survey of "nursing quality" for hospitals on its website (Chilgren, 2008). Hospital performance is measured by an instrument called the Hospitals Consumer Assessment of Healthcare Providers and Systems (HCAHPS). CMS states that:

"The survey is designed to produce comparable data on the patient's perspective on care that allows objective and meaningful comparisons between hospitals on domains that are important to consumers".

Currently, participation in HCAHPS is voluntary and surveys are administered by mail, telephone or mixed.

In view of the above, the proposals presented in this research which are expected to lead to the possibility of patients having access to real-time information on quality and satisfaction levels of different hospital departments in order to inform the choice they make, cannot be far-fetched.

1.3. The research boundaries

Experience gained during the course of this research has made it necessary to clearly define what this research is not about.

This research is **NOT**

- A study to develop a questionnaire for assessing satisfaction
- A study to develop the key quality indicators for healthcare
- A simulation project
- About clinical outcomes
- Concerned fundamentally with strategic quality but with operational quality of care. That is *quality as experienced by the patient at the point of care.*

1.4. Thesis structure

Figure 1. 1 shows the organisation and flow of the chapters of this thesis.

Chapter 2 presents previous research on quality and customer satisfaction in industry and healthcare. The major quality problems are highlighted with particular focus on service quality measurement. The origin of the quality problem is also investigated by a historical comparative study between quality assessment in healthcare and other industrial systems. The evidence shows a focus on conceptual model development. There was little evidence of methods of continuous monitoring and improvement of quality as put forward in this thesis by the implementation of the HPI and the S-PSRM models in E-Track NHS.

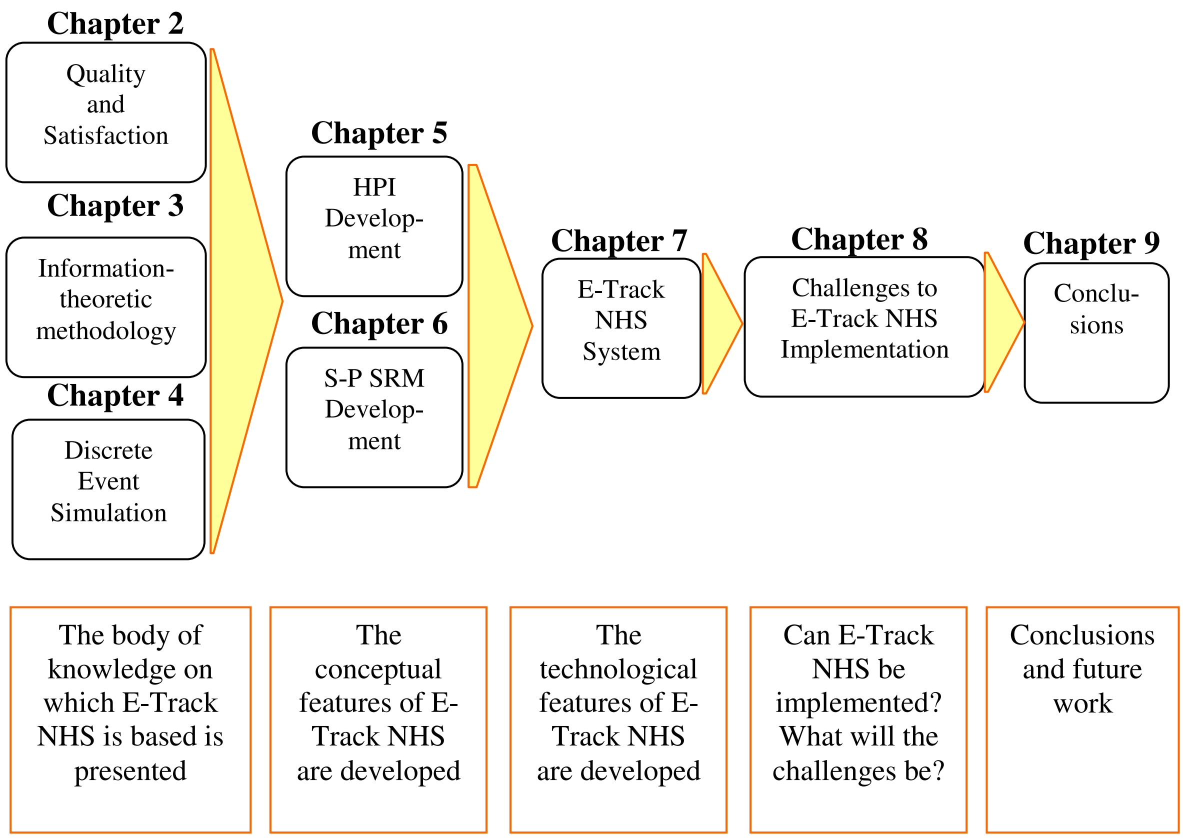


Figure 1. 1: Outline of thesis

Chapter 3 Focuses on the assessment of methodology for modelling the HPI and the S-PSRM. Two major groups of methodologies are discussed – information-theoretic methods involving Bayes' theorem, Fuzzy theory and information-theoretic entropy and stochastic methods involving queuing theory.

The information-theoretic entropy is used for developing the HPI and queuing theory is used for developing the S-PSRM.

Chapter 4 continues the review of previous research into the application of DES and real-time DES techniques industrial systems and in healthcare. Particular applications for quality improvement purposes are briefly discussed. The general concept of E-Track NHS is presented here in the context of the existing method of healthcare quality improvement employed by the Healthcare Commission in England.

Chapter 5 explains the concept of the Healthcare Performance Index (HPI) and its formulation and testing. The formulation is based on the information-theoretic entropy methodology. A Monte Carlo experimentation with the HPI is presented to test the robustness of the index. An empirical study with an application of the HPI as a Healthcare Quality Index (HQI) is also presented.

Chapter 6 presents the concept of Effective Satisfaction in a healthcare system and the formulation of the Staff-Patient Satisfaction Relation Model (S-PSRM). The empirical study for developing the staff satisfaction model is reported and the determination of the Effective Satisfaction Level (ESL) is also presented. The ESL concept is developed based on the application of Little's Law and an M/G/1 queuing methodology.

Chapter 7 involves the description of the development of the computer application for the implementation of the E-Track NHS concept. This chapter is intended to explain the integration of the HPI and S-PSRM models developed in the previous chapters into a simulation model to proof the concept of the real-time quality monitoring system proposed. The system development is not complete but certain key features are demonstrated.

Chapter 8 discusses some of the potential barriers to implementation of E-Track NHS and also discusses its limitations.

Chapter 9 finally draws conclusions to the research, highlights the key contributions to knowledge and also gives some direction for future work.

2. Background research into quality and customer satisfaction

"The best definition of quality is a satisfied customer"

Ross (1996)

This chapter presents previous research on quality and customer satisfaction in industry and healthcare. Three major quality problems – its nature, definition and measurement - are highlighted with particular focus on the problem of measurement. Quality measurement is a prerequisite for its continuous management in healthcare as proposed in this research work. Under the measurement of quality, two streams of research are identified – quality of product and quality of services. The review further narrows down on service quality by identifying five issues of debate in this area. More attention is given to the debate on the conceptual representation of the concept of service quality and the key research papers in the area are appraised.

The distinction is also made between strategic quality and operational quality since this research is not primarily concerned with quality at the strategic level. The review shows that, a considerable amount of research has focused on the development of the conceptual representation of quality. Moreover, there is little evidence in the literature of methods for continuous monitoring and improvement of quality in the healthcare service sector as put forward in this thesis by the implementation of the HPI and the S-PSRM in E-Track NHS.

In order to identify the key ingredients of quality service, the origin of the quality problem is investigated by a historical comparative study between quality assessment in healthcare and the manufacturing industry. Healthcare and industry are found to be significantly different in three major ways – the initial concerns for quality, the trend in the demand and supply of quality and the tools for quality evaluation. In addition, three events in history have been found to have caused the quality problem over the years. These are: the separation between the producer and the buyer, the industrial revolution and the technological explosion. The key ingredients of high product or service quality are identified to be *trust, commitment and ownership* on the part of the service provider as in the early days of the village market place. It is suggested that modern quality improvement initiatives must involve these ingredients.

The concept of satisfaction has also been reviewed firstly from the point of customers in general and secondly from the perspective of the patient as a special type of customer. It is found that whilst satisfaction and service quality may be considered as two different constructs, it is still debated whether the two have separate antecedents. It is concluded that the two constructs may be different but possibly correlated. In this chapter, the link between staff satisfaction, patient satisfaction and service quality has been briefly discussed providing the necessary background for the formulation of the Staff-Patient Satisfaction Relation Model (S-PSRM) developed in chapter 6.

In summary, the chapter presents an overview of the quality problem in section 2.1, discusses product and service quality in section 2.2 and distinguishes between strategic and operational quality in section 2.3. A comparative analysis of the evolution of quality methods in industry and healthcare is presented in section 2.4 whilst the concept of satisfaction evaluation is introduced in section 2.5 and finally the use of indices as a means of measuring performance (mainly quality and satisfaction) is discussed.

2.1. The quality problem: An overview

Despite the obvious importance of the quality of products and services to the success of every business, there are still considerable difficulties in its management. The main reasons for this difficulty may be listed as: (1) The definition of quality remains a problem; (2) The measurement of quality presents technical and practical challenges, and (3) Consequently, continuous quality improvement requires long term strategies that are robust against inherent uncertainties. According to Ekinci & Riley (1998), progress in quality measurement has been hampered by inappropriate assumptions of the psychological processes of perception and evaluation.

Indeed, like most fundamental concepts in science, this issue poses challenges at different levels of thought. At the philosophical level, the challenge is to understand the meaning of quality. At the psychological level, the challenge is to develop a unified understanding of the process of perception and evaluation on the part of the consumer, and at the physical level we are forced to develop reliable and consistent measurements for the concept of quality. Unfortunately, there has not been a logical progression through these levels in the literature which seems to slow down progress in this area (Ekinci & Riley, 1998).

The rest of this section highlights the problems faced when dealing with the nature and definition of quality, and focuses more on the measurement problem. It also draws on historical evidence to support the approach of continuous measurement and improvement presented in this research.

2.1.1. The nature of quality

Quality has a fundamentally abstract nature (Harteloh, 2003). The problem with understanding the nature of quality stems from the fact that it is a heterogeneous and relative concept (Grewal, 1995). Most quality experts (Juran, Deming, and Crosby) seem to agree on this problem but this agreement may be seen as part of the difficulty in arriving at a unified understanding of what quality really is. This is because most researchers feel justified in having their own views of quality. This has resulted in various ways of thinking about quality. To pursue the philosophical debate on the nature of quality will be a distraction from the aim of the current research. The interested reader is referred to the literature (e.g. Harteloh, 2003; Hardie & Walsh, 1994; Pirsig, 1974, pp. 185-213).

What is important about the debate is that our perception of the nature of quality affects our definition of the concept as seen in the various definitions presented in section 2.1.2.

2.1.2. Definition of quality

The search for a universal definition for quality has yielded inconsistent results (Reeves & Bednar, 1994; Reeves & Bednar, 1995; Sousa & Voss, 2002). Researchers and practitioners agree that a definition of quality is a perennial problem (Idvall, Rooke & Hamrin, 1997). Due to different perceptions of the concept in different contexts, several definitions have been proposed. In the industrial context, Deming (1986) cites and shares W. A. Shewhart's view that the problems around defining quality emanate from the difficulty in translating future requirements of the user into measurable characteristics so that the product or service can be designed and turned out to satisfy the user. A look at a few of the major definitions will be helpful at this point.

Five of the major categories of definitions compiled by Garvin (1988) will be presented.

1. Transcendent definitions

    - "Quality is neither mind nor matter, but a third entity independent of the two…. Even though quality cannot be defined, you know what it is." (Pirsig, 1974, pp. 185-213).

    - "…a condition of excellence implying fine quality as distinct from poor quality…quality is achieving or reaching for the highest standard as against being satisfied with the sloppy or fraudulent." (Tuchman, 1980, p. 38).

2. Product-based definitions

    - "Differences in quality amount to differences in the quantity of some desired ingredient or attribute." (Abbott, 1955, pp. 126-127).

    - "Quality refers to the amounts of the unpriced attributes contained in each unit of the priced attribute." (Leffler, 1982, p 956).

3. User-based definitions

    - "Quality consists of the capacity to satisfy wants…" (Edwards, 1968, p. 37).

    - "In the final analysis of the marketplace, the quality of a product depends on how well it fits patterns of consumer preferences" (Kuehn & Day, 1962, p 101).

    - "Quality is fitness for use." (Juran, 1974, p. 2).

4. Manufacturing-based definitions

    - "Quality means conformance to requirements." (Crosby, 1979, p. 15).

- “Quality is the degree to which a specific product conforms to a design or specification.” (Gilmore, 1974, p. 16).

5. Value-based definitions

   - “Quality is the degree of excellence at an acceptable price and the control of variability at an acceptable cost.” (Broh, 1982, p. 3).

   - “Quality means best for certain customer conditions. These conditions are (a) the actual use and (b) the selling price of the product.” (Feigenbaum, 1961, p. 1).

The above list is not exhaustive. There are several other definitions in the literature (e.g. Deming, 1986, p. 176; Taguchi, 1986). This is however considered sufficient evidence of the uncertainty that surrounds the proposition of a definition for the concept of quality.

It can be seen from the list above that even definitions within the same category do not entirely agree. Take the transcendent definitions for example: Whilst Pirsig (1974) sees quality as something that cannot be defined; Tuchman (1980) believes it is a condition that can be achieved. Whilst Tuchman’s definition tries to make sense of the concept of quality, it still remains abstract since “reaching for the highest standard” does not mean anything in absolute terms. Similar arguments can be raised with definitions in the other categories as well. However, the current research employs the user perspective of quality therefore definitions in that category will be briefly discussed.

None of the definitions presented under the user-based category is considered suitable for the current research. Edwards (1968) stresses the “capacity to satisfy wants”. Kuehn & Day (1962) referred categorically to the “quality of a product” as *dependent upon* how well it fits user preferences. This implies that quality is not in itself “fitness for use” as defined by Juran (1974) but it is only dependent on the fitness for use. These definitions seem inclined towards the quality of a product and how this product meets the users’ needs. In a service environment these definitions fall short.

In Gronroos’ (1984) service quality model for example, two of the factors that influence perceived quality of service are the technical quality (*what* the customer receives) and the functional quality (*how* the customer receives the service). Customers are usually more able to judge the latter than the former. In a healthcare environment for instance, technical quality will refer to the quality of the clinical services (e.g. accuracy of diagnosis, accuracy of a surgical operation etc.) which patients are unable to judge (Lee et al., 2000). The functional quality in this case will refer to issues as cleanliness, waiting time, care by doctors and nurses, which patients are more able to judge. It must be noted that what the patient wants by attending the hospital is basically the clinical service, but a service that meets the patient's needs alone does not represent good quality in this case. To a patient, "quality" means how well a service was delivered, not how technically superior the actual service or clinical component turned out (Chilgren, 2008) though this is the primary purpose of attending. It is, however, fair to state that Kuehn & Day (1962) did not only provide the definition quoted by Garvin (1988) above, but also stressed that "…thinking of product quality simply as a function of the commercial grade of materials used or the technical perfection of design and manufacture is a denial of 'consumer orientation'."

According to Ross (1996), "the best definition of quality is a satisfied customer". This is the basis for the preferred definition of the quality of healthcare used in this research as stated below;

Quality healthcare service is the healthcare service that consistently meets the health and experiential needs of all patients.

In this research however, the focus is on patient experience, that is, it is assumed that the quality of the clinical services are acceptable. It is also assumed that all staff are committed to delivering high quality of care.

For a more detailed discussion on the definitions of quality, the reader is referred to Hardie & Walsh (1994) and Reeves & Bednar (1994).

The issues regarding the nature and definition of quality are problematic but they do not prohibit the task of quality measurement. A logical reasoning will, however, support the conclusion that the choice of a definition will significantly influence the measurement approach employed. The literature on the measurement of quality is reviewed next in section 2.2.

2.2. The measurement of quality

The majority of the literature on quality is focused on exploring its measurement, improvement and management. The measurement, improvement and management of quality are also the focus of the current research. To examine this effectively it is helpful to review the literature under the two major streams of research usually found there: The quality of products and the quality of services. This is presented in section 2.2.1 with greater emphasis on service quality than product quality.

2.2.1. The quality of products and services

Products are tangible whilst services are intangible (Parasuraman, Zeithaml & Berry, 1988). As such the methods of measuring their qualities differ significantly. Environment, attitude and culture contribute significantly to the measurement and management of quality of services (Seth, Deshmukh & Vrat, 2005). First we briefly look at previous work on measuring product quality in the manufacturing sector.

2.2.2. Product quality

Historically, product quality has often been measured in terms of the purity or grade of materials used, the technical perfection of design, and conformance to standards of production (Kuehn & Day, 1962). Perhaps the history of product quality measurement is as old as the concept of quality itself. The methods of assuring quality however have evolved over the years.

The early days of product quality assurance were days of 100% visual or functional inspection sometimes using Go-No-Go gauges. With the growth of industry and increases in volumes of production, this approach did not only become difficult but prohibitive in time and cost. The solution to this problem was to inspect only part of a large number of products. This became the beginning of Acceptable Quality Level (AQL) in quality where a customer accepted a large number of products based on the satisfactory inspection of a chosen sample. The need for a standard method of determining a fair sample started the search for rigorous and mathematical methods of quality assurance.

The study of statistics became important to provide a structured approach focused on product inspection.

In the 1920s, Walter Shewhart applied his knowledge of statistics to the quality of the production process instead of the product itself. Shewhart focused on reducing variability in the process, implying that a stable process will produce good quality products. Shewhart's work led to the well known Statistical Process Control (SPC). Other rigorous and statistically based methods to follow were Design of Experiments (Taguchi, 1986) and Six Sigma by Smith (1993) at the Motorola Company. A more detailed historical perspective on the developments in quality measurement is reviewed in detail in section 2.4 where the manufacturing industry is compared with healthcare. The purpose of this short account is to present a brief summary of the trend in product quality in the context of the discussion in this subsection.

In today's competitive and customer driven business environment, however, it is easily observed in the quality literature, that the narrow definition of product quality as the technical perfection of design and high grade materials, is grossly inadequate (Godfrey & Endres, 1994). The concept has now expanded to accommodate user satisfaction to a large extent. Businesses and organisations are now facing the challenge of satisfying and retaining their customers in order to remain active.

This PhD research focuses more on service quality, particularly in a healthcare environment. The literature on service quality concepts, models and measurements will now be examined.

2.2.3. Service quality

Service quality is a relatively newer concept that emerged from the USA in the 1980s (Wisniewski & Wisniewski, 2005). However, it seems to pose even greater challenges than the measurement of product quality (Parasuraman, Zeithaml & Berry, 1985). Several models have been proposed for understanding and measuring service quality. Seth, Deshmukh & Vrat (2005) present a comprehensive review of 19 service quality models. They evaluated the models against the 11 factors listed below;

1. Identification of factors affecting service quality.

2. Suitability for variety of services in consideration.
3. Flexibility to account for changing nature of customers' perceptions.
4. Direction for improvement in service quality.
5. Suitability to develop a link to the measurement of customer satisfaction.
6. Diagnosing the needs for training and education of employee.
7. Flexible enough for modifications as per the changes in the environment/conditions.
8. Suggests suitable measures for improvements of service quality both upstream and downstream of the organisation in focus.
9. Identifies future needs (infrastructure, resources) and thus provide help in planning.
10. Accommodates use of IT in services.
11. Capability of use as a tool for benchmarking.

The key limitation of the study is that, Seth, Dreshmukh & Vrat (SDV) (2005) did not provide any basis for using the above list. There is also no explanation of how they judged a model's conformance or otherwise to the above factors. Unfortunately, this limitation reduces the value of the finding that none of the models satisfied all the factors. The question is why should a model satisfy all of those factors? Why should there be further research into finding a model that satisfies all the factors as they suggest? Though the answers to these questions may be implied, the researchers could have explicitly provided the answers.

Nevertheless, SDV's review provides very useful information on the various models. A critical observation of the models reviewed raises some interesting questions. Four of these questions which are relevant to the development of a model for continuously monitoring quality of care as proposed in the current research will be highlighted here.

First, why is it that nearly all the models focus only on representing service quality at the conceptual level without mentioning how the inputs should be measured? It is obvious that the expected outcome of all the models will be a measure of service quality, but will this be affected by the way the input variables are measured? This leads to the second question.

Can the method of data collection or input variable measurement affect the validity of the conceptual representation and subsequently the outcome? For instance, about 53% of the 19 models reviewed by SDV used survey questionnaire (which is often administered face to face, by post or by telephone) for measuring different antecedents to service quality irrespective of the conceptual representation. For example, Parasuraman, Zeithaml & Berry, (1985) used interviews and focus groups for data collection in developing the conceptual "GAP" model. In 1988 the authors used data collected from respondents recruited in a shopping mall and in 1991 they used data from postal surveys. Do these different methods have any implication for the accuracy of the model?

Thirdly, can the method of data analysis affect the validity of the conceptual model? About 37% of the models used some form of factor analysis (e.g. Principal-Axis factor followed by Oblique rotation in the Gap Model). How do the assumptions behind analysis techniques used affect the conceptual representation? For example, Garson (2008) presented 13 assumptions behind factor analysis including "no selection bias" of factors and "no outliers". Could this have any effect on model validity?

The fourth question is; why do other researchers seem to ignore the assumptions behind some of the models? For instance several researchers (e.g. Youssef, Nel & Bovaird, 1996; Desombre & Eccles, 1998; Wisniewski & Wisniewski, 2005) used or referred to the "GAP" model of Parasuraman, Zeithaml & Berry (PZB), (1985) and its associated SERVQUAL instrument (PZB, 1988, 1991) without reference to its limitations and how it affects their works.

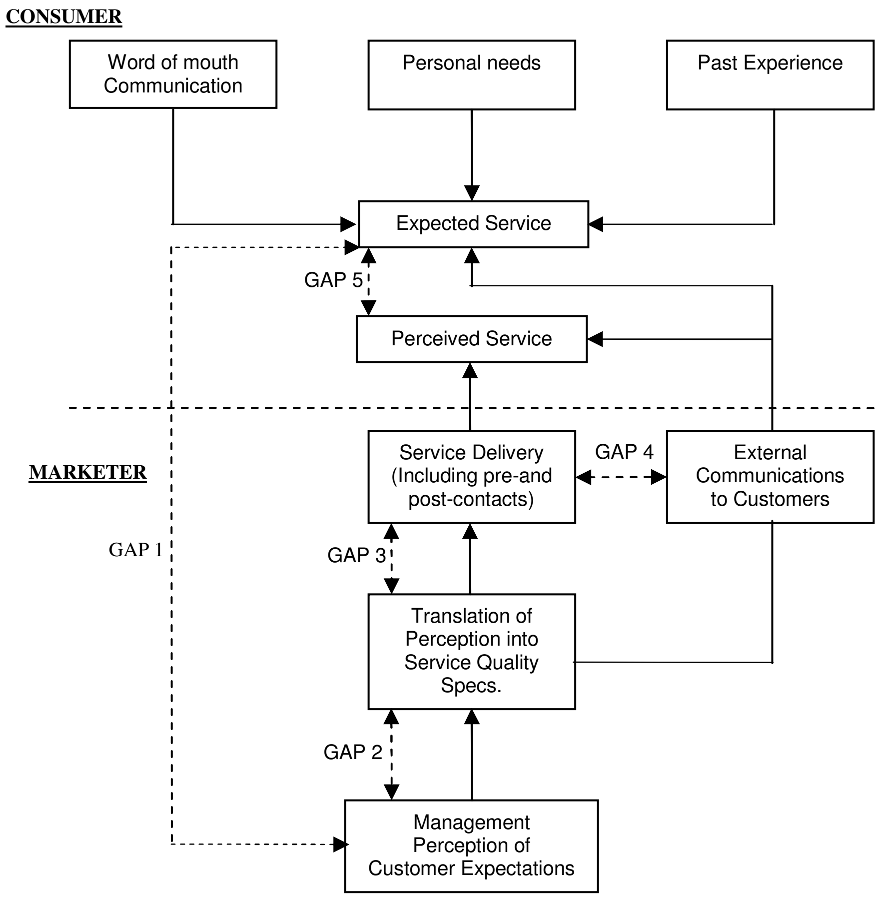
In spite of these questions, the service quality literature reveals several streams of ongoing debates. Johnston (1994) identified five major debates taking place in the service quality area. Firstly, he identified debate concerning the similarities and differences between the constructs of service quality and satisfaction. Secondly, debate on the efficacy of the expectation-perception gap concept of service quality. Thirdly is debate on the development of models that help our understanding of how the perception gap arises and how managers can minimise or manage its effect. The fourth debate he identified was on the definition and use of the zone of tolerance. The zone of tolerance is the range of variation in service performance that does not significantly affect customer satisfaction (Berry & Parasuraman 1991, cited in Johnston 1994). The fifth debate concerned the identification of the determinants of service quality. Though all the debates mentioned are interrelated and very relevant to the advancement of the field, only the second debate which involves the conceptual representation of quality will be explored further as it relates more directly to the current research. Nevertheless, parts of the other debates will also be alluded to where necessary.

The Expectation-Minus-Perception (GAP) model (Parasuraman, Zeithaml & Berry, 1985) shown in Figure 2. 1 seems to be the most widely used model in the service quality field (Seth, Dreshmuk & Vrat, 2005; Coulthard, 2004; Badri, Attia & Ustadi, 2008). However, it may also be regarded as the most criticised model in the service quality literature: Firstly, the question about the validity of its conceptual representation (Cronin & Taylor, 1992, 1994). Secondly, its methodological approach of GAP scoring (Coulthard, 2004) and thirdly, claim of the model's associated SERVQUAL instrument for universality regarding the dimensions of service quality is rejected by some researchers (Finn & Lamb, 1991; Ekinci & Riley, 1998).

The "GAP" model was based on interviews conducted with executives of four service organisations (in retail banking, credit card, securities brokerage and product repair and maintenance) and 12 focus group interviews of customers in the selected service sectors. According to the researchers, the main thesis of their service quality model is that "consumers' quality perceptions are influenced by a series of distinct gaps occurring on the marketers' side" (see gaps on marketer and consumer side in Figure 2. 1). They further represented the "GAP 5" which is the difference between a consumer's expected service and perceived service as a function of GAPs 1 through 4. That is:

$$GAP5 = f\left(GAP1, GAP2, GAP3, GAP4\right) \tag{2.1}$$

Mathematically, this means that there is a relationship between GAP5 and the other GAPs or that GAP5 depends on GAPs 1 to 4. The authors did not show the nature of this relationship. They did, however, suggest in the study that the key challenge for future research was to develop methods to measure the GAPs accurately. After more than a decade, neither the authors themselves, nor any other research, to the knowledge of this author, has attempted to establish the nature of the relationship between these gaps.



***Source:** Parasuraman, Zeithaml & Berry, 1985*

Figure 2. 1: The GAP model of service quality

On the contrary, the SERVQUAL instrument developed by the authors, which measures only GAP 5 for five major dimensions of service quality, has been used extensively in the service quality field (Youssef, Nel & Bovaird, 1996; Desombre & Eccles, 1998; Wisniewski & Wisniewski, 2005). Many researchers (e.g. Cronin & Taylor, 1992; Cronin & Taylor, 1994; Ekinci & Riley, 1998; Brady, Cronin & Brand, 2002; Jain & Gupta, 2004; Coulthard, 2004) have also critiqued various aspects of the “GAP” model and the associated SERVQUAL instrument.

Cronin & Taylor (1992) objected to the perception-expectation concept of service quality, arguing that perception (or performance) alone is a better measure of service quality. The authors investigated the conceptualisation and measurement of service quality together with its relationship to customer satisfaction and purchase intentions. They showed from literature that perceived service quality is fundamentally an attitude that tends to be modified by satisfaction. They used the SERVQUAL scale developed by PZB (1988) for their data collection but used only the performance responses for the SERVPERF analysis using regression techniques. For example, they found that Adjusted R^2 values for the four sectors studied were respectively 0.46511, 0.36515, 0.30747, 0.41534 and 0.47895, 0.38760, 0.44675, 0.47585 for SERVQUAL and SERVPERF. This means that the variability in the data is explained better by SERVPERF than SERVQUAL. Following further empirical evidence they rejected the conceptual framework of the SERVQUAL model, maintaining that service quality is better evaluated by perceptions only, without expectations. They also highlighted that quality evaluation could also be independent of the important weighting of the quality attributes of products (or services) using equation 2.2 or 2.3.

$$\text{Service Quality} = (\text{Performance}) \qquad 2.2$$

Or

$$SQ_i = \sum_{j=1}^{k} P_{ij} \qquad 2.3$$

where

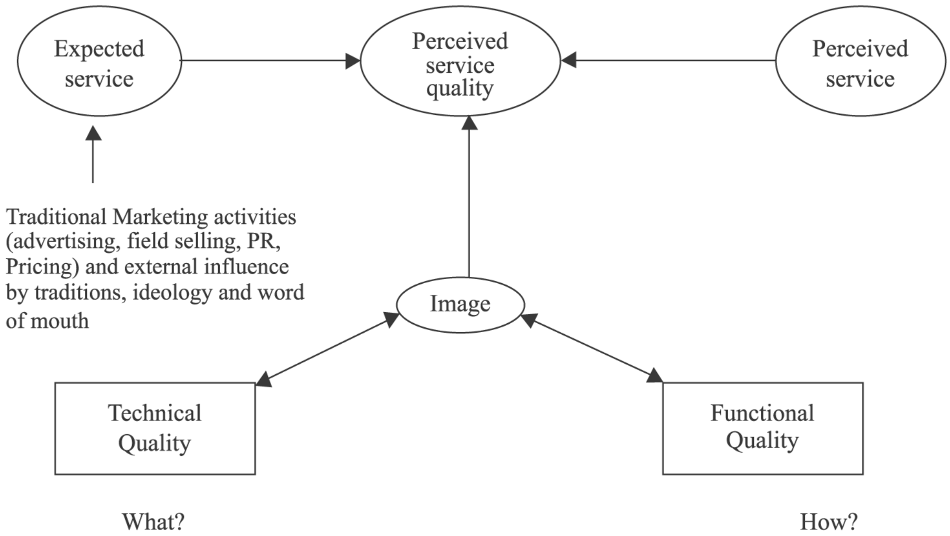
SQ_i = Overall service quality as perceived by individual i

k = Number of attributes

P_{ij} = Performance perception of attribute j for individual i

This is commonly known as the SERVPERF model of service quality. SERVPERF may seem a conceptually more plausible model than SERVQUAL but it should be noted that its reliance on the same Likert scales makes it also vulnerable to the numerous inaccuracies from respondent bias through cognitive processes (Coulthard, 2004). This brings back the questions raised above on the effects of the data collection and analysis processes on the conceptual representation of the models. These are issues that are not given prominence in the literature and this research seeks to suggest a single model that integrates appropriate data collection, data analysis and data presentation methods.

On service quality conceptualisation, Gronroos (1984) developed the functional-technical model of service quality (Figure 2. 2) before PZB's GAP model, but it has not been applied as much. This could be due to the fact that the proposed model does not provide sufficient framework for measurement.



Source: Grönroos (1984)

Figure 2. 2: Technical and Functional model of service quality

However, there seems to be a conceptual similarity between Gronroos' model and that of PZB in that they both regard customer expectations and perceptions as antecedents for perceived service quality. Gronroos' aim was to develop a service quality concept, a way of thinking about service quality, whilst PZB attempted to suggest a method for the measurement of service quality. Despite the limitations of Gronroos' model in its application for the measurement of service quality, its clear and simplified representation of the concept of service quality could be considered as its strength. Gronroos' concept of service quality affirms the definition for healthcare service quality as posited above in section 2.1.2.

In summary, the literature shows that there are at least 19 different models of service quality, but there is no evidence of a universally agreed model. Observation of the models raised four questions:

1. Why do all the models focus on conceptual representation?
2. Can the data collection method affect the conceptual representation?
3. Can the data analysis method affect the conceptual representation? and
4. Why do most researchers seem to ignore the assumptions behind some of the models?

Evidence shows that the most widely used SERVQUAL model has been challenged both conceptually and empirically (Ekinci & Riley, 1998; Cronin & Taylor, 1992; Brady, Cronin & Brand, 2002).

Five streams of debate in the service quality area have been identified by Johnston (1994). The debate on the efficacy of the expectation-perception gap view of service quality was explored in detail. It was found that the SERVQUAL and SERVPERF models are at the centre of this debate. Whilst the SERVPERF model seems to be gaining acceptance amongst researchers, it was highlighted that it could also be vulnerable to the numerous problems that arise from the use of the Likert scale.

What is needed, as suggested by Ekinci & Riley (1998), is an acceptance that the dimensions of service quality are flexible and may take different forms in different circumstances. However, the suggestion by the authors for "service quality research to look at the concept of job satisfaction *rather than* consumer satisfaction" cannot be accepted. This is because the two are complementary and not exclusive.

It is worth noting, that within the area of service quality management, there are the strategic and the operational levels that need to be tackled. This is briefly reviewed in the following section where the research focuses more on operational quality in healthcare. This means healthcare service quality as measured at the point of delivery.

2.3. Service quality management: Strategic verses operational quality

In this research thesis, the author forwards the debate of the distinction between strategic and operational quality in the context of quality management. Strategic and operational qualities mainly depend on the factors used as the indicators of quality and how they are measured. Strategic quality provides useful information at national levels, sector levels and board levels of organisations. These measures are very broadly scoped and often do not guarantee that actual performance will always meet an individual customer's expectations. For example in the healthcare sector, medical outcomes such as perinatal mortality, surgical fatality rates, and social restoration of patients discharged from psychiatric hospitals have often been used as indicators of quality care (Donabedian, 1966). Some strategic indicators of quality in industry include improved market shares and improved return on investment (Alavi & Yasin, 2008). This level of quality measurement, however, is not the focus of this research.

This research is primarily interested in how to measure and monitor the operational level of quality in a healthcare environment in real-time. Operational quality is measured at the point of operation in an industrial sector or the point of care in a healthcare setting. Alavi & Yasin (2008) identified efficiency, productivity and reduced operating cost as outcomes of quality at the operational level.

It is difficult to clearly distinguish between the literature that concentrates on strategic quality and operational quality as separate entities. Strategic quality in recent years has emerged as the assurance of total quality and, specifically, the implementation of Total Quality Management (TQM) and similar management philosophies (Tummala & Tang, 1996; Mehra & Agrawal, 2003; Alavi & Yasin, 2008). One of the things Deming, Juran and Crosby agreed on was that quality management should start with top management (Tummala & Tang, 1996).

Before stating the main thesis resulting from this review, however, a few more questions must be answered. What are the key ingredients of a high quality of service? Apart from a good model, what other factors contribute to a high quality of service? The answers to these questions are relevant to an attempt to develop a new approach to the measurement of the concept in this research. To explore these questions, a comparative study is conducted of quality development efforts in manufacturing and healthcare. This is presented in the section 2.4.

2.4. The origins of the quality problem: A historical perspective

In order to develop a new approach to the measurement and management of operational quality in healthcare, some understanding of the historical perspective is necessary. This is presented here as a comparison of the developments in quality in industry and healthcare.

2.4.1. A comparative study between industry and healthcare

It seems an undisputed fact amongst researchers (e.g. Dooley, 2000; Maguad, 2006) that the concept of quality is of ancient origins. This section therefore examines the following questions:

"Why do we have problems with quality? When did this problem start, and what has been driving quality over the years? "

Amongst the major scholars of quality (Deming, 1986; Juran, 1995; Crosby, 1979; Feigenbaum, 1961), Juran did the most work in terms of exploring the historical developments of quality management (see for example, Juran, 1999; Juran, 1995). This review follows Juran's perspective and similarly oriented scholars in discussing the evolution of quality in industry and healthcare. Three major themes that were identified are:

1. The differences in the initial concerns for quality.

2. Differences in the demand and supply of quality over the years.

3. Differences in the methods of quality evaluation techniques.

The full comparative study may be found in Komashie, Mousavi & Gore (2007a, 2007b).

2.4.1.1. Initial concern for quality

Juran (1999), Ellis & Whittington (1993), Berwick & Bisognano (1999), Maguad (2006), and Dooley (2000) all agree that the concept of quality is timeless both in industry and healthcare. However, a close examination of the literature shows that there has been a difference in the concerns underpinning quality improvement across these two contexts. In the days of the village market place, the *caveat emptor*, which means “let the buyer beware”, was the norm. The producer supplied the goods but the buyer was responsible for assuring the quality of the goods before making a purchase. Juran (1999) explains that the buyer “looked closely at the cloth, smelled the fish, thumped the melon, and tasted the grape.” It can be deduced from this evidence that the primary concern for quality in that era was the need to obtain value for money. Thus the buyer did everything to avoid any dissatisfaction that may arise after paying for goods. This value for money principle remains inherent in some quality techniques or methods today, for example customers are allowed to try on clothes in the shop before buying.

Consumers of healthcare on the other hand have not had much choice until recent years. There is therefore little historical evidence of healthcare consumers demanding any level of quality. Bull (1992) noted that from 1854 to 1870 in Great Britain, the motivation for systematic quality evaluation in healthcare was primarily a professional quest. The Hippocratic Oath, the work of Ignaz Semmelweis and Florence Nightingale were all cases of professional concern. Thus, it can be hypothesised that the pursuit of healthcare quality came out of a concern for better health or reduction in lost lives as perceived by individual professionals. In recent years, however, it is evident that the primary concern for quality comes from a pressing need to satisfy the customer (or patient) both in industry and healthcare. This has become the prerequisite for staying in business and most of the experts in the field have argued that focusing on quality is more beneficial than focusing on profit (Deming, Juran, Crosby, and Feigenbaum). Top involvement of senior management in any sector is regarded as vital in this context.

In summary, it is found that quality for products or services in industry was conceived by the concern of the customer to obtain value for money whilst in healthcare, it was out of a concern of the professionals to provide better care (e.g. reducing lost lives) for their patients.

2.4.1.2. The demand and supply of quality in industrial and healthcare systems

In this section, the "demand" for quality refers to the level of customer awareness and quest for quality, whilst the "supply" of quality refers to how well the quality of products and services provided meets the expectation of customers.

In examining the "demand" and "supply" of quality in industry, three key events are identified: the separation between the producer and consumer, the industrial revolution and the technological explosion in the latter part of the 20th century.

It was found that during the primitive years leading to the era of the village market place, men produced their own goods; there were no issues with quality because the producer was the same as the consumer (Juran, 1999). It can therefore be argued that the first event that led to the issue of quality was the separation of the producer from the consumer as a result of growth in society. Since this event, one could observe a deliberate demand for some level of quality from the consumer and the conscious attempt by the producer (craftsman in those days) to meet or exceed the demanded level of quality for their products. From the era of the village market place up until the time of the industrial revolution in the mid eighteenth century, the supply for quality remained above its demand. Further evidence was found for this in the structure of the village society which ensured *trust, responsibility and ownership*. Ellis & Whittington (1993) relate that in such contexts, it was possible for individual customer's wishes to be designed into the product at any time even in the presence of the customer.

On the contrary, the industrial revolution ushered in an era of production that led to the fall of the craft system and degradation of quality of products (Maguad, 2006). Dooley (2000) adds that products continued to be made from non-standardised materials using non-standardised methods resulting in products of variable quality. Productivity became the goal of the manufacturing industry and the demand by consumers for quality began to rise above its "supply". The most common form of quality control then was the inspection of the product by the buyer under *Caveat emptor* which was not feasible in all situations involving complex high volume products (Dooley, 2000).

Then the technological explosion in the latter part of the twentieth century further degraded quality by the complexity of the resulting systems and products. With the consumerism of the twenty-first century, it has become even more difficult to satisfy customers as the demand for quality goods and services continues to rise (Thatcher & Oliver, 2001).

In contrast, consumers of healthcare did not have much choice and were less informed about health issues around the time of the village market place. Thus the quality of healthcare was “supplied” by professionals and improved gradually as they sought ways to avoid unnecessary deaths and errors. Berwick & Bisognano (1999) noted rather arguably that the modern era of quality in healthcare, particularly in America, began at the turn of the twentieth century. This may have been due to some of the forces of social change related to industrial and technological advancement and also due to the increased patient education. This demand for quality of care rose very quickly to levels that left healthcare organisations in search of new ways for assuring healthcare quality (Ferlie & Shortell 2001).

The observations made here are that, the quality problem started with the separation of the producer from the consumer. Following this separation, quality in industry started with a demand from the consumer, whilst, in healthcare, it started with the supply by the professional, since patients did not have much choice until recently. These were, however, not huge problems due to the elements of *trust, responsibility and ownership* that were key ingredients in village societies prior to the industrial revolution of the mid-eighteenth century. The industrial revolution and the subsequent technological explosion further degraded quality by the shift of focus from product customisation towards productivity (i.e. reduction in cost and increased resource utilisation). With the emergence of patient education and choice, the demand for quality healthcare has now risen beyond its supply.

The benefits of these observations are to help researchers realise that a perfect conceptual representation of service quality in healthcare is not enough. The key elements of *trust, responsibility and ownership* must be considered within the environments where the conceptual models are implemented. Understanding the difference between the manufacturing sector and healthcare should also facilitate the appropriate application of existing manufacturing-oriented techniques in healthcare as has become the trend in recent years.

As a result of these differences in the fundamental concerns for quality in industry and healthcare and the trend in its demand and supply in both contexts, the tools and methods used to manage quality have also changed considerably. The most relevant quality evaluation techniques developed to date will be discussed in the following section.

2.4.1.3. Quality evaluation techniques and tools

A. Quality evaluation techniques in industry

Measuring and improving quality requires the use of specific methods or tools. Table 2. 1, adapted from Komashie, Mousavi & Gore (2007b), summarises the historical developments of quality methods in industry and healthcare. A brief introduction to the historical developments in product quality measurement techniques was presented in section 2.2.1 above. A number of the key industrial methods will be reviewed in this section.

The visual and functional inspection of products remained the key quality techniques prior to the introduction of control charts borrowed from statistical techniques. The development of control charts in the early parts of the twentieth century by Shewhart (1931) shows the rigour with which the manufacturing industry approached the quality problem. Hare (2003) states that, faced with the problem of process variability, Shewhart had to find an answer to the question "How much of a scientific observation is deterministic and how much of it is random?" Shewhart concluded that the answer was in the application of statistical methods and began to define the notion of "quality control":

"A phenomenon will be said to be controlled when, through the use of past experience, we can predict, at least within limits, how the phenomenon may be expected to vary in the future. Here it is understood that prediction within limits means we can state, at least approximately, the probability that the phenomenon will fall within the given limits." (Quoted in Hare, 2003).

This is evidently a focus on the process and may be interpreted to mean that the quality of the product is in the process. The concept of reduced variability (control) resulting in improved quality has been shown to be effective over the years and still remains the fundamental principle in some modern quality philosophies like Six Sigma. Shewhart's work laid the foundation for industrial quality methods for the subsequent years. His work led to the development of Statistical Process Control (SPC).

Statistical Process Control (SPC) is one of the major quality techniques used in manufacturing. It depends on the fact that products or services are the results of one or more processes. If a product is to meet or exceed customers' requirements, then it must be produced by a process that is capable of operating with little variability around a target value of the product's quality characteristics (Montgomery, 2005). The goal of SPC is thus to improve process stability and capability by reducing variability. The notion that products resulting from a stable process will meet customers' demands is not entirely true. This objection is based on an understanding of some of the modern quality management techniques such as QFD, TQM and Six Sigma (6σ), which focus on understanding the customer's needs and producing products that meet those needs, rather than focusing on the process that produces the products.

During the period between 1920 and 1960, statistical methods in quality assurance began to gain root. Professional regulations were put in place demanding the use of statistical methods. Quality societies began to emerge and quality publications appeared on the scene. Around the same time, the concept of the Design of Experiments (DOE) was developed by the Japanese engineer Genichi Taguchi (Montgomery, 2005).

Taguchi methods are now widespread. The concepts underlying Taguchi's methods may be summed up in two statements: (1) Quality should be measured by the deviation from a specified target value, rather than by conformance to preset tolerance limits. (2) Quality cannot be ensured through inspection and rework, but must be built in through the appropriate design of the process and product (Lofthouse, 1999). According to Genichi Taguchi cited in Mitra (2006), "quality is the loss imparted to society from the time a product is shipped". In his view, the loss to society includes loss to the customer in the form of repairs, disposal etc, and the loss incurred in the production process in the form of non-conformance, rework and resulting wastes. Discussing this technique, Ross (1996) observed that the best definition of quality is a happy customer. Thus Taguchi considers a failure to meet customer's requirements as a loss, because it leads to loss of goodwill and eventually loss of market share.

The basis for Taguchi's technique is his contention that the loss due to unsatisfactory performance is proportional to the square of the performance characteristic's deviation from the target value. This relationship is popularly known as the loss function. Inherent in this is the claim that variability is the key concept that relates product quality to monetary value. The experimental design component of the Taguchi methods tends to stress his claim that:

"*Quality must be designed into the product and not to be inspected".*

Whereas Taguchi's technique is well accepted in the quality arena, there are criticisms of the statistical aspects of his design of experiments but these are outside the objectives of this section (see Mitra, 2006). However, the proponents of the Taguchi methods (e.g. Lofthouse, 1999) are of the view that though statistical techniques are an important component of the methods, it is the conceptual framework of a methodology for quality improvement and process robustness that is most important.

Thus we observe a shift from the earlier inspection of the product to a focus on the production process through the works of Shewhart (1931) and then a redefinition of quality as a loss to the customer and a further change in focus to the design of the product as argued by Taguchi (1986). The trend however continued.

From the early 1980s to the turn of the century, quality measurement evolved into various management philosophies involving not only the product or production/service processes but the whole organisation where the customers (i.e. end users) played a vital role in determining the direction of a company. Notable amongst these are Six Sigma (6σ), Quality Function Deployment (QFD), and Total Quality Management (TQM). These philosophies have been considerably shaped by the works of the quality experts such as Juran, Deming, Crosby, and Feigenbaum in the 1950s.

Like SPC and DOE, Six Sigma also involves the reduction of variability, but not only in products or processes, but in all operations of an entire organisation. Pande & Holpp (2002) explained that, sigma or standard deviation in statistics is a measure of how much variability there is within a group of items or population. The higher the sigma value the greater the variability that exists. As its name implies, Six Sigma rejects defective parts outside six times the value of the variability on each side of the mean value (Montgomery, 2005). This tolerance eventually results in only 3.4 defective parts per million. In spite of the success of these variability based techniques in reducing rejected parts on the shop floor, they may not entirely be sufficient to meet customer requirements.

A more careful consideration reveals the fact that it is possible to produce what the customer does not want using the most stable processes. It was along this view that Yoji Akao in 1966 introduced the concept of Quality Function Deployment (QFD) which has also proved effective in industry. Yoji (1988) pointed out that QFD is a method for developing a design quality that will satisfy the customer and then translate these customer requirements into design targets and quality assurance measures to be used throughout the production stage. By this Yoji suggests a change in focus from ensuring a stable process to the pursuit of a stable process that produces what the customer wants.

Understanding what the customer wants, however, poses another form of difficulty. Mitra (2006) pointed out that whilst there maybe numerous advantages to using QFD, its success requires a significant time commitment and human resources due to the large amount of information it requires. Alieksiei & Aspinwall (2001) also report a lack of enthusiasm to implement QFD in the UK even in large companies. This lack of enthusiasm can be attributed to lack of understanding of the QFD concept.

Total Quality Management (TQM) has also become popular in recent years as a quality management philosophy. Oakland (1993) describes TQM as an approach to improving the competitiveness, effectiveness and flexibility of a whole organisation. Being an organisation-wide programme, it revolves around the customers, processes and people bound by the vision, mission and commitment of its management (Mitra, 2006). Thiagarajan et al. (1997) published an excellent review of TQM implementation case studies. They found amongst other things that the role of management and their leadership is critical in all quality programmes and is the foundation to the implementation of TQM.

Table 2. 1: A comparison of quality methods in industry and healthcare

Period	Industry methods	Healthcare methods
Up to 1900	**G**uilds membership Inspection Standardisation Supplier certification	**P**hysician licensing Specialty societies Individual efforts (record keeping)
1900 to 1920	**S**ystematic inspection and testing Experimental design Control Charts	**S**urveys e.g. E. W. Groves (1908) Professional certification Legislations Nursing and hospitals standardisation Follow-ups, e.g. Dr Codman (1914)
1920 to 1940	**A**cceptance sampling Statistical methods Professional regulation	**S**tudies on nursing conduct Health insurance legislations Government legislation and standards
1940 to 1960	**T**raining in statistical quality control Quality societies Quality publications Total Quality Control Experimental design Top management involvement Standards Awards e.g. "Deming prize"	**R**egulatory bodies formed Landmark publications Internal and external inspection Professional standards Performance measures Accreditation of hospitals
1960 to 1980	**Q**uality Circles SPC widespread More quality societies and publications Introduction of TQM	**D**onabedian's framework: Structure, Process, Outcome Rapid increase in literature Focus on process and inspection oriented More surveys e.g. Drew (see Sale, 2000) Supervisory and record audit Hospital accreditation Audit tools e.g. Phaneuf's audit, Rush Mediscus, Qualpacs
1980 to 2000	**S**pread of Experimental design and SPC National and international certification, awards and standards Six sigma, QFD and TQM	**I**ncrease in published standards Publications on indicators Focus on measurement and monitoring More regulatory bodies Government involvement raised
2000, beyond	**N**ew international standards e.g. ISO 9000:2000, ISO 14000 Automation of quality Enterprise quality systems	**I**mport of industrial techniques New and tighter standards Consumer societies

Montgomery (2005) agrees with Bertram (1991), cited in Thiagarajan et al. (1997) that TQM has had only moderate success due to the lack of management participation but also adds that efforts devoted to widespread utilisation of technical tools of variability reduction were insufficient. He also believed that part of the problem was the misunderstanding of the TQM mission which many organisations saw as one of training employees. Thus once a training programme has taken place, it is assumed that TQM is in place which is not always the case.

It is observed that the industrial techniques discussed above are considerably rigorous and robust due to the application of established statistical methods. The focus for achieving high quality is also seen to shift from the inspection of the product to the stability of the process, to the design of the product and finally to the entire organisation as quality assurance has turned into various management philosophies in recent times.

In order to compare this trend to what happens in healthcare, the next section (2.4.1.3 B) looks at the development of quality evaluation techniques in healthcare.

B. Quality evaluation techniques in healthcare

As in manufacturing, the concept of healthcare quality has a long history (Eagle & Davies, 1993). Berwick & Bisognano (1999), cite the quality scholar John Williamson's report of a "quality control" text in Hammurabi's (a Babylonian King) code which is said to date as far back as about 2000BC.

In England, Florence Nightingale is well noted for her quality improvement activities in the 1850s. Sale (1990, 2000) explains that Nightingale kept notes of her observations of patients, giving her information on which to establish the level of care being provided and to find ways of improvement. Bull (1992) also provides details of Miss Nightingale's activities during this period.

The key part of Nightingale's approach was the measurements and records of her observations. Measurements have remained an important part of quality evaluation in healthcare except that the quantity that is measured to represent quality has varied considerably over the years. This is probably due to the fact that quality evaluation in healthcare started with the concern of individual professionals as discussed in section 2.4.1 above. For example, in the 1950s, Abdullah, cited in Sale (2000), chose to provide a reflection of the quality of nursing care by measuring the level of dissatisfaction expressed by patients, nurses and other individuals.

Sale (2000) further reports that, towards the end of the 1960s, Drew conducted a survey of 21 hospitals in America in which it was established that 42 different quality assurance techniques were being used, all falling under one of the following categories;

- Comments from patients and others
- Special rounds of patient units
- Checks and tests on procedures
- Patient and other records
- Other, e.g. external inspection teams etc.

A close observation of the above list shows the level of quality assurance techniques in healthcare at the time to be more akin to the era of inspection in the manufacturing industry and is evidently less rigorous.

Towards the end of the 1960s, Donabedian (1966) categorised the evaluation of quality of care into the structure in which care is delivered, the process of care and the outcome of the care. Donabedian's framework has since remained a dominant approach to quality evaluation in healthcare. It was noted at the time that outcomes had been frequently used as indicators of the quality of medical care. In as much as it was agreed that there were advantages to be gained by using outcomes, Donabedian (1966) also described several limitations to using these as measures of quality of care. These limitations may result from the fact that certain outcomes are difficult to measure and their effectiveness may be interpreted differently in different contexts. It is important to note at this point that Donabedian was interested in quality at the operational level, at the physician-patient interface.

Developments in operational quality evaluation in healthcare since Donabedian are summarised in Table 2.1 and may also be found in the review studies of Wright (1984) and Eagle & Davies (1993). Wright noted that a comprehensive quality assurance programme must include elements of structure, process and outcome whilst Eagle & Davies classified all the developments in healthcare quality evaluation since 1975 into three: Structure, Process and Outcome. This shows that Donabedian's work in 1966 remains fundamental to healthcare quality methods though Eagle & Davies also concluded that quality systems in healthcare are derived from business or industrial models.

The "quality control" approach in industry was soon taken up in the healthcare context, although to begin with, this was of a reactive nature. About, the same time as Shewhart's work, a survey was undertaken by Groves (1908), cited in Bull (1992).

According to Bull (1992), Groves, a British Physician, surveyed 50 hospitals, each having over 200 beds, to assess patient mortality from surgical procedures. He was able to use this survey approach to show that mortality ranged from 9 per cent for appendectomies to 44 per cent for procedures related to malignancies. Other efforts to monitor quality around the time were professional certification and legislations (Bull, 1992; Berwick & Bisognano, 1999), nursing standardisation (Bull, 1992) and Dr Codman's recommendation to review all patients one year after surgery (Sale, 2000). In contrast to industry, while informing healthcare understanding and strategy, these efforts were based within the professional's domain and lacked an assessment of quality at the level where it matters most. If care is to be patient-, or user-centred, then the most important level is, as Donabedian (1966) suggested, the level of "physician-patient interaction." It was not until the latter part of the twentieth century and into the new millennium that the notion of "consumerism" was more fully adopted within healthcare (Berwick & Bisognano, 1999). This meant that consumers of healthcare began to make their voices heard.

At present, in the majority of cases, quality evaluation in healthcare continues to be without mathematical rigour. Whilst statistical analysis is conducted extensively in healthcare for analysing historical data, there is no evidence of any scientific theory that underlies any of the quality management methods in healthcare. Patient surveys and standards of care and various methods of outcome appraisals remain the key techniques for improvement. As shown in Table 2. 1, since 2000 the approach has been the introduction of new and tighter standards of care, together with continued attempts at importing industrial techniques into healthcare.

Before addressing the issues and implications of importing industrial techniques for quality assessment into the healthcare sector, it is important to make a case by case comparison between the evidence so far from the implementation of quality evaluation techniques in the manufacturing industry and healthcare sectors.

C. Synthesis of evidence

Whilst quality has always been an integral part of almost every product and service, our awareness of its importance and the introduction of systematic methods for its control have been an evolutionary process (Montgomery, 2005). Table 2. 1 on page 33 shows that developments in quality methods have occurred in quite distinct ways across the two sectors of healthcare and manufacturing.

Whilst manufacturing industry has employed mathematical and scientific approaches to quality assessment since the beginning of the last century, no such approach is evident in the healthcare quality literature. It has also been observed from the developments in industrial quality techniques that focus has shifted from inspection of products to process stability, to the design of the product and organisation-wide factors with the involvement of customers. In the healthcare sector, such changes in focus are not obvious. What is seen is that patients have become a key part of healthcare quality in the present time.

These historical differences in approach across industry and healthcare can quite reasonably be attributed to the difference in processes (product-profit based vs. service-based, respectively) and concern for the pursuit of quality as discussed previously. However, the methods and principles around quality improvement across the two sectors appear to be converging. The end of Table 2. 1 on page 33 (period of 2000 and beyond), shows that "automation" (which could perhaps be regarded as an extreme result of standardisation) is becoming the order of the day. It appears that whenever an organisational task can be effectively automated, it will eventually happen (Dooley, 2001). Dooley used this argument to predict that quality methods in industry will eventually be automated, and Montgomery sees this period as one in which quality improvement will break traditional boundaries into healthcare, insurance and utilities. This, together with the advent of "consumer involvement" in healthcare, may be representing a real shift in the paradigm of quality management.

However, although healthcare has been adopting certain industrial techniques – for example, Sale (2000) reports that the introduction of the Salmon Report (DoH) caused an enormous change in British nursing by its introduction of industrial management techniques, there is insufficient evidence to judge the effectiveness and appropriateness of these interventions. Therefore, it is important to understand the difference between industry and healthcare in terms of product and service orientations.

2.4.2. Emerging themes and implications

Researchers and quality professionals continue to make a strong case for the application of industrial techniques in healthcare. Some examples of such cases are Reid (2006), Young et al. (2004) and Laffel & Blumenthal (1989). The possibility of this being the norm in the near future is not far-fetched but the problems that need to be addressed are appropriateness and practicalities. Several possibilities exist but one technology that is possibly proving to be an effective decision support tool in healthcare is Discrete Event Simulation (Eldabi et al., 2007). This technology is further reviewed in chapter 4. This is the basis of the E-Track NHS concept suggested in this research. Discrete Event Simulation has the advantage of ensuring management involvement and staff ownership, as well as the flexibility for ongoing quality assessment and improvement. The E-Track NHS concept is different from previous quality measurement methods in healthcare in that it stresses the importance of real-time (continuous) data acquisition, analysis and presentation. This is discussed in more detail in chapters 4 and 7.

Of particular relevance to the current research are the works of Oliva & Sterman (2001) and Oliva & Bean (2008). In the former work, the authors hypothesised, within the context of the UK banking sector that:

"The characteristics of services – inseparability, intangibility and labour intensity – interact with management practices to bias service providers towards reducing the level of service they deliver, often locking entire industries into a vicious cycle of eroding service standards".

In testing this hypothesis the researchers assumed that the main factor influencing service quality is time spent with customers. They formulated a number of mathematical models and tested these with empirical data. The study suggested that employees reduce time spent with customers in an effort to meet throughput goals or by working longer hours. It was found that, in the absence of reliable measurements of customer satisfaction, management interprets the reduction in time spent with customers as productivity gain and reduce service capacity. Or in a healthcare setting, the effect may be a tightening of targets.

Part of the current research seeks to build upon the above finding by providing a reliable measure of customer satisfaction and relating this to available service capacity and the effectiveness of employees, as presented in chapter 6.

In Oliva & Bean (2008), the authors proposed a Systems Dynamics (SD) based Service Quality Management (SQM) simulation that captures the operational characteristics of the service delivery process. They argued that a realistic simulation environment might provide a useful context for management learning in a service setting. This application of simulation in a service environment is evidence of the feasibility of the E-Track NHS system proposed in this research. E-Track NHS, however, is based on real-time data acquisition from the service environment and used Discrete Event Simulation (DES) instead of SD.

The trend of applying manufacturing oriented techniques in service environments is increasing. It is, however, important for researchers to also investigate the impact of the product and service environments on the effectiveness of industrial quality tools in healthcare. This difference is clearly seen in the product-service spectrum shown in Figure 2. 3.

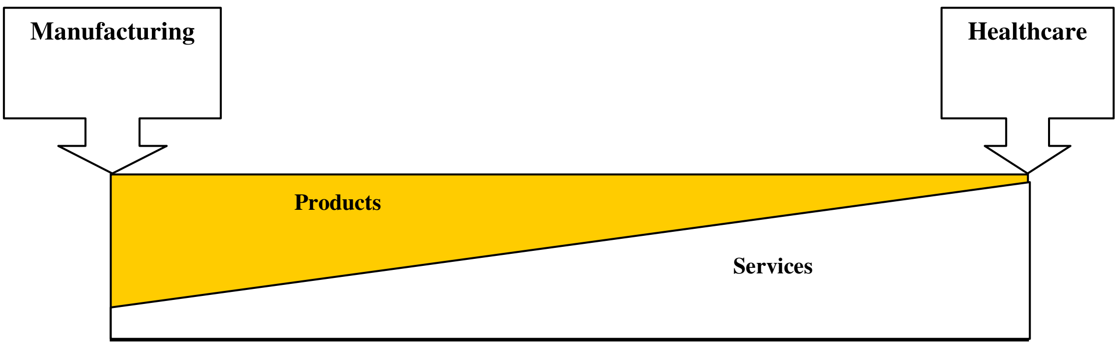


Figure 2. 3: The Product-Service Spectrum

Part of the challenge for the future will be to appropriately apply the techniques that have proved successful at the left end of the spectrum to a healthcare system at the other end. A key problem will be resistance to change, as observed by commentators such as Okes (2006). Part of the objective of this research thesis is to stimulate discussion on the appropriate customisation of industrial techniques to fit into another industry with respect to its location on the spectrum.

Most of the quality researchers and practitioners have focused on the importance of management involvement (Deming, 1986; Juran, 1995; Crosby, 1979; Feigenbaum, 1961). They have stressed that an effective quality management programme must start from the top. Unfortunately, this does not always mean that it reaches the ground level where it matters most. This is proved in a survey by Dahlgaard et al. (1998) where it was observed that although 83% of Japanese companies had management participation, only 25% continuously communicated the contents of their quality documents to all employees. Donabedian (1966) in his seminal work on evaluating the quality of care rightly stressed that his aim was almost exclusively to deal with the evaluation of care at the "level of physician patient interaction". This level of operational quality is the focus of the E-Track NHS approach.

E-Track NHS is aimed at continuously monitoring what the patient (or customer) actually feels at various points in time (e.g. stages in the "patient journey"). Previous research has mainly sought to assess what is currently going on without devising a means to also assess current performance and influence the culture of staff. This is evident from the discussion of healthcare quality and service quality presented above where there has been no evidence of a method for real-time (continuous) measurement and monitoring. This is further underscored by the observation of the present approach employed by the Healthcare Commission in the NHS as discussed in chapter 4. The current proposal seeks to develop a method for:

- Assessing the quality of care being delivered in real-time – providing ongoing feedback to healthcare staff.
- Raising the awareness of staff about quality in a non-invasive way.

- Forecasting the impact of future demand on quality of care.

This approach uses a real-time computer model of the healthcare environment that displays a Healthcare Quality Index (HQI) and other key performance factors. The benefits of this are that healthcare managers and staff on the ground can access a user-friendly approach to understanding current activity (e.g. hospital throughput, waiting times) by viewing simulation models (in the form of a "cartoon" version of the organisational workplace). Changes can be made to the current model (i.e. current picture of what is happening) in order to test for different outcomes and assess which would represent the best quality (e.g. reduced length of stay, while minimising re-admittance rates). This would represent one of the most sophisticated advancements in healthcare quality as it would allow clinicians to be directly involved in decision making on an ongoing basis, thereby improving the feeling of "ownership" and enhance efficiency at the organisational and local levels. Healthcare staff seem to place high value on involvement and "ownership" but this doesn't seem to often be the case in most hospital settings. O'Neill (2005) also underscores this with the finding contrary to his team's expectations that healthcare staff in North East Alabama Regional Medical Centre were not as concerned about remuneration as they were about being excluded from decision making and that changes to be made were never communicated to them.

It has been highlighted that the concept of quality has a long history, but the management of quality and its control in healthcare is not as advanced as in industry. There are various reasons for this, such as differences between the two sectors in terms of concerns for quality and the type of processes and outputs involved (e.g. product versus service). This section has also pointed out that with the growing interest in applying industrial techniques in healthcare, issues of appropriateness and practicality must be robustly examined. A key emerging theme from this analysis is the need to develop quality systems that give staff ongoing "ownership" and pride in a way that is akin to the era of the craftsmen (Komashie, Mousavi & Gore, 2007b). E-Track NHS, a computer-simulation based approach is proposed as one possibility in this endeavour.

As a further justification, some authors in the field, such as Hutchins (1990) have stressed that what is needed is a localisation of quality that:

". . . *encourages a feeling of ownership and greater likelihood of pride in personal and group achievement akin to the internalised values of the medieval craft groups. Without such internalisation, a climate of quality cannot be said to exist" (Jessee, 1981).*

Also noted is that:

". . . *the most accurate diagnosis of a healthcare problem and the most valid assessment of the factors contributing to it will not produce the desired improvement unless effective techniques for changing individual and organisational behaviour can be applied when necessary".*

This, together with the need to apply an approach that accounts for the fluidity of the product-service continuum, are key factors in moving quality improvement to the next level.

As highlighted in the previous chapter, the major contributions in this research study are the development of the Healthcare Performance index (HPI) with a particular application to quality and the Staff-Patient Satisfaction Relation Model (S-P SRM). The importance of seeing these models in their bigger context is reiterated here. The fundamental idea is the development of a complete system for healthcare quality management referred to in this thesis as E-Track NHS.

Up to this point, the focus has been on reviewing previous work on quality of products and services. The difference between service quality and satisfaction remains a debate in service quality and customer behaviour research. This research sees the two schools of thought as separate but closely related. The support for this position is now presented in section 2.5 on the concept of satisfaction and its evaluation.

2.5. The concept of satisfaction and its evaluation

This section details some of the research issues regarding the concept of customer satisfaction and particularly the problem of the conceptual distinction between satisfaction and service quality. The section first looks at customer satisfaction in general and then patient satisfaction in particular.

2.5.1. Customer satisfaction

Customer satisfaction, service quality and value play a major role in every service organisation (Caruana, Money & Berthon, 2000). The distinction between these concepts is often not obvious and still remains a considerable issue for debate amongst researchers and practitioners in the service industry (Iacobucci, Ostrom & Grayson, 1995). For instance Davis & Heineke (1998) interpreted the service quality modes of Cronin & Taylor (1994) and Parasuraman, Zeithaml & Berry (1994) as satisfaction models. For more on this debate the reader is referred to Spreng & Mackoy (1996) who discussed the conceptual arguments for the distinction and empirically tested models of service quality and satisfaction. The authors concluded that the two constructs were distinct in the context of their study. See also Ekinci & Riley (1998) who accept the argument that quality is something different from satisfaction but contend that they cannot be so different as to be unrelated. Most researchers however, seem to support the view that satisfaction has to do with a discrete encounter whilst service quality is better perceived based on the overall experience.

Oliver (1996) presented Figure 2. 4 as a generic model of consumer behaviour analysis depicting the consumer's mind as a 'black box' implying the impact of consumer psychology on the judgement of subjective issues like satisfaction. Understanding and operationalising the psychological processes within the "black box" leading to satisfaction or dissatisfaction is the task of satisfaction research (Davis & Heineke, 1998). This is important to our ability to accurately measure the concept of satisfaction which often leads to customer loyalty and increased revenue.

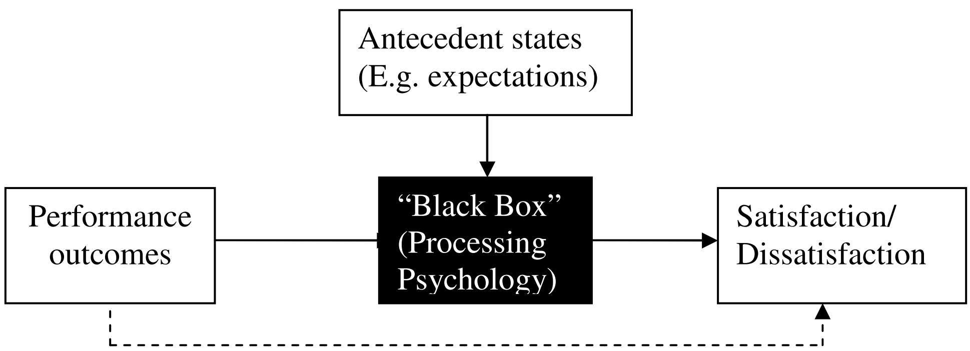


Figure 2. 4: The mediated performance model of satisfaction (Oliver, 1996)

A leading methodological approach to this task is the expectancy disconfirmation model (Grigoroudis & Siskos, 2004) proposed by Oliver (1977). Donovan et al. (2001) described the model as the level of satisfaction or dissatisfaction that results from an encounter between a service user and provider depends both on the user's expectations of the service they will receive and their perceptions of the service they have received. That is

$$\text{Satisfaction} = f(\text{Perception}, \text{Expectation})\,. \qquad 2.4$$

Other researchers (e.g. Mousavi et al., 2001) have used the above formulation but have also found that satisfaction behaviour of customers is similar to the "hypothetical value function" in prospect theory (Mowen, 1993). This hypothetical function is approximated by a hyperbolic tangent function as shown in equation 2.5 below,

$$P(\varepsilon) = \tanh(\varepsilon) \qquad 2.5$$

Where ε is the difference between a customer's expectation and actual experience of a service or product quality attribute.

The nature of the above hyperbolic tangent function is shown in Figure 2. 5 below. The advantage of applying the hyperbolic tangent curve to satisfaction measurement is that it captures the fact that there exists the concept of diminishing return and points of saturation where a customer is either completely satisfied or completely dissatisfied. This is not apparent in the original model proposed by Oliver (1977).

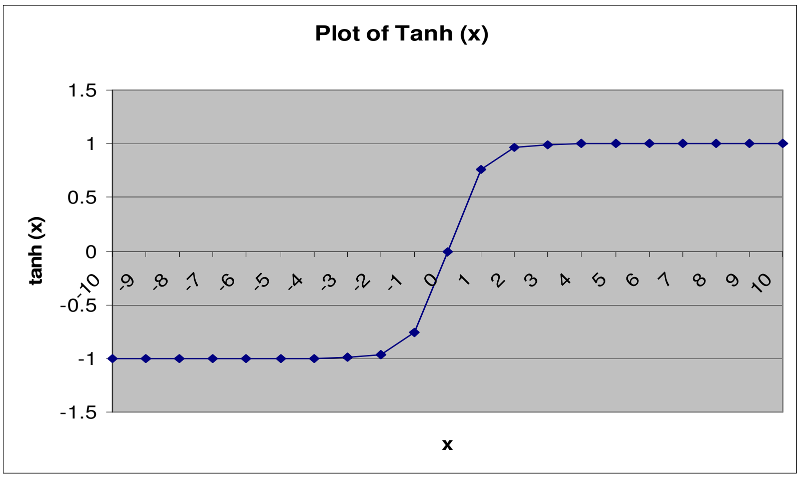


Figure 2. 5: The hyperbolic tangent curve

Using empirical studies, Mousavi et al. (2001) developed the "Customer Orientation Route Evaluation" (CORE) model for measuring satisfaction. The study enabled the authors to develop additional parameters to enhance the form of the equation in 2.1 above. A critical analysis of the CORE model is presented in appendix B. In this research, the CORE model is the main tool for the measurement of satisfaction. The reason for preferring the CORE model here is that it has the unique advantage of being able to measure the satisfaction of subjects based on their experience rather than asking for a level of satisfaction. Though the CORE model is still subject to the problems that arise from the processing psychology of customers, it is more useful because the measure is well defined mathematically. For instance the values of the constant parameters of the model may be adjusted to change the shape of the satisfaction curve (See appendix B). This means that the same model can be applied in different environments with different values of the constants.

It may be observed that the satisfaction model of Oliver (1977) and the service quality model of Parasuraman, Zeithaml & Berry (1985) seem to be measuring the same thing. The development of the concept of Healthcare Quality Index (HQI) in chapter 5 treats the two concepts as different but related as affirmed by Ekinci & Riley (1998). Satisfaction is used as the common currency in which all the indicators of healthcare quality are measured. These indicators are then integrated into a single index as a measure of healthcare quality.

In a general sense, patients are customers but for the purpose of this research into quality and satisfaction in a healthcare environment, it is helpful to review some of the key issues in patient satisfaction which may not fit the general model. The patient satisfaction literature is reviewed next.

2.5.2. Patient satisfaction

Making the patient (customer) a key part of the definition of quality means that their satisfaction cannot be neglected in the pursuit of improved quality of healthcare. According to Ross (1996), the best definition of quality is a happy patient.

Measuring the satisfaction of patients, however, presents many challenges due to the nature of the healthcare environment. In a review of the literature on patient satisfaction investigations in the emergency department, Trout, Magnusson & Hedges (2000) found that the main methodology for patient satisfaction measurement was surveys, administered by post, telephone or in person at the emergency department. The review identified several limitations to this methodology including the focus on patients' perception of waiting time without understanding how actual waiting time affects satisfaction. Boudreaux & O'Hea (2004) also conducted a similar review on patient satisfaction in the emergency department and concluded, as Trout, Magnusson & Hedges (2000) did, that the factor most strongly associated with overall patient satisfaction is the interpersonal relations with the care providers. Notice that the measure used for satisfaction in this case was the likelihood to recommend the department or intention to return.

The studies cited (Trout, Magnusson & Hedges, 2000; Boudreaux & O'Hea, 2004) were meticulously designed, selected papers were critically reviewed and several tables used to present results comprehensively. The review by Boudreaux & O'Hea (2004), however, was limited to studies conducted in the USA.

Due to the considerable methodological variability observed in the literature by Trout, Magnusson & Hedges (2000), it was suggested that research on patient satisfaction should consider the incorporation of the expectancy disconfirmation concept in the instruments for satisfaction evaluation. This limitation is addressed in this research by the use of the CORE model mentioned above. CORE avoids these limitations by calculating satisfaction instead of asking for satisfaction. This model only asks for the actual experience of patients and uses the ideal (best possible) system value as the expected value. For instance, if an emergency department with 2 doctors knows what it is capable of within 30 minutes based on available resources, this is used as the expected value. Each patient's actual time is compared to this value and the difference used to calculate the satisfaction. This provides a common basis for measuring satisfaction and provides opportunity to even exceed patients' expectations. Another advantage of this approach is that, it makes it possible to measure satisfaction against system capability and therefore facilitate improvement instead of only knowing what the patient feels.

The CORE model is also used to measure staff satisfaction with workload which is used for developing the Effective Satisfaction Level (ESL) concept in chapter 6. The relation between staff satisfaction, patient satisfaction and quality of care is briefly described next.

2.5.3. Staff-Patient satisfaction and quality of care

According to Hudelson et al. (2008), quality healthcare should result in the satisfaction of both the patient and the practitioner. More than any other factor, it is the quality and satisfaction of the healthcare professional that determines the quality of the service provided and the satisfaction of the patients (O'Neill, 2005). This is further underscored by Chilgren (2008) in stating that "without satisfied and confident employees, quality practices have no hope of being successful." This important link between staff and patient satisfaction (or employee and customers) does not seem to receive much attention from researchers (Hsu & Wang, 2008). Several studies have focused separately on patient satisfaction and staff job satisfaction but hardly the link between them.

Understanding the relationship between staff satisfaction and patient satisfaction could have significant managerial implications. For example, it will become easier to interpret quality improvement policies (e.g. targets on waiting times of patients in emergency departments) in operational terms (e.g. in terms of the resources that will be needed to meet the target) without compromising employee satisfaction.

This issue is tackled in chapter 6 of this research where the concept of "Total Satisfaction" and "Effective Satisfaction Level" are proposed instead of the existing singular focus on patient satisfaction or staff satisfaction.

It is evident from the review in this chapter that the quality of service in healthcare, patient satisfaction and staff satisfaction may be separate constructs but they are strongly interrelated (Oliver, 1996; Ekinci & Riley, 1998). The proof of the relationship between staff satisfaction and patient satisfaction is the object of the work reported in chapter 6 of this thesis. Exploiting this interrelationship to the advantage of the patient is the goal of the research presented in this thesis.

To achieve this goal, the key contributions of this PhD (the development of the Healthcare Quality Index and the Staff-Patient Satisfaction Relation Model) are placed within the concept of a proposed overall system for managing healthcare quality and satisfaction in real-time. This is referred to throughout this thesis as the E-Track NHS system. This concept is explained further in chapters 4 and 7.

The use of an index of quality is simply to provide an easy to interpret measure of quality that will be displayed to staff and managers in real-time. This is to enhance communication between management and staff about improvement efforts and also to ensure an atmosphere of ownership from a staff perspective. These issues of communication and ownership have been discussed in detail in section 2.4 above.

To end this chapter a brief review is now presented on the use of indices for measuring performance.

2.6. Measuring service performance with indices

A number of studies have looked at the use of an index for measuring healthcare performance (e.g. Rozzini et al., 2002). However, no study has been found in which the possibility of using such a quality index as the basis for continuous monitoring and control of performance in the healthcare environment is considered.

Several indices exist in real world applications (Perakis et al., 2005). Examples range from the financial market to the measurement of research output of researchers with the "h" index (Hirsch, 2005). Two main indices that focus on quality and satisfaction of customers are the Swedish Customer Satisfaction Index (SCSI) by Fornell (1992) and the American Customer Satisfaction Index (ACSI) by Fornell et al. (1996). The American Society for Quality (ASQ) has also in recent years developed a quality index derived from the ACSI (Fornell et al., 1996). The SCSI, ACSI and ASQ quality indices evaluate the performance of firms and industry sectors on an annual basis based on historical information on performance rather than real-time analysis. Fornell et al. (1996) for example, clarified that the "ACSI represents a cumulative evaluation of a firm's market offering, rather than a person's evaluation of a specific transaction." The researchers collected data from 250 respondents through telephone interviews.

Respondents' expectations were measured by asking them to think back and remember the level of quality they expected on the basis of their knowledge and experience with a good or service. This approach may confound the measurement of the underlying construct of satisfaction, and the authors acknowledge that although such post hoc measures of expectations are imperfect, the cost of obtaining expectations prior to purchase is prohibitive. The ACSI, however, remains a standard for industrial performance assessment in America used even by the ASQ due to its usefulness.

For a more detailed discussion of the major satisfaction barometers the reader is referred to Grigoroudis & Siskos (2004). A few other examples of the application of indices in healthcare in recent years are Rozzini et al. (2002), Tavana, Mohebbi & Kennedy (2003) and Miyashita et al (2006). The aim of Rozzini et al.'s work was to compare the Geriatric Index of Comorbidity (GIC) with other measures of comorbidity (the presence of one or more diseases in addition to a primary disease). They found the GIC a better predictor of mortality. Tavana, Mohebbi & Kennedy in their study proposed a Total Quality Index (TQI) for assessing the success of Total Quality Management (TQM) programmes in a healthcare environment. The researchers used the Analytic Hierarchy Process (AHP) and Delphi technique to measure ideal and actual quality management along eight critical quality factors suggested by Saraph et al. (1989). They judged the success of a programme by the size of the gap between the ideal and actual TQIs. While the study by Miyashita et al. (2006) was conducted in Japan, it still provides evidence of the use of an index to measure a concept that may have many antecedents. The authors surveyed 646 family caregivers and, based on the results, developed a Burden Index of Caregivers (BIC) using confirmatory factor analysis. Their results showed that the BIC was highly reliable and valid.

The above examples of the application of indices provide evidence of their usefulness for measuring and monitoring performance in various systems. This shows that the use of an index to measure the quality of healthcare though unique is not out of place.

2.7. Conclusions

This chapter has focused on the background research into quality and customer satisfaction.

Three basic problems in quality research: the nature of quality, the definition of quality and the measurement of quality, were identified. The measurement of quality has been explored in more detail with focus on service quality. Nineteen service quality models reviewed by Seth, Deshmukh & Vrat (2005) were examined and the observations were made that a universal model of service quality was non-existent. The research shows that most of the models focus on representing service quality at the conceptual level without emphasising the importance of the data collection and analysis method.

Five streams of debate in service quality were further identified but the review has been centred on the conceptual debate. This debate has been centred on the GAP model of Parasuraman, Zeithaml & Berry (PZB) (1985) and the SERVPERF model of Cronin & Taylor (1992). PZB suggested that service quality should be measured as a gap between expectation and perceived performance whilst Cronin & Taylor (1992) argue that performance only is a better measure of service quality.

Overall, the evidence from the critical review of the service quality literature suggests that;

1. A universal definition for service quality is problematic and that research should first focus on developing reliable definitions in various service areas before attempting the generalisation.

2. A real-time method for continuously measuring and monitoring service quality is non-existent. This is an opportunity for further research in this area.

3. Researchers have not considered an integrated view of total quality management in healthcare so as to develop models that consider data collection, analysis and presentation.

4. The psychological influence of the patients (or customers) on measures of perception needs researchers' attention.

The review included a historical comparative study of the developments of quality in industry and healthcare. The purpose of this part was to examine the origins of the quality problem and to learn some lessons from its history. It has been found that industry and healthcare differ significantly in the initial concerns for quality, the trend in the demand and supply of quality and in the evolution of the evaluation techniques.

The historical review has also revealed that three events in history of quality have contributed greatly to its fall over the years, particular in industry. These are:

- The separation between the producer (or provider) and the consumer. It has been argued that this is the very root of the quality problem. In primitive years, the producer was the same as the consumer. There were no problems with trust, ownership and commitment and hence no quality problems existed.

- The industrial revolution shifted the focus from the quality and commitment of the craftsmen to productivity and profit as it continues till this day.

- The technological advancements of the late twentieth century and the resulting complex systems.

It has also been suggested that the elements of trust, commitment and ownership must be considered in the design of modern quality improvement programmes or systems. The feeling of ownership for healthcare staff is particularly important.

Evidence was found for the trend in applying industrial techniques to healthcare and a caution was offered to ensure that the issues of appropriateness and practicality are robustly examined.

Service quality, patient satisfaction and staff satisfaction have been found to be closely related in the literature. The review of this issue led to the conclusion that service quality and patient satisfaction may follow different behavioural patterns, but they are closely related. Some evidence was also found that provides a strong argument for focusing on both staff and patient satisfaction and not on either. This provided particular support for the Staff-Patient Satisfaction Relation Model (S-PSRM) developed in chapter 6 as a component of E-Track NHS.

Finally, the main hypothesis of this research work resulting from the review in this chapter is that, an accurate conceptual representation of service quality in healthcare is not adequate for a real-time (continuous) measurement, monitoring and improvement of the quality of care. What is needed is a method with sound conceptual infrastructure coupled with the capability to integrate the process of data acquisition, analysis and presentation as proposed in E-Track NHS.

However, the contributions at this stage focus on the theoretical development and testing of the HPI and the S-PSRM as the conceptual components of the E-Track NHS system. The development of the HPI and S-PSRM require reliable methodologies.

In the next chapter, the assessment is presented of the appropriate methodologies for developing the HPI and satisfaction models. Three major information-theoretic methodologies, i.e. Bayes theory, Fuzzy theory and information-theoretic entropy are discussed in addition to one major stochastic method, queuing theory.

3. Healthcare systems and the application of information-theoretic and stochastic methods

"In making inferences on the basis of partial information, we must use that probability distribution which has maximum entropy subject to whatever is known…"

Jaynes (1957)

Events that take place in a healthcare environment (e.g. patient arrivals, wait in queues, start of treatment, end of treatment, discharge, etc.) are predominantly stochastic (random) and generate a lot of information. By nature, stochastic processes are difficult to analyse and require special techniques for measuring and controlling their behaviour. The stochastic nature of the healthcare environment and the need to make important decisions with partial and incomplete information is the reason why this research seeks to employ information-theoretic and stochastic methods for modelling the concepts of quality and satisfaction.

In this chapter, some of the major techniques used in information theory and stochastic processes are reviewed. The chapter aims to justify the appropriateness of the techniques that are used to develop the Healthcare Performance Index (HPI). Part of this chapter is to help the reader appreciate the complexity of the healthcare quality problem in its appropriate context as the nature of the environment is described.

In section 3.1, an explanation is given about the nature of the healthcare environment. Section 3.2 discusses some desirable properties of an index for measuring performance in such an environment. Section 3.3 presents the fundamental concepts of the three information-theoretic methods: Bayes' theorem, Fuzzy logic and Information-theoretic entropy. Section 3.4 looks at queuing theory as a major stochastic method and finally section 3.5 draws conclusions to the chapter.

3.1. The nature of the Healthcare environment

The need for an ideal tool, specifically designed for healthcare system analysis has been stressed by some researchers (e.g. Harell & Lange, 2001). This is because a pure manufacturing system is anything but an accurate reflection of what occurs in a typical healthcare setting. An accident and emergency manager the author of this thesis worked with summarised the problems in his department in the following words:

“There are lots we think we know but few we know we know”.

This gives a vivid picture of the nature of the environment within which management decisions are made in healthcare, particularly in accident and emergency departments.

For the assessment of their quality, healthcare systems and their operations can be divided into three categories. These categories are (1) the structure within which care is provided, (2) the process through which care is provided, and (3) the outcome which results from the care provided (Donabedian, 1966).

3.1.1. Structure

Donabedian described the structure as the setting in which the provision of care takes place and the instrumentation it involves. This may include administrative and related processes that support the direct provision of care. Campbell, Roland & Buetow (2000) further identified two domains of structure: Physical characteristics and staff characteristics.

3.1.2. Process

The process of care may also be the basis for the assessment of quality in a healthcare environment. Process is a set of activities that adopted by practitioners and between practitioners and patients and may be described as the way in which care is delivered (Donabedian, 1980, p. 80; Van Peursem, Pratt & Lawrence, 1995). The judgements on the process are based on factors such as appropriateness, completeness, physical examination and diagnostic tests, technical competence in the performance of diagnostic and therapeutic procedures etc. Using process measures as criteria for assessing quality of care requires a great deal of attention to be given to specifying the relevant dimensions, values and standards to be used in the assessment (Donabedian, 1966).

3.1.3. Outcome

Outcomes are consequences of care (Campbell, Roland & Buetow, 2000). They can be measured in terms of recovery, restoration of function and of survival (Donabedian, 1966). The outcomes can depend on structure or process directly or indirectly. For example, a patient may die from cervical cancer either because a screening service is not available (structure measure) or because her cytology report is misread (process measure).

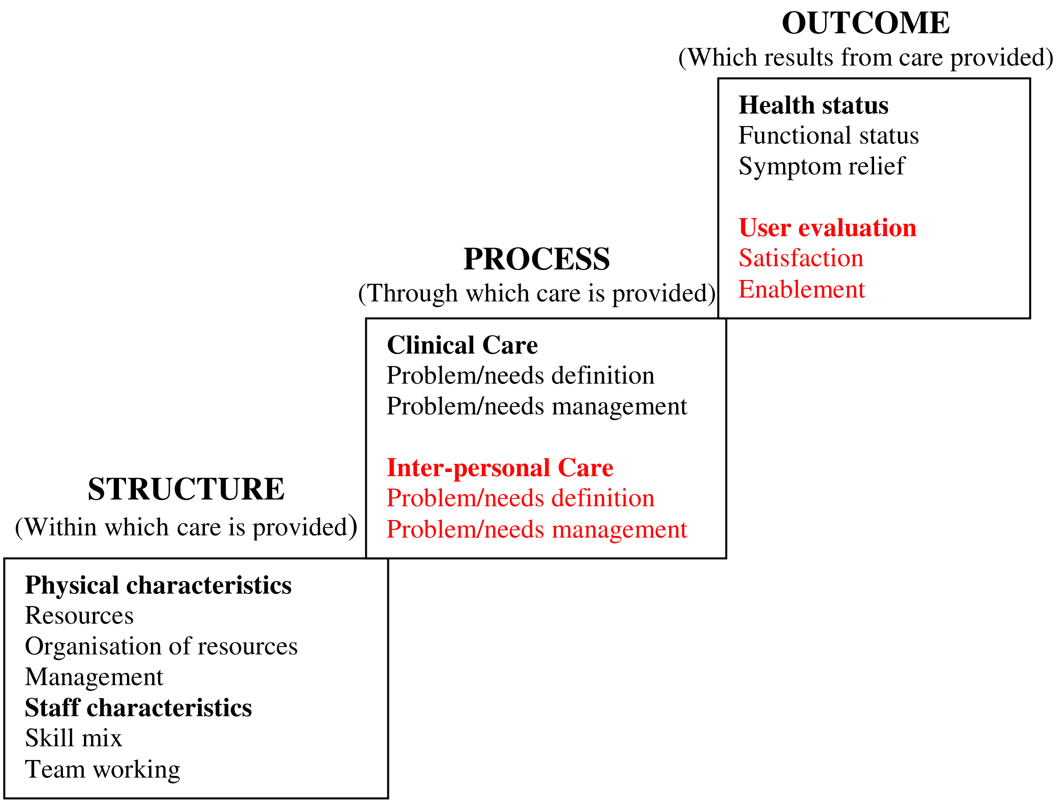


Figure 3. 1: A modified systems based model of assessing care (based on Campbell, Roland & Buetow, 2000, p. 1613)

The purpose of Figure 3. 1 and Figure 3. 2 is to show the extent of the difficulty and complexity that confronts research in service quality. It involves numerous factors at different levels that are not easily measurable (See figure 3.2). The author does not propose to offer any simple short-cut solutions that will make all the problems disappear. Nevertheless, it is believed that a more structured approach guided by the S-P-O Venn diagram proposed may facilitate progress. The purpose of the S-P-O Venn diagram is to help explain the scope of the approach to service quality management (E-Track NHS) proposed in this thesis.

The universal set (U) represents healthcare quality in its totality. This, according to Donabedian (1966), comprises the structure, process and outcome of care as described in section 3.1 above. The area marked “B” in figure 3.2 represents an approach to service quality management that addresses mainly process and outcome measures of care. This corresponds to the factors highlighted in figure 3.1 which E-Track NHS seeks to address. If an approach or methodology is developed that addresses all three aspects of healthcare, that would fall within the area marked “A”. It is expected that eventually the E-Track NHS concept would be improved to move into area “A”.

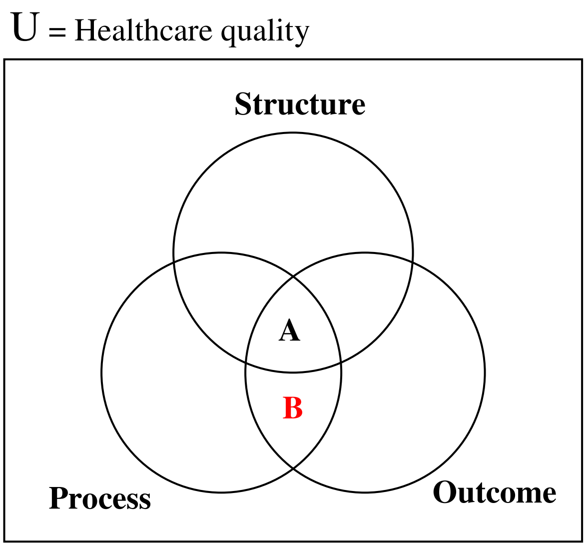


Figure 3. 2: The S-P-O Venn diagram for focusing healthcare improvement initiatives (area “A” includes methods that involve structure, process and outcome. Area “B” includes methods that involve process and outcome factors only)

The description of the healthcare environment presented above, provides some idea of the complexity in the task of an accurate evaluation of the quality of healthcare and the uncertainties involved in the process. We require good quality information relating to the quality of service in a healthcare environment and a methodology that is capable of dealing with various situations under uncertainty.

3.2. Desired properties of the HPI

From figure 3.1 it can be observed that it is difficult to develop a healthcare service quality model that covers all factors in all the aspects of quality - structure, process, and outcome. In other words, if the factors are not such as to place the quality improvement initiative in area "A" of the S-P-O Venn diagram in figure 3.2 then it cannot be said to involve all aspects of healthcare quality. This means that whenever we attempt to evaluate the quality of care, we will most likely be working with partial information.

Donabedian (1966), who proposed the three aspects of healthcare quality – structure, process and outcome, agreed on the importance of an index for measuring healthcare quality. It stated that the chief requirement for such an index is that it should be easily and sometimes routinely measured and be reasonably valid. In order to improve the validity of the HPI and to enable its applicability as a benchmarking tool across different healthcare systems the following desired properties are therefore stated according to Thomas (1994);

> Property 1: The HPI should not constrain the number of attributes or performance factors it can accommodate. This is to allow for the use of the required type and number of factors to be used as appropriate to a particular environment.
>
> Property 2: The index must be positively related to each of the performance factors.
>
> Property 3: The quantitative magnitude of the index must have a clear interpretation of its representation of quality of care both in relative and absolute terms and ideally should allow a leverage for translation into the various key quality indicators.
>
> Property 4: The index must be repeatable to enable comparison of different healthcare systems.
>
> Property 5: The index must avoid assumptions (E.g. as in Linear Regression Analysis that the scatter of data points round the best fit line

is normally distributed) in the input data patterns, which may affect its validity.

The formulation of this index requires a methodology that is suitable for dealing with situations of partial data and ill-posed problems. The mathematical problem may be ill-posed because it is difficult to be able to claim that any mathematical model can represent the concept of quality accurate.

In the next section a number of the potential information-theoretic methods are reviewed.

3.3. Information-theoretic methods

This section presents some of the information-theoretic methods used for modelling situations involving high uncertainty. Seminal publications are presented for each of the methods discussed. This discussion is focused on the fundamental principles of these methods together with their major limitations. Information-theoretic entropy is presented in more detail because this is the methodology judged to be the most appropriate for the research to develop the Healthcare Performance Index (HPI).

3.3.1. Bayes' theorem

Bayes' theorem was first introduced by Rev. Thomas Bayes, a Presbyterian minister from Tunbridge Wells, but was first published in 1763 after his death (Spiegelhalter et al., 1999). Bayesian methods are currently applied to the fields of engineering, image processing, expert systems, decision analysis etc. (Spiegelhalter et al., 1999). The major distinctive feature of Bayesian methods over classical probability theory is that it takes into account the uncertainty of future events by providing a measure of belief about the outcome of the events. Some proponents of the Bayesian method (e.g. Eddy, 2004; Lee, 1989, p. ix; Mackay, 2003, p. 457) have argued that classical probability theory and Bayes' theorem are not compatible because they sometimes give different and contradicting results. This debate will not be presented here but it is helpful to understand the importance of the subject of the debate before presenting the concept of Bayes' theorem.

Accurate prediction of future events is very important in decision making. Often decisions have to be made depending on partial or incomplete information. The stakes in decisions made in a business setting or human life or in a hospital setting could be high. Apart from the critical examples mentioned, decision making is a part of our daily lives. The virtue of making prudent decisions has always been a challenge since ancient days (Jaynes, 1978, p. 2). The moral requirement has been to use all available information but not presuming more information than is available. It is for this reason that the method used to calculate the probability of a future event is important. The question therefore is which method provides a better reflection of reality?

According to Bayes' theorem, our belief about the probability of a hypothesis (or the value of a parameter) given some evidence (its *posterior probability*) is proportional to the product of our initial belief about the hypothesis (its *prior probability*) and the evidence about the hypothesis (Lee, 1989). This is formally expressed as:

$$P(\theta \mid data) \propto P(data \mid \theta) \times P(\theta) . \qquad 3.1$$

$P(\theta)$ is the *prior probability* distribution expressing initial beliefs about the parameter of interest. $P(data \mid \theta)$ is the available evidence from data on the parameter. This is known as the likelihood function expressing the statistical model of the variability of data, given the parameter of interest. $P(\theta \mid data)$ is the *posterior* or present distribution of belief about the parameter in the presence of supporting evidence.

In summary, Bayes' theorem argues that, available evidence modifies what we already believe to put us in a new state of belief in the present time. The component of 'belief' in Bayes theorem is the most common source of criticism because it is considered subjective and external to available data (Zong, 2006). However, proponents of Bayes' theorem (e.g. Spiegelhalter et al., 1994) have argued that classical statistical techniques also use evidence external to the available data but often "such evidence is introduced in an unstructured and informal manner". The Bayesian approach on the other hand "allows a formal basis for using external evidence". The Spiegelhalter et al. (1994) argument for Bayes' theorem however does not eliminate the fact that assumptions have to be made regarding the prior distribution. Bayes' theorem often requires assumptions of the prior distribution which is often taken as uniform (Eddy, 2004)

Bayes' theorem has not been used for the estimation problem in this research mainly because of the subjectivity in the formulation of the prior distribution. One of the main requirements in this research was to minimise the assumptions about data patterns in view of the nature of the healthcare environment as described above. It is also because the estimation method is required to be a dynamic online one, for which Bayes' method may require too large a quantity of computing resource.

The author of this thesis has not come across any published work where Bayesian methods have been used specifically for developing an index for healthcare quality. However, there are examples of its application in other aspects of healthcare such as Spiegelhalter et al. (1994) for randomised trials, Spiegelhalter et al. (1999) for health technology assessment.

When solving problems that involve considerable uncertainty, Bayes' theorem is not the only method. The method of fuzzy logic is proposed by researchers to be applicable.

3.3.2. Fuzzy logic

In classical set theory, membership is either "True" or "False", a test result is either "Pass" or "Fail", a colour is either "Black" or "White" and a target is either "Hit" or "Miss" (Collan, 2004). This kind of binary logic is prevalent in most management situations but creates problems in some other cases because real-life situations may not often lend themselves to such distinct outcome definitions. Very often information available to the decision maker is imprecise, incomplete or not totally reliable (Zadeh, 1984). The imprecision in the binary logics cited above are dealt with by the use of an infinite-valued logic technique known as fuzzy logic.

Fuzzy logic is based on the concept of fuzzy sets (Zadeh, 1965). In fuzzy set theory, the conditions for classical set membership are relaxed so that an object can have a degree of membership in a set represented by a number between 0 and 1 (inclusive). Since its introduction, fuzzy set theory has been applied to the fields of language studies, control systems, pattern recognition, and healthcare. The most fundamental concept in fuzzy set theory is the fuzzy membership function (Zong, 2006).

To understand the membership function, it is important to first understand what is meant by input space and membership value. Take for instance a group of 10 patients with different levels of severity of illness. The severity of each patient can be translated into a value between 0 and 1. A patient with a headache may have a value of 0.1 whilst a patient with heart attack may have a value of 1.0. Thus, all the possible definitions of severity for all patients in the group form the input space whilst the corresponding values between 0 and 1 are the membership values which indicate the degree of severity of illness (or degree of membership) for each patient in the group (or set). A membership function (MF) is therefore a curve (or a mathematical function) that defines each point in the input space that is mapped onto a membership value (or degree of membership) between 0 and 1.

It is important to emphasise that all forms of fuzzy membership assessment may be subjective, context dependent (Turksen, 2006, ch. 3) and problem-dependent (Zong, 2006). Zong further noted that even for the same problem, membership functions are user-dependent. A detailed analysis of the measurement of fuzzy membership is presented in Turksen (2006, ch. 3).

This drawback of fuzzy logic is the main reason that it was not considered applicable in this research. The goal in identifying a feasible methodology for this research was to reduce assumptions about the input data pattern as much as possible. The technique must also be suitable for dynamic online estimation.

To his knowledge, the author has not found a specific application of fuzzy logic for the development of a unique index for measuring healthcare quality. The closest attempt was by Coletti et al. (2007) who used fuzzy modelling approach to develop a measure for healthcare quality.

Bayes' theorem, fuzzy logic and entropy attempt to deal with situations involving uncertainty and imprecision. Bayes' theorem has been found to be subjective in terms of the definition of its prior distribution. Fuzzy logic has been found to have drawbacks in the definition of its measurement function. The information-theoretic entropy methodology will now be discussed.

3.3.3. Information-theoretic entropy

This section presents the fundamental concept of the information-theoretic entropy methodology and explains the development of the Generalised Maximum Entropy (GME) formulation used in this research. It starts with Shannon's initial formulation.

3.3.3.1. Shannon's Entropy of information

Shannon (1948) introduced the concept of entropy as a measure of information, choice or uncertainty. Assuming that a set of random events, $x_1, x_2, \cdots, x_n$. with probabilities of occurrence, $p_1, p_2, \cdots, p_n$, if the probabilities are all that are known with regards to which event will occur, then the uncertainty about the outcome is given by:

$$H = -\sum_{i=1}^{n} p_i \log p_i \qquad 3.2$$

Shannon offered six main properties of *H* which further substantiate it as a reasonable measure of uncertainty, choice or information. The first two properties which are directly relevant to the formulation in this research are given as follows:

1. $H = 0$ if and only if all p_i but one are zero, where the known p_i has a value of unity. Thus the level of uncertainty (*H)* vanishes only when there is certainty about the outcome of an event, otherwise, *H* is always positive.

2. For a given number of events, *n, H* is a maximum and equal to $\log n$ when all the probabilities of occurrence, p_i are equal. Thus when $p_1 = p_2 = p_3 \cdots = p_n = \dfrac{1}{n}$. This is also intuitively the situation of maximum uncertainty.

The Shannon entropy measure does not require any fundamental assumptions regarding data patterns, though there are some elements of subjectivity in the implementation of the Generalised Maximum Entropy (GME) principle.

Shannon's entropy has been validated and applied by several researchers and practitioners (Kapur & Kesavan, 1992; Sivadasan et al., 2006; Calinescu et al., 1998; Sivadasan et al., 2002). In the following section, Jaynes' maximum entropy extension to Shannon's measure is presented.

3.3.3.2. Jaynes' Maximum Entropy Principle (MaxEnt)

As an extension to Shannon's measure of uncertainty, Jaynes (1957) gives a quantitative technique for assigning probabilities based on the strict use of only available information and avoiding the use of any additional information. This is called the maximum entropy principle and is stated as follows:

"In making inferences on the basis of partial information, we must use that probability distribution which has maximum entropy subject to whatever is known. This is the only unbiased assignment we can make; to use any other would amount to arbitrary assumption of information, which by hypothesis we do not have."

Mathematically, the principle is stated as:

Maximise $$-\sum_{i=1}^{n} p_i \log p_i \qquad 3.3$$

Subject to

$$\sum_{i=1}^{n} p_i = 1 \qquad 3.4$$

$$\sum_{i=1}^{n} p_i g_r(x_i) = \sum_{i=1}^{n} p_i g_{ri} = a_r, \quad r = 1,2,...,m \qquad 3.5$$

and

$$p_i \geq 0, \quad i = 1,2,...,n. \qquad 3.6$$

The maximum entropy principle, thus, has to do with knowledge of the probability distribution of the random variable or concept under investigation. For instance, if the satisfaction of patients with five attributes of care ($j = 1,2,\ldots,5$) is measured on a scale of 1 to 5 (*i.e.* $i = 1,2,\ldots,5$), the maximum entropy principle is concerned with estimating the distribution of the probability that a patient k will have probability i with attribute j. In practice however, most variables are not measured in the form of probability distributions hence limiting the application of the maximum entropy principle. The solution to this problem is what eventually led to the Generalised Maximum Entropy formalism developed by Golan et al. (1996).

3.3.3.3. The Generalised Maximum Entropy (GME) approach

The main idea in the GME technique introduced by Golan et al. (1996) is the re-parameterisation of the parameters of the model to be estimated and the reformulation of the problem using the re-parameterised parameters.

Re-parameterisation means re-writing the model parameters in a probability format that is consistent with the entropy principle. This is done by defining suitable support variables as explained in the next section. Given a regression model for example, the GME method will involve the following three steps:

1. Re-parameterisation of the parameters
2. Reformulation of a regression model.
3. Optimisation of the Shannon measure subject to data consistency and normalisation constraints.

The data consistency constraint ensures that the solution is consistent with the observed data and the normalisation constraint ensures that the estimated probability values for each parameter add up to 1 and are non-negative.

The concept of the support variables required to re-parameterise the model parameters is briefly discussed in section 3.3.3.4.

3.3.3.4. Definition of support variables

In order to express an unknown parameter in the form of probability, it must be written as a convex combination of expected values of a discrete random variable (called support variable) with two or more sets of points (Ciavolio & Dahlgaard, 2007; Al-Nasser, 2003; Golan et al., 1996). A convex combination is a linear combination of data points where all coefficients are non-negative and sum up to 1 (see Zadeh, 1965). For instance given the points

$$x_1, x_2, ..., x_n \text{ ,} \tag{3.7}$$

a convex combination of these points is a point of the form:

$$\alpha_1 x_1 + \alpha_2 x_2 + ... + \alpha_n x_n \text{ ,} \tag{3.8}$$

where the real numbers α_i satisfy:

$$\alpha_i \geq 0 \tag{3.9}$$

and

$$\sum_{i=1}^{n} \alpha_i = 1 \tag{3.10}$$

Any convex combination of two points will therefore lie on the straight line segment between the points.

It is generally suggested that one should choose the values of the support variable that are indicative of the nature of the observable variables. For example, if the observable variable is patient satisfaction measured between 0 and 1, then it will be appropriate to choose support points within this range of values.

In most cases where analysts are uninformed about the magnitude and sign of the model parameters (e.g. the coefficient in a regression model), it is recommended to specify a support space (range of the support variable) that is uniformly symmetric around 0 with end points being the largest magnitude (Eruygur, 2005). However, it is possible to choose values of the support variable that span the possible parameter space for each parameter, (Al-Nasser, 2003; Golan et al., 1997; Golan et al., 1996; Al-Nasser, Abdullah & Wan Endut, 2000).

The steps in the GME estimation process are summarised in Figure 3. 3 below.

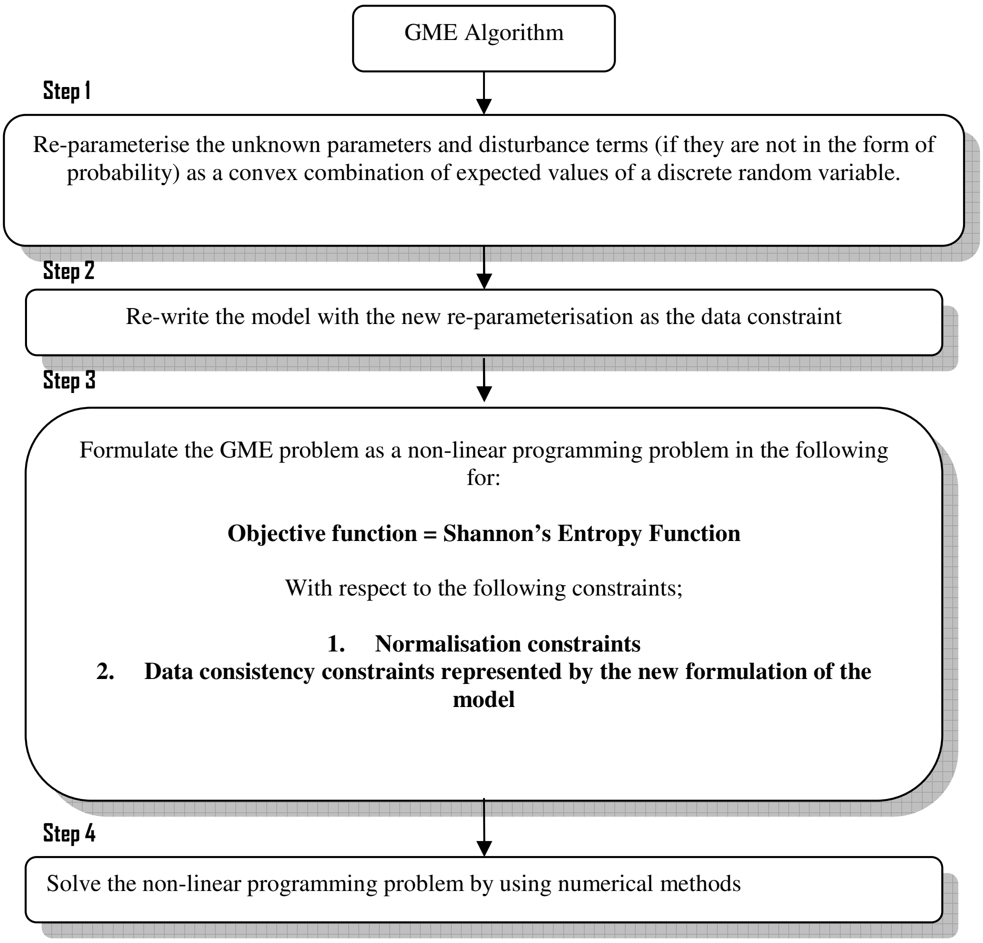


Figure 3. 3: GME Algorithm

3.3.3.5. Some applications of information-theoretic entropy

This section highlights two areas for the application of information-theoretic entropy. These areas were chosen as examples of environments where processes are stochastic and decisions are subject to uncertainties similar to healthcare environments. This choice is also to show the extremes of the application of the concept of information-theoretic entropy.

A. Manufacturing and Supply Chain Systems

Manufacturing systems operate in a complex, challenging and ever-changing environment (Efstathiou, Calinescu & Blackburn, 2002). A resulting problem for manufacturing management is the difficulty in ensuring accurate schedules and production plans with respect to the complexity of the system, operations and demand patterns.

The assessment of the complexity of manufacturing systems and supply chains is the part of the focus of the Manufacturing Systems Group (MSG) at Oxford University which has been applying information-theoretic methodology to achieve this goal. Published work from the group includes Calinescu et al. (1998), Sivadasan et al. (2002), Efstathiou, Calinescu & Blackburn (2002), and Sivadasan et al. (2006).

Unlike the GME formulation used in this research, the MSG focuses on the application of the basic form of Shannon's measure. The work of MSG has been based on entropic measures of complexity developed by Frizelle & Woodcock (1995). One example of the application of information-theoretic entropy in manufacturing operations is the attempt by Calinescu et al. (1998) to explain the relationship between the system's complexity and its performance. There is a lack of a universal modelling framework for manufacturing complexity due to the variety, dynamism and uncertainty regarding the sources of complexity in such environments (Calinescu et al., 1998). The researchers noted that the use of real-time monitoring and the accurate recording of information could considerably improve the complexity measurement process.

On the strength of the above findings of Calinescu et al. (1998), the current research suggests that the elements of variety, dynamism and uncertainty of information reasonably well describe the healthcare environment. Therefore, the choice of the information theoretic methodology and the use of real-time DES as proposed in this research, form a reasonable solution to healthcare quality management problem.

B. Econometrics

One of the leading researchers into the application of information-theoretic entropy in econometrics is Amos Golan of the American University in Washington DC, USA. The GME method described above was actually developed by Golan. Econometrics is the science (and art) of processing information from limited and noisy economic and financial data (Golan, 2007).

This also includes economic problems which are well known to be stochastic. To better appreciate the extent of the application of entropy in this area the reader is referred to a comprehensive review by Golan (2007).

Therefore the application of information-theoretic entropy to healthcare is not at all out of place. The nature of the healthcare environment makes it a good candidate for the application of such a robust method.

3.4. Stochastic methods

This section presents the fundamental concept of queuing theory which is one of the major techniques for modelling stochastic processes involving queues. A stochastic process is a function over time $t \in T$ whose value is a random variable (Askin & Standridge, 1993).

3.4.1. Queuing theory

Most real life systems involve queues. Entities (customers, patients, parts etc) arrive in the system, wait for a resource (server, doctor, machine etc), receive service, and then exit (depart from) the system. The formal investigation into queues and the emergence of the field of queuing theory emerged at the beginning of the 20th century following the work of Erlang (1878-1929). Queuing theory has since found application in several fields of study including engineering, economics, healthcare, transportation and military problems (Gnedenko & Kovalenko, 1989). Helpful introductions to the theory may be found in Askin & Standridge (1993) and Bolch et al. (2006). Preater (2002) also provide a summary of a very detailed list of bibliography (Preater, 2001) on the application of the theory in healthcare.

In queuing theory, minimising the waiting time of entities and maximising the utilisation of resources are the two most important but often conflicting goals (Fomundam & Herrmann, 2007). With a focus on healthcare systems, some work on the application of queuing theory for waiting time analysis, customer satisfaction and system design are presented in the remaining sections of this chapter.

3.4.2. Queuing theory applied to waiting time and resource utilisation analysis

Queuing theory has been applied to waiting times in healthcare to investigate various issues including patient reneging (Hall et al., 2006; Roche, Cochran, & Fulton, 2007), variable arrival rates (Worthington, 1991, 1987; Rosenquist, 1987), priority queuing disciplines (McQuarrie, 1983; Green, 2006; Siddhartan, Jones & Johnson 1996) and blocking (McManus et al., 2004; Koizumi, Kuno & Smith, 2005). These studies are discussed in detail in Fomundam & Herrmann, (2007).

Green (2006) reports on the application of queuing theory in healthcare for studying the relationship between delays, utilisation, and the number of servers. She also discusses the basic M/M/c models with its assumptions and extensions.

3.4.3. Queuing theory applied to customer satisfaction

One of the factors that significantly determines the satisfaction or dissatisfaction of a customer in a service environment is the waiting time, whether on the phone, in a shop or in an accident and emergency department of a hospital. In a review of the application of queuing theory to customer satisfaction in Pharmacy practice, Nosek Jr. & Wilson (2001) found that several thousands of dollars have been saved in the service industry through the application of queuing theory. The authors also found that queues affect the satisfaction levels of customers and their willingness to spend. They further suggested that it is a point where a lengthy wait begins to affect the customer's perception of quality.

The conclusion of Nosek Jr. & Wilson (2001) has direct relevance to the current research, in that:

"By better understanding queuing theory and the various measures associated with customer waiting time, service managers can make decisions that have a beneficial impact on the satisfaction of all relevant participants: ***customers, employees and managers****." (Emphasis added)*

In chapter 6 of this thesis the concept of effective satisfaction is developed based on queuing model techniques. This is based on the belief that staff and patient satisfactions are equally important and should be considered simultaneously. The importance of this staff-patient relationship was discussed in detail in section 2.5.3.

3.4.4. Queuing theory applied to healthcare systems design

The problem of matching demand with capacity is as important in healthcare as it is in the manufacturing industry (McManus et al., 2004). Several managerial problems on this subject exist that require the application of queuing theory at the time of design or re-design of system layouts and process plans. Examples of typical questions or problems are as follows: How much must a waiting room be enlarged to reduce the proportion of customers turned away to less that 1 in 10? Is it less costly to employ another server or to increase the size of the waiting room? How many inpatient beds should be provided for a given specialty? Several applications of this type exist in the literature. Fomundam & Herrmann, (2007) present a comprehensive review of the latest achievements in this area.

Queuing theory has been used to model Accident and Emergency (A&E) department completion times in the UK and has suggested that the current practice of setting targets for departments may be having a negative effect on true performance and patient experience. For instance, Mayhew & Smith (2008) analysed A&E completion times between the years 2002 and 2006. The researchers found that since the introduction of targets, A&E departments have developed a system for re-designating patients in order to process them more quickly within the set target. The study showed that raising the percentage of patients completed in 4 hours from 90% to 98% required a reduction of the average completion time by 43% (about 45 minutes). The authors therefore doubted if the policy makers properly evaluated the impact and credibility of the targets before introducing them. In conclusion, they suggested that steps should be taken to make targets more credible in order to avoid their distorting effects. This suggestion is further motivation for the scientific investigation of the phenomenon that relates the waiting time based satisfaction of patients to the satisfaction of healthcare staff.

Of a particular interest in this regard, is the early work of Bailey (1954), who argued that one of the fundamental administrative problems in the planning of medical services is that of matching capacity with demand and to ensure, in addition, that this demand is satisfied in a timely manner. Bailey made a strong case for the application of queuing theory for planning in-patient beds and out-patient clinics, contending that practical working methods must be underpinned by elaborate theoretical arguments.

Ad hoc working practices may be found in several areas of management in the NHS. For instance there is no existing theory that helps healthcare managers to translate quality improvement policies (e.g. waiting time targets in A&E) into operational capability (level of staffing for effective care delivery). As a result, many managers and staff have developed their own ways of coping (Wostenholm et al., 2005; Bevan & Hood, 2006b) with variances and imposed targets.

The work presented in chapter 6 of this thesis is a contribution to this endeavour by its attempt to link patient satisfaction with waiting time to staff satisfaction with workload so that a target on waiting time can be understood in terms of workload of staff and their satisfaction levels towards workload and quality of critical service.

3.5. Conclusions

A brief description of the nature of the healthcare environment has been presented. The nature of the problem of healthcare quality was also highlighted. It was suggested that in view of the complexity of the environment and factors that may influence quality, the subject of service quality in healthcare may be more complex than is presented in the literature reviewed in chapter 2. The key points raised were the incomplete nature of the information available to us about quality in healthcare and the uncertainty that should be allowed for in the conceptual models.

Three major information-theoretic methods have been discussed and critiqued. The weakness of the Bayesian method has been its assumption of a prior distribution which makes it unsuitable for the current research as it is desired to minimise assumptions about data patterns. The Fuzzy method accommodates uncertainty by avoiding crisp values but it also involves considerable subjectivity in the determination of its membership functions.

Bayes' theory and Fuzzy logic however are powerful methodologies and have been greatly applied in several fields but were not found suitable for the current application for the above reasons. Information-theoretic entropy has been preferred because it involves fewer assumptions about data patterns and is less subjective. This has therefore been applied for the formulation of the Healthcare Performance Index (HPI) in chapter 5.

Queuing theory has also been discussed as a stochastic method to be used in the modelling of the Staff-Patient Satisfaction Relation Model (S-PSRM) in chapter 6.

In chapter 2, the literature on quality and satisfaction was reviewed to justify the need for a system like E-Track NHS which is proposed as a new method for the continuous measurement, monitoring and improvement of service quality in healthcare. It was emphasised that the contribution of this research work is in the development of the HPI and S-PSRM models as the conceptual components of E-Track NHS.

This chapter has therefore focussed on the assessment of suitable methodologies for the modelling of the concepts of quality and satisfaction within a complex healthcare environment.

The next chapter presents a discussion of the applications of Discrete Event Simulation (DES) technology in industry and healthcare. The aim of the chapter is to show that E-Track NHS as a DES based system is feasible and also identify the limitations of similar applications in the healthcare sector.

4. Discrete-Event Simulation (DES) modelling

"There are lots we think we know, but few we know we know."

An A&E manager, (2004)

With the level of complexity that is found in modern industrial systems, decisions based only on intuition can lead to great financial losses and even loss of lives. As a result, the fields of decision analysis and operations research have seen considerable development over the past few decades. Prominent amongst the tools used for analysing complex systems and decisions is discrete event simulation (DES).

The research reported in this thesis does not seek to fill a gap in simulation research. The aim of this research is to fill a gap in healthcare quality management as identified in chapter 2. To achieve this aim, the proposed new approach involves a combination of prescriptive and descriptive mathematical models where the application of DES technology in a healthcare environment falls in the latter modelling technique. This application may face some opposition from healthcare professionals or managers as some industrial techniques do in healthcare environments. The purpose of this chapter therefore is to provide evidence from literature of the successful application of DES technology to complex systems, identify some limitations of current applications and to justify the feasibility of the techniques proposed in this research thesis.

The pre-requisites of a real-time (continuous) monitoring and improvement of the service quality in healthcare go beyond an accurate conceptual representation of the concept. This became evident from the review of the service quality literature presented in chapter 2. What is needed is a method with sound conceptualisation, coupled with the capability of integrating the process of data acquisition, analysis and presentation as proposed in E-Track NHS. E-Track NHS is proposed as a DES based system for achieving this objective of real-time monitoring of service quality in healthcare.

Section 4.1 therefore looks at DES application in industrial systems. Real-time applications are presented in section 4.2. Section 4.3 then looks at applications in healthcare systems. There were no applications found that specifically set out to apply DES to improve quality of care and patient satisfaction. This issue is discussed in section 4.4. The case for the E-Track NHS system vis-à-vis the current quality improvement method in the NHS is then presented in section 4.5. Conclusions are drawn to the chapter in section 4.6.

4.1. Application of DES in industrial systems

DES first emerged in the late 1950s and has since grown steadily in popularity (Robinson, 2005; Hollocks, 2006). The review presented here is brief since the developments and applications of DES are well documented in sources such as Zobel (2000), Robinson (2005), Hollocks (2006) and Semini, Fauske & Strandhagen (2006). This review focuses on applications in the area of production scheduling and planning where the majority of publications in manufacturing are found (Semini, Fauske & Strandhagen, 2006) and which are more akin to the concept of real-time monitoring proposed in E-Track NHS.

DES is capable of playing a vital role in the understanding, control and improvement of complex systems. This capability of DES has been proven in several different ways in industry. Vaidyanathan, Miller & Park (1998) developed a DES model as a daily scheduling tool in a coffee production system. They employed a hybrid approach that integrates a scheduler and a DES model. The simulation model plays the role of modifying the output from the scheduler, and the two together become a tool for day-to-day production scheduling. This provides an example of being able to test a particular schedule of resources using simulation and have the opportunity to make modifications to enhance performance.

Another example of the application of DES for the analysis of a complex system is reported in Hugan (2001). The introduction of Just-In-Time (JIT) philosophy in a manufacturing system means the delivery of smaller batches of parts more frequently. For the automobile assembly plant studied by Hugan and his team, the introduction of JIT required a method for handling and understanding the increased traffic from several suppliers and how this affected the safety and operations of the overall assembly site. DES was used to model the dynamics of ordering and receiving main body of trucks, steering columns, exhausts, seats etc. with daily trips varying from 21 to 49. The model was used to analyse time spent by delivery trucks on-site and to size the central receiving area with a maximum utilisation of 70%. This application is an excellent example of DES as a framework for design evaluation and improvement. It provides a way of organising a team of professionals toward a common goal by the ease of analysing competing scenarios with the simulation.

Lu & Sundaram (2002) also reported similar work involving the use of DES for analysing the final assembly line of the Boeing 747 aeroplane. The engineers developed models to analyse numerous 747 final assembly line scenarios throughout several phases. The paper reported an unspecified reduction in cost and flow time from the “traditionally 24 days to the targeted possible 18 days”.

By these examples involving the automobile and aircraft systems, the capability of DES as a vital tool for the analysis of complex systems is demonstrated. Despite the potential gains in this form of application as highlighted above, research in this area has resulted in more advanced applications involving DES as a platform for real-time control and monitoring in manufacturing systems.

The focus of the current research involves the application of DES in healthcare. However, in order to appreciate the limitations in the application of DES in the healthcare environment, a number of the real-time applications in manufacturing industry will now be discussed.

4.2. Real-Time DES

A manufacturing enterprise is a large and complex system of interrelated production activities. There is a continuous transformation taking place inside these enterprises. The result of this transformation will be more computers and computer controlled equipment on the factory floor. This had led to the concept of computer integrated manufacturing (CIM) systems. In addition to this, is the quest for full automation in these systems (Jones et al., 1990). Researchers have taken advantage of the power of simulation technology to develop simulation models that can be fully integrated into complex manufacturing systems and run in real-time.

Real-time systems differ from traditional data processing systems in that they are constrained by certain non-functional requirements (e.g. dependability and timing constraints or requirements). An efficient simulation of real-time system requires a model that satisfies both simulation objectives and timing constraints, Lee et al. (2001).

Onut et al. (1994) show how simulation was integrated into a complete shop floor control system for a semi-integrated Manufacturing System (S-IMS). They developed a framework that interfaced the simulation system with a Material Requirement Planning (MRP) system, a host computer, a database Management System (DMS), a shop floor control system and a supervisory input system. The reported work seemed to have enhanced the effectiveness and control of the manufacturing operations by providing the ability to respond quickly to changes in operations.

Son et al. (2001) developed a structure and architecture for automatic simulation model generation for very detailed simulation models intended to be used for real-time simulation based shop floor control. They identified two essential stages to be automated for automatic simulation model generation: system specification and the associated model construction.

In this work, Son et al. (2001) proposed a methodology for generating an Arena simulation model from a resource model (in MS access 97) and a message-based part state graph (MPSG) based shop floor control model. This was made possible because the Arena simulation software supports visual basic application (VBA), which enables application integration and automation. Lee et al. (2001) undertook the development of a modelling methodology to efficiently model real-time systems to satisfy given simulation objectives and to achieve arbitrary timing requirements.

A more recent work has been done by Gupta et al. (2002) on shop floor scheduling with simulation based proactive decision support. They modelled a manufacturing system in which the flow of materials and information is highly complex. The system involved multiple product parts, sequence dependent setup, moulding machine specifications, mould restrictions etc. with a variety of scheduling and operational choices. Gupta et al. (2002) developed a simulation model that generates a feasible schedule and has the ability to reschedule the system when sudden changes occur. This resulted in a great improvement of the efficiency and effectiveness of the system in which scheduling and planning were previously based on historical and statistical data analysis.

Potoradi et al. (2002) also developed a simulation-based scheduling tool to maximise demand fulfilment in a semiconductor assembly facility. They used simulation as an engine to generate schedules and to control various machines at execution time and also to control the flow materials in the system. Their scheduling tool adapts to “unforeseen” changes on the shop floor by the use of online data availability. One limitation, however, is that their data entry from the shop floor and planning system is not fully automated; as a result the model-update is quite slow, requires an expert and is not done frequently.

Up to this point, the literature review has focused on development and applications in the manufacturing sector even though it is not the main focus of this work. It is clear that simulation has been used most extensively in manufacturing than probably any other field (Zobel, 2000; Robinson, 2005; Hollocks, 2006). It is for this reason that it was desired to review the nature of the developments and applications in this area so as to draw some analogies or inferences that may inform the healthcare application proposed in this research. The remaining part of this literature review is therefore dedicated to some applications in healthcare.

4.3. Application of (DES) in healthcare performance analysis

Healthcare systems are humanistic and subject to the uncertainties of human behaviour. Harrell & Lange (2001) stress the need for an ideal tool, specifically designed for healthcare systems performance analysis. According to Harell & Lange (2001), a pure manufacturing systems performance analysis approach could be inappropriate in dealing with healthcare services since the two environments differ significantly. For this reason, the application of traditional DES in healthcare is not as advanced as it is in the manufacturing industry. There is therefore no evidence, to the author’s knowledge, of the application of real-time DES in healthcare. There are, however, several examples of the successful application of traditional simulation in the healthcare environment which are mainly dependent on historical data irrespective of the setting.

For instance, Saunders et al. (1989) developed a computer simulation model of emergency department operations. Their model used multiple levels of patient priority, assigned each patient to an individual nurse and physician, and incorporated all standard tests, procedures, and consultations. The model also incorporated the parallel, sequential or repetitive processes that occurred in a typical emergency department. The model helped to identify the factors that influenced patient throughput and the length of time spent in the emergency department with respect to variations in patients' inter-arrival and processing times. This was mainly developed, used and became a "throw away model" (Son & Wysk, 2001) rather than a tool for monitoring the healthcare system.

Like Saunders et al. (1989), Kilmer et al. (1995) report the development of a simulation model of the operations of an emergency department. The authors further developed a meta-model of the simulation using Artificial Neural Network (ANN) techniques. They compared the performance of the ANN to that of the simulation for estimating the mean and variance of patient time in the emergency department. The authors claimed that the ANN meta-modelling technique was a more efficient means of optimising the performance of the system over a wide range of parameters but in conclusion found that the stochastic variability of the simulation output is lost rendering the meta-model deterministic. Though the use of the ANN meta-model may be efficient in optimising the performance of the simulation, the model is still subject to the limitations of traditional DES models in terms of its dependence on historical data.

Traditional DES models help to assess the resource planning and scheduling requirements in other areas of healthcare. Centeno et al. (2001) investigated possible effects of changes of operational procedures in a Labour and Delivery room using simulation. They believed that the inefficiencies of the patient flow in the department were due to poor scheduling of patients, staff, and the operating rooms. The authors claimed that their simulation model helped to improve doctor scheduling and better staffing levels. However, these improvements could only be based on the quality of the available input data. In an environment as dynamic as healthcare, input data patterns can change very quickly leaving the model output less relevant.

As a final example, Baesler et al. (2001) developed a multi-objective simulation optimisation for a cancer treatment centre. Their new stochastic methodology was able to find a global optimum for a multi-response simulation optimisation problem. Though this study attempts to demonstrate a more rigorous approach to the analysis of simulation output by determining parameters of the system that satisfy more than one objective, it does not consider ways of using the model as a basis of continuous monitoring of the system.

Other applications of DES in healthcare may be found in Ramis et al. (2001) and Barnes et al. (1997). However, all the references discussed above have a common limitation irrespective of the setting: they all run on historical data and hence, in a healthcare environment, the model outputs could easily become irrelevant when the input data become too old.

This limitation is the key motivation behind the current research. This research, in a broad sense, seeks to overcome this limitation by the use of a combination of historical and real-time simulation as suggested by the E-Track NHS system presented in section 4.5.

The contributions in this thesis, however, have focused on the development of special performance measures that could be implemented in the E-Track NHS system: the Healthcare Performance Index (HPI) developed in chapter 5 and the Staff-Patient Satisfaction Relation Model (S-PSRM) in chapter 6. These two measures are based on the concepts of service quality and satisfaction.

4.4. DES as a platform for improving quality of care and patient satisfaction

The specific application of DES for the purpose of improving service quality and satisfaction in a healthcare environment seems not to have been tackled previously. There are numerous applications of simulation that seek to achieve some improvement in healthcare systems though they do not categorically state the improvement of quality and satisfaction as an objective. A few examples in this respect are Harrel & Price (2000), Su & Shih (2003), Sinreich & Marmor (2004), and Komashie & Mousavi (2005).

The work of Komashie & Mousavi (2005) was particularly the motivation for exploring the possibility of real-time DES for the improvement of service quality in healthcare. It was realised during this simulation project conducted in an A&E department in London that the planning and scheduling of some resources, such as consultants, were not strictly implemented. Secondly, it was observed that the results of the project were useful but did not remain so for long, because they were based entirely on historical data. In such dynamic environments as A&E, the validity of historical data depreciates quickly. The researchers therefore proposed a more dynamic method for data acquisition where historical data can be enriched with real-time data and provide a more realistic representation of the current state.

E-Track NHS seeks to create a platform to use real-time DES to improve the quality of healthcare operations and patient and staff satisfaction with regard to key industrial performance indicators.

4.5. The case for E-Track NHS

Before presenting the concept of E-Track NHS, the current method of service quality improvement in the NHS as performed by the Healthcare Commission is first described.

4.5.1. System performance analysis cycle in the NHS

The NHS is currently a target driven system. This target setting approach to driving improvement has resulted in considerable improvements but in some cases the validity of reports on improvements seem to be doubtful (Bevan, 2006a). Figure 4. 1 shows the elements of this annual cycle of target setting, delivery and monitoring events. This approach, analogous to a three stage governance system – Targets, Inspections and Rewards – often results in unacceptable practices aimed at meeting the targets and getting the reward (Bevan & Hood, 2006b).

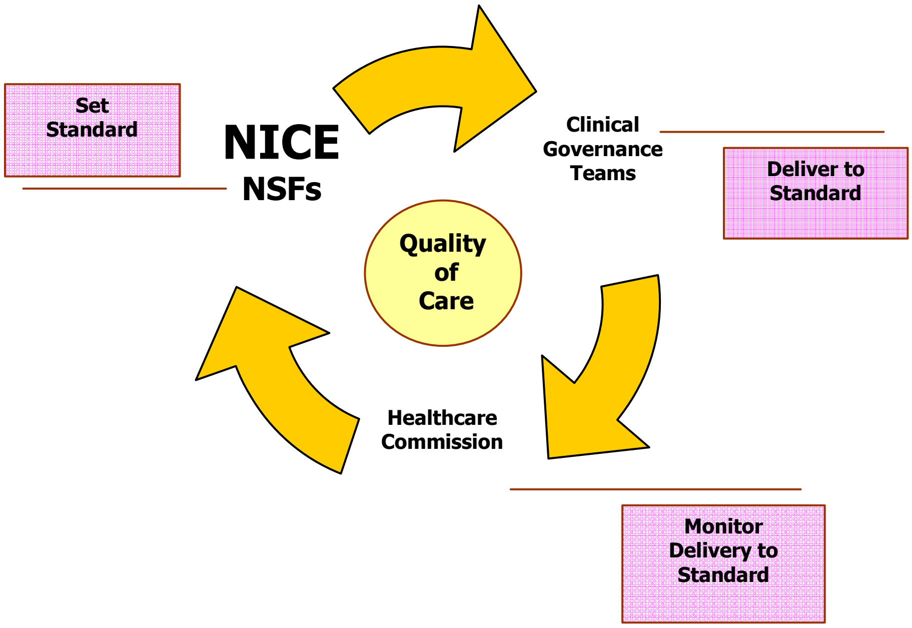


Figure 4. 1: Existing NHS improvement cycle

The National Institute for Health and Clinical Excellence (NICE) working with the Department of Health (DoH) and other professional bodies set the standards for NHS Trusts. For instance NICE has recently been given the mandate to play a central role in the reforms set out in the Lord Darzi report (Lord Darzi, 2008). This mandate includes the setting and approval of more independent quality standards from 2009 (NICE, 2008).

All NHS organisations also have Clinical Governance Teams which are accountable for continuously improving the quality of their services and safeguarding high standards of care (Scally & Donaldson, 1998).

The Healthcare Commission then acts as the watchdog monitoring NHS Trusts to assess whether they are delivering to the predefined standards. This is mainly done through an annual patient survey and assessment exercise published as performance ratings for all Trusts. A summary of the methodology is presented below with an example of how a Trust was rated in 2007.

4.5.1.1. Healthcare commission rating methodology

The Healthcare Commission is responsible for publishing annual performance ratings for every NHS trust. The objective is to make it easier for patients and the public to learn about their local NHS organisations. The general methodology for this performance rating system is summarised as follows:

A. All NHS trusts in England receive 2 ratings for quality of service and use of resources.

1. *Quality of services* – the score that a trust achieves is determined by its performance against 24 core standards, existing and new national targets.

2. *Use of resources* – the score that a Trust achieves is based on an annual financial risk rating awarded by “Monitor”, the independent regulator of Foundation Trusts.

B. All NHS trusts in England are given 1 of 4 possible scores for the 2 ratings:

- Excellent
- Good
- Fair
- Weak

It is important to note that the ratings depend on the data supplied by the various NHS Trusts as to their performance against the preset targets and the results of the annual postal patient surveys (Healthcare Commission, 2006).

From the information in Table 4. 1, it seems that “The Trust” has been rated “excellent” on both quality of services and use of resources. This type of analysis and rating may be useful information for comparing NHS Trusts at the strategic level but it also raises two important questions:

1. Would this be the experience of patients in all areas of The Trust’s operations: in the A&E, wards, outpatient etc.? This is an issue of homogeneity of performance.

2. Would this excellent rating be the manifestation of the Trust’s operations at all times till the next assessment exercise? This is an issue of the dynamic stability of performance.

These issues, which require a dynamic and operational level performance monitoring, do not seem to be considered within the current performance and service quality literature.

Table 4. 1: Example of Healthcare Commission's performance rating

Example of the Healthcare Commission's 2007 performance rating

This example is the actual 2007 rating of one of the NHS Trusts in London which would be referred to here as "The Trust".

Quality of services

- The Trust's overall score was Excellent – a significant improvement on 2006 when The Trust's score was Good.
- The Trust was among the best 16% of NHS trusts in England
- How did The Trust compare with other NHS trusts? 8% were Weak; 45% were Fair; 30% were Good; 16% were Excellent.

Use of resources

- The Trust overall score is Excellent – a significant improvement on 2006 when The Trust score was Fair.
- The Trust is among the best 14% of NHS trusts in England
- How did The Trust compare with other NHS trusts? 26% were Weak; 36% were Fair; 23% were Good; 14% were Excellent.

In conclusion The Trust was one of the only 19 NHS Trusts in England (only 3 in London) that scored 'excellent' for both quality of services and the use of resources: this puts The Trust in the top 5% of NHS trusts nationally.

The argument for E-Track NHS therefore is that it is possible to provide this information, at least those relevant to the patients, staff and other resources and operations in real-time, when it is most needed and at a lesser cost. This research, however, has not investigated the extent of cost saving that is possible with E-Track NHS. The research reported in this thesis mainly focuses on the conceptual developments of the HPI and S-PSRM which are intended to facilitate the provision of real-time information that is relevant for improving service quality. The major components of the system are briefly described below.

4.5.2. Impact of E-Track NHS

Figure 4. 2 shows the anticipated impact of the E-Track NHS system. The reason measurements are taken is in most cases to help drive improvements.

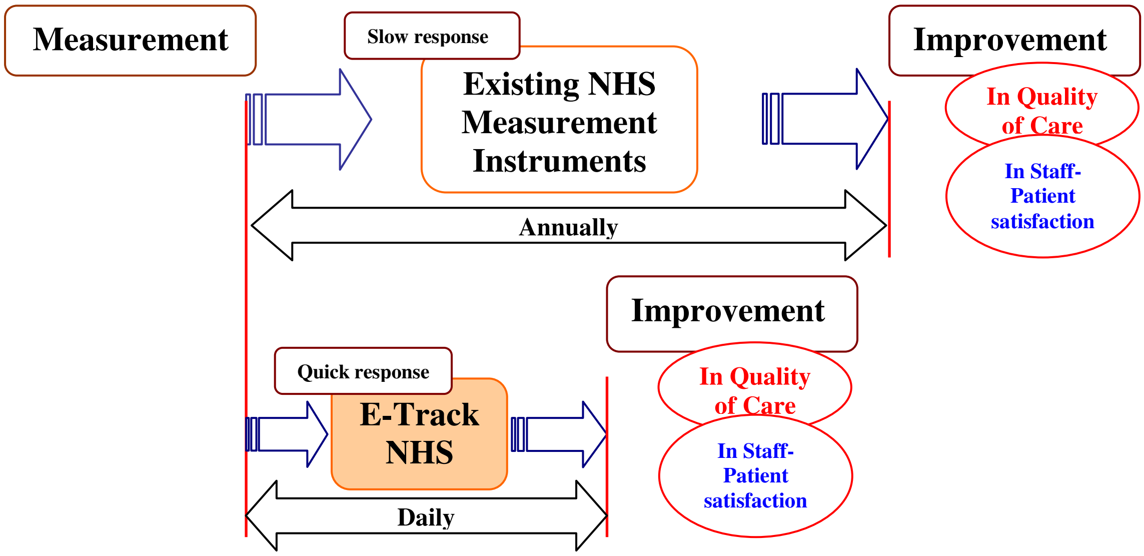


Figure 4. 2: Anticipated impact of E-Track NHS

The figure shows that between measurement and observable improvement is the measuring system or instrument. The intent of the E-Track NHS system is to provide a standardised method of data acquisition, analysis and presentation with as little bias as possible and to facilitate the measurement of patient's perspective of hospital care. While the Healthcare Commission and many NHS Trusts collect data on patient satisfaction annually, there is no means of using real-time patient response data for this purpose. The proposed system is therefore meant to complement the data collection and assessment process exercise by the HC leading to the possibility of having an online real-time comparison of various aspects of different NHS Trusts. This concept is already under consideration in the USA but is currently based on historical data supplied by interested participating healthcare providers (Chilgren, 2008). See section 7.3 for a detailed discussion of the American concept.

4.5.3. Overview of the E-Track NHS concept

The full details of the development of the E-Track NHS system are presented in chapter 6. Only a brief overview is presented in this section.

So far in this thesis, the review has been presented on quality, satisfaction and discrete event simulation as key aspects of the proposed system. Figure 4. 3 shows how all the various components would work together.

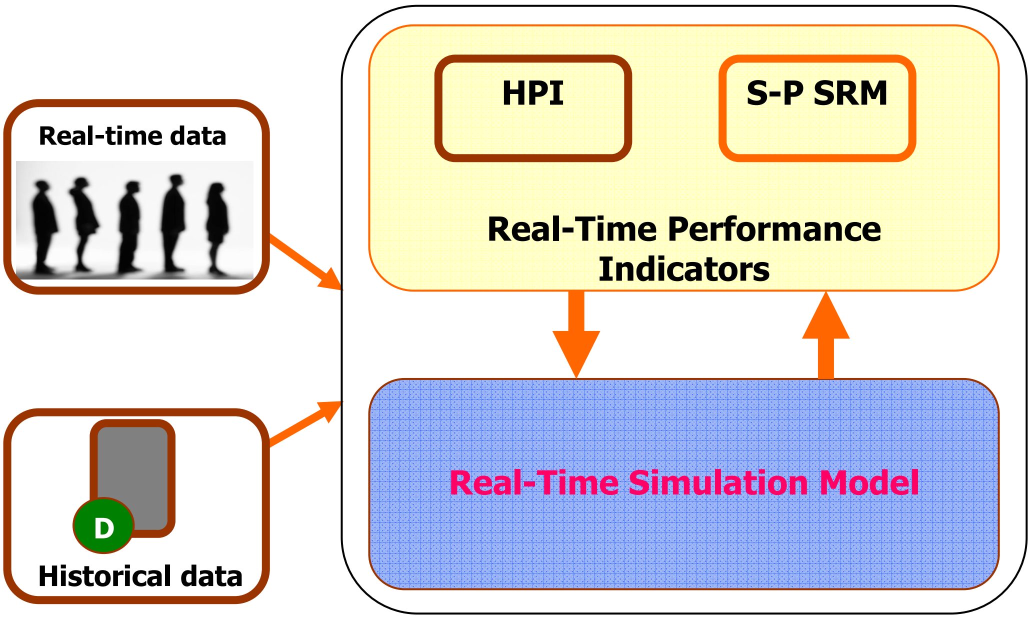


Figure 4. 3: E-Track NHS concept

Traditionally, discrete event simulation as discussed above relied solely on historical data as input. The great disadvantage of using historical data in a dynamic healthcare environment is that after a while, things change, the input becomes old and the output irrelevant. The idea in the proposed system is to use a combination of real-time data and historical data as input to the real-time simulation model which then outputs real-time performance measures including an index of performance (quality) and levels of satisfaction.

The main reason for using real-time technology is the ability to capture system parameters and their estimated variances at the time of occurrence. This will allow for a more accurate and enriched statistical analysis as the models and the parameters of the system vary with time.

4.6. Conclusions

The findings in this chapter include the evidence of some applications of discrete event simulation in healthcare. It was, however, noticed that in spite of the these applications, there were no examples that categorically set out to apply simulation to improving quality of care and satisfaction as intended in this research.

The major limitation of all the healthcare applications of DES identified is the heavy dependence on historical data. This limitation can greatly reduce the usefulness of these models especially over time.

It has also been argued that the current annual cycle of quality improvement efforts by the NICE, clinical governance teams and the Healthcare Commission is more useful at the strategic level of quality management than at the operational (ongoing) level. This is because annual performance assessments cannot guarantee the operational level of performance between assessments.

Due to the above weakness of the current quality improvement cycle, the gap was identified for the provision of a dynamic, operational level system of performance monitoring as proposed in this research.

An overview of the E-Track NHS system has also been presented in this chapter to show the interrelation of the various components.

This chapter ends the background work for this research – the body of knowledge upon which the contributions in this thesis are based.

The next chapter therefore presents the development and testing of the Healthcare Performance Index (HPI).

5. The Healthcare Performance Index (HPI)

“The American Customer Satisfaction Index measures the quality of the goods and services as experienced by the customers that consume them.”

Fornell et al. (1996, p. 16)

This chapter aims at showing the development and testing of the HPI and its particular application as a Healthcare Quality Index (HQI). The test is designed to show the robustness and consistency of the proposed index. The robustness and consistency tests of the index are necessary to ensure that the index is a valid and meaningful measure of performance. This will also make it possible to use the index to benchmark similar aspects of different healthcare systems.

The HPI conceptual model is first presented in section 5.1 followed by the mathematical formulation in 5.1.1, where the Generalised Maximum Entropy (GME) formalism is applied to the problem definition. The index is then tested using the Monte Carlo simulation experimentation technique in section 5.2. The experiments involve comparisons between GME estimation and Least Squares Regression (LSR) estimation. LSR is adopted in this problem due to the fact that it is one of the most frequently used methods in the service quality literature (Seth, Deshmukh & Vrat, 2005).

In section 5.3, the HPI is empirically tested as a Healthcare Quality Index (HQI) using data from the Healthcare Commission’s 2006 in-patient survey. Three quality indicators - dignity, confidence and communication - were used for developing the HQI. A sensitivity analysis is then conducted to examine how the index responds to variations in the quality indicators.

The chapter concludes in section 5.4 by highlighting the contributions and key findings emerging from the development of this unique index for performance measurement.

5.1. Conceptual development of the HPI

Consider healthcare providers interested in estimating the quality of the care that they provide to their patients using an index. This quality of care depends on numerous factors, most of which may not even be apparent to them. Figure 5.1 shows a conceptual representation of how these numerous factors are integrated into the HPI. A Key Performance Indicator (KPI) in the figure represents an attribute of the service that directly or indirectly affects the performance measure represented by the index. The factors under each KPI are the sub-attributes that directly contribute to the KPI. For example, if performance is measured in terms of quality of care in an emergency department, then, the index will become a quality index. Examples of the indicators will be waiting time and cleanliness. Some factors under waiting time may be waiting in queue or waiting for blood results. Some factors under cleanliness may also be nurses washing their hands and cleanliness of the toilets. This information is normally obtained from patient surveys.

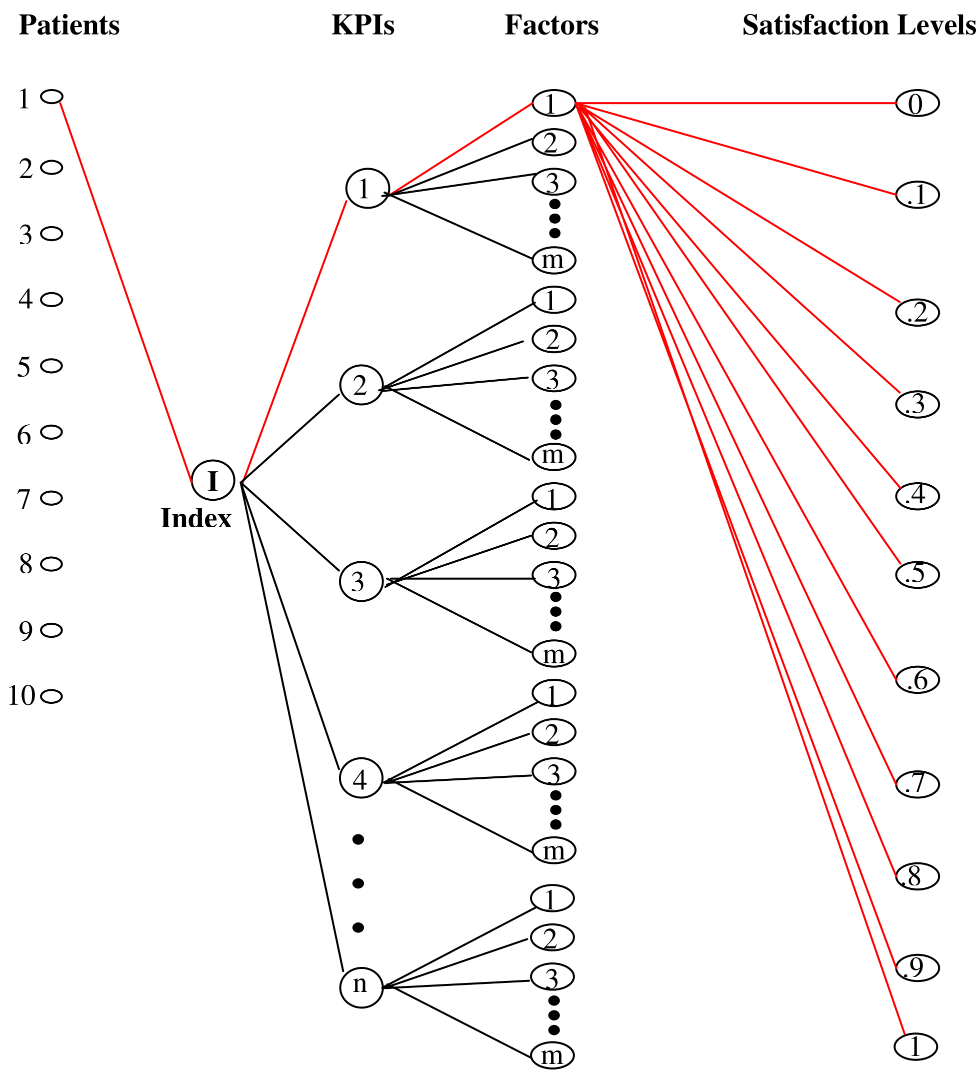


Figure 5. 1: Conceptual representation of the HPI formulation

The figure shows that the index value for each patient will be made up of *n* KPIs, each one having *m* factors. Each factor is measured according to the patient's satisfaction with the factor. The satisfaction values vary between 0 and 1 and are measured using the CORE model (Mousavi et al., 2001). Thus for each factor, a patient's satisfaction can be between 0 and 1 but the exact value is not known.

Therefore in the current formulation, if the healthcare providers decide to estimate this index by using the proportion of patients that are satisfied with various aspects of the care they receive, then:

Let j be the number of Key Performance Indicators (KPIs) that directly or indirectly affect the performance of the system,

$$j = 1, 2, 3, \ldots, n \qquad 5.1$$

Let i be the number of factors under KPI j.

$$i = 1, 2, 3, \ldots, m \qquad 5.2$$

Let S be the level of satisfaction of a patient k with factor i under indicator j

$$S_{ijk} = 0, 0.1, 0.2, \ldots, 1 \qquad 5.3$$

where 0 and 1 correspond to the minimum and maximum satisfaction values.

Also let the proportion of patients having satisfaction level s with factor i under KPI j be given by p_{jis}. This is equivalent to the probability that a randomly selected patient k will have a satisfaction level of s with factor i under KPI j.

Given that the service providers may not know all the factors which contribute to the level of performance as discussed in chapter 3 with respect to quality, it is reasonable to state that their uncertainty or ignorance about the quality of care would be maximum, unless they have some new information to make them more certain. The measure of this uncertainty is given by the Shannon's Entropy measure:

$$H = -\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{s=1}^{S} p_{jis} \ln p_{jis} \qquad 5.4$$

Hence the distribution of p_{jis} that maximises this uncertainty is the most realistic and most honest basis on which to measure the quality of the care that is being provided.

For example, it has been proven (see Kapur & Kesavan, 1992, p. 29) that, given a random variable $X = x_1, x_2, ..., x_t$ with corresponding probabilities, $p_1, p_2, ..., p_t$, subject only to the normalisation constraint, the distribution of p_t that maximises H is a uniform distribution. Thus when

$$p_1 = p_2 = \cdots = p_t = \frac{1}{t} \quad 5.5$$

A non-uniform distribution of p_t will result in $H < H_{max}$. However, according to Shannon, and by common sense, the only way we become more certain ($H < H_{max}$) is by having more information. This implies that the method that offers a non-uniform distribution of p_t is built on the assumption of the availability of additional information. This assumption may be wrong, given the lack of any additional information.

For the development of the HPI, we will make some reasonable assumptions which will provide us with more information about the distribution of p_{jis}. We assume that the number of indicators and factors that contribute to the index are known. This additional information is the only information we have. The relationship between the indicators and their factors will also be modelled as a linear regression. We therefore maximise our uncertainty based on these constraints and without any further assumptions about data patterns.

In a regression model, the uncertainty will be associated with an unknown regression coefficient, which is how much each factor contributes to its indicator and subsequently to the index that is to be measure (i.e. based on p_{jis}).

There is also uncertainty associated with the unknown errors in the regression model (Golan et al., 1996). The GME estimator includes the unknown and unobserved errors in both the entropy function and its constraints.

5.1.1. The mathematical formulation of the HPI

Let's assume that the index is a weighted linear combination of all latent variables given by:

$$I = \gamma_1 y_1 + \gamma_2 y_2 + \gamma_3 y_3 + ... + \gamma_j y_j + ... + \gamma_n y_n \quad 5.6$$

where

γ_j is the importance weight for KPI y_j

We further assume that the performance indicators are each a linear combination of their respective factors given by a multiple regression model as:

$$\begin{array}{l} y_1 = \beta_{11}x_{11} + \beta_{12}x_{12} + \beta_{13}x_{13} + ... + \beta_{1i}x_{1i} + ... + \beta_{1m}x_{1m} + \varepsilon_1 \\ y_2 = \beta_{21}x_{21} + \beta_{22}x_{22} + \beta_{23}x_{23} + ... + \beta_{2i}x_{2i} + ... + \beta_{2m}x_{2m} + \varepsilon_2 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ y_j = \beta_{j1}x_{j1} + \beta_{j2}x_{j2} + \beta_{j3}x_{j3} + ... + \beta_{ji}x_{ji} + ... + \beta_{jm}x_{jm} + \varepsilon_j \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ y_n = \beta_{n1}x_{n1} + \beta_{n2}x_{n2} + \beta_{n3}x_{n3} + ... + \beta_{ni}x_{ni} + ... + \beta_{nm}x_{nm} + \varepsilon_n \end{array} \quad 5.7$$

where

β_{ji} is a regression coefficient and

x_{ji} is a satisfaction value for a sub factor *i* under KPI y_j

Covariance and multi-colinearity between the covariants are not considered because the GME approach is capable of handling such problems. Ciavolino et al. (2007) and Al-Nasser (2003) proved this by deliberately introducing multi-colinearity into a set of data and compared results for the GME and Partial Least Squares (PLS) estimation methods and discovered that the GME results yield better estimations.

In Matrix form,

$$\mathbf{H} = \mathbf{X} \cdot \mathbf{B} + \mathbf{E} \quad 5.8$$

where

$\mathbf{H}$ is an $n \times 1$ column vector of KPI values

$\mathbf{B}$ is an $m \times 1$ column vector of regression coefficients

$\mathbf{X}$ is a $n \times m$ matrix of sub factor values

$\mathbf{E}$ is a $n \times 1$ vector of residual errors in the regression equations

5.1.2. Re-parameterisation

We now need to re-parameterise the unknown parameters and disturbance terms according to the requirements of the GME estimation principles (see chapter 3). The matrix equation in 5.8 can therefore be expressed as:

$$\mathbf{H} = \mathbf{X} \cdot \mathbf{Z} \cdot \mathbf{p} + \mathbf{V} \cdot \mathbf{w} \qquad 5.9$$

where

$\mathbf{H}$ is an $n \times 1$ column vector of KPI values

$\mathbf{X}$ is a $n \times m$ matrix of sub factor values

$\mathbf{Z}$ is an $m \times m$ diagonal matrix of support variables for the coefficients. Each element of $\mathbf{Z}$ is a row vector

$$\mathbf{z}_i' = \begin{bmatrix} c_{i1} & c_{i2} & \cdots & c_{iM} \end{bmatrix} \qquad 5.10$$

c_{iM} is the support variable for the coefficient terms and *M* is the total number of support points in $\mathbf{z}_i'$.

$\mathbf{V}$ is a $n \times n$ diagonal matrix of support variables for the residual terms. Each element of $\mathbf{V}$ is a row vector:

$$\mathbf{v}_j' = \begin{bmatrix} b_{j1} & b_{j2} & \cdots & b_{jN} \end{bmatrix} \qquad 5.11$$

b_{jN} is the support variable for the residual terms and *N* is the total number of support points in $\mathbf{v}_j'$.

$\mathbf{p}$ and $\mathbf{w}$ are probability vectors associated with the coefficients and random errors. That is;

$$\mathbf{p} = \begin{bmatrix} \mathrm{p}_1 \\ \mathrm{p}_2 \\ \vdots \\ \mathbf{p}_i \\ \vdots \\ \mathrm{p}_m \end{bmatrix} \qquad 5.12$$

and

$$\mathbf{p}_i = \begin{bmatrix} \mathrm{p}_{i1} \\ \mathrm{p}_{i2} \\ \vdots \\ \mathrm{p}_{i.M} \end{bmatrix} \qquad 5.13$$

$$\mathbf{w} = \begin{bmatrix} \mathrm{w}_1 \\ \mathrm{w}_2 \\ \vdots \\ \mathbf{w}_j \\ \vdots \\ \mathrm{w}_n \end{bmatrix} \qquad 5.14$$

and

$$\mathbf{w}_j = \begin{bmatrix} \mathrm{w}_{j1} \\ \mathrm{w}_{j2} \\ \vdots \\ \mathrm{w}_{j.N} \end{bmatrix} \qquad 5.15$$

Therefore the coefficients and error terms will be written as:

$$\boldsymbol{\beta} = \mathbf{Z} \cdot \mathbf{p} = \begin{bmatrix} \mathbf{z}_1^{'} & 0 & \cdots & 0 & 0 \\ 0 & \mathbf{z}_2^{'} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & 0 & \vdots \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \mathbf{z}_m^{'} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \vdots \\ \vdots \\ \mathbf{p}_m \end{bmatrix} \qquad 5.16$$

$$\boldsymbol{\varepsilon} = \mathbf{V} \cdot \mathbf{w} = \begin{bmatrix} \mathbf{v}_1^{'} & 0 & \cdots & 0 & 0 \\ 0 & \mathbf{v}_2^{'} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & 0 & \vdots \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \mathbf{v}_n^{'} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \vdots \\ \vdots \\ \mathbf{w}_n \end{bmatrix} \qquad 5.17$$

The general form of the equation therefore can be expressed as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{z}_1^{'} & 0 & \cdots & 0 \\ 0 & \mathbf{z}_2^{'} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{z}_m^{'} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \vdots \\ \mathbf{p}_m \end{bmatrix} + \begin{bmatrix} \mathbf{v}_1^{'} & 0 & \cdots & 0 \\ 0 & \mathbf{v}_2^{'} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{v}_n^{'} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \vdots \\ \mathbf{w}_n \end{bmatrix} \qquad 5.18$$

5.1.3. Reformulation

With the re-parameterised version of equation 5.13, the GME equation can now be expressed as a non-linear programming problem subject to linear constraints. Thus maximising

$$H(p, w) = -\mathbf{p}_{1,M}^{'} \ln \mathbf{p}_{M,1} - \mathbf{w}_{1,N}^{'} \ln \mathbf{w}_{N,1} \qquad 5.19$$

Subject to the data consistency constraint expressed in equation 5.13, and the summation constraints:

$$\sum_{f=1}^{M} p_{if} = 1, \quad \forall i \qquad 5.20$$

$$\sum_{g=1}^{N} w_{jg} = 1, \quad \forall j \qquad 5.21$$

The solution to this optimisation problem yields the probability values which together with the support variables help to obtain the beta coefficients ($\boldsymbol{\beta}$) and residual errors ($\boldsymbol{\varepsilon}$) for the regression model.

5.1.4. Solution algorithm

The optimisation problem is one of maximising a nonlinear objective function subject to linear equality constraints. According to Kapur & Kesavan (1992), the

Lagrange method of undetermined multipliers is the ideal tool for solving this problem. They find that because of the nature of the Shannon measure, this method helps avoid some difficult problems that are normally faced in constrained optimisation. For example, when the Lagrange method is used to maximise Shannon's measure, subject to linear constraints, the maximising probabilities are all greater than zero thereby automatically satisfying the non-negativity constraint. In all constrained optimisation problems, this is a difficult constraint to satisfy. The Lagrange method is also used in some cases for entropy optimisation (e.g. Golan, Judge & Karp, 1996; Kesavan & Kapur, 1989) and suggested for general constrained optimisation problems in microeconomics (Maberly & Pierce, 2004).

A summary of the Lagrange method is given in appendix E following Kapur & Kesavan (1992), Golan & Judge (1996), Golan, Judge & Karp (1996) and Kesavan & Kapur (1989).

5.2. Test of robustness with Monte Carlo experiments

5.2.1. Objective

The objective of this simulation experiment is to assess the robustness of the GME methodology as a reliable estimator of the quality of healthcare and compare its performance to the Least Squares (LS) or the Weighted Least Squares (WLS) regression method (Irving, 2008).

It is assumed here that there would not usually be outliers in the input data since it would normally be pre-processed. For this reason the LS method should behave optimally provided the distribution of residual errors is normal.

It is important to note that properly designed and applied estimators are very useful for online processing of physical measurements (Irving, 2008) as is anticipated in the use of the HPI.

5.2.2. The estimation problem

Figure 5. 2 helps to explain the estimation problem. Assuming that all factors affecting the performance of a department were known and could be accurately measured, the curve "A" in Figure 5. 2 may represent the true distribution of the

perception of a patient of that particular performance measure. According to the statistical theory, true values can never be known. Therefore, the attempt is to estimate the value of the true parameters as well as possible. As shown in Figure 5. 2, a Least Squares Regression (LSR) method will result in the estimate “B” of “A” whilst a Generalised Maximum Entropy (GME) method will give the estimate “C”. The problem here therefore is to determine which of the estimates “B” or “C” and, for that matter, LSR or GME may be a better, more reliable and more robust estimator of “A” given the known input variables. The standard errors, bias, mean squared error and relative efficiencies are reliable measures for assessing the reliability of the estimated distributions (Martinez & Martinez, 2002).

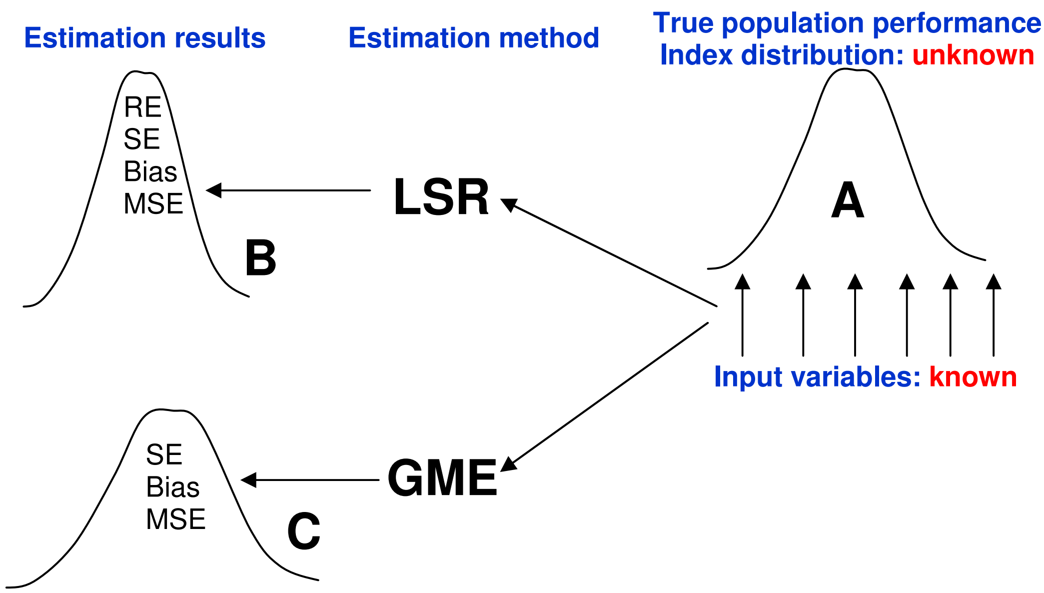


Figure 5. 2: Population performance estimation problem

5.2.3. Design of the experiment

A factorial designed Monte Carlo experiment based on the work of Gentle (2003) was the framework used at this stage. It was expected that the most robust estimation procedure will produce the least bias and standard errors. The method should also be less affected by ill-conditions, model under-determination, insufficient data, and non-normal distribution of residual errors.

The experiment was therefore designed so that these “effects” could be measured for each set of factor combinations. The estimation methods may be regarded as the “treatment”. The experimental factors considered are listed below;

- The sample sizes
- The distributions of independent variables
- The estimation methods (Least Square regression vs GME)

We now define all the possible levels for each of the experimental factors in the Monte Carlo study.

- Factor 1: Data sample size, *n*, with levels l,
  - Level 1: $n = 4$
  - Level 2: $n = 10$
  - Level 3: $n = 20$
  - Level 4: $n = 200$
  - Level 5: $n = 1000$
- Factor 2: Distribution of the independent variables with the following levels, *k*:
  - Level 1: Normally distributed over the range
  - Level 2: Uniformly distributed over the range
- Factor 3: Estimation method, with levels *i:*
  - Level 1: Least Squares (LS) Estimation
  - Level 2: Generalised Maximum Entropy (GME) Estimation

The factorial design is shown in Table 5. 1.

Martinez & Martinez, (2002) present four measures that are effective for assessing the performance of an estimator listed below:

- The Bias of the estimate of the parameter
- The Mean Squared Error (MSE) of the estimate of the parameter

- The Relative Efficiency (RE) of the estimate of the parameter
- The Standard Error (SE) of the estimate of the parameter

All the above measures are calculated in the experiment but only RE is used in the hypothesis test to determine the more reliable estimation method. The choice of RE is because it is based on the MSE of both estimates. The methods of calculating the measures are briefly described in the following section.

Table 5. 1: Complete factorial design

Test	Factor 1 levels (Sample size)	Factor 2 levels (Independent var. dist.)	Factor 3 levels (LSR or GME)
1	1, n = 4	1, Normal	1-2
2	1, n = 4	2, Uniform	1-2
3	2, n = 10	1, Normal	1-2
4	2, n = 10	2, Uniform	1-2
5	3, n = 20	1, Normal	1-2
6	3, n = 20	2, Uniform	1-2
7	4, n = 200	1, Normal	1-2
8	4, n = 200	2, Uniform	1-2
9	5, n = 1000	1, Normal	1-2
10	5, n = 1000	2, Uniform	1-2

5.2.4. Statement of null hypothesis

The null hypothesis is that the GME method is not a better estimator of the Healthcare Performance Index (HPI) than the LSR estimator. This statement is true if the Relative Efficiency of LSR estimated index to GME estimated index is greater than 1. Mathematically, the hypothesis may be stated as:

$$H_0 : RE(I_{LSR}, I_{GME}) > 1 \qquad 5.22$$

where

$RE(I_{LSR}, I_{GME})$ is the relative efficiency of I_{LSR} to I_{GME}

I_{LSR} is the LSR estimated value of the index

I_{GME} is the GME estimated value of the index

The alternative hypothesis therefore may be stated as:

$$H_1 : RE(I_{LSR}, I_{GME}) < 1 \qquad 5.23$$

which if accepted, will imply that the GME estimated index is a rather more efficient estimator of the healthcare performance.

The value of the Relative Efficiency can be calculated from the formula:

$$RE(I_{LSR}, I_{GME}) = \frac{MSE(I_{GME})}{MSE(I_{LSR})}. \qquad 5.24$$

where

$MSE(I_{GME})$ is the Mean Squared Error of the GME estimated index

$MSE(I_{LSR})$ is the Mean Squared Error of the LSR estimated index

The MSE can readily be obtained once the bias is known. Typically, the bootstrap method is an ideal method for estimating the bias and standard error in cases where it is not desired to make parametric assumptions about the distribution of the underlying population (Gentle, 2003). This approach is briefly explained in the following section.

5.2.5. Bootstrap estimates of Standard Error and Bias

The general Bootstrap techniques (Martinez & Martinez, 2002) are used here to estimate the values of the Standard Error and Bias in the experiment. Bootstrapping is used because it is not desirable to make any parametric assumptions about the underlying population or distribution of the actual performance. This means that no assumptions are made about the distribution "A" in Figure 5. 2. The estimated distribution of the index is therefore used as an estimate for the population. This subsection is not intended to introduce the concept of bootstrapping but rather to state its application. The interested reader is referred to Martinez & Martinez (2002) and Gentle (2003) for detailed information on the method.

5.2.5.1. Standard Error

The parameter of interest here is the variance, V , of the distribution of index values obtained by each of the methods under test.

Let the bootstrap estimate of V be $\hat{V}$. Therefore the Standard Error in the estimate is given by:

$$\hat{SE}_B\left(\hat{V}\right) = \left\{ \frac{1}{B-1} \sum_{b=1}^{B} \left(\hat{V}^{*b} - \bar{\hat{V}}^{*} \right)^2 \right\}^{\frac{1}{2}}, \qquad 5.25$$

where

$$\bar{\hat{V}}^{*} = \frac{1}{B} \sum_{b=1}^{B} \hat{V}^{*b}$$

$\hat{V}^{*b}$ is the bootstrap replicate of the variance and

B is the number of bootstrap re-samples

5.2.5.2. Bias

In addition to the standard error, the bias is another important measure of the performance of an estimator. To obtain the bootstrap estimate of the bias, the empirical distribution is used. The empirical distribution is the distribution that represents the estimates of the parameter of interest. This is used in place of that true distribution that underlies the actual population. The statistic (in this case the variance of the estimated index) is then calculated using each bootstrap resample from the empirical distribution, yielding the bootstrap replicates, $\hat{V}^{*b}$. The replicates are then used to estimate the bias as follows.

$$bi\hat{a}s_B = \bar{\hat{V}}^{*b} - \hat{V} \qquad 5.26$$

where

$\hat{V}$ is the statistic computed from the empirical distribution

and $\bar{\hat{V}}^{*b} = \frac{1}{B} \sum_{b-1}^{B} \hat{V}^{*b}$

With the bias, the mean squared error can then be calculated using the expression;

$$MSE(I) = V(I) + [bias(I)]^2 \qquad 5.27$$

where

$V(I)$ is the variance of the index.

5.2.6. The experiment

The experiment was conducted using MATLAB R2007a on an Intel Pentium 4 processor, 3.20GHz and 0.98GB RAM computer. The bootstrap technique was implemented using the "*bootstrp"* function in MATLAB.

The experiment is in two parts:

1. Observational study: intended for a more detailed study of the behaviour of both estimators. Therefore for each point in the experimental factor space, the following measures will be recorded *m* times, where *m* is the number of Monte Carlo trials.

    - Bias
    - Mean Square Error
    - Standard Error
    - Relative Efficiency

2. Hypothesis testing: intended to determine a simple and easy to understand ground for supporting GME as a better estimator of healthcare performance. This will only involve the subset of points in the experimental factor space where the null hypothesis is applicable. The following steps are taken:

    - Matching results at identical points in the experimental factor space for LSR and GME.
    - Determine the Relative Efficiency of LSR at each of these points.
    - Count the number of times the null hypothesis is rejected.

- Determine *p*-values and the significant levels at each point.

5.2.6.1. Experimental conditions

Based on these requirements a complete factorial design was employed involving a 20 point factor space. The experiment was implemented according to the program logic in appendix C.

The main computation in the program is to determine the values of the MSE for each method which helps to obtain the relative efficiency for the null hypothesis. These computations are performed at each setting of the experimental factors and for any given realisation of the random sample.

For consistency and in order to provide a sound basis for comparison, the tests are performed on the same pseudorandom datasets. Also, because we are interested in the shape of the power curves, we may want to use the same pseudorandom dataset for each value of the relative efficiency; that is to use the same set of errors in the model.

Finally, following similar reasoning, the same pseudorandom datasets are used at each setting of the distribution of each independent variable. The program structure used for the experiment is presented in appendix C.

5.2.7. Results and discussions

This section details and discusses the results of the Monte Carlo experiments conducted for testing the robustness and consistency of the HPI.

5.2.7.1. Objectives and summary of experimental context

The objective of this experiment was to assess the robustness of the Generalised Maximum Entropy (GME) Estimation method and the Least Squares Regression (LSR) Estimation method under a combination of experimental factors. A statistical procedure is robust if its output and accuracy are insensitive to violations of assumptions made (Moore & McCabe, 2003). Secondly, it was intended to directly compare the performance of both estimation methods by testing the null hypothesis that the relative efficiency of the LSR estimator to the GME estimator is greater than one. This will mean that LSR estimation has less mean squared error than the GME method.

Outcomes of the two estimation methods were compared using the One-Sample t-test (Moore & McCabe, 2003). The difference between the two methods was quantified using their relative efficiency, which is a consistent and reliable measure of performance for comparing estimators (Martinez & Martinez, 2002). The relative efficiency is the ratio of the Mean Squared Errors (MSE) of the two methods. A lower-tailed test is used since the alternative hypothesis required that the relative efficiency value be less than the null value. A bootstrap estimation technique was used for estimating the MSEs. The non-parametric Lilliefors' composite goodness-of-fit test was used to check the normality of the data before applying the t-test. A significance level of 0.05 was used throughout the experiment.

5.2.7.2. Observed experimental results

Tables 5.2 and 5.3 show a summary of the experimental results. More tables and figures from the experiment are shown in appendix D. For all the measures of performance considered, the LSR and GME estimates tend to converge at high values of sample size. The GME method, however, turns out to be more robust against the direct and combined effects at lower sample sizes than the LSR method. This is the main result of this experiment and seems to add to what is already known about the robustness of the GME method compared with others, like Partial Least Squares (Ciavolino, 2007; Ciavolino & Dahlgaard, 2007; Al-Nasser, 2003). These researchers found the advantage of the GME method by looking at effects of individual factors, but the current experiment confirms the robustness of GME even with the combined effects of multiple factors.

Table 5. 2 shows the average values of the index and variances as obtained by LSR and GME for the various experimental factor combinations. It should be noted that the sample size for relative efficiency observations (M=1000), which is equal to the number of Monte Carlo trials, is the same for all the tests irrespective of the data sample size.

Table 5. 2: Mean, variance and standard errors of index

Test	Mean of Index		Variance of Index		Standard Error	
	LSR	GME	LSR	GME	LSR	GME
1	66.5974	95.4982	30.1518	12.1272	13.4619	5.5655
2	72.2974	99.7896	56.3931	19.6517	25.2016	8.8177
3	66.2376	81.1096	16.3251	8.7105	5.8297	3.1084
4	71.8766	85.5806	31.476	14.9431	11.0558	5.3689
5	66.2105	74.4939	10.8676	7.2908	3.0207	2.039
6	71.7272	79.2356	21.083	12.6917	5.7731	3.5532
7	66.0886	67.0201	6.2498	5.96	0.6117	0.5826
8	71.613	72.4431	11.8668	11.2802	1.1521	1.0962
9	66.108	66.2909	5.8793	5.8531	0.2622	0.2611
10	71.6123	71.7801	11.0657	11.0336	0.4828	0.4833

5.2.7.3. Confidence in experimental results

Confidence in the experimental results is subject to the various tests and techniques employed. All tests were conducted at 95% confidence. The 95% confidence interval for the location of the estimated means and variances of the index by LSR and GME are also given in Table 5. 3.

Also, it is found that the robustness of the GME estimation method over the LSR method is very consistent. Figure 5. 3 shows the bias in the two estimators.

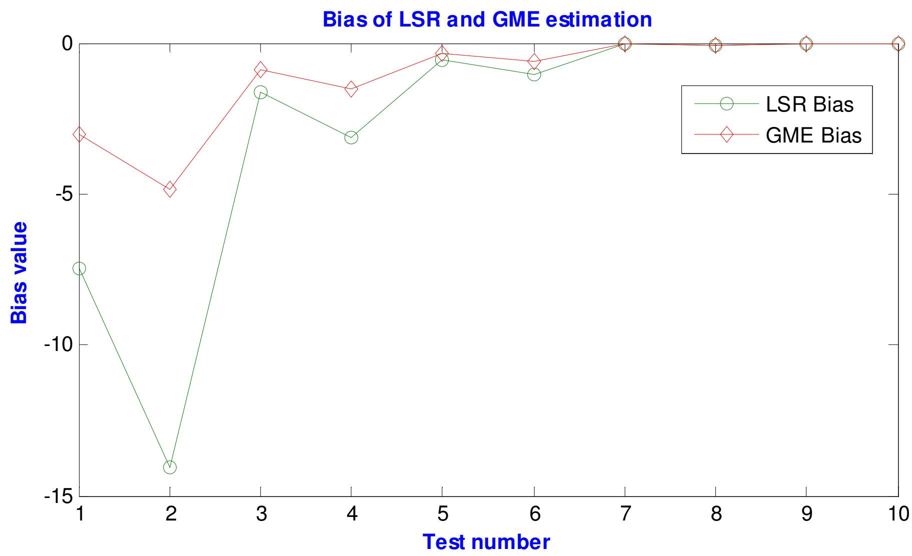


Figure 5. 3: Bias for LSR and GME estimation

It is helpful to note that the data sample sizes increase with the test number. That is tests 1 and 2 have n = 4. The two estimators tend to converge at high sample sizes (n = 1000 in tests 9 and 10). This pattern of convergence is seen in all the graphs, as shown in appendix D, suggesting that the GME method is more robust in cases of minimal data and irregularities in the distribution of the sample. It may therefore be concluded that the GME method is a better estimator.

Another reason to have more confidence in the results is the power of the test (the ability of the test to reject the null hypothesis if it were really false). The power curves for the first three tests are shown in Figure 5. 4. The power value at a true value of zero for the relative efficiency is referred to in this experiment as "Extreme power" to indicate the fact that the smallest possible value of the relative efficiency is zero. At this point it is reasonable to expect the power of the test to be highest, since it is the furthest point away from the value under the null hypothesis. Note that by definition (see equation 5.24) the relative efficiency (RE) cannot be less than zero.

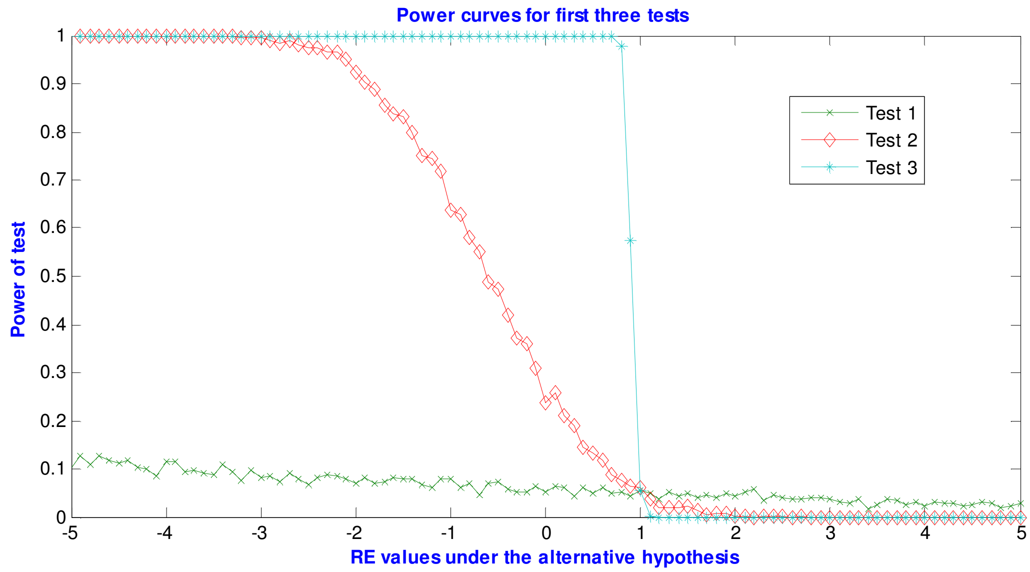


Figure 5. 4: Power curves for tests 1, 2 and 3

The "Extreme power" mainly gives an idea of what the actual power of the test may be for a true value of RE not equal to zero. Table 5. 3 shows "Extreme power" values of 0.053, 0.237 and 1.0 for test numbers 1, 2 and 3 respectively which are consistent with the curves in Figure 5. 4 (also see Table D. 1 in appendix D).

5.2.7.4. Quality of experimental results

The use of factorial design techniques in this experiment enables one to enhance the quality and validity of the results. It makes it possible to analyse the results from different perspectives. Figure 5. 5 for instance shows the consistency of all the tests at the various factor combinations. The figure shows plots of the relative efficiency and the One-Sample t test h value. The value of h is either 0 or 1. If h = 0, it means that the null hypothesis cannot be rejected because the relative efficiency is indeed greater than unity.

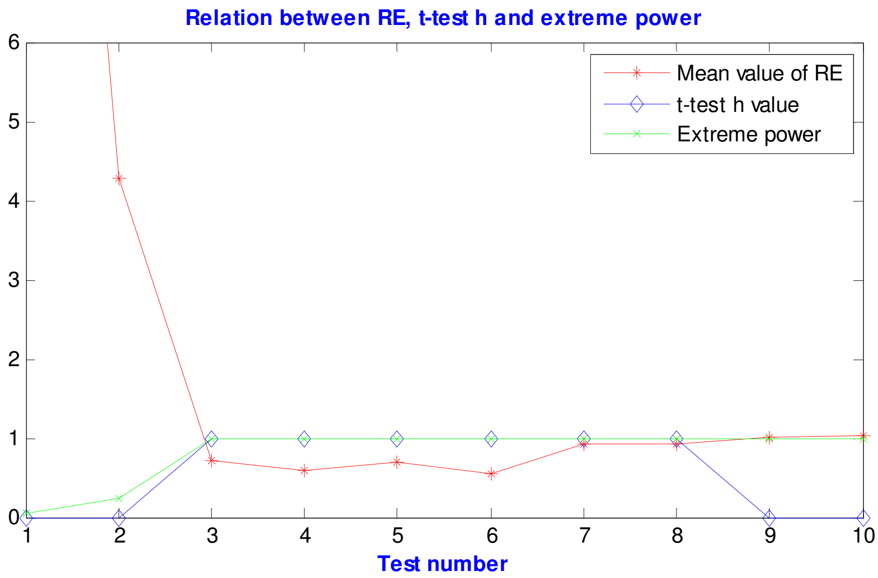


Figure 5. 5: Plot of relative efficiency, One-Sample t test h values and "Extreme power"

It can be seen from Figure 5. 5 that the value of h is 0 whenever the relative efficiency is greater than or equal to 1. Also for tests 1 and 2 where h equals 0, the values of the "Extreme power" are 0.053 and 0.237. These power values are very low and mean that the tests are not capable of rejecting the null hypothesis when it is truly false. Probably, this is the reason why the tests accept the null hypothesis (i.e. with h = 0). Table 5. 3 provides further measures for checking the performance of the tests and quality of the results. The Lilliefor's test is a test of normality in the distribution of the values of the relative efficiency. When H = 0, the test shows normality in the data. This and the power values provide more insight into the reliability and the quality of the t test results.

Table 5. 3: Hypothesis test results

Test	Lillietest			One-Sample, lower tail t-test				Extreme power
	H	**P**	**STAT**	**h**	**P**	**CI** (to –inf)	**t**(999)**-stats**	
1	1	0.001	0.482	0	0.9113	41.1391	1.3497	0.053
2	1	0.001	0.4442	0	0.9997	5.8688	3.4024	0.237
3	1	0.001	0.334	1	0	0.8124	-5.1689	1
4	1	0.001	0.2967	1	0	0.65	-11.6504	1
5	1	0.001	0.182	1	0	0.7272	-13.6027	1
6	1	0.001	0.1689	1	0	0.5819	-26.1484	1
7	1	0.001	0.053	1	0	0.9435	-9.7433	1
8	1	0.001	0.0638	1	0	0.9397	-10.4981	1
9	1	0.001	0.0687	0	0.9778	1.0247	2.0119	1
10	1	0.001	0.0507	0	0.9999	1.0357	3.6501	1

5.2.7.5. Significance of experimental results

The main concern of the experiment is to show that GME is a better estimator of the quality of healthcare due to the nature of the healthcare environment and the incomplete information that may be available. The reliable results obtained within the limits of the experimental conditions, show that the robustness of the GME estimator compared to the LSR method is not by chance.

It can also be seen from Table 5. 3 that whenever the null hypothesis is rejected, the *p-Value* is almost always zero, less than the significance level (0.05) used in the experiment.

In the first two tests, the null hypothesis was supported (t-test h = 0) with *p-values* of 0.9113 and 0.9997 respectively. The corresponding values of 0.053 and 0.237 for the "Extreme power" of these tests, however, make the support for the null hypothesis less convincing. This is because such low values of the "Extreme power" mean that the test is not capable of rejecting the null hypothesis if it were really false which may be the case in the first two tests.

The significance of these experimental results is that they provide considerable insight into the performance of the GME estimation method under various combinations of sample size and independent variable distributions. This is a significant contribution because whilst other researchers (e.g. Ciavolino, 2007; Ciavolino & Dahlgaard, 2007; Al-Nasser, 2003) have found that the GME estimator is superior to other methods; their findings were based on single factors such as sample size, data pattern or the presence of multi-colinearity. In addition, this experiment shows that GME is still superior even under the combined effects of several factors. One significant observation from Figure 5. 6 and Figure 5. 7 is that at high values of sample size, the two methods converge in performance. Thus the effects of the input variable distribution pattern on the mean squared error and standard errors as well as the bias seem to disappear.

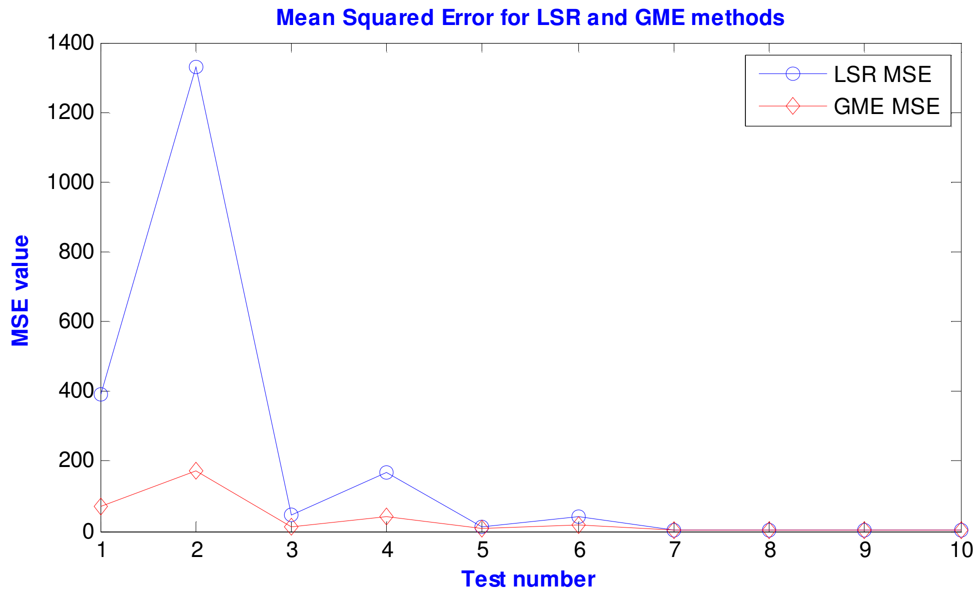


Figure 5. 6: Mean squared error for LSR and GME methods

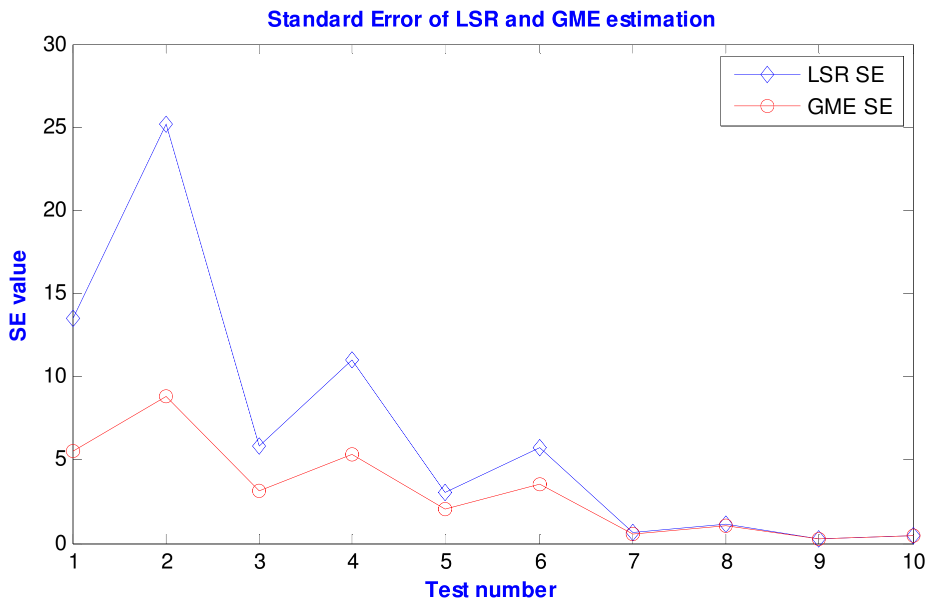


Figure 5. 7: Standard errors for LSR and GME methods

5.2.7.6. Implications and conclusions from experimental results

The results have suggested that the null hypothesis can be rejected in favour of the alternative hypothesis. This leads to the conclusion that the GME estimator is a more robust estimator of the performance of healthcare than the LSR method.

The conclusion confirms the fact that the GME method has numerous conceptual advantages that makes it the most ideal real-time estimator in an environment where most factors follow a random behaviour. For the E-Track NHS concept to have any practical implications, it requires a real-time (continuous) estimation of the index, and needs a methodology that is robust as the GME method has proved to be.

Another important implication of having a robust and reliable index of performance is that it makes it possible to readily obtain an index for any attribute that is used to define performance in any aspect of healthcare. The only requirement being that the relationship between the index and performance indicators should meet the linearity assumption used in the formulation (see section 5.1). For instance if performance is measured in terms of cost, quality of care, patient satisfaction etc., then a cost index, quality index or patient satisfaction index can be obtained.

To test the index, an empirical application as a Healthcare Quality Index (HQI) is presented in section 5.3.

5.3. Empirical study: Healthcare Quality Index (HQI) of an Emergency Department

The work presented so far may be likened to the development and design of a physical measuring instrument that has been tested in the laboratory and found to be capable of achieving its purpose. The next stage is to test this instrument with empirical data to further validate its functionality.

An empirical study with the HPI model that underscores the reliability, validity and robustness of the index is presented. This study is based on a combination of data obtained by interviewing patients (n = 25) in an accident and emergency department in London as part of a wider research study approved under the Research Governance Framework (Gore et al., 2008), and data from the Healthcare Commission's 2006 survey of adult in-patients. A number of key quality indicators and factors to be used are identified in the next section. By this application of the HPI specifically to the concept of quality as a measure of performance, it is subsequently referred to as the Healthcare Quality Index (HQI).

5.3.1. Determination of the Key Quality Indicators (KQIs)

The key quality indicators used for this empirical study were extracted from a study conducted by the Picker Institute, Europe for the NHS patient survey programme. The aim of the study was to determine the most important indicators of quality in various aspects of emergency care. These indicators were included in the 2003 NHS Acute Trust Emergency Department Survey (see appendix A). Sample size *n* was equal to 21.

Based on the above, as well as further data on the patient experience collected as part of the wider research study (Gore et al., 2008), and in order to keep the current project reasonably manageable, the following factors have been chosen as the Key Quality Indicators (KQIs) of emergency and inpatient care to be used for the study:

- Dignity
- Confidence in doctors/nurses
- Communication/Information

The above list also included cleanliness and waiting time, but due to problems explained in section 5.3.3, these had to be eliminated. Each indicator has five factors as shown in Table 5. 4. The numbers in brackets stand for the question number in the Healthcare Commission's survey questionnaire used as the indicator. Question number 66 was used as patients' perception of the overall quality of care they received and used to validate the estimated healthcare quality index.

The data used in this study, belongs to an NHS Trust that was not highly rated in the 2006 survey (this is not the same NHS Trust where primary data was collected). To help interpret the HQI values obtained in this study, note the response of patients to a major question in the survey (see question 66 of appendix I):

“Overall, how would you rate the care you received?”

This Trust scored 64 out of 100. The threshold score on the above question for the best 20% of NHS Trusts was 80. Given that the data used in this study was obtained from this NHS Trust, the values of the HQI cannot be expected to be significantly high.

Table 5. 4: Key Quality Indicators and their factors variables (values in bracket represent question number of a variable as it appears in the Healthcare Commission's 2006 in-patient survey)

KQIs	*FACTOR VARIABLES*
1. Dignity (64)	F1. Were you given enough privacy when being examined or treated in the Emergency Department? (8) F2. While staying in hospital, did you ever use the same bathroom or shower area as patients of the opposite sex? (19) F3. Did doctors talk in front of you as if you weren’t there? (28) F4. Did nurses talk in front of you as if you weren’t there? (32) F5. Were you involved as much as you wanted to be in decisions about your care and treatment? (36)
2. Confidence (27)	F1. Did you have confidence and trust in the nurses treating you? (31) F2. Sometimes in a hospital, a member of staff will say one thing and another will say something quite different. Did this happen to you? (35) F3. Did you find someone on the hospital staff to talk to about your worries and fears? (39) F4. How would you rate how well the doctors and nurses worked together (65) F5. In your opinion, were there enough nurses on duty to care for you in hospital? (33)
3. Communication (7)	F1. Did a member of staff tell you about any danger signals you should watch for after you went home? (60) F2. When you had important questions to ask a doctor, did you get answers that you could understand? (26) F3. When you had important questions to ask a nurse, did you get answers that you could understand? (30) F4. How much information about your condition or treatment was given to you? (37) F5. Did hospital staff tell you who to contact if you were worried about your condition or treatment after you left hospital? (62)

5.3.2. Data collection

In order to validate the Key Quality Indicators, primary data was collected via semi-structured interviews with patients (n = 25) in a district general hospital undergoing radical change (new acute hospital model) (see appendix G). The questions used were based on a questionnaire developed for use in the wider evaluation of this new hospital model. NHS ethical approval was granted for the research and informed consent obtained in all cases. The assessment of the performance of the hospital is outside the scope of this research work.

5.3.2.1. Problems with data

The Healthcare Commission's raw data on the national patient survey was used in the current study. This secondary data was obtained from the UK data archive for the 2006 in-patient survey. A few problems were, however, encountered with the acquired data set:

- Out of 850 records, only 9.5% of the data (n = 80) contained all the factor variables in the selected quality indicators. This placed a limit on the sample size. This problem is an additional reason for the need for a real-time data acquisition and holding system as proposed in this research.

- In cases where questions were posed with the possibility of indecision (e.g. a response of "can't remember" or "did not need help"), such responses were counted as high satisfaction. It has been estimated that five out the 18 questions used in this study had that possibility and on average only 9% of responses are affected by this assumption.

5.3.3. Data pre-processing

The data obtained were pre-processed by converting every patient response to a satisfaction value to provide one common unit of computation. This conversion was done with the CORE satisfaction evaluation algorithm proposed by Mousavi et al. (2001). This pre-processing is advantageous in that it reduces all the responses to a value between 0 and 1.

Furthermore, it provides added consistency in that though the key quality indicators and factors are different subjective measures, it is still possible to add them up because they are all converted into a common construct - satisfaction level.

5.3.4. Result of HQI test

The main goal of this study was to apply the Healthcare Quality Index to real data and estimate how well it measures patients' perception of quality of care. Figure 5. 8 shows plots of the estimated overall HQI and empirical quality measured by patients' responses to question 66 in the Healthcare Commission's in-patient survey (appendix I).

The means of the quality of care obtained empirically (Data Set 1) and that predicted by the HQI (Data Set 2) were compared using a two-tailed, two-sample t-test. The test rejects the null hypothesis that the means (0.514 for empirical data and 0.618 for estimated data, n = 80) of the two data sets are equal with a *p-value* of 0.0206 at 5% significance level and two-tail (see Table 5.5). This means that the estimated quality of care using the HQI is significantly different from the empirical values.

Table 5. 5: Two sample t-test of means of empirical and estimated quality of care

	Empirical	*Estimated*
Mean	0.5139875	0.6177625
Variance	0.114848781	0.04198188
Observations	80	80
Hypothesized Mean Difference	0	
df	130	
t Stat	-2.34380918	
P(T<=t) one-tail	0.010302128	
t Critical one-tail	1.656659413	
P(T<=t) two-tail	0.020604256	
t Critical two-tail	1.978380378	

This result can be attributed to the data sample size and the fact that the Key Quality Indicators used are less than what is required to represent the total perception of patients regarding the quality of care.

However, in view of the limitations of the study, the performance of the index is very satisfactory in that it is consistent with increases and decreases in the empirical values and has less deviation from the mean. In other words the behaviour of the index is satisfactory.

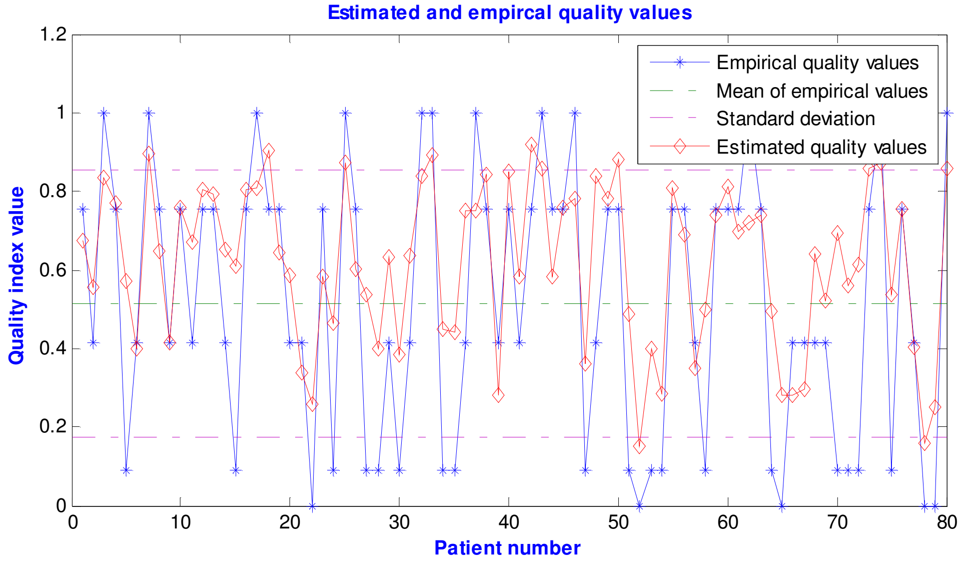


Figure 5. 8: Plot of estimated quality index and empirical quality

Figure 5.9 shows plots of the predicted values of the three Key Quality Indicators – Dignity, Confidence and Communication. The mean values of the indicators were found to be 0.62, 0.75 and 0.69 for Dignity, Confidence and Communication respectively. These are levels of satisfaction, which means that on average, patients were most satisfied with the confidence they had in the doctors and nurses.

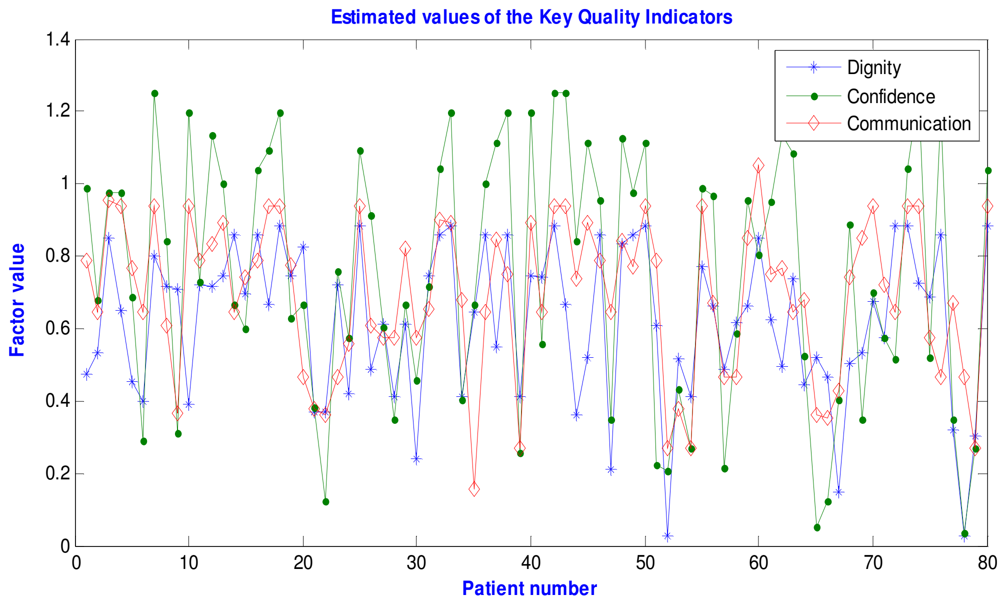


Figure 5. 9: Estimated values of the key quality factors

5.3.5. Sensitivity analysis

In equation 5.6, the HQI was expressed as a linear combination of Key Quality Indicators (KQIs) where each indicator has an importance weight. The importance weight was assumed to be 0.3 in this test for each HQI. Figures 5.10, 5.11 and 5.12 therefore reflect the importance of the indicators with reference to how they change with the index values.

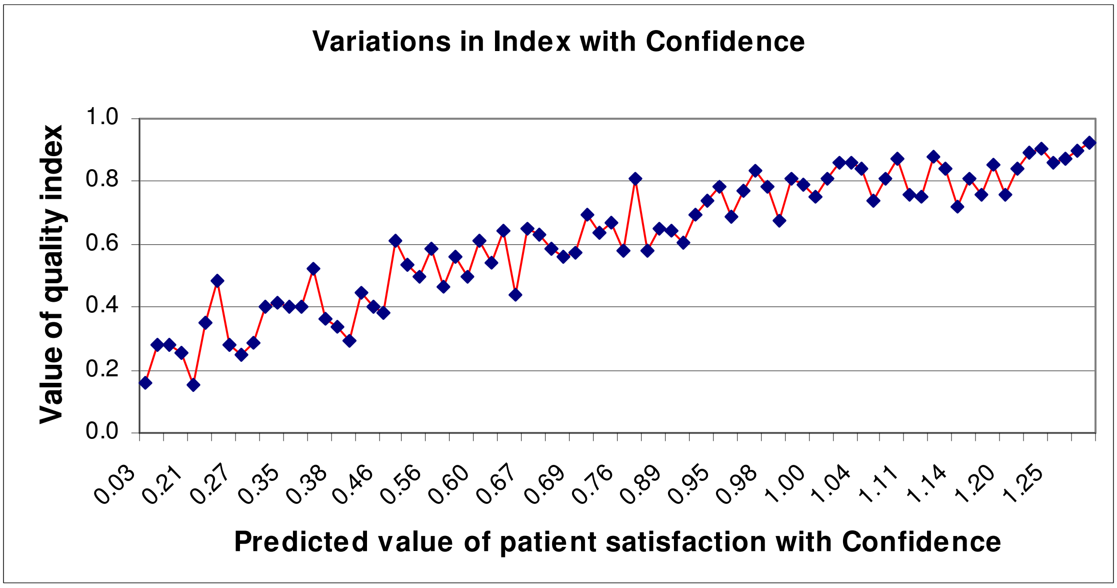


Figure 5. 10: Variations in index with Confidence

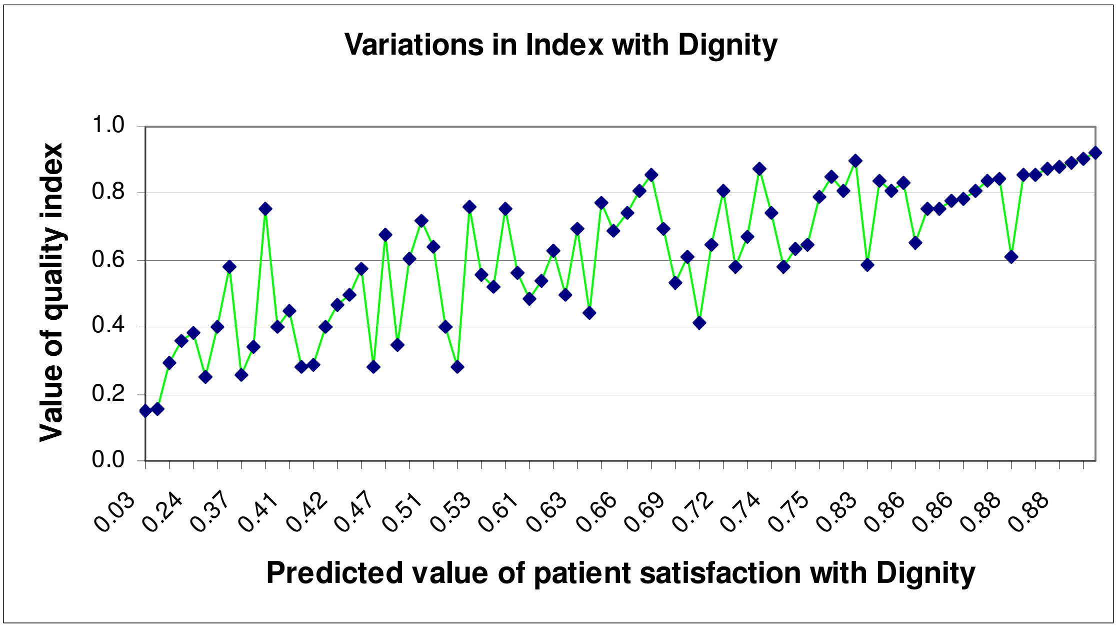


Figure 5. 11: Variations of index with Dignity

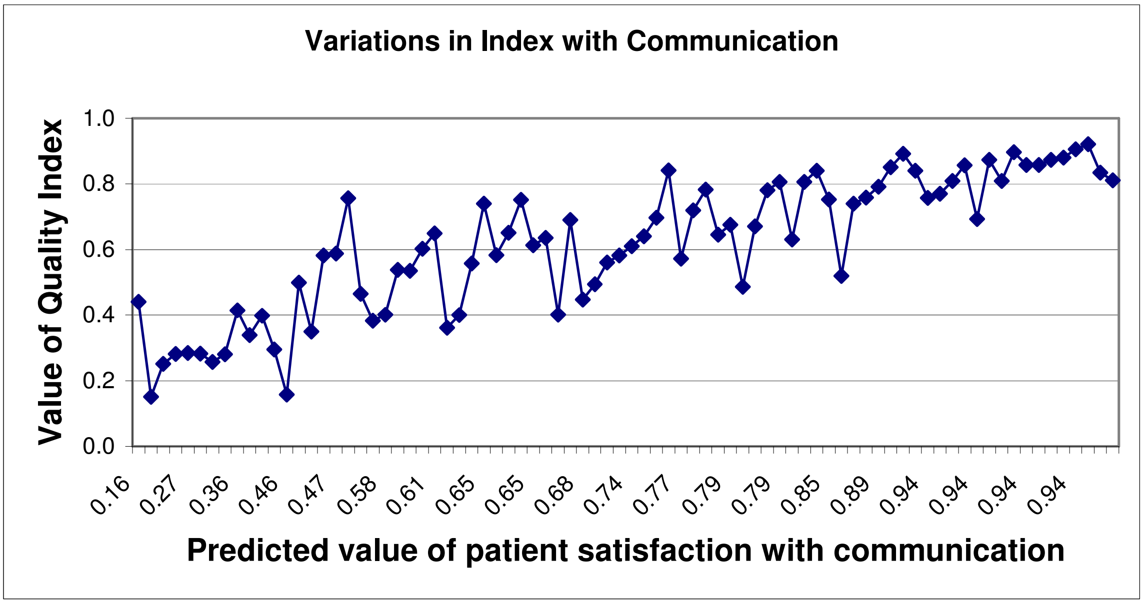


Figure 5. 12: Variations of index with Communication

Also in equation 5.7, the HQIs were represented as linear combinations of the various factor variables. These factors together with the KQIs are shown in Table 5.4. The beta coefficients of equation 5.7 were estimated using the entropy optimisation principle.

The entropy estimated coefficients are shown in Table 5.6. F1, F2, F3, F4 and F5 are the factor variables shown in Table 5.4. One of the desired properties of the HQI or HPI (see chapter 3) is that the index should respond well to changes in the values of the KQIs. It was also desired that the index should increase with increases in the KQIs. The entropy principle uniquely satisfies these properties by the estimation of beta values that are all positive as shown in the table.

Table 5. 6: Entropy estimated coefficients for the factor variables

Factor	Dignity	Confidence	Communication
F1	0.2395	0.2678	0.0989
F2	0.2207	0.2448	0.3895
F3	0.0704	0.3422	0.2225
F4	0.3023	0.2138	0.2393
F5	0.0491	0.1814	0.1851

This study is mainly concerned with the reliability of the index developed in this chapter and not with the identification of the most important factors that influence quality of care at this stage. However, the first KQI – Dignity - would be briefly discussed to provide an indication of how the index may be affected by changes in the factor values.

It may be observed from Table 5.4 that the KQI – Dignity - has patients' response to the following factors:

F1 – Were patients given enough privacy when being examined?

F2 – Did patients use the same bathroom or shower with the opposite sex?

F3 – Did doctors talk in front of patients as if they were not there?

F4 – Did nurses talk in front of patients as if they were not there?

F5 – Were patients involved as much as they wanted in decisions about their care?

Results in Table 5.6 show that patients' perception of dignity is most sensitive to how nurses talk in front of them (F4) with a coefficient of 0.3023. The results also show that the respondents' perception of dignity were least affected by whether or not they were involved in decisions regarding their care.

These results are, however, not entirely accurate since the predicted values did not perfectly match the empirical data. Figure 5.13 shows plots of the random errors in the estimation. The residual errors seem randomly distributed since no obvious bias may be observed in the plot. This is a required condition for a reasonable estimation process (Keller & Warrack, 2003).

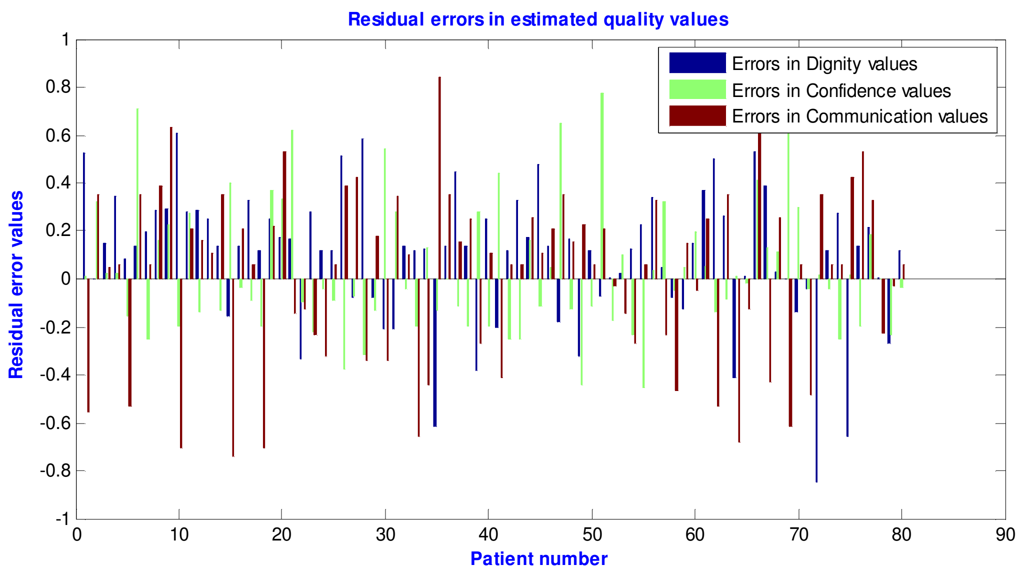


Figure 5. 13: Residual errors for estimated indicator values

Before concluding this chapter, a brief comparison of the application of the HQI and the current performance rating system in the NHS is presented.

5.3.6. Comparison with Healthcare Commission performance rating

Consider the example of the Healthcare Commission performance rating in Box 4.1 (chapter 4). “The Trust” was rated “Excellent” both in quality of service and use of resources. And as shown in the box, “The Trust” had made improvements from last year’s performance.

The questions that were posed are:

1. Can patients expect that “Excellent” level of performance in all departments of “The Trust”?
2. Can the same level of quality be maintained until the next assessment?

These questions form the main motivation behind the development and testing of the HPI in this chapter. The argument is repeated here that by continuously monitoring the quality, there will be the opportunity to detect changes in quality of care and thus be able to take action and improve quality within shorter lead-times. Furthermore, the automated or real-time process would avoid loss of data and provide continuous feedback on the performance of the system.

5.4. Conclusions

This chapter argued that in an environment where there is bound to be uncertainty, the GME estimator is a more robust and less biased technique for describing system parameters than the LSR method.

This implies that in the dynamic estimation of performance in a healthcare environment where many of the determining factors are hidden, the GME estimation method should be preferred since it requires less assumptions and is not significantly affected by sample size and data patterns.

Using the GME methodology, the HPI was formulated to be applicable to a range of performance measures in healthcare. The only caution here is that it was assumed that the index is a linear combination of the Key Performance Indicators and hence any application of it must conform to this requirement.

An empirical test was conducted with the HPI applied as a Healthcare Quality Index (HQI). The HQI was to predict values of healthcare quality based on data obtained from the Healthcare Commission's 2006 adult in-patient survey. A two-sample t-test showed a significant difference between the means of the predicted quality values and empirical value of patients' perception of service quality. The differences in the quality values have been attributed to the problem that the data used included a limited number (3) of Key Quality Indicators (KQIs) due to shortcomings in the available data.

In spite of the data problem the index was observed to respond satisfactorily to changes in the key quality factors of dignity, confidence and communication. The gradient of the relation between each of the factors and the quality index did not seem significant partly because all the factors were given the same importance weighting in the study.

One weakness of the GME estimation method that was observed during the experiment was the settings of the support space. This has been found to require a compromise between accurate results and avoiding errors in the estimation process. The wider the error support range specified the less likely it is to encounter problems during the estimation, but that is at the cost of slightly higher error estimates.

The primary objective of the HPI is to implement its algorithm in E-Track NHS for the real-time monitoring of its values. The focus of the empirical work in this chapter has been the test of the HQI as a reliable measure of quality of care.

E-Track NHS has two main performance measures – The HPI and the S-PSRM. The next chapter logically presents the development and empirical test of the S-PSRM.

6. Effective Satisfaction in Healthcare Systems

"Ideally, quality healthcare should result in the satisfaction of both the patient and the practitioner."

Hudelson et al. (2008, p. 33)

In the previous chapter, the concept of the HPI and its formulation were presented.

The concept and mathematical formulation of the Staff-Patient Satisfaction Relation Model (S-PSRM) are discussed and argued for in this chapter. The mathematical formulation aims to:

1. Explain the variations between staff satisfaction and workload (measured in terms of time spent with patients).

2. Demonstrate that there is a strong relationship between patient satisfaction with waiting time and staff satisfaction with their workload.

3. To explain how service improvement policies may be mapped onto satisfaction values operational capability (resource availability and utilisation).

The literature review discussed in chapter 2 suggests that there are established models that quantitatively measure the satisfaction of customers with key service attributes. However, if one takes a system view of any organisation, it may be argued that the ability to measure patient (customer) satisfaction to drive performance may be necessary but not sufficient for the overall wellbeing of the system. It is argued here that better performance is attainable when the effective satisfaction level of the system is considered by understanding the complex relationship between service provider satisfaction and that of the service users. In this chapter, the philosophy and the mathematical representation of this relationship is proposed. Effective satisfaction as used in this chapter basically means a focus on finding a synergy between patient satisfaction and staff satisfaction and then using this synergistic approach to help define and drive improvements in service quality.

The NHS in England has become target driven, which has resulted in considerable improvements, but also a change in focus towards "meeting targets", at the cost of patient and staff experiences (Bevan & Hood, 2006b). Some researchers have questioned if the NHS is sufficiently resourced or just trying to cope (Wolstenholme et al., 2005). The constraints on resources are set to rise, as the European Working Time Directive (EWTD) approaches its deadline in August 2009 (DoH, 2007). According to this directive, all junior doctors are required to reduce their weekly working hours to 48hrs. This has been established by English law and is not optional for any NHS organisation. It is important to note that the rationale for the EWTD is to reduce staff workload which is believed to have a positive impact on customer or patient experience.

No theory or principle has been found, to the author's knowledge, which tries to explain the dynamics of the relationship between patient satisfaction with waiting time and its effect on staff so as to guide policy makers and inform the target setting process. The importance of this relationship is underscored by Avedis Donabedian (1966) in saying that:

"…before one can make judgements about quality, one needs to understand how patients and physicians interact and how physicians function in the process of providing care."

Section 6.1 presents the rationale for the S-PSRM. The application of Little's Law to healthcare systems is then discussed in section 6.2. Section 6.3 focuses on the development of the model and its testing. In section 6.4, the statistical hypothesis tests are presented. Section 6.5 discusses how the basic model may be extended to a network of queues and the implications of the S-PSRM are presented in section 6.6. The work in this chapter is then summarised in section 6.7.

6.1. The rationale for the Staff-Patient Satisfaction Relation Model (S-PSRM)

Satisfaction research in healthcare has been solely focused on patients (Thompson et al., 1996; Trout, Magnusson & Hedges, 2000; Iezzoni et al., 2002; Chan & Chau, 2005; Vukmir, 2006). Several other researchers have looked at the subject of customer satisfaction together with employee satisfaction (Schmit & Allscheid, 1995; Vilares & Coelho, 2003; Wagner, 2006) in other areas. Vilares & Coelho (2003) described the lack of attention of the cause and effect relationship between employee behaviour and customer satisfaction in the European Customer Satisfaction Index (ECSI). The literature shows that these models are mainly descriptive in attempting to explain the cause and effect relationship between the two key aspects of service provision. To this date, as seen from the literature review presented in chapter 2, no analytical model has been proposed for this relation particularly at the operational level of measuring service quality and customer satisfaction. This could therefore be considered a key contribution in this research work.

The rationale for the S-PSRM model comes from an observation of the queuing (waiting time) problems and the effects of targets on services in the NHS.

6.1.1. Evidence of the queuing problem in the NHS

Targets introduced in the NHS, resulted in the reduction of the number of patients waiting more than four hours in Accident and Emergency in England from 23% in 2003 to 5.5% in 2004. Similar improvements were observed in ambulance trusts and elective hospital admissions (Bevan & Hood, 2006b). Bevan & Hood offered some reasons why recorded improvement may be doubtful. The reasons were:

- In order to meet the 4hr target, some Accident & Emergency (A&E) departments drafted in extra staff during performance assessment periods.
- Patients had to wait in ambulances until staff were confident to meet the target before they admitted them into the A&E.
- 1/3 of ambulance trusts had “corrected” response times to be less than 8min in order the meet the target.

Mayor (2003) also conducted a survey of 100 A&E consultants and found that 56% used temporary medical and nursing staff to reduce patient waiting times during the monitoring weeks. 25% also reported that they allow staff to work double hours during this period. These problems may be the result of ignoring the underlying systemic nature of the healthcare environment (Umble & Umble, 2005).

These problems indicate the need for further research into how to build up confidence in the annual monitoring reports, since the smallest amount of defective data may be misleading (Bird et al, 2005).

Bevan & Hood (2004) suggest the introduction of random performance assessments at the expense of transparency to limit the problem of targets. This may be helpful, but it may result in counter measures by staff consequently resulting into a trust crisis, lower staff morale and affecting service. Umble & Umble (2006) suggested and demonstrated that the use of buffer management systems may help improve the queuing problem. Cronin & Wright (2006) suggested the use of Breach Avoidance Facilitators (BAF). All of these suggestions fail to address the root of the problem – lack of understanding of the interaction between systems elements and how policies (or targets) affect operational capability. This problem has resulted in a gap between policies and operational capability. This part of this research is intended to stimulate debate about this problem and make a contribution towards the solution.

The above evidence (or gap in the state-of-the-art in healthcare quality management) is the premise on which the S-PSRM model is proposed from a systems point of view, where staff themselves will take ownership and would be able to detect system critical shortages and take actions. This is reminiscent of the Total Quality Management (TQM) philosophy which has been successful in other sectors.

The statements of the hypothesis for the model are presented and stated in the following section.

6.1.2. Statements of hypothesis

Customer satisfaction evaluation methods have been discussed in chapter 2. It was found that established methods exist for measuring the satisfaction of customers with various attributes of products or services. Thus the relationship between patient satisfaction and waiting time in queue can be measured by established methods as highlighted in the review. To establish the S-PSRM model, three hypotheses are defined for testing:

H_0^1 - There is no relationship between staff satisfaction and workload (measured in terms of service time).

H_0^2 - There is no relationship between staff workload and patient waiting time.

H_0^3 - There is no relationship between staff satisfaction with workload and patient satisfaction with waiting time in queue.

These hypotheses are treated theoretically in the following sections and tested in an empirical study.

6.2. Healthcare systems and Little's Law

Any queuing system that does not follow Little's Law (Askin & Standridge, 1993) will eventually become unstable, inefficient and lead to inability to satisfy its customers (Wolstenholme et al., 2005).

According to Little's Law, the number of entities (e.g. patients) waiting in a process will be proportional to the total time they spend in the process, assuming that the service rate is constant and the system is in steady state (i.e. the arrival rate is equal to service rate). This is mathematically given by;

$$N_p = \mu \; W_T \tag{6.1}$$

Where N_p = Average number of entities in process (WIP)

μ = Average servicing rate of entities (Production rate)

W_T = Average total time spent by a patient (Throughput time)

With Figure 6. 1, an intuitive explanation can be provided that if there are five patients in the system (i.e. $N_p = 5$) and the doctor can see 10 patients per hour (i.e. $\mu = 10$), then each patient will have to spend a total time of half an hour in the system (i.e. $W_T = 30$min). This simple example means that it is impossible to reduce the waiting time to below half an hour if the service time and rate of arrival into the system remain the same. Thus assuming the system is in a steady state, any attempt to do so will be breaking the law which will not work in the long run.

One may therefore ask, “Has the 4hr target on Accident and Emergency (A&E) departments been translated into such operational capability for staff and managers to have a mutual understanding of its validity?” The evidence suggests that the present targets have resulted in instability and an over-stretched healthcare system, thus leading to a negative effect on the morale of NHS staff.

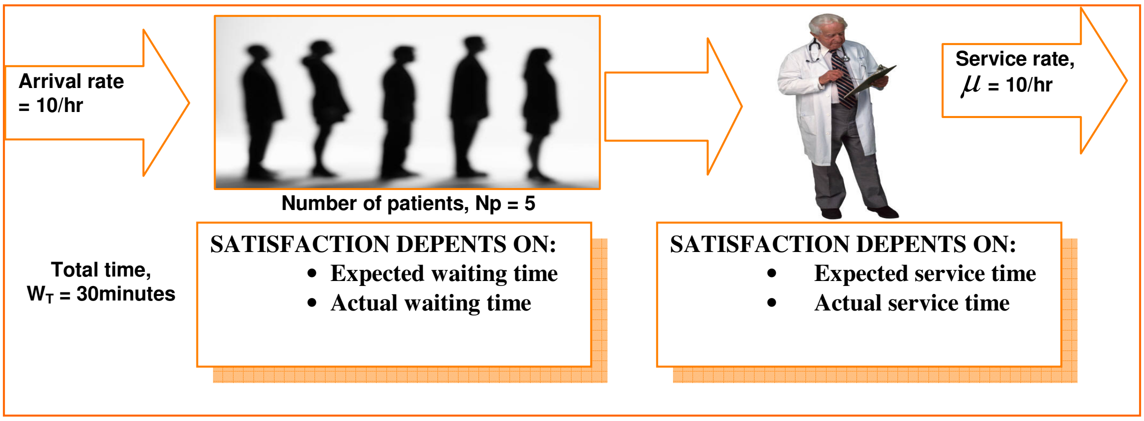


Figure 6. 1: A single server A&E system

Based on this observation, the proposed analytical model will help managers to understand the dynamics of how queuing systems behave and hence affect the satisfaction of both patients and staff.

Thus, considering patient and staff satisfactions in isolation will not be sufficient. Therefore, a method for determining an Effective Satisfaction Level (ESL) for the system, where both staff and patients are satisfied, resulting in increased quality of care, is proposed.

From this discussion it should be sufficient to reject the hypothesis H_0^2 and conclude that there is a relationship between patient waiting time in queue and service time or workload of staff. The hypothesis claims that patients' waiting time is not affected by staff service time which is the time staff spend seeing patients. From the above discussion however, this is clearly false.

Based on the single server queuing system (M/G/1) in Figure 6. 1 the model is developed in section 6.3 and then built up into the A&E as a network of queues in section 6.5.

6.3. Staff-Patient Satisfaction and Queuing theory

As shown in Figure 6. 1, the satisfaction of patients with waiting time in queue will depend on their expectations of how long they should wait and how long they actually wait. Similarly, the satisfaction of staff with time they spend with the patient depends on how long they assume to be ideal for the process (the process stands for a staff seeing a patient whether for triage, assessment or treatment) and how long they actually have to spend with the patient. For the purpose of the empirical work, this information was collected through a survey of A&E staff at one of the NHS Trusts in the West of London.

6.3.1. Assumptions of the model

A number of assumptions are made in the application of the queuing theory that must be borne in mind whilst interpreting the results obtained so far.

1. A key assumption of Little's Law is that the system is in steady state where the arrival rate into the system is equal to the departure rate from the system.
2. The entire A&E system has been considered as a system with a single doctor and a single queue (M/G/1) queuing model.
3. It was also assumed that the arrival process into the simplistic A&E system is Markovian therefore inter-arrival times are exponentially distributed.
4. The service times were also assumed to be any general distribution (e.g. triangular or exponential).
5. Patients in queue were also assumed to be served on a First Come First Served (FCFS) basis.

6.3.2. Model formulation for a single server queuing system (M/G/1)

This section presents the theoretical underpinnings for the S-PSRM model. The theoretical models for patient satisfaction, staff satisfaction and how they are related through service time and waiting time are discussed.

6.3.2.1. The evaluation of patient satisfaction

The Customer Orientation Route Evaluation (CORE) model proposed by Mousavi et al. (2001) is presented here as the preferred basic model for evaluating the satisfaction of patients with waiting time. The model is slightly modified to take into account the fact that waiting time is a "smaller-is-better" attribute and to take advantage of the entire satisfaction curve (see next subsection). According to the CORE model, the function for user satisfaction with a service attribute is given by;

$$S_{ij} = \arctan\left[\ln\alpha_{ij} + \frac{\pi}{2}\right] \times \left(-\frac{e^{-\varepsilon_{ij}} - e^{\varepsilon_{ij}}}{e^{-\varepsilon_{ij}} + e^{\varepsilon_{ij}}}\right) + 1 \qquad 6.2$$

$$= \omega \tanh(\varepsilon_{ij}) + 1 \qquad 6.3$$

Where

α_{ij} is the level of importance of an attribute

$$\omega = \arctan\left[\ln\alpha_{ij} + \frac{\pi}{2}\right] \qquad 6.4$$

$$\tanh(\varepsilon_{ij}) = \frac{e^{\varepsilon_{ij}} - e^{-\varepsilon_{ij}}}{e^{\varepsilon_{ij}} + e^{-\varepsilon_{ij}}} \qquad 6.5$$

CORE evaluates the value of ε_{ij} as follows;

$$\varepsilon_{ij} = -abs\left[\frac{v_i - v_{ij}}{v_i}\right] \qquad 6.6$$

$$-1 \le \varepsilon_{ij} \le 0 \qquad 6.7$$

Where

i is the service attribute,

j is the customer,

v_i is the ideal value of the attribute (that the best possible with available resources) i,

v_{ij} is the actual value of service attribute i, for customer j,

ε_{ij} is the distance between the ideal value for attribute i, and the actual value for customer j.

CORE puts a boundary on the attribute value. In the formulations above (equations 6.2-6.7), the boundary value for the actual customer experience is the ideal (v_i), so that the actual value (v_{ij}) cannot be less than the ideal value, since it is interpreted as the best possible value. This is true for a "smaller is better" service attribute such as waiting time. The smallest possible value is 0 minutes when there is no wait. For a given system, the ideal value may be set at a reasonable level based on available resources. The ideal value is used here in place of the customer's expectation as in the disconfirmation model discussed in chapter 2. In this way, knowing the customer's actual experience we can calculate his or her level of satisfaction with waiting time based on the difference between the actual and the ideal values of the waiting time. The CORE model however, has some limitations that make it difficult for it to be applied in its original form.

A generalisation of the CORE model is therefore suggested and applied for the measurement of patient and staff satisfaction in this chapter. The purpose of the generalised model is firstly, to define parameters that can extend the applicability of the basic CORE model and facilitate cross industry or sector comparison. Secondly, this generalisation is necessary as to extend the range of values of the relative distance for which satisfaction can be obtained as shown in Figure 6. 2.

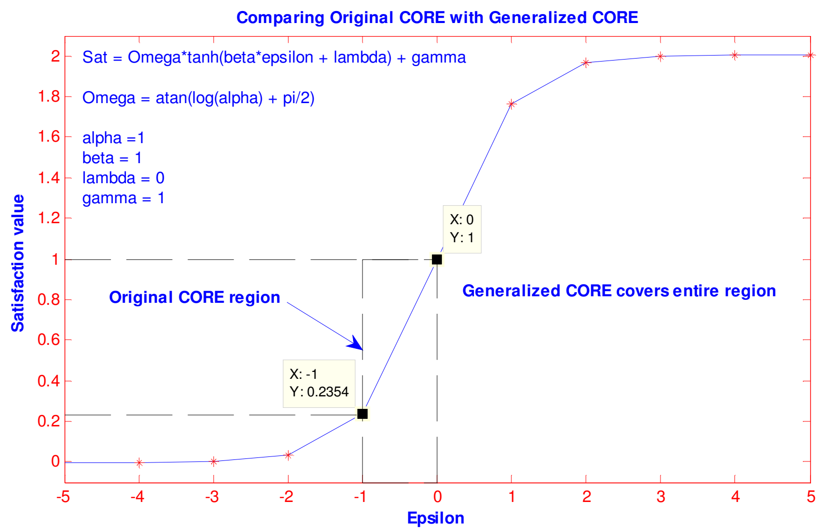


Figure 6. 2: Limitations of the original CORE model

It is also important to note that for the current application, it is desired to sometimes convert an actual service time value into a corresponding actual waiting time for patients. This will help to predict the level of patient satisfaction with waiting time at a desired level of actual service time. Preliminary tests have shown that this may sometimes result in relative distance (ε_{ij}) values for waiting time outside the basic CORE region (shown above) and hence the need to widen the range. A detailed description of the modification is presented in appendix B.

6.3.2.2. The generalised CORE model

A generalised customer satisfaction model is suggested with well defined parameters to facilitate its application in different areas. The generalisation is proposed based on an analysis and scrutiny of the model developed by Mousavi et al. (2001).The generalised model is stated as:

$$P(\varepsilon_p) = \omega \tanh(\beta \varepsilon_p + \lambda) + \gamma \tag{6.8}$$

Where

ω is the range factor, $\omega \neq 0$

β is the sensitivity factor, $\beta \neq 0$

λ is the horizontal location factor

γ is the vertical location factor

$$\varepsilon_p = \frac{W_{ideal} - W_{act.}}{W_{ideal}} \qquad 6.9$$

W_{ideal} is the ideal or expected waiting time. It may also be referred to as the target waiting time.

$W_{act.}$ is the actual waiting time in queue for a patient.

ω has the effect of closing or widening the range satisfaction values for the function. For all the curves in Figure 6. 3, the value of ω is 1 but if for example ω is set to 0.5 for the $P(\varepsilon) = \tanh(\varepsilon) + 1$ curve, its values will start from 0.5 to 1.5 instead of from 0 to 2 as shown in the figure.

β is the sensitivity factor and has the effect of increasing or decreasing the sensitivity of the function. Figure 6. 3 shows a curve with β = 2.

λ, the horizontal location factor is used to adjust the location of the curve along the horizontal axis. This is useful in determining at which value of the function ε_p = 0. Figure 6. 3 shows curves with λ = 1.

γ, the vertical location factor is also used to adjust the location of the curve along the vertical axis. This is also useful in ensuring that all values of the function are positive. Figure 6. 3 shows curves with γ = 1.

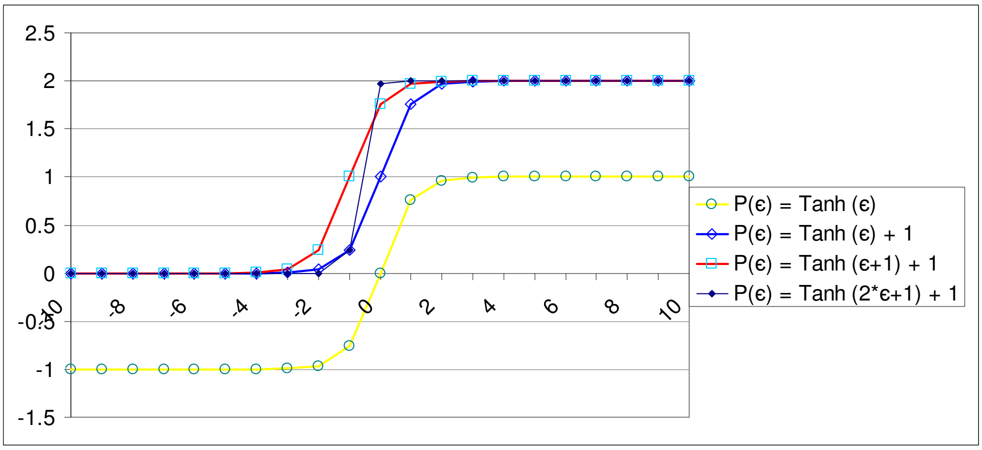


Figure 6. 3: Effects of the parameters of the generalised satisfaction model

Equation 6.3 therefore can be seen as a special case of the generalised model where $\beta = 1$, $\lambda = 0$ and $\gamma = 1$.

Figure 6. 4 is therefore the form of the CORE satisfaction model that would be applied in this chapter because it is closer to the satisfaction behaviour of patients. The value of lambda the horizontal locator is set to 2 so that the maximum value of satisfaction occurs at a relative distance (epsilon) equal to 0. The value of beta is set to 3.

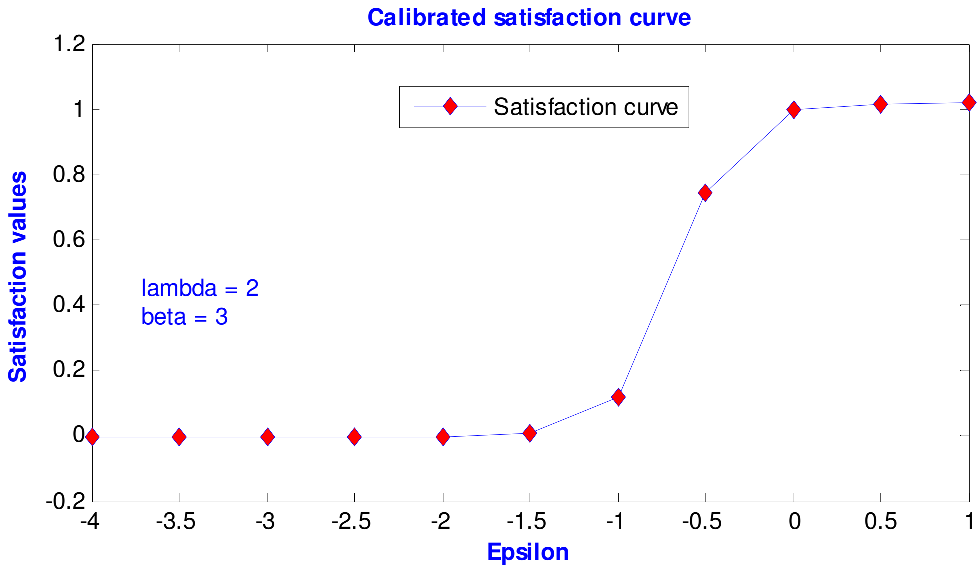


Figure 6. 4: The generalised satisfaction curve

6.3.2.3. Evaluating Staff satisfaction

This section presents the theory behind the staff satisfaction model. This model is firstly developed for measuring the satisfaction of staff but it also provides a means of relating the satisfaction of staff to that of patients as shown in the empirical study in section 6.3.3.

Three conceptual model options were tested in theory to represent the satisfaction of accident and emergency staff with service time (workload). The first two are the inverted catenary function and a Gaussian model which are both excluded from this discussion because they were not considered appropriate for modelling the relationship between staff satisfaction and service time. The catenary function has a symmetric form but the empirical data showed that the relationship between satisfaction and service for staff was not symmetric. The Gaussian model was also not appropriate because the form of the model that fitted the empirical data was considered too complicated

The third option was to use the hyperbolic tangent function as in the CORE model, but in two parts. This was desirable because of the well defined parameters of the model. One form of the model is shown in Figure 6. 5. The actual shape of the curve will be determined when the model is tested against empirical data and its parameters are determined.

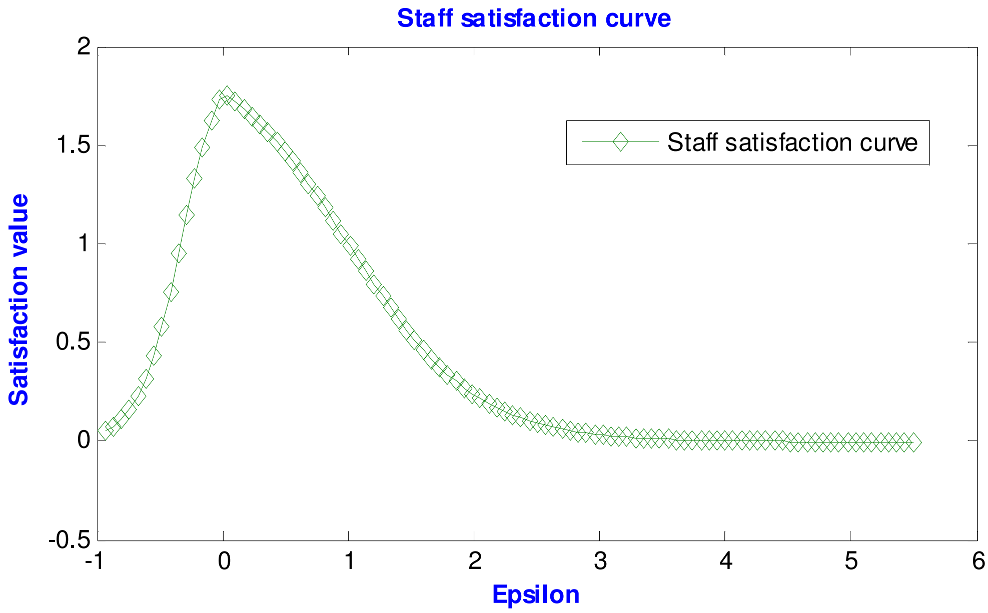


Figure 6. 5: The staff satisfaction curve

Mathematically, this is given by;

$$S(\varepsilon_s) = \omega_1 \tanh(\beta_1 \varepsilon_s + \lambda_1) + \gamma_1 + \omega_2 \varepsilon_s \tanh(\beta_2 \varepsilon_s + \lambda_2) + \gamma_2 \qquad 6.10$$

Where

ω_1 is the range factor for the first half of the curve, $\omega_1 \neq 0$

β_1 is the sensitivity factor for the first half of the curve, $\beta_1 \neq 0$

λ_1 is the horizontal location factor for the first half of the curve

γ_1 is the vertical location factor for the first half of the curve

ω_2 is the range factor for the second half of the curve, $\omega_2 \neq 0$

β_2 is the sensitivity factor for the second half of the curve, $\beta_2 \neq 0$

λ_2 is the horizontal location factor for the second half of the curve

γ_2 is the vertical location factor for the second half of the curve

and

$$\varepsilon_s = \frac{S_{act} - S_{ideal}}{S_{ideal}} \qquad 6.11$$

S_{ideal} is the ideal service time, thus time staff are happy to spend with patients to enable them to work effectively.

S_{act} is the actual service time, that is the amount of time the staff actually spend.

The above mathematical representations form the basis on which hypothesis H_0^2 in section 6.4.2 would be tested. The objective will be to fit this model to empirical data to determine appropriate values of the parameters and to determine if the R^2 value of the model's fit to the empirical data exceeds 70%.

6.3.2.4. Relating staff service time and patient waiting time in queue

It is possible to estimate the variations in staff satisfaction with waiting time by establishing a relation between service time and waiting time in queue (Askin & Standridge, 1993). We will first use a single server queuing model analysis and then later generalise the model to cover a network of queues.

A. The initial system assumptions:

- There is only one doctor/nurse serving a single queue of patients as shown in Figure 6. 1.
- The queuing discipline is First Come First Serviced (FCFS) - this will be extended to cover a priority based queue.
- The arrival process is a Poisson distribution therefore inter-arrival times are exponentially distributed (Kelton, Sadowski & Sturrock, 2007).

- Service time is any general distribution (triangular in this case)

B. Known parameters

The following parameters are known for the above system;

- Average inter-arrival rate = λ
- Average service rate = μ
- Average service time = S = μ^{-1}
- Number of servers = c
- Utilisation factor = $\rho = \dfrac{\lambda}{c\mu}$

C. Unknown parameters

We want to know:

- The average total or throughput time for patients in the system, W_T
- The average time in queue, W_q
- Total Number of patients in the system or WIP, N_p

Note: that Little's law is the basis for the following analysis. The statement of the law is as follows:

$$N_p = \mu \ W_T \qquad 6.12$$

Where

N_p = Number of patients in process (WIP)

μ = Servicing rate of patients (Production rate)

W_T = Average total time spent by a patient (Throughput time)

D. M/G/1, FCFS (exponential inter-arrival, any general service distribution, 1 server, with a first come first served queue)

For an *M/G/1* queuing model, Askin & Standridge (1993) provide the following solutions;

Estimated total time of patients would be,

$$E(W_T) = E(S_{act}) + \frac{\lambda E(S_{act}{}^2)}{2(1-\rho)} \tag{6.11}$$

Estimated total number of patients in system,

$$E(N_p) = \rho + \frac{\lambda^2 E(S_{act}{}^2)}{2(1-\rho)} \tag{6.12}$$

From the above, we may obtain the estimated time in queue as,

$$E(W_{act}) = E(W_T) - E(S_{act}) \tag{6.13}$$

The expected or ideal service time for staff, S_{ideal}, has been determined from interviews with staff for most of the A&E processes. The staff interviews were part of a wider study at one of the major district hospitals in London (Gore et al., 2008) and specifically designed also to address this research study. Full details of the development of the interview schedule for staff are presented in section 6.3.2. The expected or ideal service time for staff is considered to be the time staff are happy to spend seeing a patient at a particular stage. As a result this is their highest satisfaction point.

When a target is imposed on the system as to how long patients should wait in a queue, W_{act}, this can then be translated into the actual or required service time for staff, S_{act}, using equation 6.11, which then helps to determine their satisfaction at that target.

W^i_{act} is the best possible level of service that the system can provide within given resource constraints and is not likely to be the prevailing level of operating performance (W^o_{act}). Using this to estimate the satisfaction of patient and staff may not give a good reflection of reality. This will, however, be very useful in determining how well the system is performing against what it is capable of doing.

W^o_{act} on the other hand is the current level of performance which may be easily estimated from operating conditions and should give a better reflection of satisfaction values.

6.3.2.5. Relating staff satisfaction to patient satisfaction

A relationship between staff and patient satisfaction that will enable managers to understand the impact of queue related patient satisfaction on staff is proposed. The novel performance measure proposed here is termed the Effective Satisfaction Level (ESL) and is defined as the highest level of patient satisfaction at which a system can be operated in order to maximise staff satisfaction with workload. This analysis is considered important, because in reality queues cannot be considered in isolation, since they are an integral part of the system. Every effort to reduce queues without consideration for system capacity will not yield the desired results.

The object of the analysis in this section is to provide the functions of patient satisfaction (equation 6.8) and staff satisfaction (equation 6.9) on the same axes of ε_p. With this, it will be possible to estimate patient satisfaction and staff satisfactions at a given level of actual waiting time (W^o_{act}). This is shown in Figure 6. 6.

Operating in the direction of arrow "B" (thus to the left of the ESL) e.g. at point "C", means staff are taking longer than they expect for their processes and hence queues will increase and result in lower values of patient and staff satisfaction. Similarly, operating in the direction of arrow "A" (thus to the right of the ESL), e.g. at point "D", means additional capacity is injected into the system or staff are working at faster rate than they would normally like to do, so this will potentially reduce patient waiting time in queue but at the cost of staff satisfaction due to the fact that they may not be spending enough time with patients thereby affecting other quality indicators such as communication and treating patients with dignity. This analysis therefore is helpful in understanding the performance of staff under this condition.

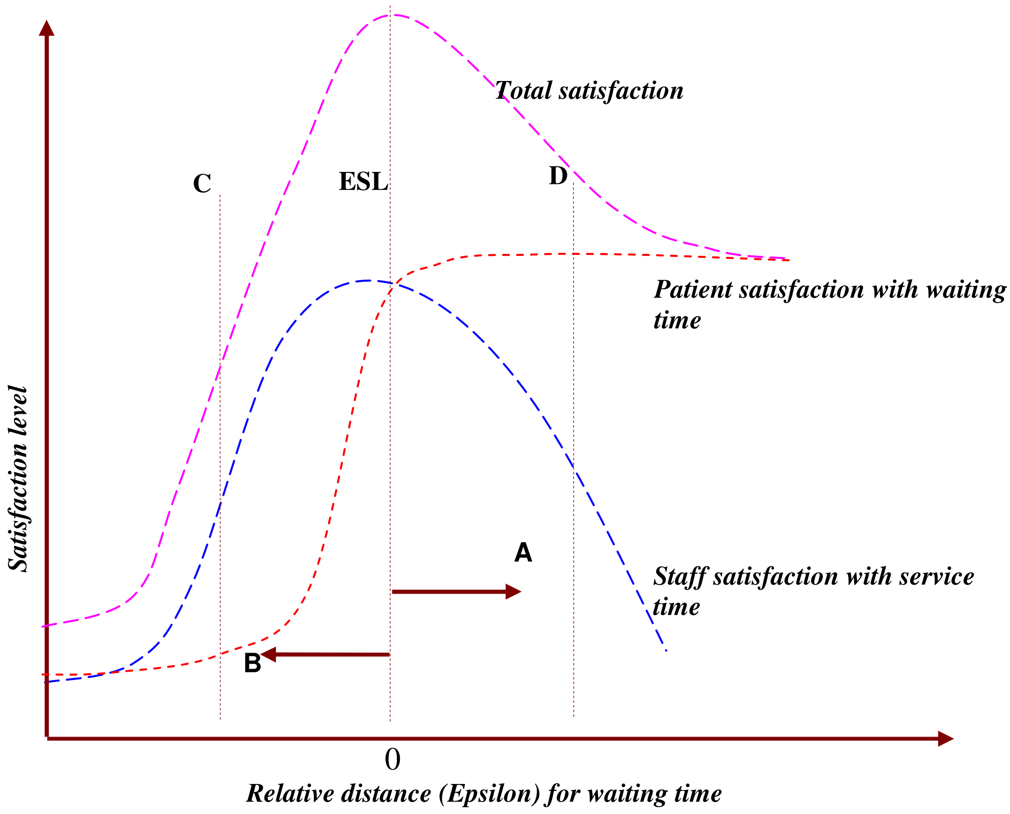


Figure 6. 6: Staff-Patient satisfaction relation

6.3.3. Design of empirical study

6.3.3.1. Objective

1. To show that staff satisfaction is a function of the time they spend with patients. This is done by estimating the proportion of staff population that exhibit changes in satisfaction with respect to changes in their service time.

2. To show the nature of the relationship between staff satisfaction with service time and patient satisfaction with waiting time.

3. To use the combination of the above objectives to determine an Effective Satisfaction Level (ESL) for the healthcare system.

6.3.3.2. Population

The total number of A&E staff in the NHS Trust where empirical data was gathered is estimated to be 200.

6.3.3.3. Parameters

- The first parameter is the relative distance between ideal service time and actual service time (ε_s).
- The second parameter is the proportion of the sample that shows satisfaction or dissatisfaction with changes in the service time.

6.3.3.4. Hypothetical model to be tested

$$S(\varepsilon_s) = \omega_1 \tanh(\beta_1 \varepsilon_s + \lambda_1) + \gamma_1 + \omega_2 \varepsilon_s \tanh(\beta_2 \varepsilon_s + \lambda_2) + \gamma_2 \qquad 6.14$$

From the above model, the following null hypotheses may be stated:

$$H_0^1 : \; S \neq S(\varepsilon_s) \qquad 6.15$$

$$H_0^2 : \; S(\varepsilon_s) = \omega_1 \tanh(\beta_1 \varepsilon_s + \lambda_1) + \gamma_1 + \omega_2 \varepsilon_s \tanh(\beta_2 \varepsilon_s + \lambda_2) + \gamma_2 \,,$$

$R^2 < 70\%$ 6.16

$$H_0^3 : \; S(\varepsilon_s) = \phi P(\varepsilon_p), \qquad \phi = 0 \qquad 6.17$$

6.3.3.5. Data collection

A semi-structured interview schedule used in the wider hospital evaluation project (Gore et al., 2008) was adopted and modified for the data collection (see appendix F). This was designed to specifically capture details of waiting time and service time issues from a staff perspective. There were 68 doctors and nurses who took part in the survey at two Accident and Emergency (A&E) departments in the NHS Trust where data was collected. The interview schedule used for patients is provided in appendix G. 25 patients were interviewed in the A&E department to find their perception of expected waiting times and actual waiting times.

The sampling framework involved the determination of the sample size (n = 65) based on an estimated population of 200 doctors and nurses at two A&E units of the NHS Trust. A confidence level of 95% and a confidence interval of 10 were specified for determining the proportion of staff that would exhibit changes in satisfaction with changes in their service time (used as a proxy for workload).

The confidence interval could have been reduced but the practical difficulties of having access to doctors and nurse in such a busy and critical healthcare environment as the A&E required the above sample size to be considered satisfactory.

The selection of doctors and nurses for the study involved several visits to the study sites. Due to the busy nature of the A&E department, the selection process could not be entirely random. For instance, if a doctor or nurse were very busy, he or she had a lesser chance of taking part in the study. Staff whose shifts did not coincide with the study visits or had been on holidays during the study period could not take part. Involvement in the study was therefore based on staff willingness and availability.

Staff who took part in the study varied in qualification from healthcare assistants to consultants. As a result, some of them were unable to respond to some of the questions. This explains the variations in the sample sizes as would be seen in the results. These were treated as missing data in the analysis.

It is commonplace to observe that data are not always complete during analysis (O'Rourke, 2003). One method of dealing with missing data is the deletion procedure; either *Listwise deletion* or *Pairwise deletion* (see Magnani, 2006; Tsikriktsis, 2005; Faris et al., 2002). *Pairwise deletion* was used in this study where records are not entirely removed from the data set but eliminated when there is no response to particular variables.

According to Kim & Curry (1977), cited in Tsikriktsis (2005), randomly deleting 10% of the data from each variable in a matrix of five variables can easily result in eliminating 59% of cases from analysis. Tsikriktsis (2005), however, noted that despite the fact that large loss of data reduces statistical power and accuracy (Little & Rubin, 1987), *Listwise deletion* is the default option for analysis in most statistical software packages.

It is, however, expected that the results of this study would be interpreted accordingly hence the inclusion of the sample sizes where appropriate, in the tables and figures.

6.4. Statistical hypothesis tests, results and analysis

The three hypotheses stated above are now tested using data from the survey described.

6.4.1. Part 1: Hypothesis H_0^1:

Hypothesis H_0^1 was stated as:

$$S \neq S(\varepsilon_s)$$

The hypothesis suggests that staff satisfaction is not a function of staff workload (measured in terms of their service times).

6.4.1.1. General responses

To test this hypothesis, some general staff responses to specific questions are first presented. These questions also provide a general understanding of staff perception of the effect of patient waiting times on their satisfaction with workload. Some of the results are summarized as follows:

Staff were asked:

"In your opinion, does the number of patients waiting in a queue put pressure on you as you work? Please select from 5 (Yes, very high pressure) to 1 (no pressure at all)"

The responses are shown in Table 6. 1 and Figure 6. 7. The results show that 87.1% of A&E staff believe that the number of patients waiting in a queue puts very high pressure on them as they work.

Table 6. 1: Effect of queues on staff (n = 62)

Response	Description	Number (%)
5	Yes, very high pressure	54(87.1)
4		2(3.2)
3		2(3.2)
2		0(0)
1	No pressure at all	4(6.45)

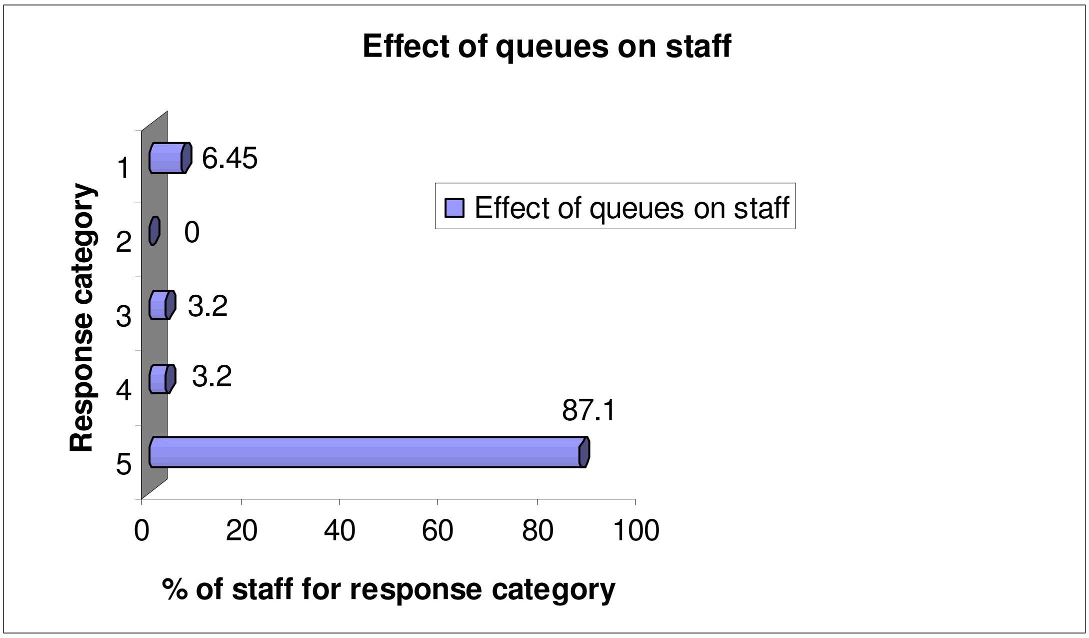


Figure 6. 7: The effect of queues on staff (n = 62)

The next question was then designed to investigate if this pressure affected staff satisfaction with their workload.

"Does that affect your satisfaction with your workload? Please select 5 (Yes, definitely) to 1 (No, not at all)"

Table 6. 2 and Figure 6. 8 show the responses to the question. The majority of staff (78%) agree that the number of patients waiting in queues does not only put pressure on them as they work but also affects their satisfaction with their workload.

Table 6. 2: Effect of queues on staff satisfaction (n = 59)

Response	Description	Number (%)
5	Yes, definitely	46(78)
4		2(3.4)
3		4(6.8)
2		1(1.7)
1	No, not at all	6(10.2)

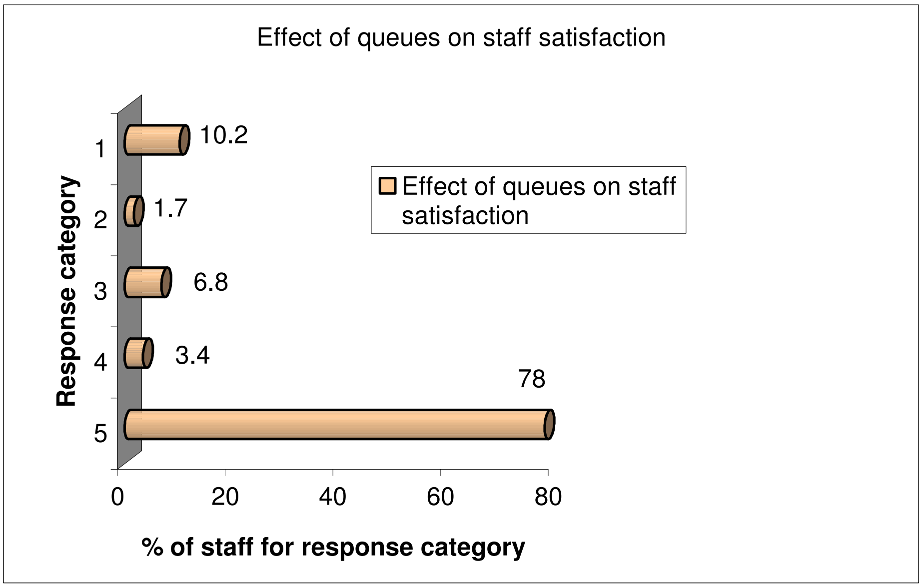


Figure 6. 8: Effect of queues on staff satisfaction (n = 59)

The third question was to investigate if according to the staff, there is a relationship between their satisfaction and that of their patients.

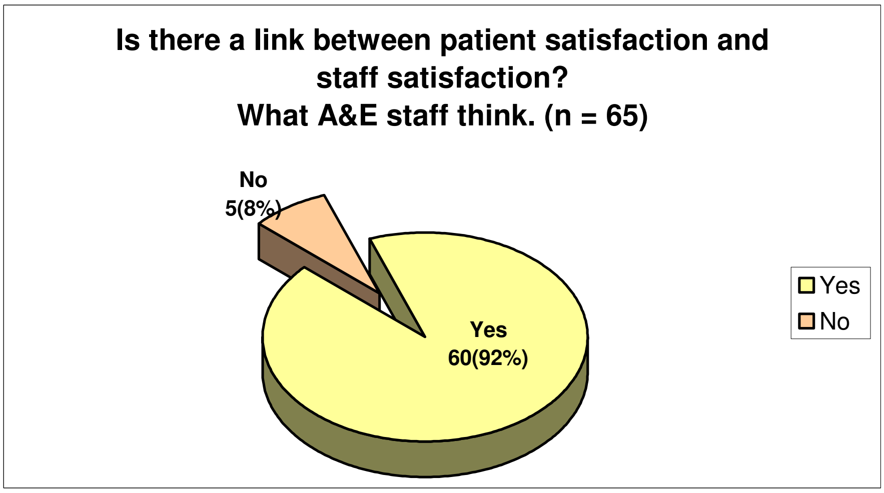


Figure 6. 9: A&E staff view on link between patient satisfaction and staff satisfaction

The results shown in Figure 6. 9 suggest that staff believed there was a link between their satisfaction and that of their patients.

These results provide considerable insight into the hypothesis under test. The hypothesis claims that there is no relationship between staff satisfaction and their workload. To the contrary, the majority of staff have indicated that queues put very high pressure on them. They have shown that this pressure affects their satisfaction and also that there is a link between their satisfaction and that of their patients. To explore this further, a closer look is taken at the A&E process and the key stages involved.

There are three key stages of the A&E journey. These are triage, first examination and second examination. Interviewed staff know from experience how much time they would be happy to spend with patients at each stage in order for them to work effectively. If the actual time spent was more or less than this ideal, staff will be dissatisfied. Table 6. 3 shows the results at these stages and also for staff satisfaction with the overall time of patients in A&E (see question 4, 5,7,8,9 and 10 of appendix F).

Table 6. 3: Staff satisfaction at key stages in the patient journey and overall time

Stage	Less time than desired			More time than desired			n
	%Satisfied	%Dissatisfied	%Neutral	%Satisfied	%Dissatisfied	%Neutral	
1	12.2	83.7	4.1	42.9	34.7	22.4	49
2	2.3	84.1	13.6	36.4	43.2	20.5	44
3	13.5	70.3	16.2	27.03	45.9	27.03	37
Overall	78.33	11.67	10	13.33	66.67	20	60

It is observed from the table that up to 84.1% of staff are dissatisfied spending less time than desired. On the other hand a much lesser proportion of staff (up to 45.9%) are dissatisfied spending more time than desired. This is an indication that staff satisfaction is more sensitive to reductions rather than increases in the actual service.

It is also observed that whilst the majority of staff were dissatisfied with spending less time than desired at each of the key stages in the patient journey, 78.33% said they would be satisfied if patients' total time was less than they thought was ideal. This provides some indication that staff do not fully appreciate the relationship between service time and waiting time. This is a misconception because patients' total time is the sum of time spent at all stages in the A&E journey. Thus one would expect that if staff are dissatisfied for spending less time than they thought was reasonable (or is necessary for them to work effectively) at the key stages, they should also be dissatisfied if the total time of patients was less than they thought reasonable. This shows that staff do not interpret the total time of patients in terms of the detailed process times. In other words, they treat each individual process in isolation of other pending processes.

In order to fully understand this variation in staff satisfaction with changes in actual service time, a more detailed question was asked at each of the key stages. This was done by recording the satisfaction of staff with gradual changes in the actual service time further away from the ideal on both sides. Table 6. 4 shows samples of staff responses at the triage stage. S_{ideal} stands for the ideal service time (this is the time that staff think is reasonable to enable them to work effectively) for the triage stage. S_{ideal}-5, S_{ideal}-10 etc. stand for actual service times that are 5 minutes and 10 minutes respectively less than the ideal. Staff satisfaction was assigned values from 1 (Very dissatisfied) to 5 (Very satisfied).

These data were analysed in two ways to obtain sufficient evidence for the acceptance or rejection of hypothesis H_0^1.

Table 6. 4: Sample response of detailed staff satisfaction

Sideal - 20	*Sideal - 10*	*Sideal - 5*	*Sideal (min)*	*Sideal +5*	*Sideal +15*	*Sideal +20*
1	2	5	15	2	1	1
1	1	2	15	2	1	1
1	1	2	15	2	1	1
1	2	5	30	5	4	4
1	2	5	30	5	2	1
1	2	5	10	5	2	1

6.4.1.2. Frequency distribution of satisfied staff

The number of staff that responded with satisfaction levels of 4 or 5 were counted at each point above and below the ideal service time at each stage. The distributions for the three stages (triage, first assessment and second assessment) are shown in Figure 6. 10, Figure 6. 11 and Figure 6. 12 respectively.

The results visually show differences in the number of staff satisfied with changes in service time. This also seems to decrease further away from the ideal value. In order to decide on the hypothesis, a two-sample z-test is used to test the means of each pair of points from the ideal. The purpose of this test is to establish statistically whether the differences between satisfaction levels at each pair of points are significant or just a random occurrence.

Figure 6. 10: Frequency of satisfied staff at stage 1

Figure 6. 11: Frequency of satisfied staff at stage 2

Figure 6. 12: Frequency of satisfied staff at stage 3

6.4.1.3. Test of means of satisfaction

In Tables 6.5 and 6.6, L1, L2, L3 correspond to the three points below the ideal service time and R1, R2 and R3 also correspond to the three points above the ideal. The value of staff satisfaction is highest (point 5 on the Likert scale) at the ideal value of service time. The mean values are shown in Table 6. 5 for all stages with 95% confidence levels specified.

Table 6. 5: Mean satisfaction values and 95% confidence level at each point from the ideal

	L3	L2	L1	IDEAL	R1	R2	R3
TRIAGE	1.186	1.93	3.90	5	4.419	2.837	1.4186
95%CL	0.2623	0.3384	0.445	0	0.363	0.484	0.344
1^{ST} ASS.	1.125	1.8125	3.78	5	4.438	2.75	1.53
95%CL	0.2549	0.3598	0.54	0	0.429	0.557	0.4294
2^{ND} ASS.	1	1.724	3.66	5	4.448	2.86	1.5517
95%CL	0	0.3356	0.5776	0	0.472	0.599	0.4723

Table 6. 6: p-values from the two-sample z-test for means

				STAGE				
	L3	L2	L1		R1	R2	R3	
L3	-	0.000226	0	**TRIAGE**	0	0.00000071	-	**R3**
L2		-	0.000*		0.000000066	-		**R2**
L1			-		-			**R1**
L3	-	0.000737	0.0000000003	**1^{ST} ASS.**	0.00000049	0.0002045	-	**R3**
L2		-	0.0000000003		0.00000049	-		**R2**
L1			-		-			**R1**
L3	-	0	0	**2^{ND} ASS.**	0.00001025	0.000217	-	**R3**
L2		-	0.000000002		0.00001025	-		**R2**
L1			-		-			**R1**

* is 0.00000000000004

The two-sample z-test for means was conducted at 0.05 significance level. The null hypothesis was that the difference between the means of any two pairs of points (L1, L2 and L3) or (R1, R2 and R3) is zero. For the difference to be statistically significant, the *p-value* of the test must be less than or equal to the significance level (0.05). As shown in Table 6. 6, all the differences are significant since all the *p-values* are less than 0.05.

This means that the differences in satisfaction at various points of service time away from the mean are not by chance. This is conclusive evidence of the existence of a relationship between the satisfaction of staff and changes in service time. Therefore the hypothesis H_0^1 can be rejected. Therefore, the universal alternative that a relationship exists between service time and staff satisfaction with workload is accepted.

However, the fact that a relationship exists between service time and staff satisfaction, does not explain the nature of the relationship. The next step, therefore, is to investigate the nature of this relationship.

6.4.2. Part 2: Hypothesis H_0^2

Hypothesis H_0^2 was stated as:

$$S(\varepsilon_s) = \omega_1 \tanh(\beta_1\varepsilon_s + \lambda_1) + \gamma_1 + \omega_2\varepsilon_s \tanh(\beta_2\varepsilon_s + \lambda_2) + \gamma_2, \quad R^2 < 70\% \qquad 6.18$$

The claim of this hypothesis is that the model $S(\varepsilon_s)$ does not sufficiently explain the relation between staff satisfaction and service time.

The goal of this section therefore is to find the parameters of the model that will provide the best fit for the empirical data and give a coefficient of determination, R^2 value greater than 70%.

Figure 6. 13 shows the empirical values for all three stages and their corresponding mean satisfaction values. Stage 1 corresponds to triage, stage 2 is first assessment and stage 3 is second assessment. The values in the brackets are the relative distance (epsilon) values (see satisfaction evaluation in section 6.3.1).

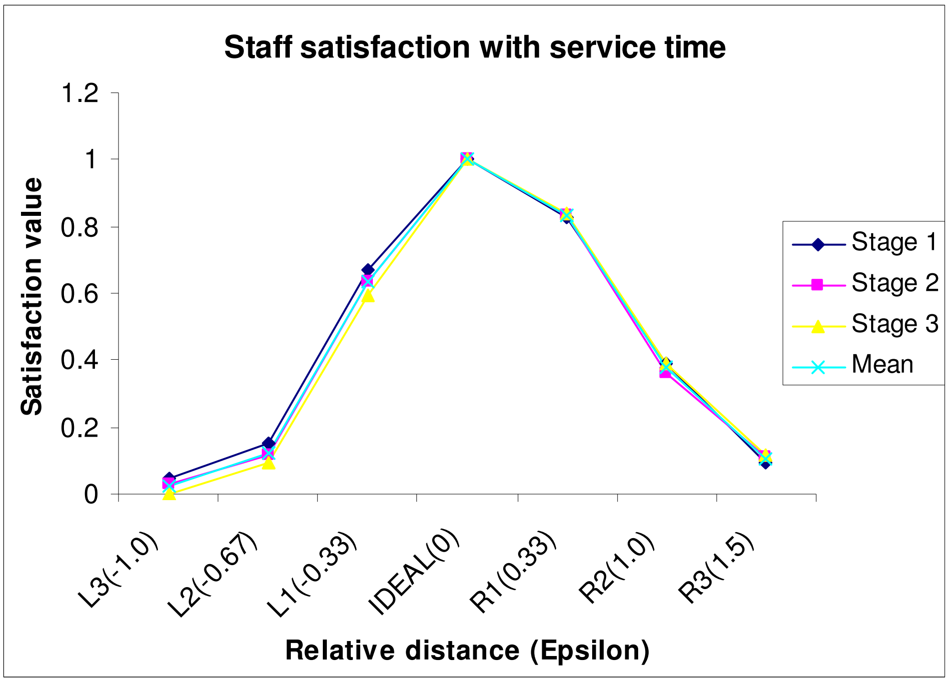


Figure 6. 13: Empirical staff satisfaction with service time

Figure 6. 14 shows the empirical data and the fitted model. The residuals of the model are shown in Figure 6. 15.

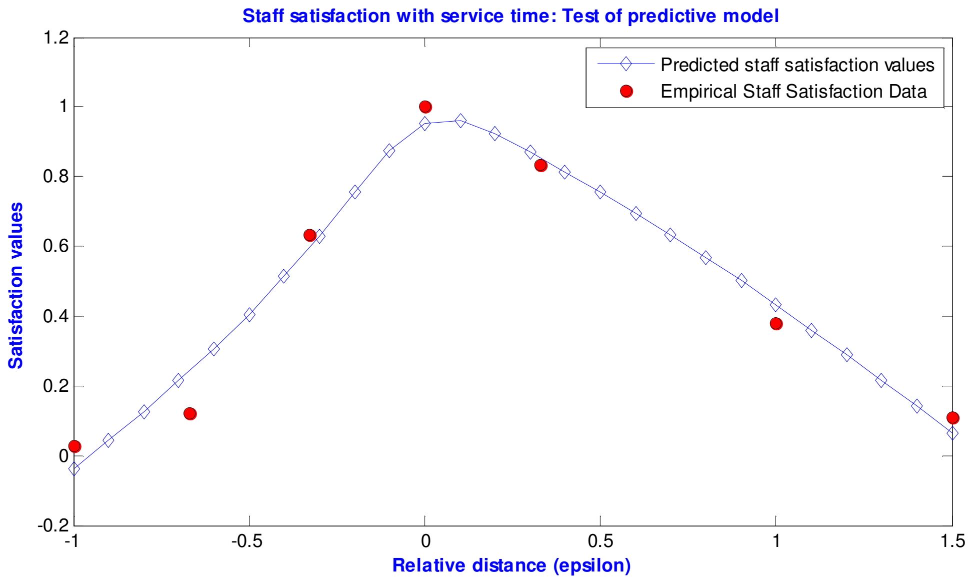


Figure 6. 14: Fitting the model to the empirical data

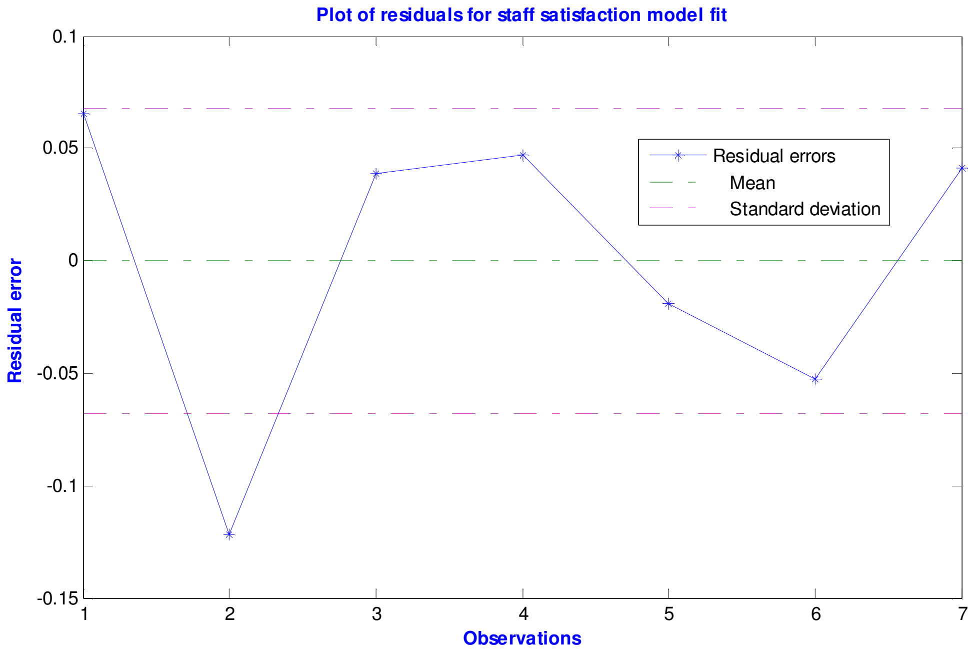


Figure 6. 15: Plot of the residual errors

Table 6. 7 shows the values of the estimated model parameters and the corresponding 95% confidence interval. The fitted model may now be stated as;

$$S(\varepsilon_s) = 0.25\tanh(1.72\varepsilon_s) + 0.55 + 0.76\varepsilon_s \tanh(-4.83\varepsilon_s) + 0.4 \qquad 6.19$$

Table 6. 7: Estimated model parameters

Parameter	Value	95% Confidence Interval
ω_1	0.251	-4.232, 4.734
ω_2	0.7569	-14.31, 15.82
β_1	1.724	-38.77, 42.22
β_2	-4.83	-524.4, 514.7
γ_1	0.5531	-5.377e+016, 5.377e+016
γ_2	0.4	-5.377e+016, 5.377e+016
λ_1	0	0
λ_2	0	0

The goodness-of-fit of this model can be judged from the parameters in Table 6. 8. The parameter stated in the null hypothesis is the R-squared value, which in this case is 96.91%. Since R-squared for the model is greater than 70%, the null hypothesis can be rejected.

Table 6. 8: Model goodness of fit measures

Goodness measure	Value
Sum of squared errors (SSE)	0.0276
Root mean squared error (RMSE)	0.1661
R-squared	0.9691
Adjusted R-squared	0.8148

Equation 6.19 therefore sufficiently represents the relationship between the satisfaction of staff with changes in their workload (service time).

The hypotheses H_0^1 and H_0^2 have been tested and both rejected. This means that first of all, there is a relationship between staff satisfaction and their workload (service time) and secondly that this relationship is sufficiently represented by equation 6.19. The final hypothesis regarding the existence of a relationship between staff satisfaction and patient satisfaction is presented next.

6.4.3. Part 3: Hypothesis H_0^3:

Hypothesis H_0^3 was stated as:

$$S(\varepsilon_s) = \phi P(\varepsilon_p), \qquad \phi = 0 \qquad 6.20$$

Having determined the model for staff satisfaction $S(\varepsilon_s)$ it is now possible to relate the satisfaction of staff with service time to the satisfaction of patients with waiting time.

The claim of this hypothesis is that, the value of ϕ is zero. If this is true, then it means there is no observable relationship between the satisfaction of staff, $S(\varepsilon_s)$ and the satisfaction of patients $P(\varepsilon_p)$.

6.4.3.1. The Staff-Patient Satisfaction Relation Model (S-PSRM)

To test this hypothesis, the single server queuing model presented in section 6.3.1 is used together with staff satisfaction model in equation 6.19 and the Generalised CORE model in equation 6.8.

Thus staff satisfaction is given by

$$S(\varepsilon_s) = 0.25\tanh(1.72\varepsilon_s) + 0.55 + 0.76\varepsilon_s \tanh(-4.83\varepsilon_s) + 0.4 \qquad 6.21$$

where

$$\varepsilon_s = \frac{S_{act} - S_{ideal}}{S_{ideal}} \quad 6.22$$

Patient satisfaction is given by

$$P\left(\varepsilon_p\right) = \tanh\left(3\varepsilon_p + 2\right) + 1 \quad 6.23$$

where

$$\varepsilon_p = \frac{W_{ideal} - W_{act}}{W_{ideal}} \quad 6.24$$

and

$$E(W_T) = E(S_{act}) + \frac{\lambda E({S_{act}}^2)}{2(1-\rho)} \quad 6.25$$

$$E(W_{act}) = E(W_T) - E(S_{act}) \quad 6.26$$

The values of ω, β, λ and γ (1,3,2 and 1 respectively) in equation 6.23 were chosen experimentally with the objective of obtaining values of the parameters that allow sufficient range of satisfaction values corresponding to the range of service time for staff.

The steps involved in implementing the model in MATLAB R2007a are shown in Figure 6. 16.

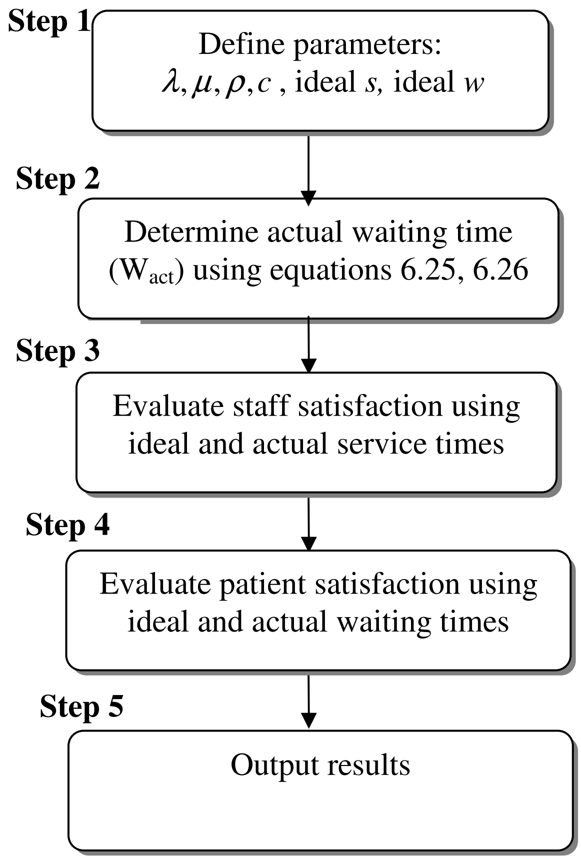


Figure 6. 16: Steps for implementing the S-PSRM model

Figure 6. 17 shows the results of the simulation of the above steps with values of μ, the service rate (number of patients processed per hour) ranging from 0.25, in steps of 0.25 up to 20. Note that the actual service time is the reciprocal of the service rate (i.e. varying from $1/0.25$hrs to $1/20$hrs). Ideal service time was set and held constant at 2hrs. The ideal waiting time was also varied from 0.5hrs, in steps of 0.5 up to 5hrs. The figure shows the effects of changes in the ideal waiting time on staff and patient satisfaction whilst the ideal service time remained constant.

It can be observed that for an ideal waiting time of 0.5hrs, staff satisfaction rises and falls when patient satisfaction is still almost zero. Similarly, maximum staff satisfaction occurs at lower values of patient satisfaction for ideal waiting times of 1.0hr and 1.5hrs. At the ideal waiting time of 2.0hrs, maximum staff satisfaction occurs almost at the point of maximum patient satisfaction. Beyond this point, there is not much gain in patient satisfaction but staff satisfaction begins to fall rapidly.

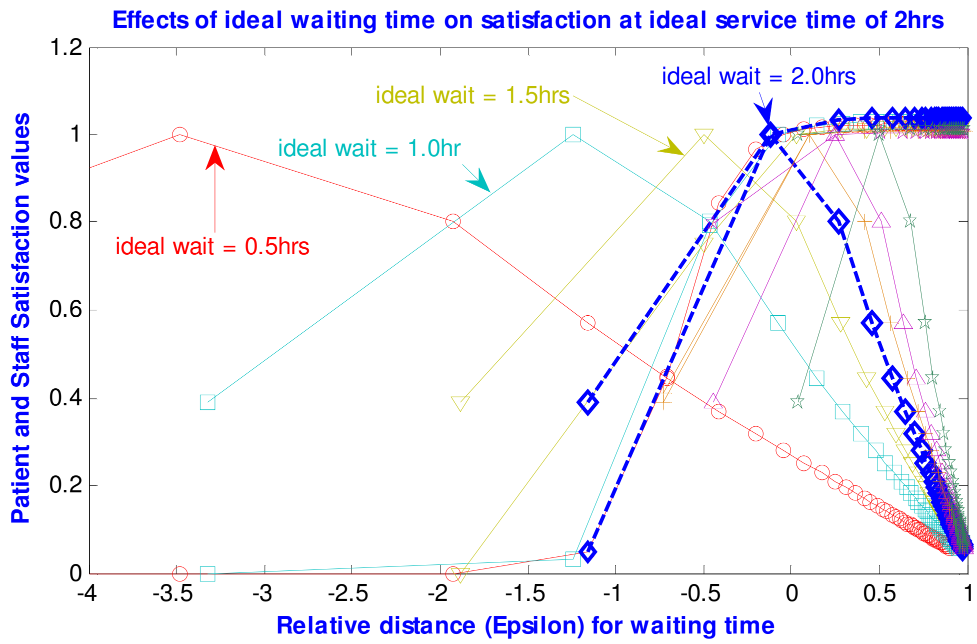


Figure 6. 17: Mathematical model results showing effects of variations in ideal waiting time on satisfaction

Figure 6. 18 shows the direct relationship between staff satisfaction with service time and patient satisfaction with waiting time. The figure also shows how differences in ideal service time and ideal waiting time affect the relationship between staff and patient satisfaction.

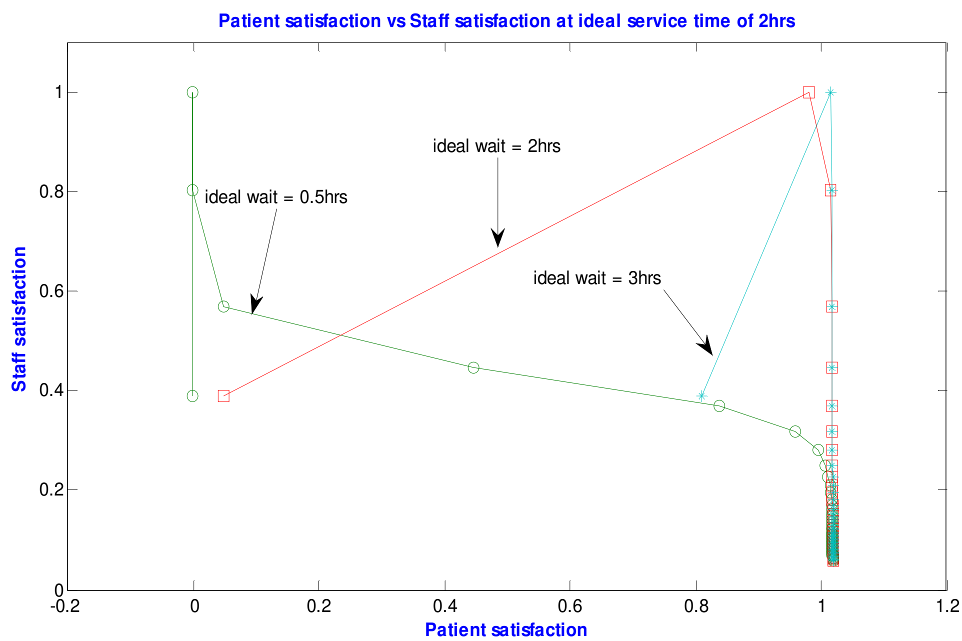


Figure 6. 18: Mathematical model results showing staff satisfaction vs patient satisfaction

Figure 6. 17 and Figure 6. 18 show the variations in the patient satisfaction values against variations in staff satisfaction. If there were no relationship between staff satisfaction and patient satisfaction as stated in the null hypothesis, the plots would have shown no trend at all. It is therefore concluded that there exists a direct relationship between staff and patient satisfaction, hence the value of ϕ in H_0^3 cannot be zero. H_0^3 can therefore be rejected.

6.4.4. Effective Satisfaction Level (ESL)

With patient satisfaction and staff satisfaction superimposed on the same axis (relative distance for waiting time), we can determine the Effective Satisfaction Level (ESL).

The proposal of the ESL concept puts forward the argument that both patient satisfaction and staff satisfaction need to be considered in an attempt to improve the quality of care. By definition, the ESL is the point at which staff satisfaction with their workload and patient satisfaction with their waiting times both reach maximum level.

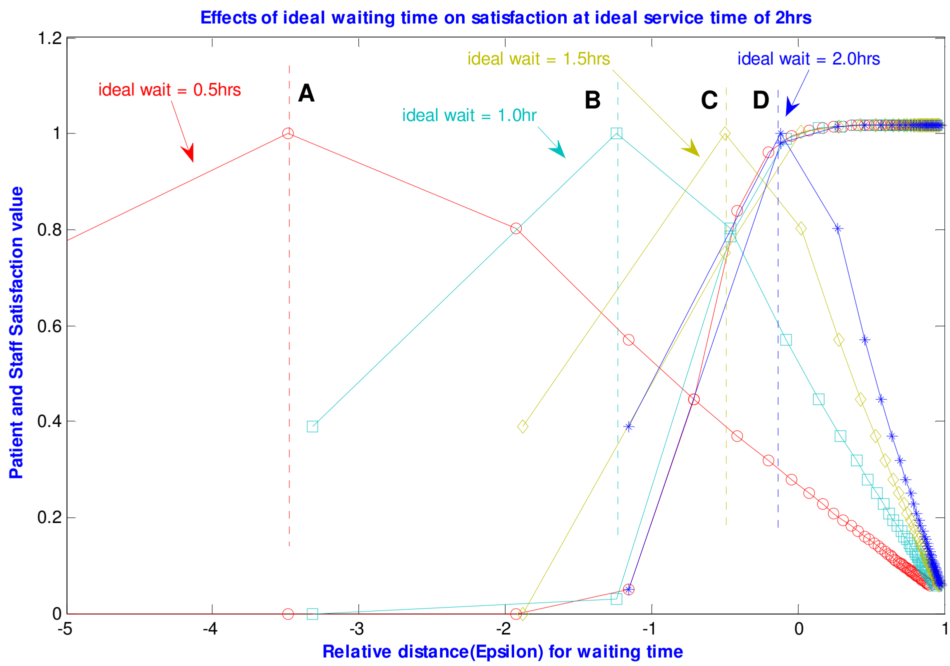


Figure 6. 19: Mathematical model results showing Effective Satisfaction Level

In Figure 6. 19, points A, B, C and D represent maximum staff satisfaction corresponding to ideal waiting time values of 0.5, 1.0, 1.5 and 2hrs respectively. Note that ideal service time is hypothetically fixed at 2hrs. At points A, B, and C the maximum staff satisfaction occurred at lower values of patient satisfaction. Point D is therefore the ESL, where staff satisfaction and patient satisfaction are at their maximum. It must be noted that this occurs when the ideal service time is equal to the ideal waiting time. To explain further, the relative distance (Epsilon) for waiting time is ε_p in equations 6.23 and 6.24. From equation 6.24 it is obvious that for a given ideal waiting time (W_{ideal}), the maximum possible value of ε_p will be 1, which occurs when the actual waiting time, W_{act} is zero. This corresponds to a high level of satisfaction for patients since waiting time is zero but this results in an actual service far below the ideal for staff and hence a fall in their satisfaction as shown in the figure. It is observed that beyond the ESL (point D), the satisfaction of patients becomes saturated as such there is no gain.

It is therefore suggested that the ESL (point D) must be the goal of every healthcare system with respect to their resource capacity and planning. This concept uniquely provides a meaningful method for assessing the capability of any healthcare system and can even be used to determine whether a target imposed on the system is realistic or not.

The introduction of the ESL opens numerous opportunities for exploration and understanding of the queuing problem in the NHS. For instance questions like what is the optimum level of resources required for a system to operate at the ESL? Or what level of demand can a system accept without moving off the ESL? Or how many patients waiting in a queue is acceptable at the given ESL?

The development so far has been based on the single server queuing model presented in section 6.4.2 above. The formulations therefore have been subject to the assumptions listed in section 6.4.1. It is however possible to extend this model by relaxing some of these assumptions as briefly discussed next in section 6.5.

6.5. Extension of the model to a network of queues

The formulations in this section are mainly derived from Askin & Standridge (1993) and Bolch et al., (2006).

6.5.1. System considerations

The A&E system is here modelled as a network of queues in which staff are the servers and patients are the customers. We shall consider the A&E as a system with a number of services provided in a set of stages. A patient enters the system, visits a required number of stages then leaves the system. The first question is which network model best represents the A&E system?

1. **Open network:** In this network, an external arrival process generates customers that arrive at one or more stages and enter into the system. In this case there will be no limit placed on the amount of work-in-process.

2. **Closed network:** This system has a constant work-in-process (WIP). It releases a new customer as one is completed.

3. **Hybrid network:** This system has a limited work-in-process (WIP). Jobs are entered into the system on arrival unless there are already N jobs in the system. N is the critical loading level.

A&E departments have limited number of beds and in extreme cases will divert ambulances to other facilities, to avoid an increase in WIP beyond acceptable limits. It is therefore reasonably accurate to model these systems as a hybrid network of queues.

6.5.2. The A&E as a Hybrid Network of Queues

6.5.2.1. Aim of this analysis

The relationship between patient satisfaction and staff satisfaction with waiting times for a single server A&E system was established in section 6.4. Naturally, the next step would be to extend the model to a network of queues.

The aim here is to link the following performance factors to the satisfaction of patients.

- The average number of patients in the system
- Resource utilisation
- Patient throughput
- Response time T
- Waiting time W
- Queue length Q
- Number of patients in the system at any given time, K

6.5.2.2. Further assumptions

- The system has M workstations. (reception, triage, first assessment, second assessment, investigation, treatment)
- Workstation $j = 1,\ldots.M$ has c_j number of servers.
- External arrivals to workstation j are Poisson with mean rate of λ_j. External arrivals are new patients from outside the system that enter when n < N, i.e. the system capacity is not exceeded.
- Workstations schedule patients as First Come First Served (FCFS). Consideration of priority is another extension to be considered later.
- Service rates are exponential with mean service times, μ_j^{-1}.
- A patient at station j transfers to station k with probability of P_{jk} on completion at j. Patients leave the system with probability $P_{jo} = 1 - \sum_{k=1}^{M} P_{jk}$
- Queue sizes are unlimited (no blocking)

6.5.2.3. Typical characteristics of an A&E department

These characteristics are based on observations made during patient mapping exercises as part of the data collection in this research.

- Patients may not physically move from station to station. The concept of a station is a virtual one and is considered as Doctors and Nurses perform different tasks on patients at various times during the patient's journey, i.e. a station represents a defined place of interaction between staff and patients during which specified operations are carried out on the patients and a set of resources allocated to them.

- Doctors and Nurses (resources) may serve at different stations.

- When a patient has to wait for a test result, Doctors and Nurses will normally be seeing some other patients if there are any waiting.

6.5.2.4. Limited WIP in a Hybrid System

A&E departments practically have limited capacity and a variable work-in-process. As a result, they are neither fully closed nor fully open queuing systems.

This characteristic of A&E departments is akin to a manufacturing system where the dispatching rule is to enter a job on arrival into the system, unless there are already *N* jobs in the system (Askin & Standridge, 1993). This rule satisfies the objective of keeping workstations busy without running the risk of overwhelming the system. The value of *N* may be determined from the production rate verses WIP curves for the system.

For an A&E department, it may be reasonably assumed that patients above the *N* limit will be diverted to a different facility (it may be possible to use the model to determine how often this may happen and if it may be predicted).

A hybrid system therefore contains elements of both closed and open systems. Buzacott & Shantikumar (1980) cited in Askin & Standridge (1993, p.400) suggested the following procedure for modelling hybrid queuing systems:

1. For $1 \leq n \leq N$ solve the closed network model of the system assuming *n* jobs in process. Set $\mu(n)$ to the determined aggregate production rate.

2. Solve the *M/M/1* queue model with arrival rate, λ and state-dependent service rate $\mu(n)$. Let $p(i)$ be the probability of *i* jobs in the system and the dispatching queue. For this model therefore:

$$p(i) = p(0).\prod_{n=1}^{i} \frac{\lambda}{\mu(n)} \qquad 6.27$$

and

$$\sum_{i=0}^{\infty} p(i) = 1. \qquad 6.28$$

Various performance measures can then be computed for this model.

6.5.3. Solving the A&E system as a closed network model

6.5.3.1. Mean Value Analysis (MVA)

In a closed network, the number of jobs in process is kept at a fixed level of *N*. A new job is dispatched when a job finishes its processing and leaves the system.

The MVA was developed for the analysis of closed queuing networks with product-form solution (Bolch et al., 2006). The advantage of this method is that performance measures can be computed without explicitly computing the *normalisation constant.*

The MVA is based on two fundamental equations;

- *Little's theorem:* This expresses the relationship between the number of jobs, the throughput, and the mean response time for a node or the overall system;

$$N = XT \qquad 6.29$$

Where *N* is the mean number of jobs, *X* is the mean production rate, and *T* is the total time in the system (Little, 1961).

- *Theorem of the distribution at arrival time (or arrival theorem):* The *arrival theorem* states that in a closed product-form queuing network, the probability mass function (pmf) of the number of jobs seen at the time of arrival to a node *i* when there are *k* jobs in the network is equal to the pmf of the number of jobs at this node with one less job in the network (Lavenberg & Reiser, 1980; Sevcik & Mitrani, 1981, cited in Bolch et al., 2006, p. 384).

To explain this further, assume a job *j* arrives in a system with *N-1* total number of jobs. The total number of jobs in the system will become *N-1+1 = N* due to the arrival of *j*. Before *j* enters the queue at the node of arrival, it is certain that the number of jobs at this node will be the same as there was at this same node when there were *N-1* jobs in the system.

6.5.3.2. Multiclass, Single Server closed Networks

MVA relies on three basic equations (Askin & Standridge, 1993, p.386). The fundamental equation of the MVA is based on the *arrival and Little's theorems* for closed product-form networks. This gives the average throughput time per visit of part type *p* to station *j* by;

$$W_{jp} = \mu_{jp}^{-1} + \frac{N_p - 1}{N_p} L_{jp}\mu_{jp}^{-1} + \sum_{r \neq p} L_{jr}\mu_{jr}^{-1} \quad \text{for all } j, p \qquad 6.30$$

This means that the average throughput time for patient type *p* at station *j* is made up of service time for the patient, time in queue waiting for other patients of its type *p*, and time spent waiting for other patient types.

The second equation gives the overall system production rate X_p. this is given by:

$$X_p = \frac{N_p}{\sum_{j=1}^{M} v_{jp} W_{jp}} \qquad p = 1, \ldots, P \qquad 6.31$$

where

N_p is the total number of type p patients in the system

W_{jp} is the average throughput time for type p at j

v_{jp} is the visit counts of p to j

The third equation relates production at each station by Little's theorem and is given by;

$$L_{jp} = X_p\left(\nu_{jp}W_{jp}\right) \quad \text{for all } j, p \qquad 6.32$$

6.5.3.3. Multiclass, Multiple Servers closed Networks

Because MVA bypasses the state balance equations, an alternative model is required to consider multiple server cases (Askin & Standridge, 1993, p.387). This can be achieved by dividing the second and third terms on the right of equation 6.30 by c_j, the number of servers at station j.

This states that all servers will always be busy emptying out the queue. This is, however, not true unless at least c_j customers are at the station. This problem is offset by the fact that when there are multiple servers, the new job can begin service as soon as only c_j-1 jobs are ahead of it, leaving an available server. This error is small when the number of patients at a station is large with respect to c_j.

Seidman, Schweitzer & Shalev-Oren (1987) found that better estimates, particularly of expected waiting times, could be obtained by modelling a multiple server workstation as a fast single server station followed by an ample server station or infinite capacity server.

Processing time is divided between the two pseudo-stations. The original processing time, μ_j^{-1}, is divided such that the fast single server must work μ_{jp}^{-1}/c_j and the Ample Server (AS) or infinite capacity station serves (delays) the patient $\left[\left(c_j - 1\right)\mu_{jp}^{-1}\right]/c_j$.

The expression for the throughput time when station j has multiple servers is then

$$W_{jp} = \frac{\mu_{jp}^{-1}}{c_j} + \frac{N_p - 1}{N_p} L_{jp} \frac{\mu_{jp}^{-1}}{c_j} + \sum_{r \neq p} L_{jr} \frac{\mu_{jr}^{-1}}{c_j} \qquad 6.33$$

for the original station and

$$W_{jp} = \frac{c_j - 1}{\mu_{jp} c_j} \qquad 6.34$$

for the accompanying ample server or infinite capacity server station.

6.5.4. Priority Queuing Discipline: Extending the MVA

For a system with priority scheduling, the first equation of the MVA needs to be modified. The following changes must be made to the equation;

- Eliminate waiting for lower priority patient types and add waiting for higher priority patients whilst the patient is in the queue.
- Jobs (patients) are not pre-empted, so higher priority arrivals during processing are not included.
- The last part of the equation should be limited to those jobs (patients) with higher priority than patient type *p*.

If the average time in queue $\left(W_{jp} - \mu_{jp}^{-1}\right)$ for a patient, and the arrival rate for higher priority patients $\left(\nu_{jr} X_r \text{ for patient type } r\right)$ are known, then we can adjust the equation by adding the extra term

$$\left(W_{jp} - \mu_{jp}^{-1}\right) \sum_{r:pr(j,r)>pr(j,p)} \frac{\nu_{jr} X_r}{c_j \mu_{jr}} \qquad 6.35$$

where $pr(r, j)$ is the priority of part r at j.

Hence equation 6.30 becomes

$$W_{jp} = \mu_{jp}^{-1} + \frac{N_p - 1}{N_p} L_{jp} \mu_{jp}^{-1} + \sum_{r \neq p} L_{jr} \mu_{jr}^{-1} + \left(W_{jp} - \mu_{jp}^{-1}\right) \sum_{r:pr(j,r)>pr(j,p)} \frac{\nu_{jr} X_r}{c_j \mu_{jr}} \quad \text{for all } j, p \qquad 6.36$$

6.5.5. The MVA Algorithm

All three equations of the MVA must be satisfied by the steady-state solution. Due to the non-linearity of the equations, finding a direct solution is more challenging. An algorithm proposed by Askin & Standridge (1993) is employed here.

The objective in the algorithm is to find a set of L_{jp}, W_{jp} *and* X_p that satisfies all three equations given the system parameters N_p, c_j, μ_{jp} *and* ν_{jp}.

The iteration starts with an initial guess of the queue length and *j*, L_{jp}. This enables the estimation of values for the corresponding production rate and queue length using the second and third equations. The new queue length becomes the initial guess for the next iteration. The process continuous until the estimates converge, thus when mean values change by less than 1%.

The steps of the algorithm are;

STEP 1: INITIALISE. $\tau = 0$. For all *p* let Z_p be the number of stations visited by part (patient) type *p,* that is, the sum over *j* of the number of nonzero ν_{jp}. Set $L_{jp}^{(0)} = N_p / Z_p$.

STEP 2: UPDATE W. $\tau = \tau + 1$. For all *j,p* compute $W_{jp}^{(\tau)}$ from the appropriate form of the first equation.

STEP 3: UPDATE THROUGHPUT. For all *p* compute X_p^{τ} by the equation 6.31

STEP 4: UPDATE L. For all *j,p* compute L_{jp}^{τ} from equation 6.32. If any$\left[\left(L_{jp}^{\tau} - L_{jp}^{\tau-1}\right) / L_{jp}^{\tau}\right] > 0.001$, go to step 2, otherwise stop.

6.5.6. Solving the A&E as an *M/M/1* queue

This part of the network analysis is similar to what was presented in section 6.4. It is based on using a specified arrival rate of λ and the service rates of $\mu(n)$ obtained from the close network analysis. The probability of *i* jobs in the entire system, $p(i)$ may then be calculated using equations 6.27 and 6.28. By obtaining $p(i)$, it is then possible to obtain other performance measures such as the average number of patients in the system, average number of patients under treatment and a long-term average of throughput times.

In section 6.4 the S-PSRM model formulations were tested based on an *M/G/1* queuing model. This section has presented the possible ways of relaxing the assumptions of the single server model to better reflect reality. By considering multiple classes of patients, multiple servers and priority scheduling the model should become more realistic and more acceptable to practitioners.

Further testing of the network model discussed here is left for future work. The implications of the S-PSRM model to the delivery of healthcare are now presented in section 6.6.

6.6. Implications of the S-PSRM model

With the understanding of the relationship between the satisfaction of staff and that of patients, the targets imposed on healthcare systems can become more realistic. In a system with limited resources, it should now be possible to know the highest level of patient satisfaction that can be achieved without sacrificing staff satisfaction with workload. The resulting balance in between patient and staff satisfaction will drive improvements in the quality of care since *"Ideally, quality healthcare should result in the satisfaction of both the patient and the practitioner." (Hudelson et al., 2008, p. 33)*

There should also be no more need for healthcare managers to use unacceptable methods of meeting waiting time targets (Wolstenholme et al., 2005), since any unrealistic expectations can be justified with the proposed model.

6.7. Conclusions

It has been suggested that the current approach to managing queues in the NHS through targets and performance ratings may be problematic. Significant improvements have been attributed to targets in the NHS. However, evidence of "coping" strategies employed by NHS Trusts during assessment periods are also well documented, making published improvement results sometimes doubtful.

It has further been found that, in the management of queues in the NHS, significant emphasis is placed on satisfying the patients without understanding the effects on the staff that are the key resources in the system. This chapter has focused on showing, via empirical evidence, the strong link that exists between the service time of staff and the waiting time of patients and hence between the satisfaction of staff with workload and patient satisfaction with waiting time. Three null hypotheses were tested and were all rejected on the grounds of empirical evidence.

The hypothesis that there was no relationship between staff satisfaction and service time was rejected when two-sample z-tests revealed statistically significant differences between mean satisfaction values at various values of service time.

Based on the empirical data, a model has been developed for measuring the satisfaction of staff with service time. The model fitted the empirical data with an R-squared value of 96.91%. The development of this model made it possible to directly relate the satisfaction of staff to that of the patients.

By analytically relating the satisfaction of staff to that of patients, the concept of the Effective Satisfaction Level (ESL) was developed. This concept suggests a shift from the focus on patient satisfaction to a point of operation where both patient and staff satisfaction are maximised. It is argued that all healthcare systems must ideally operate at the ESL and where this is not possible due to resource constraints, it is still important to know how far a system is from its ESL. It has been found that the ESL occurs when the ideal service time equals the ideal waiting time.

Possible implications of the ESL are that, targets would become more meaningful and it will become easier to determine whether a system is sufficiently resourced to meet set targets or otherwise. The intention of providing information on quality and satisfaction in real-time to both staff and managers is novel and has the potential to significantly enhance staff ownership in the quality improvement process.

The empirical study also suggests that there is to some extent, a level of ignorance towards understanding the relationship between patients' waiting time and staff workload. This is because up to 84% of staff were dissatisfied if they had to spend less time with patients than they felt was necessary at each stage of the patient journey, yet 78% of staff were very satisfied if the patient total time in the A&E is less than they expect to be ideal.

This and the previous chapters have developed the conceptual components of the E-Track NHS system – the HPI and the S-PSRM. In the following chapter, the discussion will focus on the technological features of this proposed system. The system integration and data acquisition methods are described.

7. E-Track NHS System Development

“Measuring ‘goodness’ requires accurate data used appropriately, and it must be done without demoralising and demotivating staff.”

Pringle, Wilson & Grol (2002, p. 704)

As discussed in section 6.1.1, the accuracy of data is an important part of the measurement of quality and satisfaction. In many cases in the NHS, lack of accurate data or information in the proper format has confounded performance analysis and has in some cases caused incoherency in results. In proposing a system that complements existing methods of performance assessment, the issue of data collection is of prime importance. The proposed method in E-Track NHS is real-time data acquisition.

The discussion in this thesis so far has been centred on the conceptual features of E-Track NHS. The proposed E-Track NHS system has two main features;

1. Conceptual features: The Healthcare Performance Index (HPI) and the Staff-Patient Satisfaction Relation Model (S-PSRM).

2. Technological or functional features: To provide capability for automatic and semi-automatic data acquisition and model generation, a platform for real-time discrete event simulation and capability for fast forward (look ahead) simulation.

This chapter employs a systems engineering approach to integrate the key concepts of E-Track NHS and outlines the overall architecture for the implementation of the E-Track NHS system including a description of the user and system requirements.

Section 7.1 describes the systems approach. Sections 7.2, 7.3 and 7.4 present the user requirements, system requirements and a description of the systems architecture respectively. The system components, software design and some demonstration of the key feature are presented in sections 7.5, 7.6 and 7.7 respectively. Section 7.8 draws the conclusions to the chapter.

7.1. The systems approach

Systems engineering involves creating effective solutions to problems and managing complexities (Stevens et al., 1998). In proposing the E-Track NHS system, the systems engineering life cycle is employed. As shown in Figure 7. 1 the cycle starts with the user requirements for the system and ends with delivered operational capability.

Figure 7. 2 also helps one to understand the current stage of development and efforts required to make the E-Track NHS system operational.

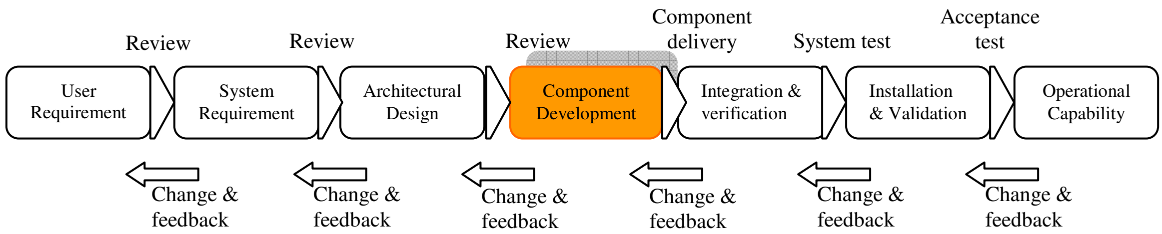


Figure 7. 1: The simple systems life cycle (modified from Stevens et al, 1998, p.8)

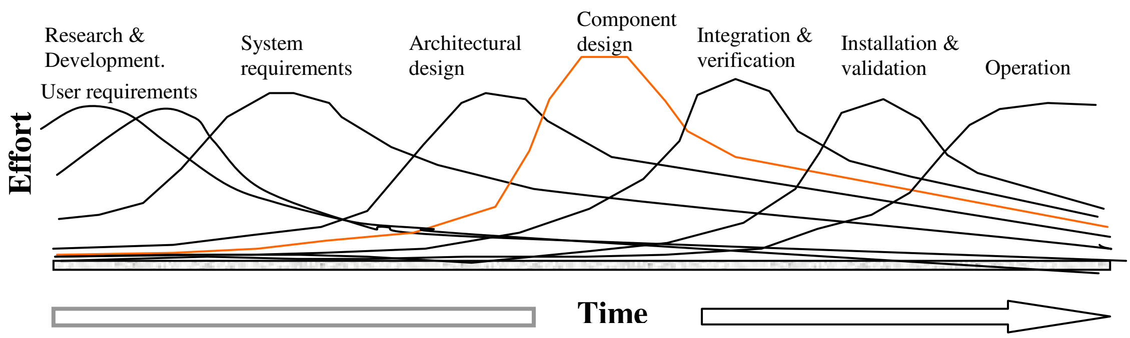


Figure 7. 2: Systems cycle effort and commitment (modified from Stevens et al, 1998, p.10)

7.2. User requirements

In a typical industrial setting where projects are initiated based on customer requirements, Quality Function Deployment (Yoji, 1988) could be a tool used to capture the requirements of the user and convert them into finished products.

As shown in Figure 7. 1, the preparation of the user requirements is the first stage of the system engineering life cycle. Stevens et al. (1998) identify several sources of user requirements including interviews with the users, derivations from business requirements, working in the environment etc.

The current system, however, is born entirely out of research, hence the user requirement gathering phase overlaps with the research development phase. The user requirements presented here were obtained from interviews with healthcare managers and from review of literature and an understanding of the current state of affairs in the NHS. For this reason, some of these requirements may not be elementary (Gilb & Bodie, 2005, p.45)

7.2.1. General description

A detailed description of the user requirements is presented in this section.

7.2.1.1. System perspective

E-Track NHS is proposed as an alternative to the current slow response, costly and resource demanding approach of the annual survey of patients. The proposed system primarily focuses on the concepts of quality of healthcare and total satisfaction in a healthcare system. It is intended to be installed in a hospital environment as stand alone or integrated into the existing system. The key capabilities of the system are highlighted below.

7.2.1.2. General capabilities

The key capabilities expected from the E-Track NHS system are:

- Automatic model generation: the system must not require users to be simulation experts to build and run models of the healthcare system. An interface is therefore required where managers can respond to interactive dialogue boxes and create models at the click of a mouse.

- Real-time simulation runs: the simulation should be integrated and synchronised with the real system so that simulation results will reflect the current state of the system.

- Scenario generation and testing: the system should also have facility for testing the effects of different system configurations and comparing results.

- Fast-forward capabilities: in order to predict future state of the system, E-Track NHS must also have facility for looking ahead based on up to date information obtained from a combination of obtained historical and real-time data.

- Real-time patient and staff tracking using Radio Frequency Identification (RFID) tags: the system must be able to identify patients and staff in the system and acquire relevant real-time data. Staff would have the option to turn the tags on or off for the sake of privacy and to avoid the feeling of being strictly watched. Patients however, do not have that option and would therefore be provided with wrist bands that would be least disruptive.

- Real-time monitoring of quality of care and staff-patient satisfaction: the system should also be capable of providing information of the HPI and S-P SRM to staff and managers in real-time.

- Display of information: the system should also be able to display information on the performance measures to staff and managers and where appropriate to patients.

7.2.1.3. General constraints

There are certain constraints that will affect the design and operation of the system. A few of these with particular reference to the A&E departments are listed below:

- The system setup should not require too much of staff time: A&E staff and managers are very busy and are always uncomfortable to spend time outside direct patient care. 69.1% (n = 68) of A&E staff interviewed about the use of the proposed system were pleased with the concept. One staff commented *"Depends if it won't put extra pressure".* (see question 17 of appendix F)

- The system shall be available 24/7: since the A&E department operates 24hrs a day, the system should also be run as such.

- Patient and staff tracking must be non-invasive: the system must not require more than the unique IDs of patients and staff.

- Staff must have the option to turn tracking off and on: with comments like *"Because not everything is black and white. Patients are different. Management will pick on you".* Some staff preferred a system that will not follow them everywhere.

- The system must not be too costly: some managers also wondered if it won't be a costly system to implement.

- Tracking systems should not interfere with existing wireless devices: some managers also feared the implications of using the RFID system in the healthcare environment and if it may interfere with existing life critical devices.

- The system must be able to run as standalone without requiring information from existing patient database records.

7.2.1.4. User characteristics

Four categories of users are identified for the E-Track NHS system:

- Healthcare managers: based on the author's experience from simulation projects undertaken with healthcare managers (see Komashie & Mousavi, 2005; Komashie, Mousavi & Gore, 2007), it is anticipated that managers would like to:

    a. be able to build simple models of the system by responding to dialogs and clicking the mouse.

    b. test different scenarios of the system and update an existing model with a preferred scenario.

    c. be able to run the simulation model to predict future states of the system.

d. observe service quality and satisfaction levels and other performance measures in real-time.

e. be able to overwrite simulation results with actual current system values where the two differ

- Doctors: will mainly need to view real-time displays of performance measures on screen.
- Nurses: like doctors, nurses will also need to view real-time displays of performance measures
- Patients: will have to be able to enter or respond to questionnaires or fill in forms on a portable device. Patients may also want to observe values of measures such and the Healthcare Quality Index (HQI).

7.3. System requirements

The purpose of the system requirement is to convert the user requirements into systems specifications.

In this section a tabular approach is used to present this information. The capabilities and user requirements are written in two ways under the system requirements, i.e. as what must be done during design time and what must happen during runtime to ensure that the user requirements are met (see Table 7. 1).

Table 7. 1: E-Track NHS System requirements

User requirement	System requirements	
	Design time (To Do)	**Runtime (To Happen)**
Automatic model generation	Define appropriate data structures. Implement real-time connectivity with RFID. Design simulation model in code. Provide functionality for running model. Display performance factors during model run.	Dynamically generate model.
Scenario generation and testing	Define all appropriate data structure. Design simulation model in code. Provide function for running model	Call report generator Display report Overwrite scenario 0 with best scenario.
Predict future state of system	Prepare data for FF simulation Implement FF simulation.	Call report generator and display
Monitor performance measures in real-time	Implement HQI algorithm Implement S-PSRM algorithm Obtain expressions for measures to be displayed	Display HQI, S-PSRM and other measures in real-time as Arena plots.
Entering real-time data from mobile device	Implement *Satistica* mobile Integrate *Satistica* output with Arena RT.	Pass *Satistica* output to HQI and S-PSRM in real-time.

7.4. System architecture

The complete basic architecture for the system is shown in Figure 7. 3. This part of the research is being undertaken by other members of the research team in the Systems Engineering Research Group in the School of Engineering and Design (see Tavakoli, Mousavi & Komashie, 2008a; Tavakoli, Mousavi & Komashie, 2008b).

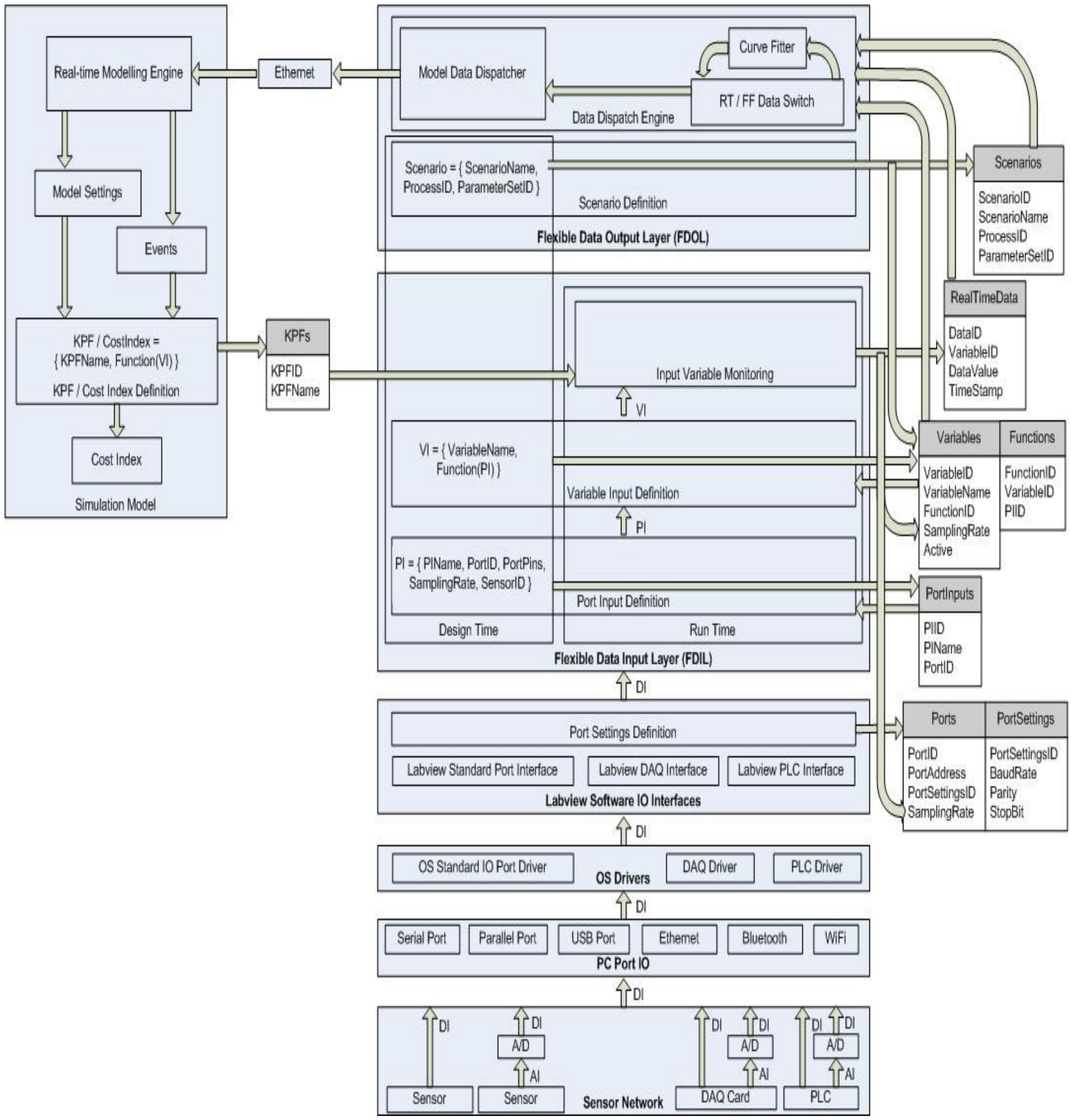


Figure 7. 3: Basic system architecture

The architecture focuses on data flow and the various layers involved. It was designed to be generic in application and starts from the lowest level of data collection, which, in the current application, are the RFID tags on patient and staff and portable device interfaces for patient surveys.

Detail descriptions of aspects of the architecture are given in Tavakoli, Mousavi & Komashie (2008a) and Tavakoli, Mousavi & Komashie (2008b).

7.5. System components

The E-Track NHS system has seven major components as shown in Figure 7. 4. These components are described briefly in sections 7.5.1 through 7.5.7.

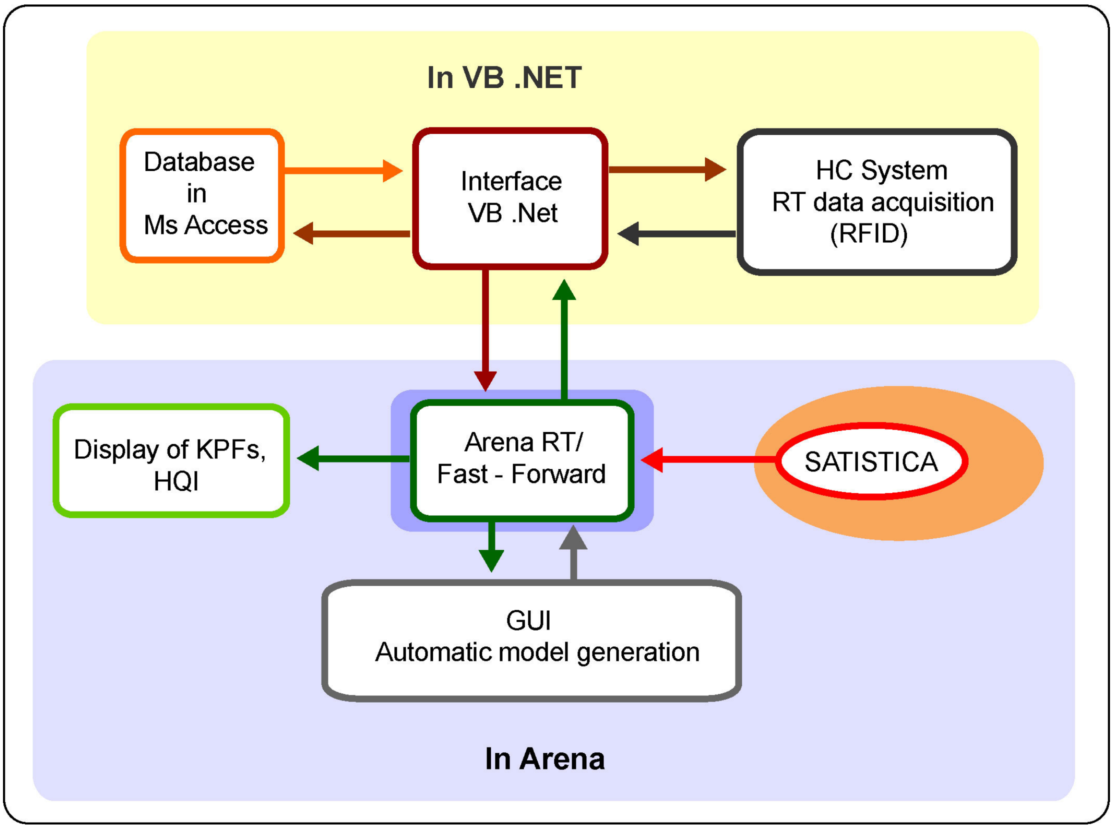


Figure 7. 4: System components

7.5.1. Interface in VB .Net

This component retrieves real-time data from a field data acquisition system and feeds it to the real-time simulation. It also retrieves processing and arrival times from simulation and deposits them into the database. It is also responsible for retrieving and analysing data from database and feeding them to the fast-forward simulation.

7.5.2. MS Access database

This is simply a repository of data.

7.5.3. Real-Time data acquisition using RFID

This is the interface with the real systems and tracks and acquires data on patient arrivals and movements in the healthcare system. It also tracks resource availability in the healthcare system.

7.5.4. Real-Time Display of performance factors

This component is responsible for providing dynamic display of system performance measures.

7.5.5. Arena RT Model/Fast-Forward

This is a Discrete Event Simulation (DES) model with real-time and fast-forward functionalities. The primary model (representation) of the actual system with the corresponding logic is accomplished here. This also provides real-time simulation functionality and also is the platform for the Fast-Forward simulation functionality.

7.5.6. SATISTICA

This component is available mainly to convert patient responses to satisfaction values for the computation of the healthcare quality index and patient satisfaction values.

7.5.7. Graphical User Interface (GUI)

This is to facilitate the automatic model generation for non-simulation professionals. It provides control over mode of system operation. It also provides controls for scenario description and testing.

7.6. Software design

Figure 7. 5 shows the structure of the software with the major classes required and their interactions. The variables and functions involved are briefly described in appendix H.

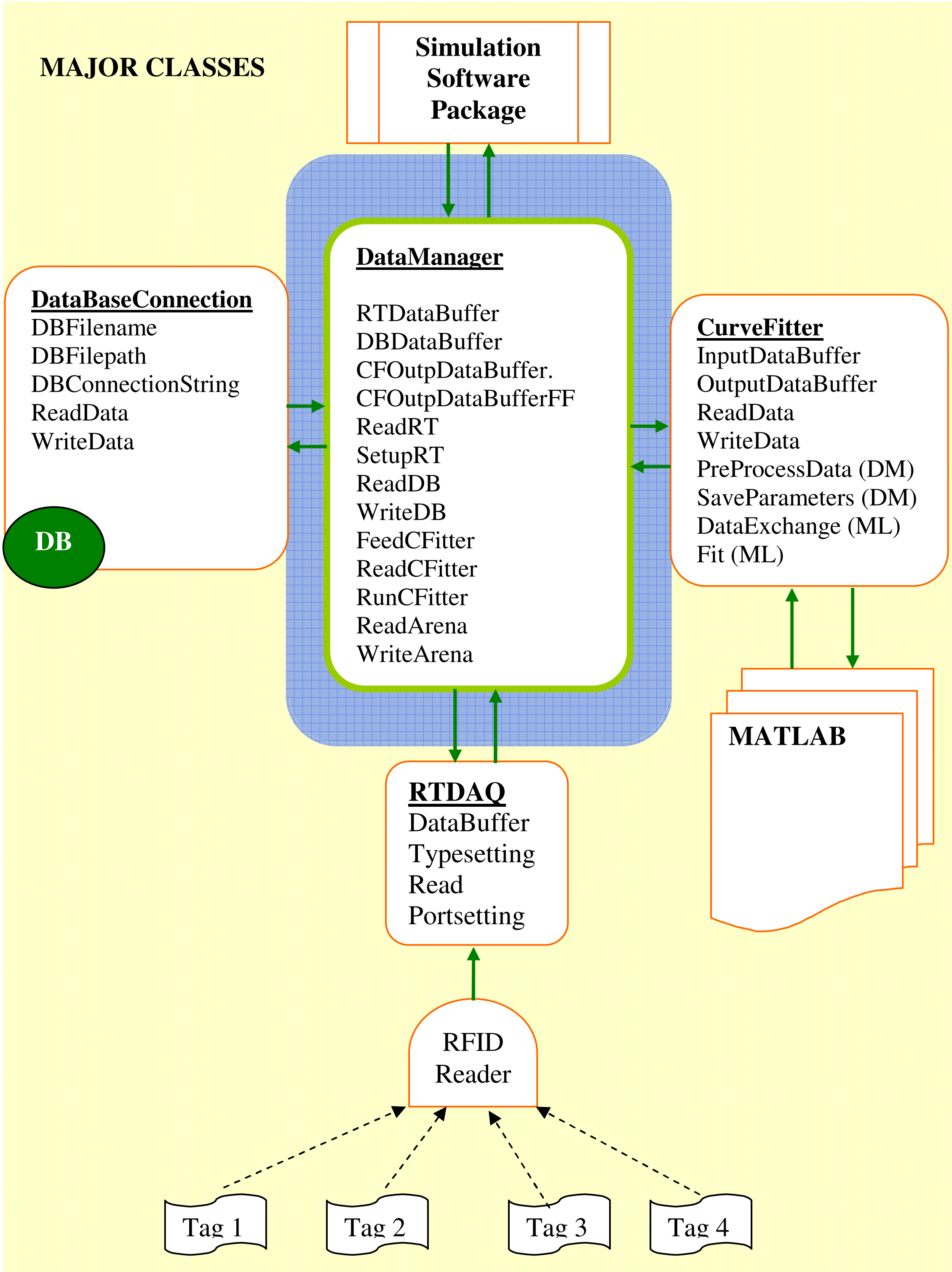


Figure 7. 5: Software structure

7.7. Demonstration of key features

7.7.1. Automatic model generation

Figures 7.6 to 7.10 offer a number of snapshots of the developed software for automatically generating a simulation model in the ARENA simulation software. The software is still under development.

Figure 7. 6: Start screen for automatic model generation demo

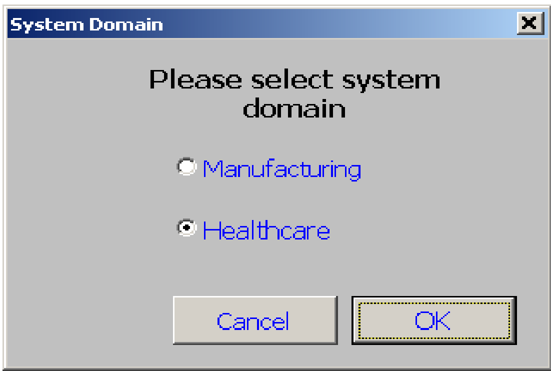


Figure 7. 7: Domain selection for automatic model generation

Figure 7. 8 and Figure 7. 9 illustrate the page where a user may define model parameters. A sample entry on this page is shown Figure 7. 9. Once these parameters are defined the “Create Model” button is enabled and the user can then create a simulation model in Arena with the click of the mouse. A simple model automatically generated by this demo is shown in Figure 7. 10.

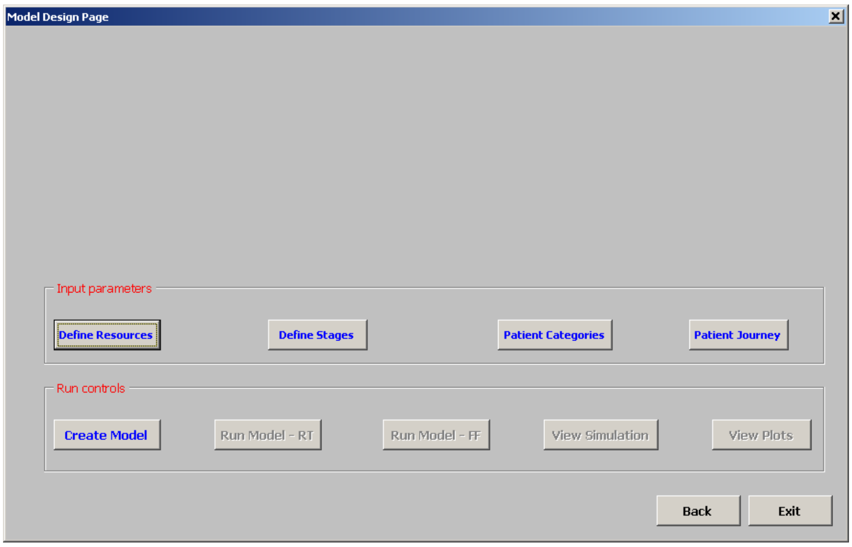


Figure 7. 8: Model design view for automatic model generation

Once the model is created other functionalities in the model design are enabled so that the user can run experiments and view results.

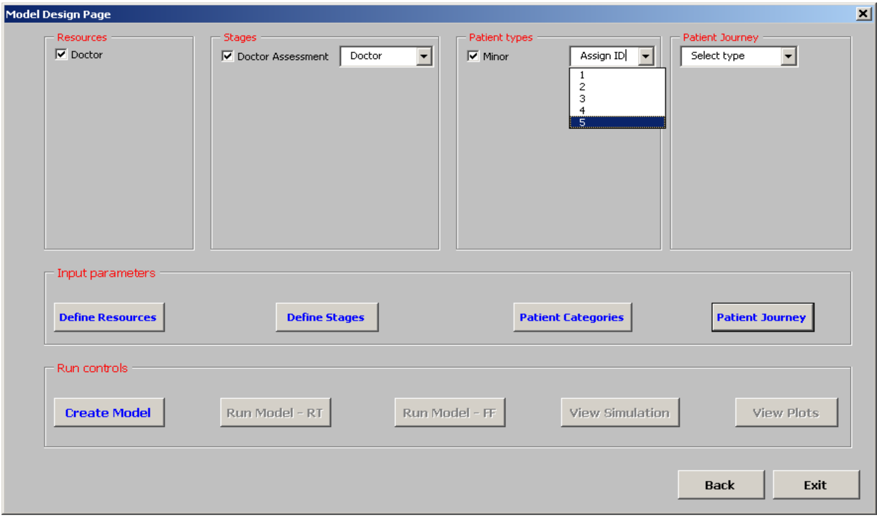


Figure 7. 9: Model design view with some parameters

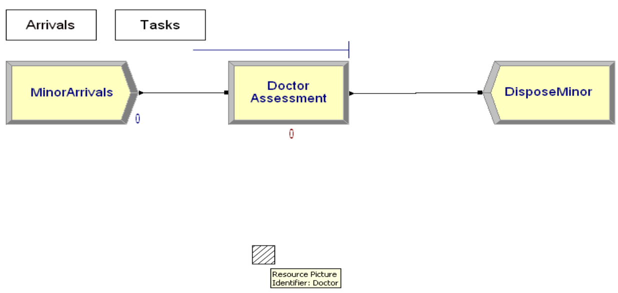


Figure 7. 10: Automatically generated Arena model

7.7.2. Real-time simulation

The complete hardware and data acquisition system was developed by Siamak Tavakoli, a member of the SERG team for a manufacturing environment. What is shown here therefore is an adaptation into the proposed healthcare system. The proposed E-Track NHS system is intended to run in real-time, fully integrated into the actual healthcare system. Figure 7. 11 shows a photo of the laboratory setting where the system is being tested. One computer in the photo runs the simulation model and the other runs the data acquisition software. The active RFID tag reader can be seen between the two computers with the readers on the desk. Figures 7.12 and 7.13 close shots of the running model and the display of performance indicators. The active RFID tags are used to track resources (staff) whilst patients are tracked with passive tags which are not shown in the photo.

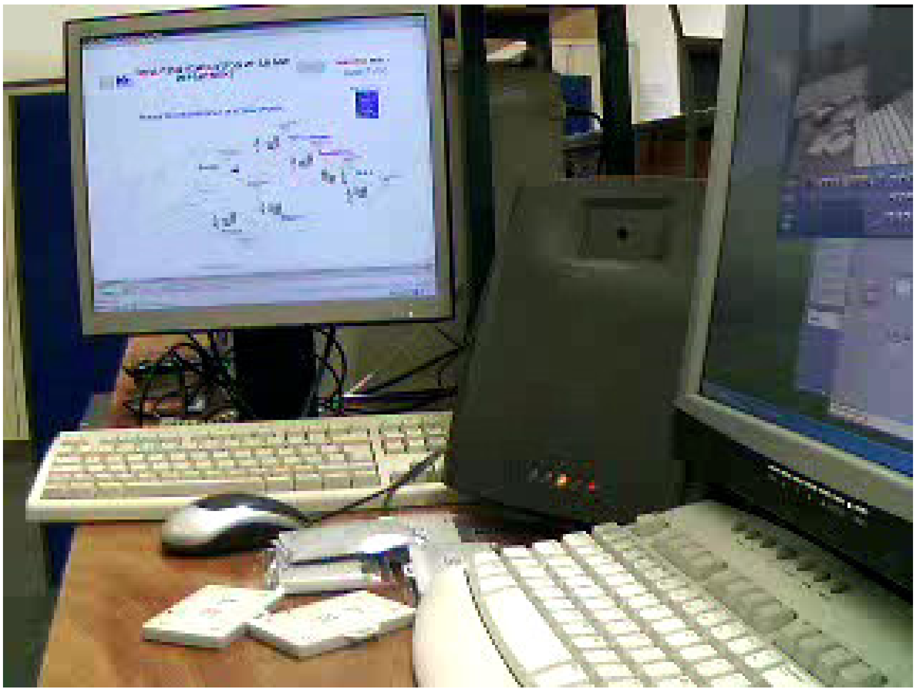


Figure 7. 11: Laboratory setting showing modelling computer, data acquisition computer RFID reader and tags.

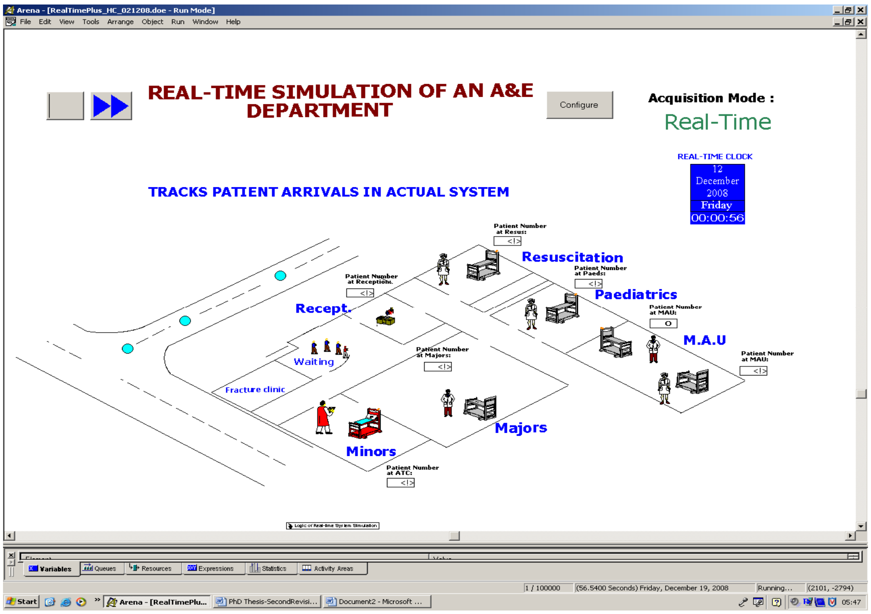


Figure 7. 12: Snapshot of the model running in real-time

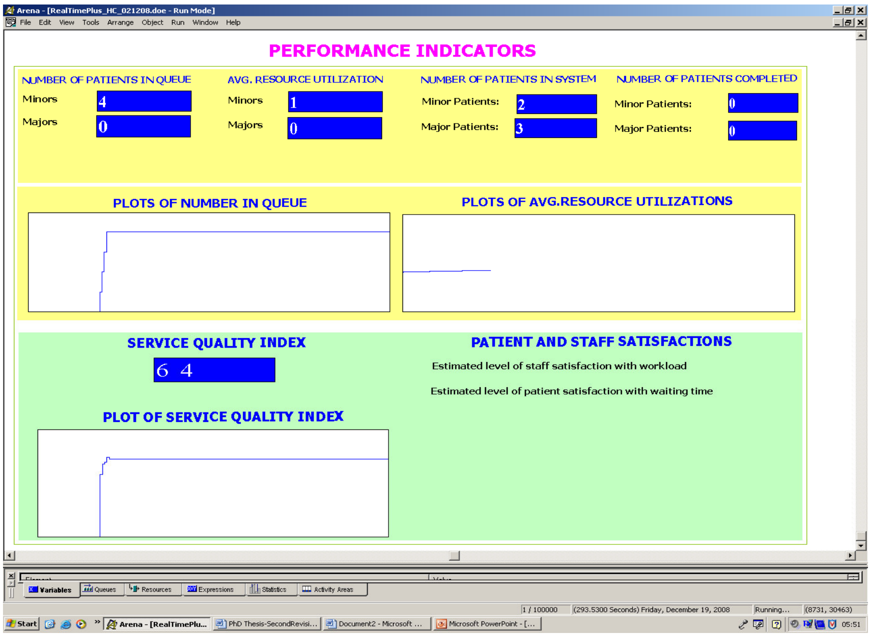


Figure 7. 13: Snapshot of the display of system performance indicators

The communication between the RFID readers and the model is implemented through a messaging system in Arena RT. This messaging system is coordinated by the data acquisition and interface manager developed by this author's colleague Siamak Tavakoli (Tavakoli, Mousavi & Komashie, 2008b). A version is shown in Figure 7. 14.

When a patient arrives in the actual system, the arrival is detected by the reader and a message is sent to the real-time simulation which then creates a patient entity into the simulation model and advances the patient (entity) according to its process plan. The messages sent and received are shown in the two columns in Figure 7. 14.

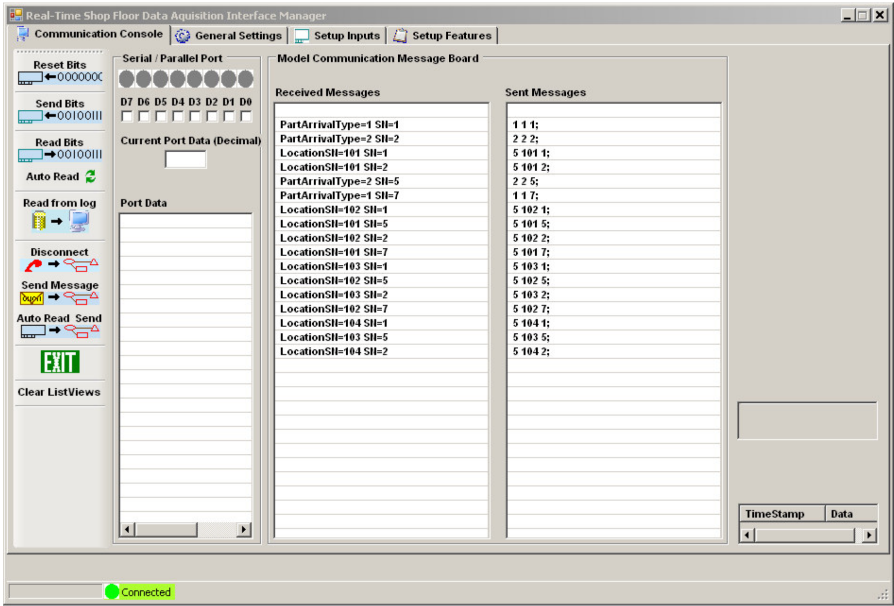


Figure 7. 14: Data acquisition and messaging interface for real-time simulation

7.8. Conclusions

The main features of the E-Track NHS system were presented:

- Automatic model generation
- Real-time simulation runs
- Scenario generation and testing
- Fast-Forward capabilities
- Real-time patient and staff tracking using RFID tags
- Real-time monitoring of HPI and S-PSRM
- Display of system information.

The main requirements of the system have been defined and the system architecture introduced.

The key components of the system were described and some of the key capabilities were also demonstrated.

This completes the research work done so far on E-Track NHS and further work will be required for completion. The current stage of work is clearly indicated on the system development life cycle as shown in Figures 7.1 and 7.2.

However, if E-Track NHS is to become a reality in the NHS, there will be barriers to overcome.

The next chapter therefore examines some of the key challenges that may be anticipated in the implementation of E-Track NHS.

8. Challenges to the implementation of E-Track NHS

"There cannot be a greater mistake than that of looking superciliously upon practical applications of science. The life and soul of science is its practical application."

Lord Kelvin, (1883)

If E-Track NHS is to become a reality in the NHS, it is bound to come against challenges. This chapter is therefore important for all stakeholders and all who recognise the importance of a quick response system that provides up to the minute real-time quality and satisfaction information to NHS patients and eventually to the public. E-Track NHS has been proposed as a new approach to managing quality of care and patient satisfaction in a healthcare environment with a balanced focus on patient and staff. In previous chapters, the relevance of such a system has been presented. It has also been suggested that with the concept of E-Track NHS, the annual cycle of patient survey by post can become a daily reality resulting in considerable savings in cost, time and resources. Measuring the extent of these savings in cost, time and resources, however, requires further investigation.

Furthermore, it has been emphasised that the strength and uniqueness of E-Track NHS is in the integration of its conceptual models of quality and satisfaction with the technological features of real-time simulation, automatic model generation and predictive capabilities as developed in chapters 5, 6 and 7 respectively. However, like every new technology, there are challenges and limitations to the application of this system.

In section 8.1, the inevitability of change and some challenges are discussed. Section 8.2 discusses the limitations of the system and section 8.3 finally summarises the discussions in this chapter.

8.1. Inevitability of change

Healthcare systems including the NHS are highly resistant to change both structurally and culturally (McKee & Healy, 2002; Plamping, 1998). However, this resistance is not unique to healthcare but rather general as vividly portrayed by the following quote from Marcel & Jeffrey (1991):

"Routine – the same route, the same technique, and the same results – pushes off the need to make choices. Innovation – the imaginative attempt to introduce something new or to solve some problem – smashes routine and demands choice, even if only the choice to retain the status quo."

Thus in any organisation with an established culture of work, change and innovation will always have to break barriers and overcome obstacles. Furthermore, current evidence suggests that planned organisational change is difficult to implement and presents serious challenges to both management and healthcare professionals (Iles & Sutherland, 2001; Paton & McCalman, 2000). However, the fact that change is the greatest constant of modern times (Sterman, 2000) makes it important to find appropriate ways of overcoming such obstacles to change. A number of observations specific to the NHS are discussed below. These have mainly been identified via the literature around change management in healthcare (e.g. Iles & Sutherland, 2001; McNulty & Ferlie, 2002) and observations made in the wider evaluation (Gore et al., 2008) under which this research study was conducted. The wider evaluation identified many positive outcomes of the new hospital model that was studied, while some potential barriers to change were identified, as found in most hospital change programmes of this scale.

8.1.1. The NHS barriers to change

Some of the barriers identified in the literature which may be applicable to E-Track NHS are as follows.

8.1.1.1. Staff ownership in the change process

One of the key barriers to change is attempting to introduce change without ensuring that staff on the ground feel part of the process. The hospital change programme that was evaluated (Gore et al., 2008) showed that many attempts were made to involve staff and users at each key step of the way, and this enhanced the developmental progress. A review conducted by Komashie et al. (2007), into the origin of the *quality problem* revealed that the level of ownership felt by the craftsmen during the era of the village market place was significant to the quality delivered. This era was evidently an era of high quality and satisfied customers as shown in the study. The review therefore suggested that modern quality improvement methods should give staff ownership and pride in a way that is akin to the era of the craftsmen. By providing information on quality and patient satisfaction in real-time to staff and managers as implemented in E-Track NHS, staff will be able to quickly respond to changes in performance and patient views, and will also see when their efforts directly result in performance improvements.

8.1.1.2. Cultural barriers and traditionalism

To some staff, a new way of doing things involving new technology may be perceived as an attempt to "police" them. It is therefore important that the intentions of any change are made clear and staff are assured of the purpose and value of using a technology. It is true that

"…The most accurate diagnosis of a healthcare problem and the most valid assessment of the factors contributing to it will not produce the desired improvement unless effective techniques for changing individual and organisational behaviour can be applied when necessary" (Jessee, 1981).

E-Track NHS thus provides a system whereby staff do not have to wait for an annual report on how a department has performed but will have this information on a daily basis, facilitating continuous improvement and change perception of how quality is managed.

8.1.1.3. Fear of using new technology and its implications

Fear of using new technology, and what impact it may have on staff is an important factor to consider. For example, how would staff cope with seeing patient satisfaction go up and down as they work? What will staff who achieve high levels of patient satisfaction during their shift think of colleagues on shifts with lower satisfaction? The argument for E-Track NHS in this context is that, the problem is not so much with the information on levels of satisfaction achieved but rather how that information is used. This is similar to efforts of healthcare professionals and researchers to ensure a safe environment for reporting medical errors. A sympathetic and learning (rather than blame) culture is important for such technology to be applied optimally. This also requires a systems approach (Stratton et al., 2004). E-Track NHS provides an environment that facilitates quick response to problems by making information available in real-time. Therefore it may be expected that before satisfaction drops to unacceptable levels it would be identified and the cause addressed before it gets worse. Furthermore, this is also in line with current cultural shift in NHS care, where there is a move towards "payment-by-results" and greater transparency and accountability; and greater use of patient experience data.

8.1.1.4. Management and staff understanding of the technology involved

Some management and staff may be resistant to a technology or system they find difficult to understand. Any new system therefore needs to be clearly communicated and easy to understand. In this regard, E-Track NHS has been developed using concepts that healthcare managers and staff already understand – quality of care and patient satisfaction. The development has also been based on empirical evidence from the ground level and therefore has reality built into it. The automatic model and scenario generation interface is also meant to make the system friendly to non-experts of simulation. More evaluation is required around user-acceptability.

8.1.1.5. Cost issues

With the current huge financial pressure in the NHS, a high cost system will be an obvious barrier to change. As discussed in chapter 3, the current annual cycle of assuring quality using surveys conducted by the healthcare commission, is slow, costly, time consuming and resource demanding. E-Track NHS has been designed to be a quick response and cost effective system by eliminating the cost of postage, data analysis and avoiding loss of important aspects of patient experience by acquiring the information whilst patients are onsite instead of months after visiting. However, in order to estimate the practical financial benefits, more evaluation, piloting and cost-benefit analysis will be required.

8.1.1.6. Possibility of engendering team competition

Team competition could be beneficial in terms of enhancing quality but in some cases it may become discouraging to staff. This problem would rather require a management strategy for mitigation. The wider hospital evaluation identified that the “whole systems” approach to managing change has become a popular focus of managers and clinicians working in the NHS (Iles & Sutherland, 2001). This approach avoids emphasis on only one or a few aspects of the whole system, therefore may reduce the risk of one team or group having a competitive edge. Also the entire NHS is now moving even more towards a multi-disciplinary approach and so E-Track NHS which adopts a systems approach to managing quality, should be seen as a device for measuring a more ‘unified healthcare team performance’ rather than that of an individual.

8.1.1.7. Radio Frequency regulations

Any device that relies on radio frequency is usually a source of concern particularly in the healthcare environment. The three key areas of prime concern are data security, interference with operation of existing devices and human exposure. Since E-Track NHS proposes the use of Radio Frequency Identification (RFID) wrist bands for acquiring patient data, the implications were given considerable attention. This involved consultation with experts in the field and reference to existing guidelines on radiation based devices.

One expert consulted is Professor Anthony Furness, the technical director of AIM UK a body that provides guidance for industrial application for RFID devices. Professor Furness has worked extensively in the area of RFID and the healthcare sector and is an acknowledged authority on RFID.

Professor Furness advised that the WHO International EMF Project (WHO, 2009) asserts that "No major public health risks have emerged from several decades of EMF research, but uncertainties remain". This supports the need for a precautionary approach (*personal communication*). This precautionary approach is facilitated by guidelines published by the International Commission on Non-Ionising Radiation Protection (ICNIRP).

A study published by Van der Togt (2008) demonstrated that RFID readers can, under certain conditions, interfere with medical equipment typically used in critical care settings. Analysing this finding, Moore (2008) noted that the study's authors used equipment set to its highest power levels to test for worst-case scenarios. While worst-case testing is valid, it does not necessarily represent real world issues. Thus, while adverse effects were observed, the conditions under which they were created were not those likely to exist in an actual healthcare setting.

8.1.2. Implications of E-Track NHS to healthcare delivery

Following all the analysis presented in this thesis, it may be considered feasible that apart from the expected impact of this system on the quality of healthcare and the satisfaction of patient and staff, the costly and resource demanding annual monitoring exercise by the Healthcare Commission may also be complemented by the proposed E-Track NHS with:

- A fraction of current costs
- High accuracy of results
- High usability
- Enhanced Scientific Predictability

This is consistent with the renewed vision of the NHS as stated in the Lord Darzi report.

"An NHS that gives patients and the public more information and choice, works in partnership and has quality of care at its heart" Lord Darzi (2008)

8.2. Limitations of the E-Track NHS system

In presenting the models developed in this research it is important to note that they are not without assumptions and limitations.

In the development of the HPI, it was assumed that the index was a linear combination of the performance indicators. Though this is not far fetched, it must be seen as a hypothesis.

The key quality indicators for the HQI were also formulated as linear combinations of their corresponding factors as shown in Table 5. 4. The process of identifying these factors was considerably subjective.

Although this is a limitation, the model has been developed in such a way that any user can define and use indicators of their choice and still have the advantage of the robustness of the model formulation method.

The development of the staff-patient satisfaction relation was also based on the model of the A&E department as a single server queuing system (*M/G/1*) in a steady state. This limitation, however, can partly be relaxed by extending the model to a network of queues as discussed in chapter 6. Further research is required for this extension and testing.

8.3. Conclusion

Change is inevitable but resistance to it can be strong in human-based systems.

Some of the barriers to change identified are lack of staff ownership in the change process, work culture and traditionalism, the fear of new technology, lack of understanding for new system, cost issues, fear of ensuing competition and frequency regulations. The features of real-time quality monitoring of the E-Track NHS system was expected to make the quality monitoring process more transparent and give staff more ownership in the process.

Some limitations of this research were also presented including the assumptions of linearity in the formulation of the HPI and the single server queuing model used to develop the staff-patient satisfaction relation.

The next chapter presents the conclusions to this work and provides some direction for future research.

9. Conclusions and future work

"Essentially, all models are wrong, but some are useful"

George E.P. Box (1987)

This chapter summarises the goals and the key contributions of this research. It also provides some direction for future work.

9.1. Summary of research goals and key contributions

The goal of this research has been stated as the investigation and development of a new approach to the management of service quality and satisfaction in healthcare. The constructs of service quality and satisfaction have been identified to be fundamentally different but in fact inseparable. This research has focused on the challenge presented at the physical level of quality management, which involves finding better methods for the accurate measurement of service quality particularly in healthcare.

The service quality literature shows evidence of considerable efforts to represent quality at the conceptual level. At least nineteen different conceptual models of service quality have been found. Amongst these models, the GAP model and its SERVQUAL instrument (Parasuraman, Zeithaml & Berry, 1985) have become the most widely used. The GAP model, however, confounds the constructs of service quality and customer satisfaction by its emphasis on expectation-minus-performance as a measure of service quality. This and other limitations of the model have been strongly challenged by Cronin & Taylor (1992) and others yet it remains the most used model amongst researchers even in healthcare.

The evidence suggests that researchers have not yet considered the possibility of an integrated view of the concept of service quality so as to develop models that involve appropriate data collection, analysis and presentation methods. As a result, a real-time method of continuously measuring and monitoring service quality is non-existent and this has been the object of this research.

The current research which seeks to investigate a new approach to the measurement and management of service quality in healthcare, commenced with a historical comparative study into the origins of the quality problem in industry and healthcare.

9.1.1. Comparative study of quality in industry and healthcare

The purpose of this comparative study was to examine the origins and the history of the quality problem and to explore the application of quality assessment techniques in manufacturing and healthcare. It has been found that industry and healthcare differ significantly in the initial concerns for quality, the trend in the demand and supply of quality and in the evolution of the evaluation techniques.

The historical review further revealed that three events in history of quality have contributed greatly to its fall over the years, particular in industry. These are:

- The separation between the producer (or provider) and the consumer. It has been argued that this is the very root of the quality problem. In primitive years, the producer was the same as the buyer. There were no problems with trust, ownership and commitment and hence no quality problems existed.

- The industrial revolution shifted the focus from the quality and commitment of the craftsmen to productivity and profit which continues till this day.

- The technological explosion of the late twentieth century and the resulting complex systems.

It has been suggested that the elements of *trust, commitment and ownership* must be considered in the design of modern quality improvement programmes or systems. The feeling of ownership for healthcare staff is particularly important.

A caution was offered to ensure that the issues of appropriateness and practicality must be robustly examined in all attempts to apply industrial techniques to the improvement of service quality in healthcare.

9.1.2. Identification of the gap in the application of real-time quality improvement in healthcare.

Some applications of discrete event simulation in healthcare were found. It was, however, noticed that in spite of the number of applications, there were no examples that categorically set out to apply Discrete Event Simulation to improve quality of care and satisfaction as put forward in this research.

It has been shown that the current annual cycle of quality improvement efforts by the National Institute for Clinical Excellence (NICE), clinical governance teams and the Healthcare Commission are more useful at the strategic level of quality management than at the operational level. The current methods of data collection, analysis and presentations also mean a long time lag between quality measurement and improvement.

Due to the above weakness of the current quality improvement cycle, the gap was identified for the provision of a dynamic, operational level system of performance monitoring as proposed in this research by the concept of E-Track NHS.

The current practice in the NHS is for Trust to be rated as Excellent, Good, Fair, or Weak. This method of performance rating of NHS Trusts by the Healthcare Commission raises two very important questions from the patients' point of view. That is, for an NHS Trust rated excellent, one may ask:

1. Can a patient expect an excellent level of service in all areas of a Trust rated "Excellent"? And

2. Can a patient expect an excellent level of service at all times until the next rating a year after?

The former is an issue of homogeneity, the latter an issue of consistency and both are important in our attempts to drive up sustainable improvement in the quality of care.

The above questions together with knowledge of the key ingredients of high quality – trust, commitment and ownership, led to the main hypothesis of this research that, an accurate conceptual representation of service quality in healthcare is not adequate for a real-time (continuous) measurement, monitoring and improvement of the quality of care. What is needed is a real-time method with sound concept but also capable of integrating the processes of data acquisition, analysis and presentation at the operational level as proposed in E-Track NHS. This requires a reliable measure of the service quality and satisfaction that can be monitored in real-time. It is for this purpose that the Healthcare Performance Index (HPI) and the Staff-Patient Satisfaction Relation Model (S-PSRM) were proposed.

Whilst E-Track NHS represents the proposed system in the broad sense, the key contributions of this research focus on the theoretical development and testing of the HPI or HQI and the S-PSRM.

9.1.3. A unique index for monitoring quality of healthcare has been developed

In developing an index for measuring quality, it has been shown that in an environment where there is bound to be uncertainty, the GME estimator is more robust and less biased compared with the LSR method.

This implies that in the dynamic estimation of performance in the healthcare environment where many of the determining factors are not known, the GME estimation method should be preferred since it does not require a large number of assumptions and is not significantly affected by sample size and data patterns.

One weakness of the GME estimation method is the setting of the support space. This has been found to require a compromise between accurate results and avoiding errors in the estimation process. The wider the error support range specified the less likely it is to have problems during the estimation but error estimates would be slightly higher.

9.1.4. Introduction of the Effective Satisfaction Level (ESL)

It has been found that the current approach to managing queues in the NHS through targets and performance ratings are partly problematic. Significant improvements have been attributed to targets in the NHS. However, evidence of "coping" strategies employed by NHS Trusts during assessment periods may make the results doubtful.

It has also been found that in the management of queues in the NHS, significant emphasis is placed on satisfying the patients without understanding the effects on staff that are the key resources in the system. This research has therefore focused on showing the strong link that exists between the service time of staff and the waiting time of patients and hence between the satisfaction of staff with workload and patient satisfaction with waiting time. Three hypotheses were tested and were all rejected on the grounds of empirical evidence.

The hypothesis that there was no relationship between staff satisfaction and service time was rejected when two-sample z-tests revealed statistically significant differences between mean satisfaction values at various values of service time.

Based on the empirical data, a model has been developed for measuring the satisfaction of staff with service time. The model fitted the data with an R-squared value of 96.91%. The development of this model made it possible to directly relate the satisfaction of staff to that of patients.

By analytically relating the satisfaction of staff to that of patients, the concept of the Effective Satisfaction Level (ESL) was developed. This concept suggests a shift from the focus on patient satisfaction to a point of operation where both patient and staff satisfaction are maximised. This is a critical and original postulation of this research. It is argued that all healthcare systems must ideally operate at the ESL and where this is not possible due to resource constraints, it is still important to know how far a system is from its ESL. It has been found that the ESL occurs when the ideal service time equals the ideal waiting time.

The possible implications of the ESL are that targets would become more meaningful and it will become easier to determine whether a system is sufficiently resourced to meet the preset targets.

The empirical studies suggest, in part, that even the staff of the emergency department may not fully understand the effect of patient waiting time on staff workload. Up to 84% of staff were dissatisfied if they had to spend less time with patients than they would want at each stage of the patient journey, yet 78% of staff were very satisfied if the patient total time in the A&E is less than they expect is ideal.

9.1.5. An architecture for the implementation of the proposed system

The key capabilities of the proposed E-Track NHS system have been presented. The main requirements of the system have been defined and the system architecture introduced. The key components of the system were described and some of the key capabilities also demonstrated. The current state of the development of the system has been located on the simple systems life cycle to help the continuation of the project.

E-Track NHS is based on the concept of real-time measurement and monitoring the quality of healthcare. The ability of making performance information available to staff and managers in real-time is of high importance. Apart from enhancing the feeling of ownership of staff in the quality improvement process, it will also make staff more able to respond quickly to causes of poor quality than they could if they had to wait for an annual survey to be published.

The key conceptual limitation of E-Track NHS as a real-time system, however, is the fact that patients will not be able to provide information on the effectiveness of the medical treatment. This is because patients are more able to judge this from their recovery progress after they have left hospital.

It is in view of this limitation that two assumptions were stated in section 2.1.2 firstly, that the quality of clinical services are acceptable and secondly, that all staff are committed to delivering high quality care.

9.2. Future work

The introduction of the Effective Satisfaction Level (ESL) opens numerous opportunities for exploration and understanding of the queuing problem in the NHS. The following questions may be candidates for further investigations;

1. What is the optimum level of resources required for a system to operate at the ESL? Variations of this question may be investigated depending on different contexts.

2. What level of demand can a system accept without moving off the ESL?

3. What is the realistic waiting time for a system operating at the ESL, given a fixed level of resource?

It may also be of interest to extend the model to cover a network of queues in order to relax most of the assumptions applied in the current form.

Another opportunity will be to test the HQI with more complete data to fully validate its accuracy in practice.

The current research did not attempt to quantify the cost benefits of implementing E-Track NHS. This may be a subject for further investigation.

Finally, the piloting of the proposed E-Track NHS system at one or more candidate NHS sites to test the responses of staff and patients, as well as its practical application, is an important next step in the evolution of this unique technology.

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Appendix A: Importance rating of key quality indicators

Importance study of Aspects of Emergency Department Care

Position	**Aspect of care**	**% rating issue as 'most important'**
1	Confidence in doctors and nurses	95%
2	Being treated with respect and dignity	91%
3	Explaining condition in way I can understand	91%
4	Being told what danger signals regarding my illness or treatment to watch at home	88%
5	Privacy when discussing my condition	86%
11	Not having to wait too long to see a nurse to assess my priority on arrival	77%
16	Not having to wait too long before seeing the doctor	70%
17	Fairness of the system for who saw the doctor/nurse first.	70%
20	Having someone on the hospital staff who spoke my language	69%
22	Overall cleanliness of the A&E	67%
25	Being told how long I would have to be examined.	65%
27	Cleanliness of toilets at the A&E	63%
29	Not having to wait too long for any tests or x-rays to be carried out.	63%

Source: Picker Institute Europe

Appendix B: Generalised CORE model

Original CORE model

Mousavi et al, (2001) developed the CORE model which gives the function for user satisfaction with a product attribute and includes a given importance level as;

$$S_{ij} = \arctan\left[\ln \alpha_{ij} + \frac{\pi}{2}\right] \times \left(-\frac{e^{-\varepsilon_{ij}} - e^{\varepsilon_{ij}}}{e^{-\varepsilon_{ij}} + e^{\varepsilon_{ij}}}\right) + 1 \qquad \text{B.1}$$

$$= \Omega \tanh \varepsilon_{ij} + 1 \qquad \text{B.2}$$

Where

$$\Omega = \arctan\left[\ln \alpha_{ij} + \frac{\pi}{2}\right] \qquad \text{B.3}$$

$$\tanh \varepsilon_{ij} = \frac{e^{\varepsilon_{ij}} - e^{-\varepsilon_{ij}}}{e^{\varepsilon_{ij}} + e^{-\varepsilon_{ij}}} \qquad \text{B.4}$$

The value of ε_{ij} is given by;

$$\varepsilon_{ij} = -abs\left(\frac{v_i - v_{ij}}{v_{ij}}\right) \qquad \text{B.5}$$

$$-1 \le \varepsilon_{ij} \le 0 \qquad \text{B.6}$$

Where

i is the product attribute,

j is the customer,

v_i is the actual design solution value for attribute *i*,

v_{ij} is the required value for attribute *i*, for customer *j*,

ε_{ij} is the distance between the actual design value for attribute *i*, and the value for customer *j*'s requirement.

Assumptions

$v_i \le v_{ij}$, thus the design value never exceeds the required value in magnitude.

S_{ij} is maximum (= 1) at ε_{ij} = 0 or when $v_i \ge v_{ij}$

S_{ij} varies between 0 and 1

Observations

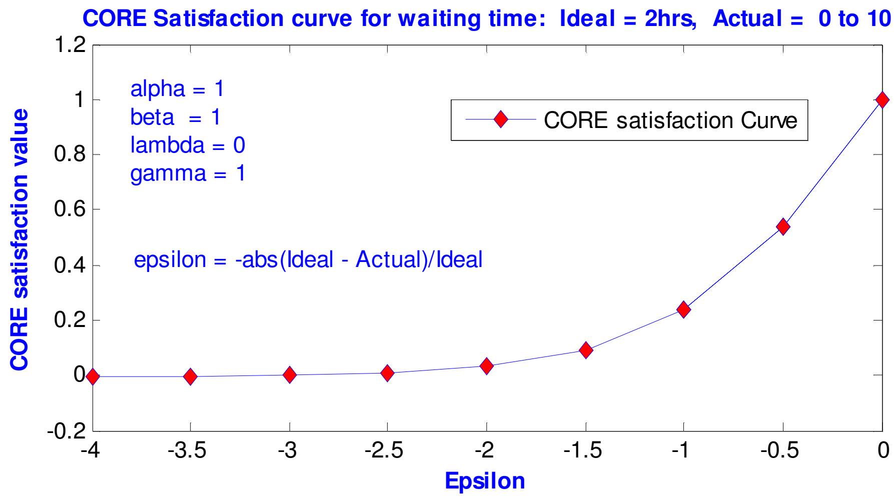
Assumption number 1 implies that the model is only applicable to 'bigger is better' attributes. Thus for a 'smaller is better' attribute, the model will take an increase in satisfaction for an increase in dissatisfaction.

Assumption number 1 will result in the waste of money spent in improving satisfaction. For example, improving an attribute two times better than required will indicate the same satisfaction as improving it just to the level required.

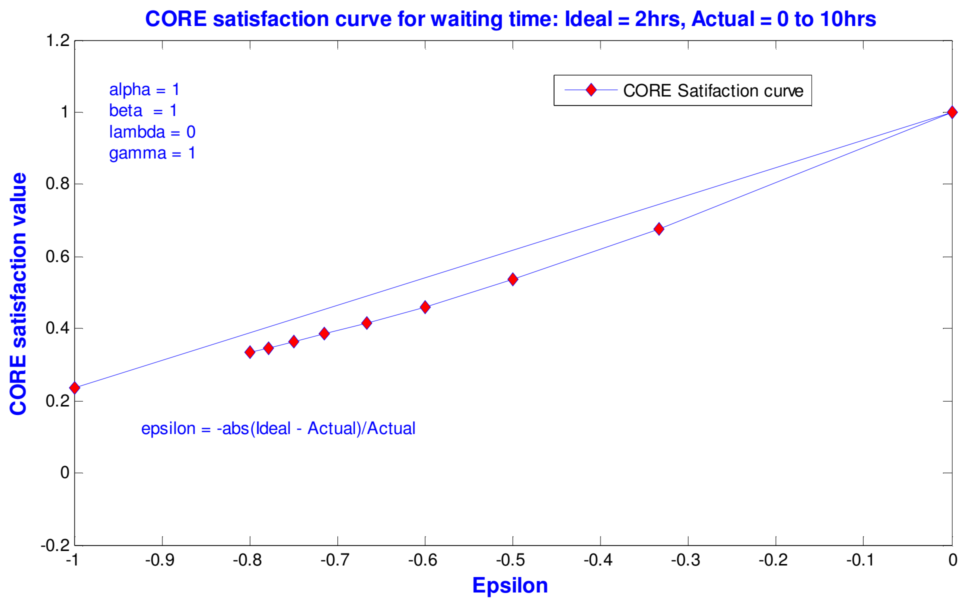
Assumption number 1 will be difficult to achieve in practice since the value of v_{ij} is not always known. Hence there is a high possibility that v_i will be found exceeding v_{ij} and be wrongly evaluated as dissatisfaction by the model.

The function S_{ij} is not maximum at ε_{ij} = 0. Assuming Ω = 1, S_{ij} will be maximum (≈ 2) at ε_{ij} = 2. However from equation 7 above ε_{ij} cannot be more than 0.

An application given in Mousavi et al, (2001) sets v_i to 5 and v_{ij} to range from 1 to 6 which makes it possible for v_i to exceed v_{ij} .

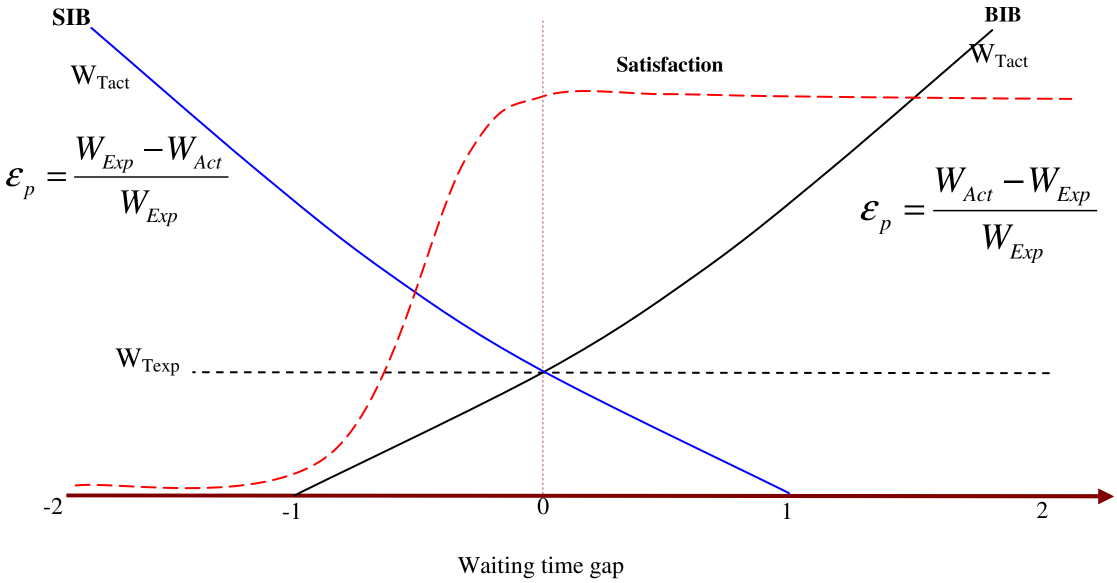


coresat	0.2354	0.5361	1	0.5361	0.2354	0.0913	0.0322	0.0096	0.0011	-0.0021	-0.0032
eps	-1	-0.5	0	-0.5	-1	-1.5	-2	-2.5	-3	-3.5	-4
actual	0	1	2	3	4	5	6	7	8	9	10



coresat	0.2354	1	0.6772	0.5361	0.4609	0.415	0.3843	0.3624	0.346	0.3334
eps	-1	0	-0.3333	-0.5	-0.6	-0.6667	-0.7143	-0.75	-0.7778	-0.8
actual	1	2	3	4	5	6	7	8	9	10

Attribute type and gap determination



The generalised CORE model

A generalised customer satisfaction model is suggested with well defined parameters to facilitate its application in different areas. The generalisation is proposed based on an analysis and scrutiny of the model developed by Mousavi et al (2001).The generalised model is stated as:

$$P(\varepsilon) = \omega \tanh(\beta\varepsilon + \lambda) + \gamma \qquad \text{B7}$$

Where

ω is the range factor, $\omega \neq 0$

β is the sensitivity factor, $\beta \neq 0$

λ is the horizontal location factor

γ is the vertical location factor

ω has the effect of closing or widening the range satisfaction values for the function. For all the curves in Figure B 1, the value of ω is 1 but if for example ω is set to 0.5 for the $P(\varepsilon) = \tanh(\varepsilon) + 1$ curve, its values will start from 0.5 to 1.5 instead of from 0 to 2 as shown in the figure.

β is the sensitivity factor and has the effect of increasing or decreasing the sensitivity of the function. Figure B 1 shows a curve with β = 2.

λ, the horizontal location factor is used to adjust the location of the curve along the horizontal axis. This is useful in determining at which value of the function ε = 0. Figure B 1 shows curves with λ = 1.

γ, the vertical location factor is also used to adjust the location of the curve along the vertical axis. This is also useful in ensuring that all values of the function are positive. Figure B 1 shows curves with γ = 1.

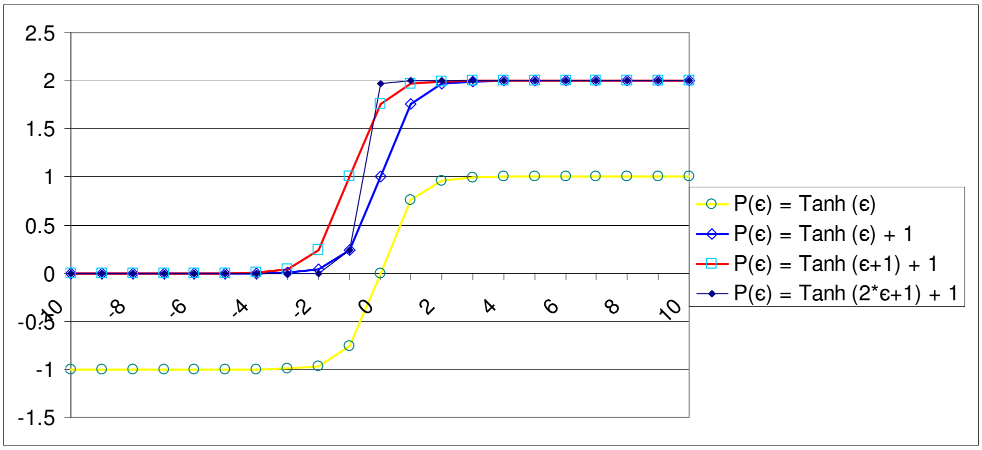


Figure B 1: The hyperbolic tangent curve

Equation 6.3 therefore can be seen as a special case of the generalised model where $\beta = 1$, $\lambda = 0$ and $\gamma = 1$.

Figure B 2 is therefore the form of the CORE satisfaction model that has been applied in this study because it is closer to the satisfaction behaviour of patients. The value of lambda the horizontal locator is set to 2 so that the maximum value of satisfaction occurs at a relative distance (epsilon) equal to 0. The value of beta is set to 3.

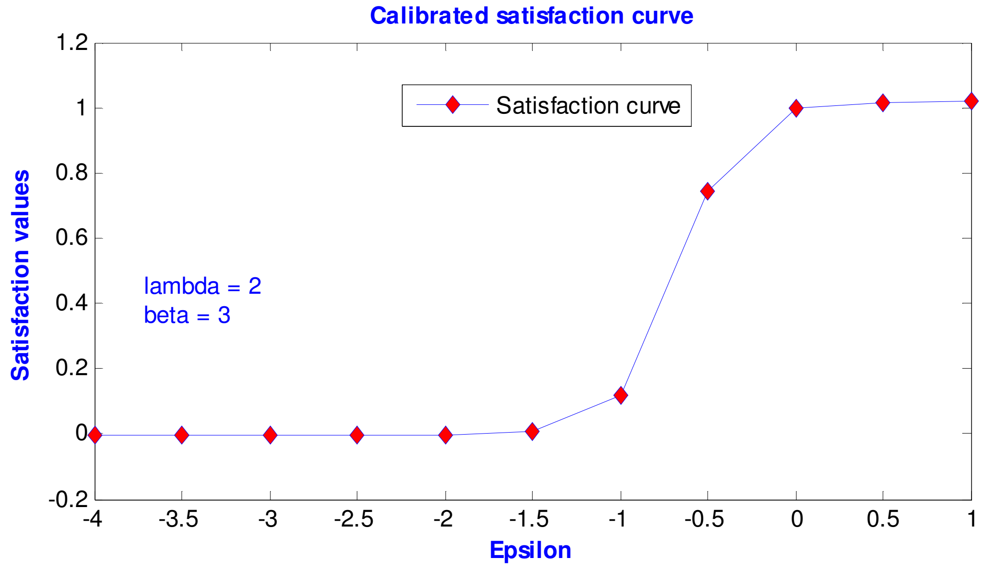


Figure B 2: The generalised CORE model

The generalised CORE model is suggested to extend the applicability of the original CORE model across industry sectors. The effects of the omega, beta, lambda and gamma parameters on the model are shown here in the following figures;

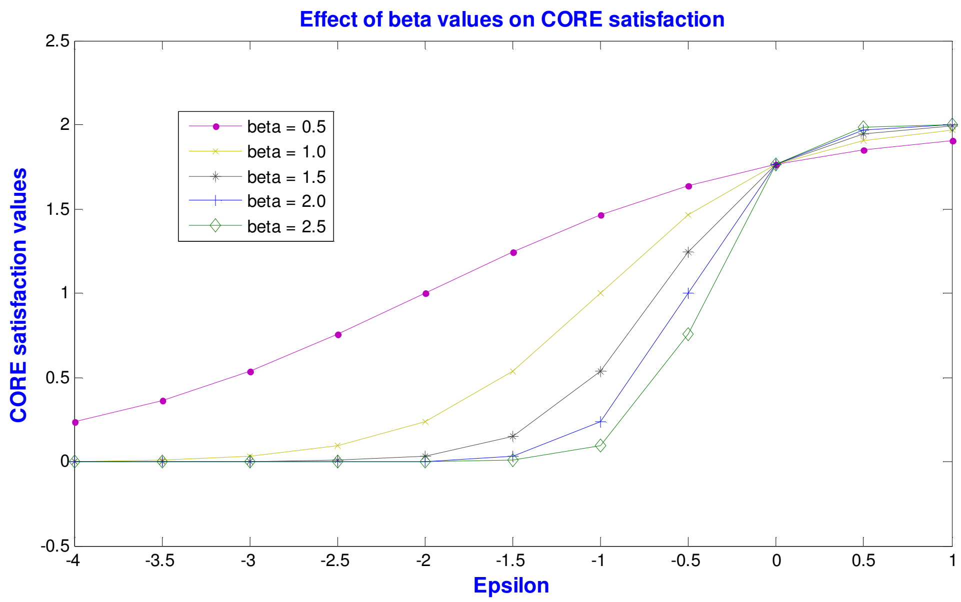


Figure B 3: Effect of beta parameter on satisfaction curve

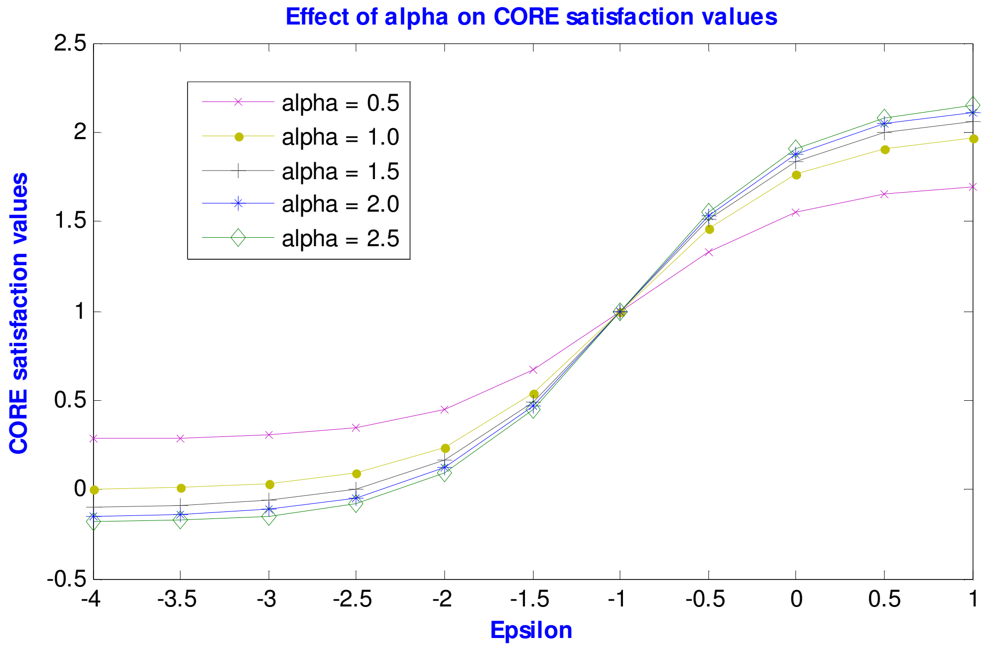


Figure B4: Effect of alpha parameter on satisfaction curve

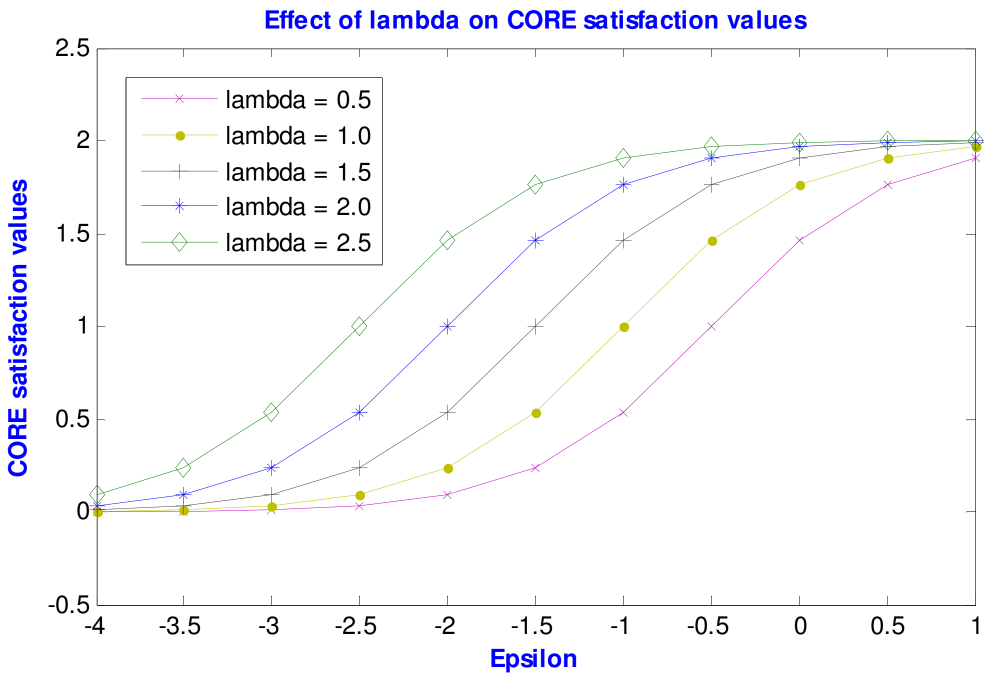


Figure B 5: Effect of lambda parameter on satisfaction curve

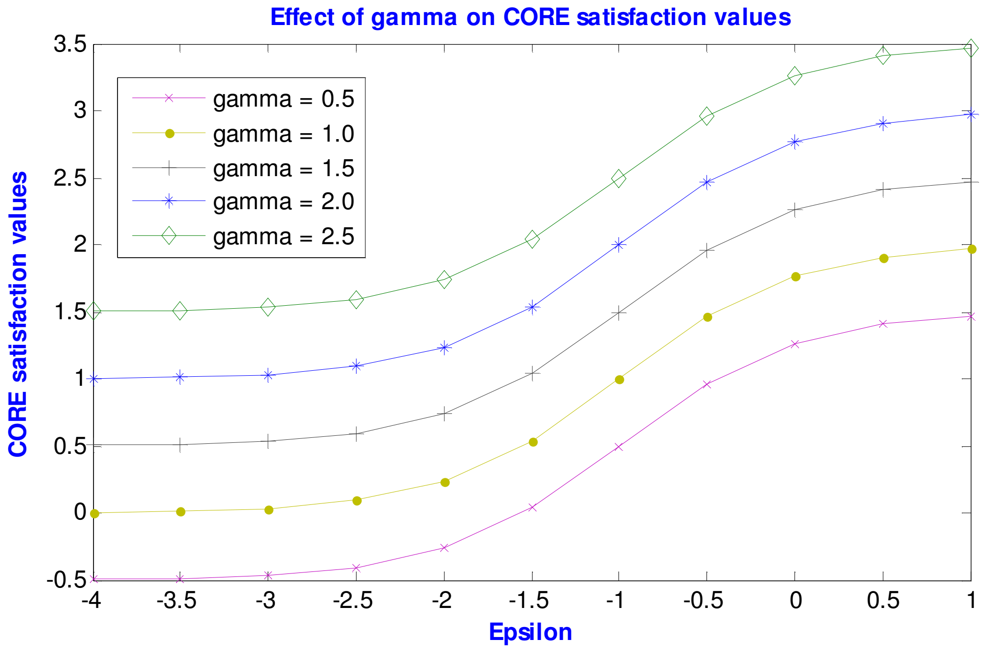


Figure B6: Effect of gamma parameter on satisfaction curve

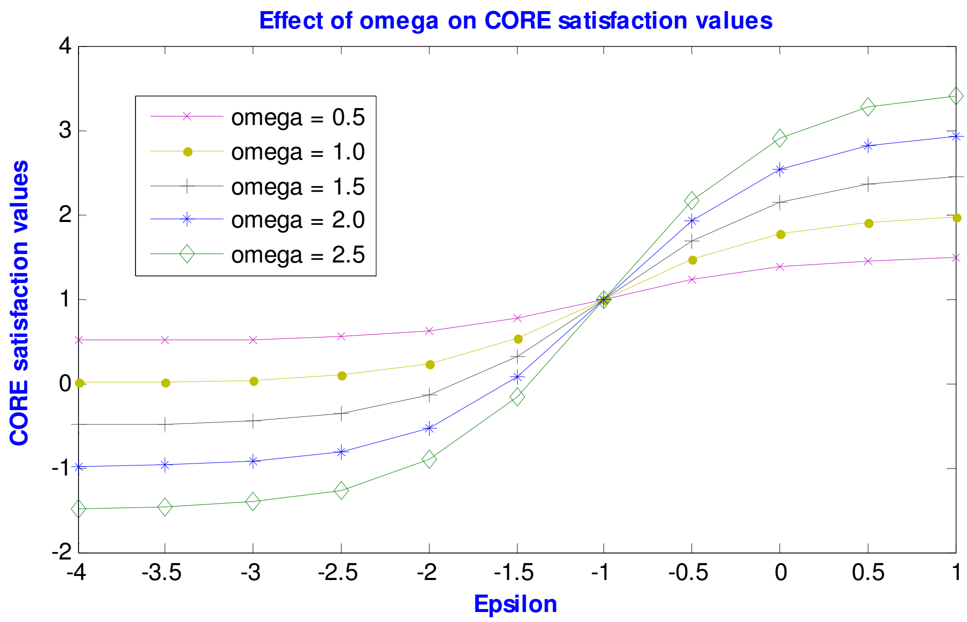


Figure B 7: Effect of omega parameter on satisfaction curve

Appendix C: Monte Carlo experiment algorithm

This appendix presents a description of the algorithm implemented for the Monte Carlo simulation experimentation.

Initialize test counts.

Set data sample size. (Loop over the sample sizes n = 4, n = 10, n = 20, n = 200 and n = 1000)

Set the distribution of the independent variable. (Loop over $k = 1$ to $k = 2$)

Start loop of m Monte Carlo replications.

For each estimation method, $i = 1$ to $i = 2$, generate a set of observations (the Index values) from the underlying linear regression model, and perform the bootstrap estimation of the performance measures.

Record results

End Monte Carlo loop

Perform the hypothesis test using a One-Sample *t* test with the distribution relative efficiencies obtained and at a 0.05 significance level.

Record test results

Update test count.

End independent variable distribution loop.

End sample size loop.

Perform computations of summary statistics.

Appendix D: Experimental results of LSR and GME methods – Figures and Tables

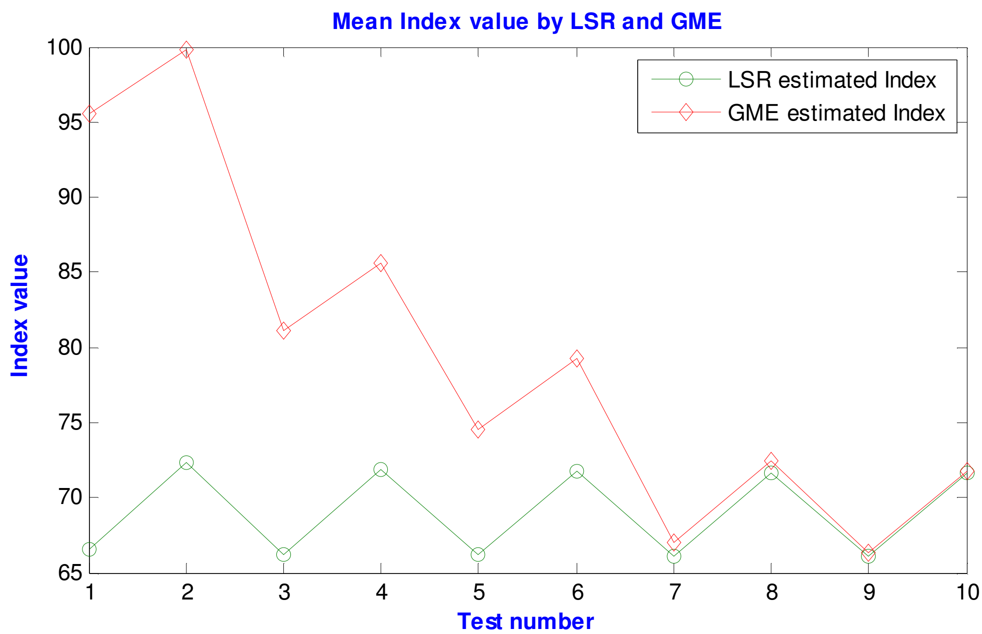


Figure D 1: Mean value of HQI by LSR and GME estimation

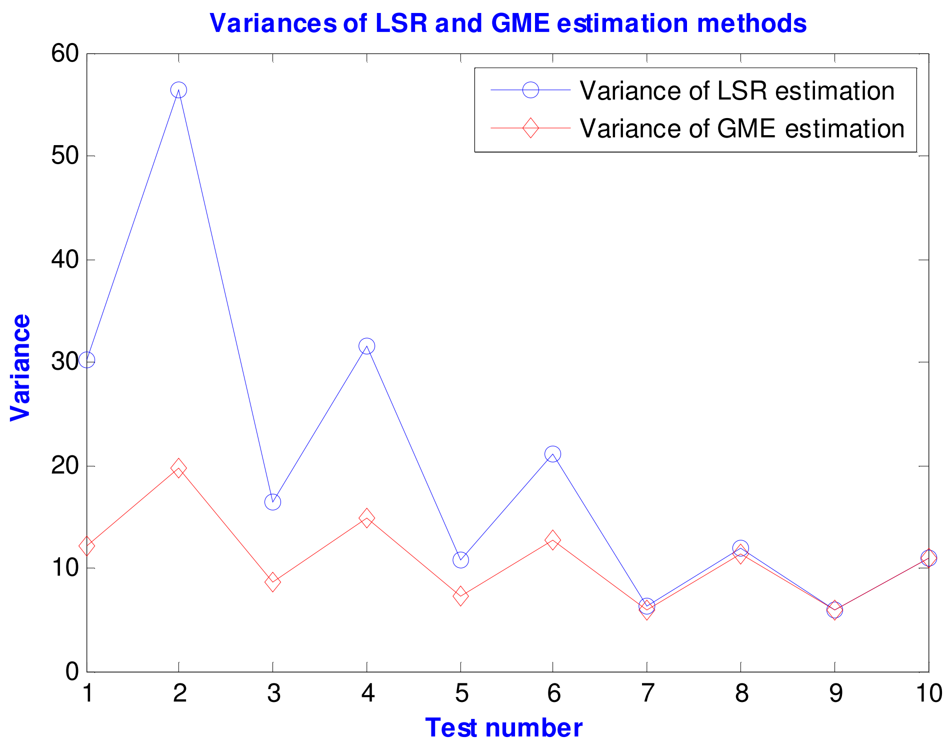


Figure D 2: Variance in HQI estimation by LSR and GME methods

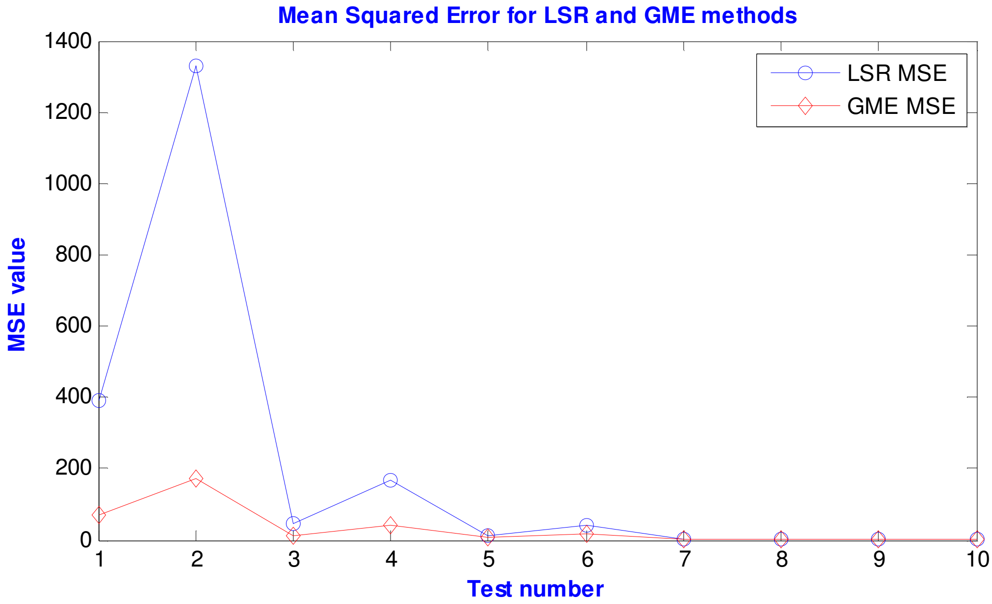


Figure D 3: MSE in HQI estimation by LSR and GME methods

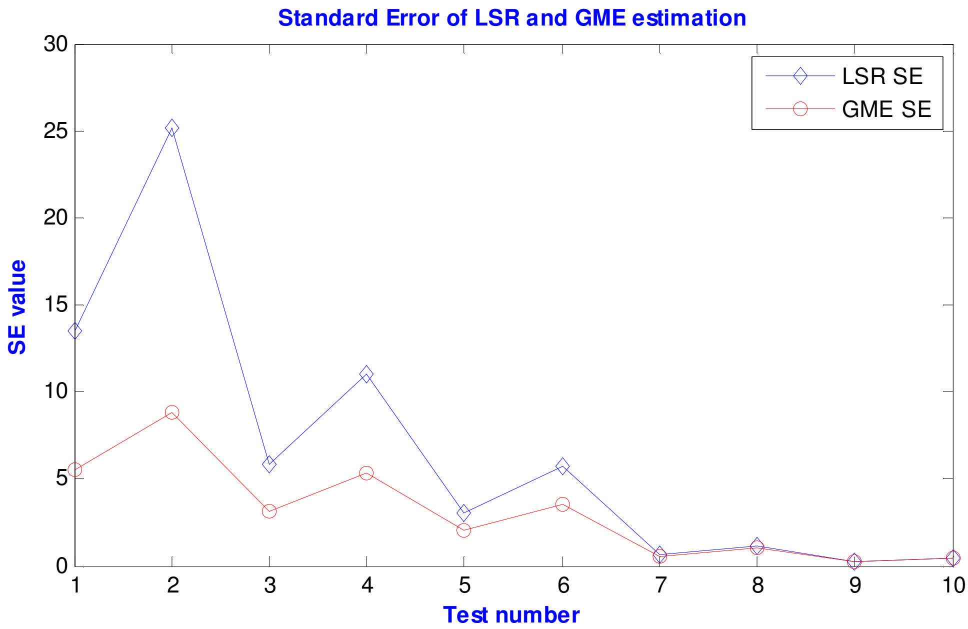


Figure D 4: SE in HQI estimation by LSR and GME methods

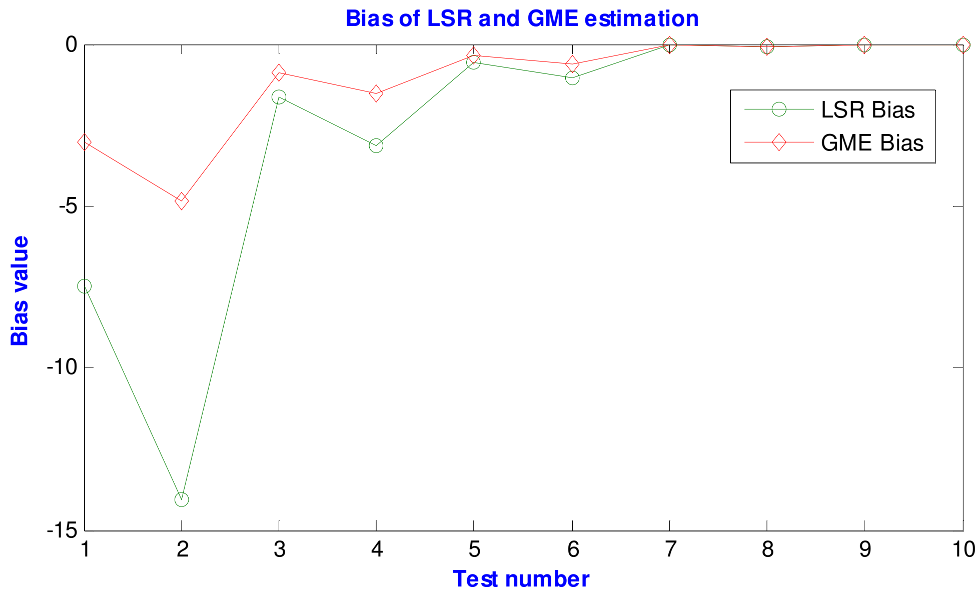


Figure D 5: Bias in HQI estimation by LSR and GME methods

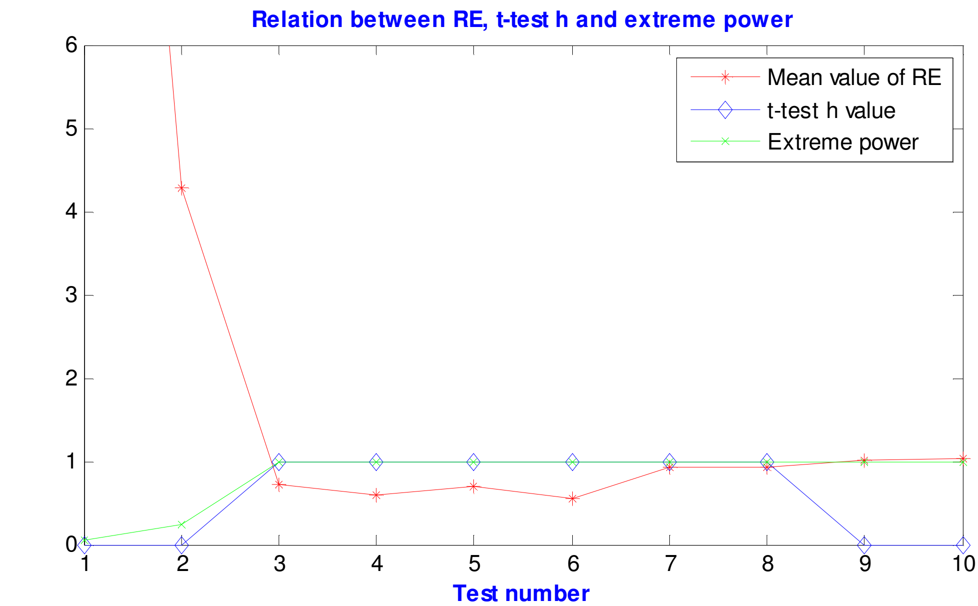


Figure D 6: Plots of RE, t-test h and Extreme power for HQI experiment

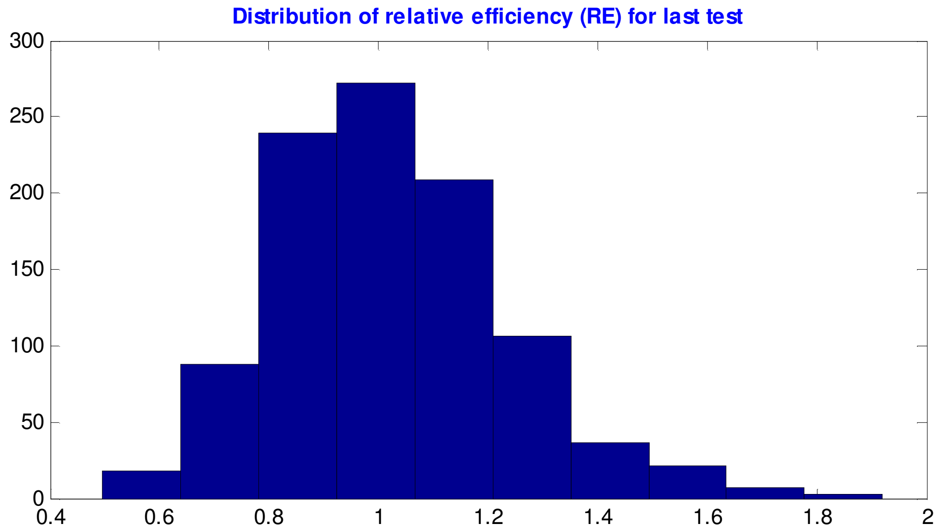


Figure D 7: Distribution of RE for test number 10

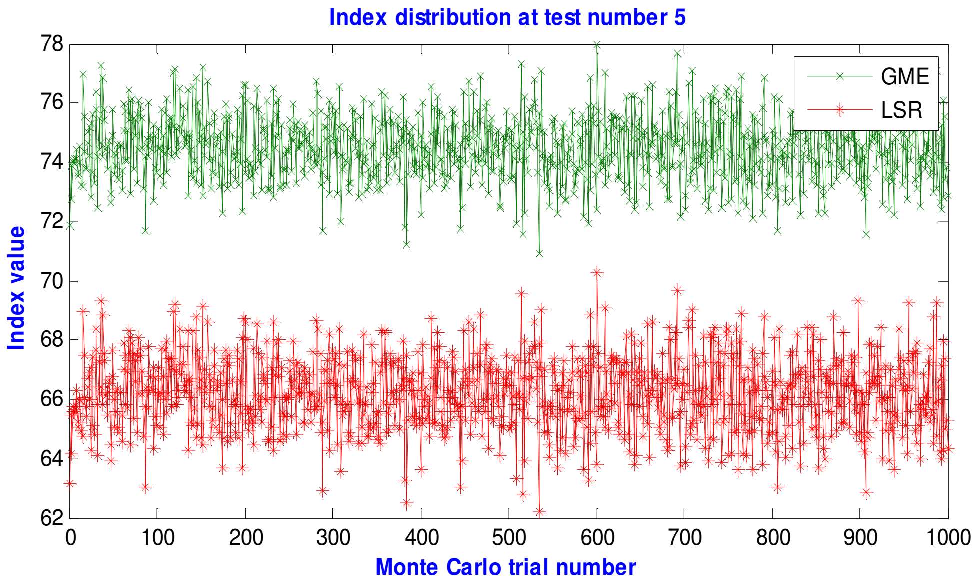


Figure D 8: Estimated HQI values by LSR and GME methods for test number 5

Table D. 1: Tests and index mean, variance and standard errors

Test	Factor 1 levels (Sample size)	Factor 2 levels (Independent var. dist.)	Mean of Index		Variance of Index		Standard Error	
			LSR	GME	LSR	GME	LSR	GME
1	1, n = 4	1, Normal	66.5974	95.4982	30.1518	12.1272	13.4619	5.5655
2	1, n = 4	2, Uniform	72.2974	99.7896	56.3931	19.6517	25.2016	8.8177
3	2, n = 10	1, Normal	66.2376	81.1096	16.3251	8.7105	5.8297	3.1084
4	2, n = 10	2, Uniform	71.8766	85.5806	31.476	14.9431	11.0558	5.3689
5	3, n = 20	1, Normal	66.2105	74.4939	10.8676	7.2908	3.0207	2.039
6	3, n = 20	2, Uniform	71.7272	79.2356	21.083	12.6917	5.7731	3.5532
7	4, n = 200	1, Normal	66.0886	67.0201	6.2498	5.96	0.6117	0.5826
8	4, n = 200	2, Uniform	71.613	72.4431	11.8668	11.2802	1.1521	1.0962
9	5, n = 1000	1, Normal	66.108	66.2909	5.8793	5.8531	0.2622	0.2611
10	5, n = 1000	2, Uniform	71.6123	71.7801	11.0657	11.0336	0.4828	0.4833

Table D. 2: Tests and index bias, mse and standard errors

Test	Factor 1 levels (Sample size)	Factor 2 levels (Independent var. dist.)	Bias		Mean Square Err.		Standard Error	
			LSR	GME	LSR	GME	LSR	GME
1	1, n = 4	1, Normal	-7.4845	-3.0359	393.5716	70.2101	13.4619	5.5655
2	1, n = 4	2, Uniform	-14.0767	-4.8539	1331.658	172.0655	25.2016	8.8177
3	2, n = 10	1, Normal	-1.6229	-0.8621	47.1912	13.4831	5.8297	3.1084
4	2, n = 10	2, Uniform	-3.1187	-1.5116	166.2094	40.8485	11.0558	5.3689
5	3, n = 20	1, Normal	-0.5587	-0.3612	11.1856	5.0279	3.0207	2.039
6	3, n = 20	2, Uniform	-1.0488	-0.6206	40.3417	15.1936	5.7731	3.5532
7	4, n = 200	1, Normal	-0.0285	-0.0318	0.3867	0.3513	0.6117	0.5826
8	4, n = 200	2, Uniform	-0.0624	-0.0554	1.3733	1.2429	1.1521	1.0962
9	5, n = 1000	1, Normal	-0.0061	-0.0059	0.0701	0.0695	0.2622	0.2611
10	5, n = 1000	2, Uniform	-0.0119	-0.01	0.2377	0.2384	0.4828	0.4833

Table D. 3: Tests and statistical test results

Test	Factor 1 levels (Sample sizes)	Factor 2 levels (Independent var. dist.)	Mean Relative Efficiency of LSR to GME	Lillietest			One-Sample t-test			Extreme power
				H	P	KSTATS	h	p	$t_{(999)}$-stats	
1	1, n = 4	1, Normal	19.0823	1	0.001	0.482	0	0.9113	1.3497	0.053
2	1, n = 4	2, Uniform	4.2811	1	0.001	0.4442	0	0.9997	3.4024	0.237
3	2, n = 10	1, Normal	0.7247	1	0.001	0.334	1	0	-5.1689	1
4	2, n = 10	2, Uniform	0.5924	1	0.001	0.2967	1	0	-11.6504	1
5	3, n = 20	1, Normal	0.6896	1	0.001	0.182	1	0	-13.6027	1
6	3, n = 20	2, Uniform	0.5538	1	0.001	0.1689	1	0	-26.1484	1
7	4, n = 200	1, Normal	0.9321	1	0.001	0.053	1	0	-9.7433	1
8	4, n = 200	2, Uniform	0.9284	1	0.001	0.0638	1	0	-10.4981	1
9	5, n = 1000	1, Normal	1.0136	1	0.001	0.0687	0	0.9778	2.0119	1
10	5, n = 1000	2, Uniform	1.0246	1	0.001	0.0507	0	0.9999	3.6501	1

Appendix E: Lagrange's method of undetermined identifiers

The basis for the Lagrangian solution presented here is contained in the work of Golan, Judge & Perloff (1996). The optimisation problem posed in equations 5.23 through 5.26 of chapter 5 may be generally written as:

Maximising

$$H = -\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{M} p_{ijk} \ln p_{ijk} - \sum_{i=1}^{n}\sum_{l=1}^{N} w_{il} \ln w_{il}$$

Subject to consistency constraint:

$$y_i = \sum_{j=1}^{m}\sum_{k=1}^{M} z_{ijk} p_{ijk} x_{ij} + \sum_{l=1}^{N} v_{il} w_{il} \quad for\ i = 1, 2, ..., n$$

And adding up (normalisation) constraints:

$$\sum_{k=1}^{M} p_{ijk} = 1 \quad for\ i = 1, 2, ..., n;\ j = 1, 2, ..., m$$

$$\sum_{l=1}^{N} w_{il} = 1 \quad for\ i = 1, 2, ..., n$$

Where $(y_1, y_2, ..., y_n)$ is a set of numbers corresponding to the observable data that are consistent with the probability distribution (P_l, P_2 . . . . . p.), where m < n. In the case of this inverse problem, to recover the probability vector p, the Lagrangian function may be formed as

$$L = -\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{i=1}^{M} p_{ijk} \ln p_{ijk} - \sum_{i=1}^{n}\sum_{l=1}^{N} w_{il} \ln w_{il}$$
$$+ \sum_{i=1}^{n} \lambda_i \left[y_i - \sum_{j=1}^{m}\sum_{k=1}^{M} z_{ijk} p_{ijk} x_{ij} + \sum_{l=1}^{N} v_{il} w_{il} \right] + \mu\left(1 - \sum_{k=1}^{M} p_{ijk}\right) + \gamma\left(1 - \sum_{l=1}^{N} w_{il}\right)$$

The first order condition may then be derived as:

$$\frac{\partial L}{\partial p_{ijk}} = -\ln \hat{p}_{ijk} - 1 - \sum_{i=1}^{n} \hat{\lambda}_i z_{ijk} x_{ij} - \hat{\mu} = 0$$

$$\frac{\partial L}{\partial w_{il}} = -\ln \hat{w}_{il} - 1 - \sum_{i=1}^{n} \hat{\lambda}_i v_{il} - \hat{\gamma} = 0$$

$$\frac{\partial L}{\partial \lambda_i} = \hat{y}_i - \sum_{j=1}^{m} \sum_{k=1}^{M} z_{ijk} \hat{p}_{ijk} x_{ij} + \sum_{l=1}^{N} v_{il} \hat{w}_{il} = 0$$

$$\frac{\partial L}{\partial \mu} = 1 - \sum_{k=1}^{M} \hat{p}_{ijk} = 0$$

$$\frac{\partial L}{\partial \gamma} = 1 - \sum_{l=1}^{N} \hat{w}_{il} = 0$$

Based on this system of n + m + 1 equations and parameters, the formal solution is

$$\hat{p}_{ijk} = \frac{1}{\Omega\left(\hat{\lambda}_1, \hat{\lambda}_2, ..., \hat{\lambda}_n\right)} \exp\left[-\hat{\lambda}_1 z_{ijk} x_{ij} - ... - \hat{\lambda}_n z_{njk} x_{nj}\right]$$

$$\hat{w}_{il} = \frac{1}{\Theta\left(\hat{\mu}_1, \hat{\mu}_2, ..., \hat{\mu}_n\right)} \exp\left[-\hat{\mu}_1 v_{il} - ... - \hat{\mu}_n v_{nl}\right]$$

Where

$$\Omega\left(\hat{\lambda}_1, \hat{\lambda}_2, ..., \hat{\lambda}_m\right) = \sum_{i=n}^{n} \exp\left[-\hat{\lambda}_1 z_{ijk} x_{ij} - ... - \hat{\lambda}_n z_{njk} x_{nj}\right]$$

and

$$\Theta\left(\hat{\mu}_1, \hat{\mu}_2, ..., \hat{\mu}_m\right) = \sum_{i=n}^{n} \exp\left[-\hat{\mu}_1 v_{il} - ... - \hat{\mu}_n v_{nl}\right]$$

are the partition functions, and $\left(\hat{\lambda}_i, \hat{\mu}_j, \hat{\gamma}_k\right)$ are the Lagrange multipliers. The multipliers are chosen to satisfy the constraints and are determined by the *m* simultaneous equations;

$$\hat{y}_i = \left(\frac{\partial}{\partial \hat{\lambda}_i}\right) \ln \Omega, \quad 1 \le i \le n$$

With the estimated values of $\hat{y}_i$, the value of the maximum entropy is then a function of the given data:

$$S\left(\hat{y}_1, \hat{y}_2 \ldots \hat{y}_n\right) = H_{\max} = \ln \Omega + \ln \Theta + \sum_i \hat{\lambda}_i \hat{y}_i$$

Appendix F: Staff interview schedule

Code: AK

STAFF INTERVIEW RECORDS SHEET
(To be used by the interviewer)

Consent process –

- ***EXPLAIN THE STUDY***
- ***GIVE INFO SHEET***
- ***SIGN CONSENT FORM***

A. INTRODUCTORY QUESTION

1. **What is your official job title / department?**

Ans:

B. PATIENT CARE

2. **Ideally, how much time would you expect to spend with a patient at reception to enable you to work effectively? (for receptionists)**

Ans:

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Have no expectations

Comments: e.g. the basis for the expectation?

3. **How satisfied are you in terms of your workload if you have to spend more or less than this amount of time? (for receptionists)**

Ans: If less	**Ans: If more**
☐ Very Satisfied	☐ Very Satisfied
☐ Satisfied	☐ Satisfied
☐ Neutral	☐ Neutral
☐ Dissatisfied	☐ Dissatisfied
☐ Very Dissatisfied	☐ Very Dissatisfied

Comments:

FOR DOCTORS AND NURSES:

4. **Ideally, how much time would you expect to spend when you <u>first see</u> a patient in order for you/your team to work effectively?**

<u>Ans:</u>

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Have no expectations

<u>Comments:</u> e.g. the basis for the expectation?

5. **How satisfied are you in terms of your workload if you have to spend more or less than this amount of time?**

<u>Ans: If less</u>	**<u>Ans: If more</u>**
☐ Very Satisfied	☐ Very Satisfied
☐ Satisfied	☐ Satisfied
☐ Neutral	☐ Neutral
☐ Dissatisfied	☐ Dissatisfied
☐ Very Dissatisfied	☐ Very Dissatisfied

<u>Comments:</u>

6. **Overall, how satisfied are you with the order in which you have to see patients?**

<u>Ans:</u>

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

Comments:

7. **Ideally, how much time would you expect to spend with a patient for <u>first examination</u> in order for you/your team to work effectively?**

Ans:

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Have no expectations

Comments: e.g. the basis for the expectation?

8. How satisfied are you in terms of your workload if they wait more or less than this amount of time?

Ans: If less	**Ans: If more**
☐ Very Satisfied	☐ Very Satisfied
☐ Satisfied	☐ Satisfied
☐ Neutral	☐ Neutral
☐ Dissatisfied	☐ Dissatisfied
☐ Very Dissatisfied	☐ Very Dissatisfied

Comments (e.g. workload issues, number of staff, teamwork):

9. **From your experience, ideally how much time would you expect to spend with a patient for his/her <u>second examination</u> in order for you/your team to work effectively (i.e. a more detailed examination where they have already been assessed previously by another professional)?**

Ans:

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Have no expectations

Comments: e.g. the basis for the expectation?

10. **How satisfied are you in terms of your workload if you have to spend more or less than this amount of time?**

Ans: If less

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

Ans: If more

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

Comments (e.g. workload issues, number of staff, teamwork. RE-CLERKING):

11. **How long would you expect a patient's main test results (such as x-ray, scan or blood test) to take before it comes back to you?**

Ans:

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Have no expectations

Comments: e.g. the basis for the expectation?

12. **How satisfied are you if it takes more or less than this time to get the results?**

Ans: If less

☐ Very Satisfied
☐ Satisfied
☐ Neutral
☐ Dissatisfied
☐ Very Dissatisfied

Ans: If more

☐ Very Satisfied
☐ Satisfied
☐ Neutral
☐ Dissatisfied
☐ Very Dissatisfied

Comments (e.g. workload issues, number of staff, teamwork):

13. **Overall, how much time should patients spend in the Emergency Department to enable staff to cope effectively?**

Ans:
☐ Less than 1 hour
☐ 1 - 2 hours
☐ 2 - 3 hours
☐ 3 - 4 hours
☐ More than 4 hours
☐ Had no expectations

Comments: e.g. the basis for the expectation?

14. **How satisfied are you if it takes more or less than this time?**

Ans: If less

☐ Very Satisfied
☐ Satisfied
☐ Neutral
☐ Dissatisfied
☐ Very Dissatisfied

Ans: If more

☐ Very Satisfied
☐ Satisfied
☐ Neutral
☐ Dissatisfied
☐ Very Dissatisfied

Comments (e.g. workload issues, number of staff, teamwork):

15. In your opinion, does the number of patients waiting in a queue put pressure on you as you work? Please select from 5 (Yes, very high pressure) to 1 (no pressure at all).

☐ 5

☐ 4

☐ 3

☐ 2

☐ 1

16. Does that affect your satisfaction with your work load?

☐ Yes, definitely

☐ Yes, normally

☐ Yes, sometimes

☐ Yes but rarely

☐ Not at all

B. RADIO FREQUENCY IDENTIFICATION (RFID) WRIST BAND

17. If you were asked to wear an identification band (called RADIO FREQUENCY IDENTIFICATION (RFID)) which is linked to a computer (like remote control) which would help to track where staff are at any given time – e.g. to find them to refer patients - would this be acceptable to you? (Note that this device uses Radio Frequencies, rather like mobile phones, and while considered generally safe, there are still uncertainties with the effects of exposure to these radiations).

Ans:

☐ Yes, definitely

☐ Yes, maybe

☐ No

Comments: e.g. what concerns staff might have?

D. FINALLY

18. In your opinion, do you think patient satisfaction is linked to staff satisfaction -and in what ways?

Ans positives and negatives:

DO YOU HAVE ANY QUESTIONS FOR ME?

THANK YOU VERY MUCH FOR YOUR TIME

Alexander Komashie. Mav/June. 2007

Appendix G: Patient interview schedule

Code: AK

BECaD Evaluation

PATIENT INTERVIEW RECORDS SHEET
(To be used by the interviewer)

<u>WARM UP</u>

On approaching the patient:

- (As you may remember me telling you earlier) I am a PhD student working on a research study to see whether any changes being made at this hospital (which is an ongoing thing) may be affecting patient care and whether any improvements are required to the service. I am employed by this hospital but I am <u>not</u> involved in your care, and if you do decide to take part, you can be as honest and open as you like with me and you should feel comfortable about this. By finding out how people such as yourself feel about the care you have received, we hope we may be able to get a better understanding of how patients are experiencing the hospital system and hopefully see what is working well and what areas of the service may require improvement. **(Get verbal agreement to continue at this stage - tell them it will take around 20-30 mins, but maybe longer if they wish)**

Brief view of what the interview involves:

- This is going to be a fairly short discussion and I'm going to just ask a few basic questions around your experiences of what you have been through while at the hospital in your own words - we often call this the 'patient journey'
- We particularly want to see what you think are the good and bad things about the service and why
- We also want to know what you think of the contact you have had between yourselves and the professionals involved
- You don't have to tell me anything you don't want to and if there is anything you don't want to talk about you <u>must</u> say so and we will move onto another question
- If you want to stop the interview for any reason then let me know - that is not a problem at all and will not affect your care in any way whatsoever…
- Everything you say will be kept totally confidential and your name will not be attached to this information - it will only be known to us as the researchers and <u>not the doctors and nurses involved in your care</u> - this is very important to understand and I absolutely guarantee this
- Are you still happy to go on?

- **<u>IF THEY HAVE NOT BEEN MAPPED – Please could you read this short information sheet and sign the consent form</u>**

A. INTRODUCTORY QUESTION

8. What was the reason for you attending the Emergency Department?

<u>Ans:</u>

<u>Comments:</u>

B. WAITING

9. How long did you <u>expect</u> to wait at the reception?

<u>Ans:</u>

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Had no expectations

<u>Comments:</u> e.g. the basis for the expectation?

Roughly, how long did you <u>actually</u> wait for? ☐

10. How satisfied were you with the <u>actual time</u> you spent at the reception?

<u>Ans:</u>

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

<u>Comments:</u>

4. Did you have any other course for dissatisfaction at the reception?

Ans:

☐ Yes

☐ No

Comments:

5. Which professional did you first see - a nurse or doctor?

Nurse ☐
Doctor ☐
Don't know ☐

6. How long did you expect to wait before first speaking to a nurse or doctor?

Ans:

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Had no expectations

Comments:

Roughly, how long did you actually wait for? ☐

7. How satisfied were you with the actual time you spent waiting to first see any type of professional?

Ans:

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

Comments:

8. **Overall, did you think the <u>order</u> in which patients were seen was fair?**

<u>Ans:</u>

☐ Yes

☐ No

<u>Comments:</u>

9. **How long did you <u>expect</u> to wait <u>before your first proper examination</u> by a doctor or special nurse?**

<u>Ans:</u>

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Had no expectations

<u>Comments:</u>

Roughly, how long did you <u>actually</u> wait to be examined? ☐

10. **How satisfied were you with the <u>actual</u> time you spent waiting to <u>be properly examined?</u>**

<u>Ans:</u>

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

<u>Comments:</u>

11. Were you told <u>how long</u> you would have to wait to be properly examined? If yes, did you wait longer or shorter?

<u>Ans:</u>

☐ Yes, but waited longer

☐ Yes but waited shorter

☐ No

<u>Comments:</u>

12. Did you have a <u>second</u> examination (e.g. more detailed one)? If yes, by who?

<u>Ans:</u>

☐ Yes, by ....

☐ No

<u>Comments – e.g. were you told why you needed a second examination?</u>

13. How long did you <u>expect</u> to wait for a second examination?

<u>Ans:</u>

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Had no expectations

<u>Comments:</u>

Roughly, how long did you <u>actually</u> wait for? ☐

14. How satisfied were you with the <u>actual</u> time you spent waiting for the second examination?

<u>Ans:</u>

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

<u>Comments:</u>

15. Did you have any tests (such as x-rays, scans or blood tests) when you visited the Emergency Department?

<u>Ans:</u>

☐ Yes

☐ No

<u>Comments (which tests):</u>

16. If patient responded yes, roughly how long did it take to get the <u>main</u> results?

<u>Ans:</u>

☐ 0-15 Minutes

☐ 16-30 Minutes

☐ 31-60

☐ More than 60 Minutes

☐ Had no expectations

<u>Comments (did this meet expectations?):</u>

17. How satisfied were you with the wait for your test results?

<u>Ans:</u>

☐ Very Satisfied

☐ Satisfied

☐ Neutral

☐ Dissatisfied

☐ Very Dissatisfied

Comments:

IF ON A WARD:

18. How long did you expect to wait to be admitted to a ward

Comments:

Roughly, how long did you actually wait for?

19. How satisfied were you with the wait to be admitted to a ward?

Ans:

- ☐ Very Satisfied
- ☐ Satisfied
- ☐ Neutral
- ☐ Dissatisfied
- ☐ Very Dissatisfied

20. Overall, how long did you expect your visit to the hospital to last?

Ans:

- ☐ Less than 1 hour
- ☐ 1 - 2 hours
- ☐ 2 - 3 hours
- ☐ 3 - 4 hours
- ☐ More than 4 hours
- ☐ Had no expectations

Comments:

21. Overall, how satisfied are you with your care?

Ans:

- ☐ Very Satisfied
- ☐ Satisfied
- ☐ Neutral
- ☐ Dissatisfied
- ☐ Very Dissatisfied

B. YOUR CARE AND TREATMENT **– are you happy to continue with the interview?**

22. Could you describe, as best as you can, the main things that happened to you during the rest of the time you spent in the Emergency Department - and I'm particularly interested to know what you felt were the 'good' things about the care you received, and also the 'bad' things? (I can help guide you through this if you wish?)

Ans:*

- ✓ Did you have enough time to discuss your problem? (1,2,3,-4)
- ✓ Did a doctor or nurse explain your condition in a way you could understand? (1,2,3,-4)
- ✓ Did doctors and nurses listen to what you had to say? (1,2,3,)
- ✓ Confidence in doctors and nurses?
- ✓ Did doctors and nurses talk in front of you as if you were not there? (1,2,3)
- ✓ Did you have enough information about your condition and treatment? (1,2,3,4)
- ✓ Were you given enough privacy when being examined?(1,2,3)
- ✓ If you needed attention were you able to get a member of staff to help you? (1,2,3,4,-4)
- ✓ Did a member of staff say one thing and another say something different? (1,2,3)
- ✓ Were you involved as much as you wanted in decision about your care? (1,2,3,-4)
- ✓ Did a member of staff explain your test results in a way you could understand? (1,2,3,-4,-5, 6)
- ✓ In your opinion, how clean was the A&E/wards? (1,2,3,4,-5)
- ✓ How clean were the toilets? (1,2,3,4,-5)
- ✓ What was it like on the wards?

Comments:

* For all answers 1 is the highest or most favourable. (–) means not applicable

Space for notes

D. RADIO FREQUENCY IDENTIFICATION (RFID) WRIST BAND

23. In the future we are thinking of asking patients arriving at the hospital if they are happy to wear a <u>wrist-band</u>, <u>linked to a computer</u> (like remote control) which <u>might</u> help us to <u>track</u> them as they go through the hospital to see where they are at any given time (e.g. at the X-Ray Dept) and how long it took for them to get there – This device uses Radio Frequencies, rather like mobile phones, and while it is thought to be generally safe, like with mobile phones there are still uncertainties with the effects of exposure to these radiations

- **If you had been asked to wear this wrist band when you came to the hospital, would you have been happy to do this?**

Yes ☐
No ☐
Don't know ☐

- If not, why?

E. FINALLY

24. Please could you sum up the worst and best things about the care received?

25. Compared to how you felt when you first entered A&E, how do you feel now?

<u>Prompts:</u> On a physical level? Anxiety? Confused?

<u>THANK YOU VERY MUCH FOR YOUR TIME – DO YOU HAVE ANY QUESTIONS FOR ME ABOUT THE RESEARCH?</u>

<u>Demographic Data</u>

AGE, GENDER, ETHNICITY, DIAGNOSIS OF CURRENT PROBLEM, RELATED TO A PREVIOUS CONDITION? CHRONIC? HOW LONG HAD CONDITION? WITH OR WITHOUT A CARER? OTHER FACTORS OF INTEREST?

Update to template by J. Gore, NWLH, 2004

Appendix H: E-Track NHS software development structure

DataManager Functionalities

RTDataBuffer – Array Variable

CFInpDataBuffer – Array Variable

CFOutpDataBuffer – Variable

CFOutpDataBufferFF - Variable

ReadRT – Function to read stream of ID and Timestamp couple data RTDAQ.

SetupRT – Function to setup reading attributes in relation to RTDAQ e.g. sampling rate

ReadDB – Function to read Timestamp data and fitted curve parameters from database for Matlab and FF simulation.

WriteDB - Function to write ID and Timestamp data and fitted curve parameters and Arena Data to database.

FeedCFitter – Function to retrieve data from DBDataBuffer and feed to curve fitter InputDataBuffer.

ReadCFitter - Function to retrieve fitted curve parameter data from curve fitter and feed to CFOutpDataBuffer.

RunCFitter – Instruction to run curve fitter.

ReadArena – Function to read process times from Arena.

WriteArena – Function to write parameters from RTDataBuffer and CFOutpDataBuffer and CFOutpDataBufferFF to Arena.

DatabaseConnection Functionalities

DBFilename – Filename Variable

DBFilepath – DBFilepath Variable

DBConnectionString – Connectionstring Variable

ReadDataFF – Function to read fast forward data from DB

ReadDataCF – Function to read curve fitting data from DB

WriteDataRT – Function to write real time data from Arena to DB

WriteDataDAQ – Function to write real time data from DAQ to DB

CurveFitter functionalities

InputDataBuffer - Array Variable

OutputDataBuffer – Variable

ReadData – Function to read data from DataManager into InputDataBuffer.

WriteData – Function to write data from CurveFitter to DataManager's CFOutpDataBuffer

PreProcessData (DM) – Function to prepare data from InputDataBuffer for onward transfer to Matlab

SaveParameters (DM) – Function to receive fitted curve parameters from Matlab and saved in OutputDataBuffer.

DataExchange (ML) – Function to implement data exchange with Matlab.

Fit (ML) – Instruct Matlab to start curve fitting

RTDAQ Functionalities

DataBuffer – Array Variable

TimeSetting – Function to set data acquisition attributes e.g. sampling rates etc.

Read – Function to read data ports

Portsetting – Function for specifying and updating port settings, e.g. port address

Appendix I: Healthcare Commission 2006 in-patient survey questionnaire

Appendix J: Staff interview (appendix F) accompanying sheet