A Business Analytics Software Tool for Monitoring and Predicting Radiology Throughput Performance

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Author Declaration

I declare that the work described in this dissertation is, except where otherwise stated, entirely my own work, and has not been submitted as an exercise for a degree at this or any other university. I further declare that this research has been carried out in full compliance with the ethical research requirements of the School of Computer Science and Statistics.

Signed:

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Stephen Jones

9th June 2014

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9th June 2014

Abstract

A primary cause for the build-up of patient wait times in radiology departments is a mismatch between capacity and demand. Lack of understanding of this mismatch as well as inefficient management of radiology resources contributes to inadequate capacity planning.

Business Intelligence (BI) software systems combine data gathering, storage and knowledge management with analytical software tools that analyse and present complex data to planners and decision makers. Business Analytics (BA) encompasses statistical analysis, predictive modelling and forecasting systems and is used as an umbrella term for decision support and Business Intelligence systems. BA software applications are currently being utilised as a driver for decision support based on past performance; however, there is little evidence of the utilisation of future predictive analysis to drive decision making in radiology departments. The primary aim of this study was to determine whether a prototype BA software tool could provide analysis of historic as well as future predictive radiology data to assist with departmental decision support towards reducing patient wait times.

A series of semi-structured interviews were conducted with key project stakeholders to determine a set of information technology requirements. Based on these requirements a prototype BA software tool was implemented. The tool combined data from the Electronic Patient Record (EPR), Radiology Information System (RIS) and Picture Archiving and Communications System (PACS) in order to display historic radiology Key Performance Indicators (KPIs) and provide functionality that allows the forecasting and modelling of future demand and capacity data through user-defined predictive scenarios.

A qualitative evaluation of the tool was carried out through a series of semi-structured interviews with key stakeholders. Feedback was collated and emergent themes were identified. The results indicated that BA software applications can provide visibility of radiology data across all time horizons. Historic KPI data provides retrospective analysis that can be used to inform and create predictive scenarios. These scenarios

can then be utilised to generate and visualise future predictive demand and capacity data. The study also demonstrated that key stakeholders believe that the visualisation of historic and future forecasted radiology data enables enhanced decision support to deliver improved operational efficiencies and wait times within medical imaging departments. It was also shown that the tool could potentially assist with optimising staff utilisation, reducing inpatient length of stay and improving quality of care.

In order to build on the perceived potential of the application, recommendations were made for a future study to determine actual evidence of benefit post-implementation. Quantitative and qualitative research conducted over a period of time would help determine the application's ability to reduce patient wait times and deliver operational efficiencies.

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Table of Contents

List of Tables

List of Figures

Abbreviations

A&E	Accident and Emergency Department
AMNCH	Adelaide and Meath Hospital Dublin (incorporating the National Children's Hospital)
AST	Average Scan Time
AWS	Amazon Web Services
BI	Business Intelligence
BA	Business Analytics
BM	Business Manager
CD	Clinical Director
CT	Computed Tomography
DDD	Data Driven Decision Making
DaaS	Desktop as a Service
EPR	Electronic Patient Record System
ETL	Extract Transform Load
GP	General Practitioner
HIQA	Health Information and Quality Authority
HSE	Health Service Executive
IDE	Interactive Development Environment
IPEM	Institute of Physics and Engineering in Medicine
IT	Information Technology

Abbreviations

KPI	Key Performance Indicator
LOS	Length of Stay
MP	Medical Physicist
MRI	Magnetic Resonance Imaging
MVC	Model –View-Controller
NHS	National Health Service
NTPF	National Treatment Purchase Fund
OLAP	Online Analytical Processing
OECD	The Organisation for Economic Cooperation and Development
PACS	Picture Archiving and Communication System
PAS	Patient Administration System
PET-CT	Positron Emission Tomography–Computed Tomography
RIS	Radiology Information System
ROI	Return on Investment
SDU	Special Delivery Unit
SCSS	School of Computer Science and Statistics
SSBI	Self Service Business Intelligence
UAT	User Acceptance Testing
VS2013	Microsoft Visual Studio 2013

1 Introduction

"There is nothing more difficult to take in hand, more perilous to conduct, or more uncertain in its success, than to take the lead in the introduction of a new order of things. Because the innovator has for enemies all those who have done well under the old conditions and lukewarm defenders in those who may do well under the new." (Machiavelli 1513)

There are major challenges ahead for our healthcare agencies.

Healthcare expenditure across EU member states has steadily increased from 5.9% of GDP to 7.2% per country in 2010. Expenditure figures are forecast to rise to as much as 8.5% of GDP by 2060, primarily due to increased and aging populations. In contrast to this are continued reductions in public healthcare annual spends, increased cost of delivery and reductions in numbers of healthcare professionals (European Commission 2012). Additionally, budget overruns within the Health Service Executive (HSE) here in Ireland were in excess of €250 million in 2013[1]. There is clearly huge scope for improvement.

As a consequence, it is imperative that operational efficiencies are maximised throughout our hospitals. This is especially relevant to diagnostic medical imaging departments where extended wait times can have a significant impact on determining a patient's definitive diagnosis and treatment (Emery et al. 2009). A reduction in patient wait times as well as timely patient access to radiology resources are key drivers towards improving operational efficiencies and patient satisfaction levels within radiology departments.

In the UK, a primary cause for the build-up of patient wait times in radiology departments is a lack of understanding of the mismatch between capacity and demand resulting in inefficient management of radiology resources and inadequate capacity planning (Silvester et al. 2004).

Similarly, poor visibility and analysis of patient demand within the radiology department at the study site is resulting in an inability to adequately plan and effectively manage the usage of radiology staff and resources, therefore contributing towards increased patient wait times. Despite significant volumes of radiology capacity and demand data being available within the department, it has proven difficult to leverage these data assets to deliver information to key decision makers in a meaningful way.

[1] http://www.hse.ie/eng/services/news/newsarchive/2014archive/jan14/openingjchc.html

Furthermore, resource management within the radiology department is predominantly reactive and based on historic performance data: a rear-view mirror approach. Forecasting and modelling of future demand and capacity data would allow radiology departments to anticipate forthcoming variations and plan appropriately. This allows a shift from a reactive 'what should we have done' mentality towards a more proactive 'what can we do' mind-set.

Business Analytics (BA) software provides a mechanism to methodically explore and visualise an organisation's data. It encompasses statistical analysis, predictive modelling and forecasting and is often used as an umbrella term for Business Intelligence (BI) and decision support systems (Cosic et al. 2012). The ability to discover meaningful patterns and identify signals within datasets enables the extraction and visualisation of powerful insights from an organisation's data assets. Data driven decision making is increasingly associated with improved productivity and performance levels within organisations (Brynjolfsson et al. 2011). Traditional methods of summarising, viewing and reporting of data are rapidly being replaced by advanced analytics, a major disruptive innovation.

BA functionality is currently being utilised within radiology departments as a driver for decision support based on past performance (Nagy et al. 2009; Prevedello et al. 2010); however, there is little evidence of the utilisation of future predictive analysis to drive decision making in radiology.

This study will implement and evaluate a prototype BA software tool utilising a combined dataset from the Electronic Patient Record (EPR), Radiology Information System (RIS) and Picture Archiving and Communications System (PACS). The tool will display a set of radiology Key Performance Indicators (KPIs) and provide functionality that allows for the forecasting and modelling of future demand and capacity data through predictive scenarios.

By implementing a software tool that enhances decision support within radiology departments there is potential to realise a number of benefits, including:

- Visibility of demand and capacity (past, present and future forecasted) to enhance departmental decision support towards improving patient wait times.
- More effective management decision making with regard to improving operational efficiencies and productivity within radiology.
- Improved departmental planning and scheduling procedures.

In addition, there is an opportunity to build on previous research work undertaken within the medical imaging department at the study site with regard to identifying and visualising radiology KPIs (Fotiadou 2013). The prototype software tool will include these recommendations for visualisation.

This study hypothesises that a computerised approach to demand and capacity management, utilising BA technologies, should lead to more effective resource management resulting in improved patient wait times. It is the intention of this study to explore and investigate this hypothesis further.

1.1 Study Context

The study site is a major academic teaching hospital delivering health treatment, care and diagnosis through the provision of healthcare services at secondary and tertiary levels. It is currently one of the largest public hospitals in Ireland, treating 25,206 inpatients, 94,868 day care patients and 223,596 outpatients throughout 2012 (St. James's Hospital 2013).

The radiology department at the study site completes in excess of 170,000 medical imaging scans per year across all major modalities including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography–Computed Tomography (PET-CT), Mammography, Interventional Radiology, Ultrasound, Nuclear Medicine and general X-ray (including Barium). The department consists of a clinical director, a business manager, a radiographic services manager, 13 consultant radiologists, 12 specialist registrars, 62 radiographers, 16 clerical staff, 16 health care assistants and 8 nurses.

In terms of devices, there are currently 2 CT scanners, 2 nuclear medicine scanners, 2 MRI devices (plus temporary access to a third device), 4 ultrasound devices, 1 interventional suite, 1 barium, 2 mammogram scanners, 4 general machines (chest, facial and general X-ray) and 1 PET-CT.

Additionally, there are 4 portable X-ray machines that provide scans to patients that are unable to attend the radiology department. There are also X-ray machines located in the Accident and Emergency department (A&E), Endovascular room, Cardiac lab and Bronchoscopy procedures.

1.2 Research Question

Through conducting this research, the author proposes to investigate the potential benefits of utilising BA technologies to improve decision support and patient wait times within the radiology department at the study site. To this end, the research question is:

"Can a Business Analytics Software Tool Facilitate Decision Support towards Improving Patient Wait Times within a Major Diagnostic Medical Imaging Department in a Public Hospital in Ireland?"

1.3 Key Stakeholders

After initial discussions with the clinical director at the study site, the establishment of a key stakeholder project team to assist with the study was proposed. The team consisted of three senior members of staff from within the radiology department representing all levels of management. The stakeholders included the clinical director, business manager and a senior medical physicist with responsibility for data analysis.

1.4 Study Aims

Study aims are twofold:

- To scope and build a prototype BA software tool to visualise radiology KPIs and model user-defined predictive scenarios utilising a BA dashboard.
- To evaluate whether the key stakeholders perceive that the prototype tool has the potential to facilitate decision support towards improving patient wait times within a diagnostic medical imaging department.

1.5 Study Objectives

Study objectives are as follows:

- To determine a set of user requirements within radiology towards:
    - Visualising existing radiology KPIs via a specially designed BA dashboard.
    - Identifying and modelling predictive decision support scenarios to enable forecasting of radiology demand, capacity and backlog data via a specially designed BA dashboard.
- To build a prototype software tool to implement the identified set of user requirements.

- To measure the validity of predictive data and to verify the accuracy of the KPI data visualised within the prototype tool.
- To evaluate whether key stakeholders perceive that the prototype tool has the potential, through the visualisation of radiology KPIs and the modelling of various predictive scenarios, to enhance decision support towards improved wait times.

1.6 Dissertation Layout

The Dissertation format is as follows:

Chapter 2: Literature Review - discusses the impact of patient wait times with a focus on radiology. Various demand and capacity management initiatives are explored, followed by a discussion on the numerous BA technologies. The section concludes by discussing evidence of the application of BA within radiology before exploring the potential for forecasting and predicative analysis initiatives.

Chapter 3: Research methodology – discusses the proposed research methods for the study.

Chapter 4: Requirements and Design – identifies the requirements as captured from the key project stakeholders. A proposed design for the prototype tool is presented based on the identified set of requirements.

Chapter 5: Prototype Implementation – discusses the prototype tool's functionality and implementation. The chapter concludes discussing the validation steps taken to ensure a robust and accurate application.

Chapter 6: Prototype evaluation - documents feedback received from the key stakeholders during prototype evaluation and discusses emergent themes as well as study limitations and potential future work.

Chapter 7: Conclusion – concludes the study and summarises the findings.

1.7 Summary

This chapter presented a background and context to the study. The research question was proposed, as well as study aims, objectives and key stakeholders. Finally, an overview of the layout of the study was presented. In the next chapter, a literature review is conducted exploring and investigating the key areas relevant to the study.

2 Literature Review

2.1 Introduction

This section of the study will investigate the impact of patient wait times and the contributing factors towards build-up of wait lists within Radiology. It will also look at the role of demand and capacity management and how it can be utilised to improve current business processes and its potential application to managing patient wait times. Finally, it will examine the potential role for Informatics in the context of demand and capacity planning, primarily focusing on Business Analytics and the benefits it can offer through delivery of improved operational efficiencies and management of patient wait times within Radiology.

2.2 Patient Wait Times

Effective management of patient wait times is an important and necessary component of successful healthcare delivery.

Healthcare delivery inefficiencies, decreased patient satisfaction levels as well increased patient suffering have all been directly linked to lengthy wait times (Hansson et al. 2012; Kreindler 2010). There is also evidence to suggest that wait times may be associated with higher patient morbidity and mortality rates (Kielar et al. 2010). As a consequence, there is an increased focus at government level, with half of all OECD countries acknowledging lengthy wait times as a policy concern (Siciliani & Hurst 2005). Equitable and improved access to healthcare is becoming an integral part of government health policy amongst many OECD countries. Much political capital is being invested in setting hospital performance targets based on timely access to healthcare services (Willcox et al. 2007).

Furthermore, many countries across the globe are now monitoring and publishing patient wait time statistics on a regular basis, with a significant number introducing or moving towards national wait time guarantees (Viberg et al. 2013). Hospital reimbursement models are also changing. In Ireland, the recently published Future Health framework for reform of the health service proposes a ‘money follows the patient model’ that incentivises improved efficiencies and higher patient throughput (DOHC 2012). At an international level, half of all OECD countries have replaced a fixed healthcare budget allocation with a productivity based allocation (van de Vijsel et al. 2011). As a result, additional burdens will be placed on healthcare providers to meet these targets; clearly improved efficiency and productivity will be required to meet these demands.

There are many potential bottlenecks along the patient care pathway that can contribute towards a build-up in wait times. Several countries are now putting attention on the identification of 'hidden waiting times' within the hospital system. This includes establishing the time it takes to access specialised services, including medical imaging diagnostics within radiology (Willcox et al. 2007).

2.2.1 Wait Times in the Context of Radiology

Recent research into radiology usage levels suggest that utilisation rates will steadily increase across all modalities in future years (Chrysanthopoulou et al. 2007). Diagnostic medical imaging services are very often a key contributor towards determining a patient's overall diagnosis. Wait times for access to specialised medical diagnostic devices, such as MRI, are especially relevant, as a delay at this point can result in delays to subsequent definitive treatment (Emery et al. 2009).

There are also implications at hospital level. Delayed inpatient diagnostic treatment has a significant impact on the number of beds available as well as overall hospital cost effectiveness (Lodge & Bamford 2008). Moreover, slow inpatient turnaround times in radiology can have a direct impact on the number of available hospital beds. This has a knock-on effect for A&E departments and hospital admissions resulting in patients being denied bed access.

General Practitioner (GP) diagnostic referrals are also under scrutiny. Measurement of hospital performance within the Irish public health service is provided to the public domain by the HSE via Healthstat[2]. Healthstat reports hospital metrics on a monthly basis in the areas of access, integration and resources (appendix A.1) for all general and regional hospitals and social care services throughout Ireland. Access metrics cover patient wait times and address a number of areas including diagnostic medical imaging (Turner 2009).

Reporting of routine GP to hospital referral wait time via Healthstat is also now mandatory. This KPI is reported to the HSE on a monthly basis and includes radiology diagnostic services (Turner 2009). In addition to patient concerns, greater transparency of radiology performance is now a key driver towards improved operational efficiencies and cost effectiveness.

It should also be acknowledged that there have been issues within the Irish GP diagnostic referral system. In 2010 Dr Maurice Hayes was commissioned to produce a report for the HSE in response to accumulations of un-reported medical images at the Adelaide and Meath

[2] http://www.hse.ie/eng/staff/Healthstat/

Hospital (AMNCH) in Dublin. Amongst the findings of the report it was highlighted that GP referrals were not being processed correctly due to a lack of protocols and, as a result, prioritisation of patient scans tended to be informal (HSE 2010). Based on this information the Health Information and Quality Authority (HIQA) recommended the establishment of a prioritisation process with appropriate monitoring. Additionally it was recommended that the HSE should coordinate access and waiting times on a national level for high demand and low capacity imaging devices, with a view to utilising such devices as a shared resource across multiple hospitals and throughout primary care (HIQA 2012a).

Sharing of imaging resources across the Irish healthcare sector is a sensible approach however the systems must be put in place in order to support such an initiative.

2.3 Demand and Capacity Management

To understand how waiting lists are created and to effectively manage wait times within radiology, we must first understand the concepts of demand and capacity management. The National Health Service (NHS) in the UK has invested significant time and resources into understanding and managing patient wait lists. It has been acknowledged internationally for its successful programme implementation and subsequent positive outcomes (Willcox et al. 2007).

The NHS provides some useful definitions[3] to enable better understanding of the key supply and demand terms in the context of healthcare management. The following definitions for key terms are provided:

Demand – All requests and referrals from all sources and the quantity of resource that is required to manage it. Resources include time required for staff, equipment and use of hospital locations.

Capacity – All current resources available to process the workload. This would include items of equipment and the staff time necessary to operate the equipment.

Backlog – This represents the waiting list and represents all demand currently in the system that has not yet been handled.

[3]http://www.institute.nhs.uk/quality_and_service_improvement_tools/quality_and_service_improvement_tools/demand_and_capacity_-_a_comprehensive_guide.html

A significant cause for the build-up of patient wait times within radiology departments is a mismatch between capacity and demand. Lack of understanding of this mismatch as well as inefficient management of radiology resources contributes to inadequate capacity planning (Silvester et al. 2004). The NHS highlights variation between demand and capacity as one of the primary contributory factors towards the formation of backlogs in the healthcare sector. They also identify visibility and subsequent analysis of capacity and demand data as a key approach to changing behaviour towards removing and reducing patient wait lists[3].

The ability to accurately measure is a necessary prerequisite to facilitate the identification of problem areas and adequate solutions (HOPE's Working Party on Management of Waiting Lists 2004). As Drucker (1991) once said, "If you can't measure it, you can't manage it".

Current lack of visibility of demand and capacity at the study site has a significant detrimental effect on wait time management. As a result, current radiology service planning is based on 'gut feel' rather than on robust data analysis. Furthermore, due to a lack of visibility of modality turnaround time metrics, clinicians operating on hospital wards frequently order a suite of medical scans for their patients. This scenario helps ensure clinicians can utilise the current quickest available modality. However, this places a significant and unnecessary burden on the radiology department in terms of planning and scheduling. Visibility of current demand and capacity within radiology at the study site would provide better decision support to clinicians. This in turn would allow them to schedule the most appropriate scan for their patients rather than placing the unnecessary burden of multiple orders on an already overloaded system. These inefficiencies must be addressed.

2.3.1 Demand and Capacity Initiatives within Radiology

In order to improve operational efficiency and cost effectiveness, healthcare providers are implementing numerous demand and capacity initiatives across the globe.

A study in Australia highlighted the potential for increasing radiologist work capacity through the transfer of reporting responsibilities from radiologists to radiographers. The study demonstrated that, as well as increasing department capacity, quality of care was maintained and, in some cases, improved (Smith & Baird 2007). Similar initiatives in the UK have also been shown to have the potential to reduce wait times (Price & Le Masurier 2007).

In Ireland, the HSE has established the Special Delivery Unit (SDU) as part of the current reform of the healthcare system. The SDU's primary focus is to more effectively manage both scheduled and unscheduled care episodes in order to deliver increased performance capability[4]. One of the major areas being addressed is improved access to diagnostics.

The National Treatment Purchase Fund (NTPF) is an independent statutory body whose remit is to ensure quicker and fairer access to elective procedures for all public patients (NTPF 2007). As part of the establishment of the SDU, the NTPF was mandated to work alongside the SDU to provide more regular hospital monitoring in order to improve overall hospital performance for scheduled and unscheduled care. In fulfilling this role, the SDU and NTPF have provided best practice guidance to implementing demand and capacity planning within the HSE. Again, there is an emphasis placed on the importance of visualising and understanding diagnostic demand in traditionally high demand areas, such as radiology. Effective alignment of capacity to demand is acknowledged as being a major contributory factor towards reduced length of stay, improved wait times and better patient care[5].

A number of solutions have been implemented for demand and capacity management across various healthcare agencies. The UK's NHS implemented a service improvement methodology within a radiology department that resulted in a reduction in patient wait times from 19 weeks to 2 weeks over a period of 5 months[3].

In addition, techniques traditionally deployed in industry have also been implemented in radiology departments. A recent study demonstrated that the application of Lean management principles as well as production planning procedures have proven beneficial towards reducing patient wait times (MacDonald et al. 2013). Similarly, the implementation of Lean methodologies has been particularly successful in the NHS. In one trust alone, waiting times were decreased from 26 weeks to 13 weeks, with the number of non-attending patients decreasing from 8% to 4%. Average inpatient wait times were also reduced to three days from five. This is estimated to have freed up 18,000 beds annually (Lodge & Bamford 2008). A major contributory factor to this success was the establishment of a single radiology waiting list accessed by all staff across the hospital. This highlights the impact of centralising radiology data; a single point of access for radiology performance data should be a given.

2.3.2 Demand and Capacity Forecasting Initiatives

In addition to initiatives utilising present and historical data, there are also opportunities to determine future demand based on historical data. Amongst many private sector

[4] http://www.dohc.ie/press/releases/2012/20120125.html
[5] http://www.ntpf.ie/home/NTPFToolkit/sdu_tech_guidance/index.html

manufacturing companies, forecasting of demand in order to inform future capacity planning is standard practice. There are also examples of demand forecasting initiatives within the healthcare domain addressing this specific problem.

Research conducted in the US highlighted definite patterns in the demand cycle for A&E services over a three-year period. This data was then utilised to successfully plan future rosters based on forecasted demand (Ong et al. 2009). A similar study conducted at the University of Utah that utilised several statistical forecasting methods to predict daily patient volume levels in A&E concurred that demand cycles are seasonal (Jones et al. 2008). This provides valuable data to forecast capacity requirements into the future.

Software tools have also been developed to assist with forecasting future demand for radiation oncology physicists. A number of inputs were provided to the software application including projected incidence of cancer, estimated retirement projections and number of graduates in the previous 20 years. Based on entered criteria, the tool forecasted a requirement for 125 oncology physicists per year by 2020. It is proposed that these numbers are used to plan for the future of the profession (Mills et al. 2010).

There is clearly potential to utilise forecasting to manage demand and plan capacity. However, whilst a number of forecasting initiatives have been successful, it is important to acknowledge that accurate historical data is necessary in order to inform meaningful future forecasting (Rais & Viana 2011).

It is also important to note that, whilst demand management strategies have been implemented in multiple countries, a number of them have struggled to make an impact. Similarly, capacity management initiatives incentivising private healthcare and utilisation of capacity planning within private hospitals have also had little effect on reducing wait times in the public sector (Willcox et al. 2007). There is clearly scope for further improvement, and innovative thinking is required to identify potential solutions.

2.3.3 A Role for Informatics

Health Informatics is a rapidly growing field that focuses on the application of Computer Science and Information Communications Technology (ICT) to medical and health data (Ali et al. 2013). A recent study into the usage of informatics within radiology departments highlighted a lack of education as the single biggest obstacle to uptake. Radiologists and managers are mostly unaware of the potential that informatics has to offer in relation to addressing their day to day requirements (Rubin 2011).

Traditional hospital ICT systems capture and store vast amounts of patient and operational data. However, capturing of the data is not sufficient in itself; the challenge is to convert this data into meaningful information. Hospital data is a corporate asset and there is significant scope for further analysis and aggregation of this information to inform effective management decision making in the area of demand management and capacity planning.

Software tools exist that can assist with the aggregation and subsequent translation of high volumes of data into relevant performance measurements and quality indicators. Business Analytic software provides a suitable mechanism to accurately visualise and analyse hospital supply and demand data. It is in this area of computer science that this study's efforts will be focused in order to evaluate potential solutions towards improving radiology demand and capacity management.

2.4 Business Analytics

Data is everywhere. We live in a connected world with people communicating more than ever. It is estimated that fifteen petabytes of new data is generated worldwide on a daily basis. This equates to approximately eight times the volume of information stored in all of the academic libraries in the US. The era of 'Big Data' has truly arrived (IBM Center for Applied Insights 2012). Without the means to harness the power of this information, however, it has no tangible benefit. Business Analytic tools provide the functionality to process large volumes of data effectively and efficiently to provide on-demand decision support information to all levels of an organisation.

This section will look at Business Analytics, define it, discuss data driven decision making and data visualisation, as well giving examples of where it has been successfully implemented within the healthcare sector, with an emphasis on radiology. It will also look at the potential for implementing forecasting and predictive analysis functionality to assist with demand management and capacity planning.

2.4.1 Definitions

BI software systems combine data extraction, data storage and knowledge management with analytical software tools that analyse and present complex data to planners and decision makers (Negash 2004). This is provided through functionality that allows users to summarise, analyse and visualise large volumes of data via dashboards, reports and web portals. BA also encompasses statistical analysis, predictive modelling and forecasting systems and is used as an umbrella term for decision support and business intelligence systems (Cosic et al. 2012).

BI is often referred to as having a 'rear view mirror' approach to data analysis (aggregation and reporting of historic performance data only) whilst BA takes a more advanced approach, implementing historic reporting alongside advanced predictive analytics (Cosic et al. 2012). In recent years, there has been a shift in terminology usage with a move away from Business Intelligence towards Business Analytics. As illustrated in figures 2-1 and 2-2, Google trends help to highlight this shift in the context of Internet user search criteria through the Google Internet search engine.

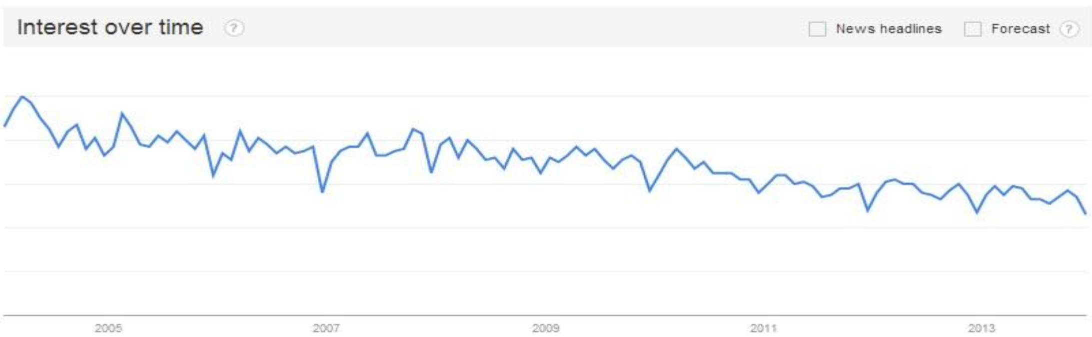

Figure 2-1: Decline in Business Intelligence Google searches, taken from Google Trends[6]

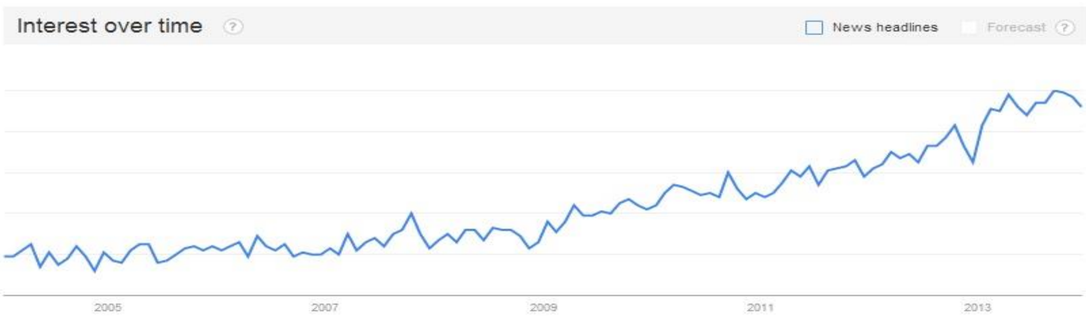

Figure 2-2- Increase in Business Analytics Google searches, taken from Google Trends[7]

There are also many inconsistencies of usage of the terms BI and BA by the various suppliers of these software systems (companies such as IBM, SAP and SAS). However, one should not be confused by nomenclature; instead, one should think in terms of the broader paradigm of decision support systems. What is of most importance is the capability to implement analytic

[6] http://www.google.com/trends/explore#cat=0-12&q=business%20intelligence&cmpt=q
[7] http://www.google.com/trends/explore#cat=0-12&q=business%20analytics&cmpt=q

solutions that allow thorough analysis across all time horizons, interpreting and analysing historic, present and future data.

There has been significant growth in the area of Business Analytics over the past twenty years fuelled by the ability to capture information to a high level of detail coupled with the reduced cost of devices that enable the storage of vast amounts of data (Chaudhuri et al. 2011). In the current era of 'Big Data', it has never been easier to extract and analyse information in order to leverage organisational efficiencies and competitive advantage. Through implementation of these software tools, access to meaningful information from the myriad of data sources is now possible (Chen et al. 2012).

2.4.2 Dimensions of Business Analytics

Modern day Business Analytic systems have their roots in the 1950s, when a research paper published by Peter Luhn of IBM research first introduced the phrase "business intelligence" (Luhn 1958). This set out the initial concepts that would be developed and enhanced over the next fifty years. Today, there are numerous technologies associated with BA. As outlined by Chauduri et al. (2011) in figure 2-3, there are multiple components within a typical BI/BA architecture.

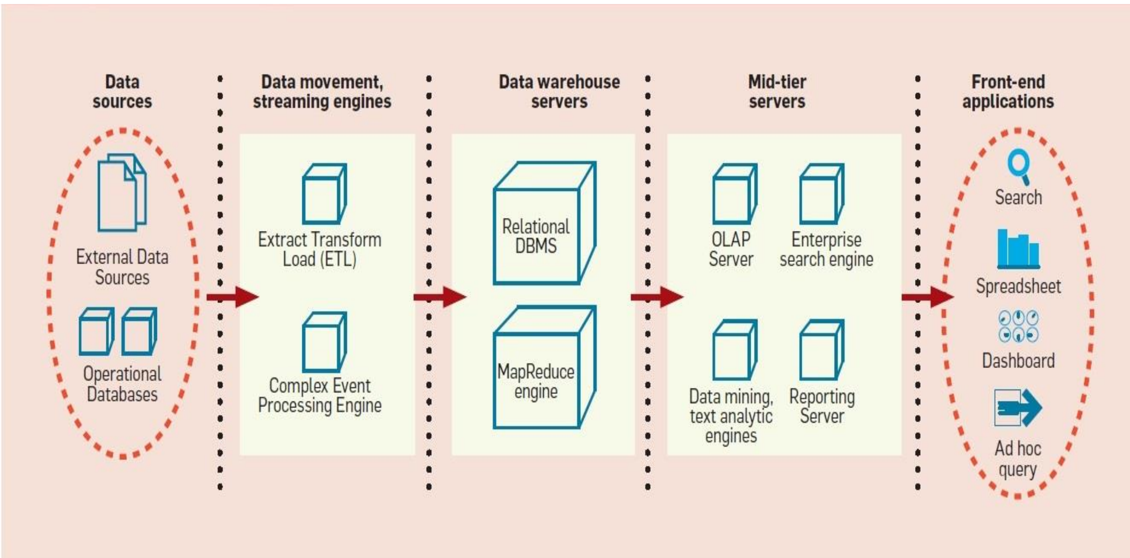

Figure 2-3: A typical BA/BI architecture, taken from (Chaudhuri et al. 2011).

These components utilise various technologies and can be further described as follows:

1) **Data extraction**

   Data is gathered from existing organisational databases or from external sources at the outset. Multiple data sources can be accessed simultaneously. Extract Transform Load (ETL) tools are then provided that allow the transformation of the data into meaningful sets of information for analysis by the BA software engine (Vassiliadis 2009). In some instances, complex event processing (CEP) engines (Robins 2010) are utilised to provide real-time access to data.

2) **Data storage**

   Once the data has been transformed into the required format, it is subsequently loaded into a data repository or data warehouse, typically utilising relational databases, or more recently, MapReduce technology (Dean & Ghemawat 2008).

3) **Data manipulation**

   The data manipulation engine is the heart of the BA tool and provides all of the functionality necessary to deliver on various analytical requirements. Online Analytical Processing (OLAP) tools provide the means to drill down, slice and dice and aggregate data to provide meaningful insights into organisational challenges (Ramamurthy et al. 2008). Reporting servers provide the functionality necessary to define, create and display user reports and ad-hoc queries. Data mining analytical engines provide advanced functionality over the traditional OLAP engine to deliver powerful functions such as predictive modelling (Shmueli et al. 2007).

4) **Data presentation**

   Having answered the necessary questions, the data can then be displayed to the end user via a number of interfaces. These include web portals, hard copy reports, visualisation of KPIs via a digital dashboard and loading of the data into spreadsheet format.

In addition to the traditional analytic technologies described above, more advanced solutions now encompass performance management tools, risk analytics and regulatory compliance functionality[8]. Demand forecasting functionality is also provided, which enables planning based on future predictive 'What-if' scenarios.

[8] http://www-03.ibm.com/software/products/en/category/business-analytics

There has also been significant growth in the area of data discovery, a technology that enables users to move away from hard-coded reports towards the interactive exploration and analysis of their datasets. In a 2012 Gartner Analytics report, data discovery was acknowledged as a mainstream technology within all of the major BA software solutions[9].

Mobile solutions are also gaining a foothold, with a significant number of vendors supplying functionality that optimises the display of analytic data for mobile devices such as phones and tablets[10]. This provides on-the-go analytics functionality to a huge audience at the touch of a button. There is significant potential for rolling out mobile analytic applications to clinicians on the wards at the study site. Clinician access to radiology KPI metric data via tablets or similar mobile devices could provide the necessary decision support required to inform appropriate ordering of diagnostic scans for their patients. This could help eradicate the multiple order scenario discussed earlier (section 2.3).

Another recent innovation is the delivery of self-service business intelligence (SSBI). This provides the various users with the capability to create and build their own analytic visualisations and reports without the need to involve Information Technology (IT) departments within the organisation (Imhoff & White 2011). This has the benefit of empowering users to analyse their own data, as well as freeing up precious IT resources.

Modern BA solutions have expanded to complement bespoke software applications, allowing the ability to embed existing BA software tools into pre-packaged software and services (Azvine et al. 2006). This provides significant scope to develop software applications outside of the confines of existing BA solutions. Complex analytic functions within many BA tools can be accessed through a standard application programming interface (API). This allows the fusion of bespoke functionality with advanced analytic capabilities in order to deliver powerful hybrid applications. This is an area that will be further investigated as part of this study.

Clearly, BA covers a wide range of concepts and technologies. The dimensions outlined are not exhaustive; additional technologies such as web analytics and prescriptive modelling are widely in use. However, for the purposes of this study the author has focused on the areas that are most relevant to the implementation of a BA demand and capacity management software tool for radiology.

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[9] http://www.gartner.com/newsroom/id/2507915
[10] http://samples.sainsburysebooks.co.uk/9781743445105_sample_143914.pdf#page=7

2.4.3 Data Driven Decision Making

With huge amounts of data now available to organisations, it is becoming increasing difficult to perform any kind of practical manual analysis to extract meaningful information. In contrast to this is the emergence of powerful computer hardware with advanced networking capability complimented by purpose-built software systems, such as BA systems, that provide the ability to interrogate and analyse data to unprecedented levels of accuracy and detail (Provost & Fawcett 2013).

Provost and Fawcett (2013) succinctly define data-driven decision making (DDD) as “the practice of basing decisions on the analysis of data rather than purely on intuition”. They also acknowledge its importance in the context of the emerging discipline of data science. Today, data driven decision management is being adopted by companies across all industry sectors in order to gain competitive advantage. It is also being implemented at a societal level to deliver improved standards of governance.

In Ireland, the Insight centre for Data Analytics[11] was established in 2013 with funding in excess of €75 million. It is a joint initiative across major Irish academic institutions aiming to support research into Data Analytics to enable better decision support at an organisational and societal level. The vision is to enable and empower a data-driven society.

Within the private sector, recent research across 179 publicly trading companies conclusively demonstrated that DDD significantly contributed towards improvements in organisational efficiency and productivity. Organisations adopting a DDD approach were found to have productivity and output levels that were between 5% and 6% higher than expected (Brynjolfsson et al. 2011).

Within the healthcare domain, decision making has traditionally been based on past experience, with resource planning and budget management frequently informed by what decision makers believe to be happening rather what is actually happening (Kaur & Wasan 2006). Mining of data through the usage of BA software tools can provide a means to transform an organisation’s approach to decision making. Access to information through analysis of factual data enables knowledge discovery, empowering key personnel to implement strategic solutions across their organisation (Kaur & Wasan 2006).

[11] http://www.insight-centre.org/

Private sector companies such as Google and Facebook have been enormously successful at leveraging their data assets. BA has the potential and the technology toolset to deliver on this vision for healthcare.

2.4.4 Data Visualisation

It is not enough to simply aggregate and extract information from a system; visualisation of this data via meaningful graphs, charts and reports is a critical step in relaying information to end users in a meaningful way. Data visualisation is the process whereby data is represented using various visual images (Negash & Gray 2008). BA and data visualisation has its roots in the earliest of methods of organisation and visualisation of information. From drawing lines in the sand to the development of the abacus, people have always strived to depict information visually.

Written data is valuable; however, it can be difficult to see emerging trends and patterns. William Playfair, a Scottish engineer and economist, attempted to address this problem in his publication 'The commercial and political atlas' (Playfair 1786). He subsequently went on to create the first pie, bar, line and circle charts (example chart in figure 2-4) and is considered the founder of graphical data visualisation.

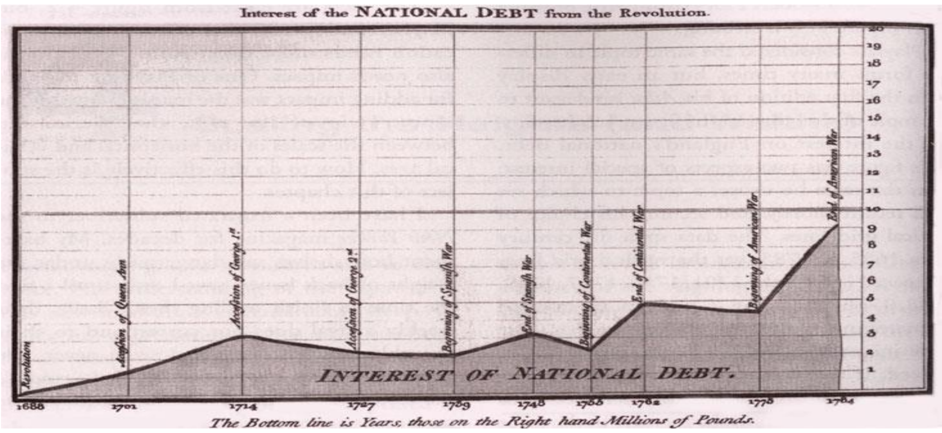

Figure 2-4: An early illustration of a line chart by Playfair from (Playfair 1786).

Initially, charts were hand drawn and cumbersome; graphical representation of data would not become mainstream until the birth of modern day computing.

Francis Anscombe, an English statistician, was one of the first individuals to demonstrate the benefits of data visualisation. In his paper 'Graphs in Statistical Analysis', he created four datasets that were statistically similar (mean, variance and linear regression) when observed in table format. Anscombe then graphed the data, and the differences in each dataset could be clearly seen (Anscombe 1973). Often referred to as Anscombe's quartet, this clearly demonstrates the advantages of visualising data to observe trends, patterns and anomalies that are not initially obvious in table format (figure 2-5).

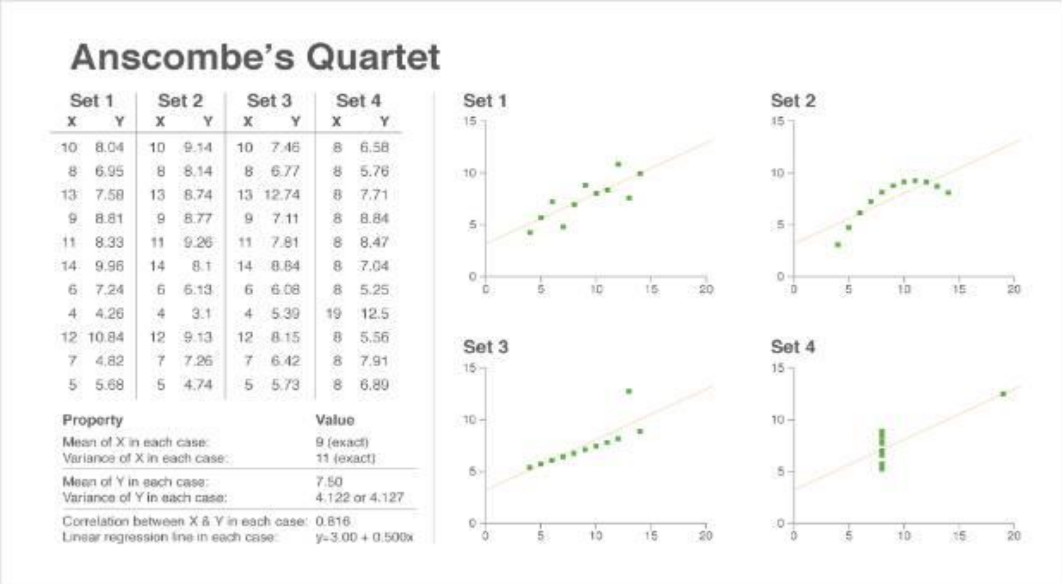

Figure 2-5: Similar datasets in table and graphical format from (Anscombe 1973)

As Anscombe illustrated, important stories live in data, and visualisation provides a powerful mechanism to extract these stories and present them to individuals. Visualisation takes full advantage of the power of human visual perception, and our rapid ability to pattern seek and identify similarities and differences, as opposed to cognitive function which operates at a slower pace (Ware 2012).

Recent research has demonstrated that data visualisation can significantly improve business insights and productivity (Eckerson & Hammond 2011). Seventy-four percent of respondents rated the impact of data visualisation on realising business insights as 'very high' or 'high'. Effective visualisation of organisational data was also shown to increase the uptake of BA tools within organisations.

Modern BA software tools have never been more powerful; they deliver a visualisation toolset that can rapidly represent extracted data in a manner that can be quickly and easily understood. Organisations are increasingly looking to determine improved methods for seeing and understanding their data. BA dashboards provide one such mechanism for visualising and interpreting complex data.

2.4.4.1 *The Potential for Dashboards*

Traditional BI systems typically present information to the end user via pre-defined static reports. Whilst providing a mechanism for viewing important and relevant data, paper-based reports are limited in the questions they can answer. There is also a requirement to define the questions in advance of report generation. Hard copy reports typically display information at a summarised level without the ability to drill-down into the detailed data (Nagy et al. 2009). Similarly, this rigid approach does not allow for further analysis of a dataset through user interaction in order to reveal additional insights. The end user has very little control over the report content or the KPIs being selected.

More recently, digital dashboards have been utilised to present data to end users. Morgan et al (2006) defines a dashboard as a "concise, context-specific display of key metrics for quick evaluation of multiple subsystems". Eckerson (2010) further elaborates on this, describing a performance dashboard as a customisable tool to convert an organisation's strategy into objectives and metrics. He describes the dashboard as a performance management system with three main functions:

1) Monitor critical processes – metric data and trigger alerts.
2) Analyse problems – identify reasons through timely access to data, viewable from various perspectives and levels of detail.
3) Manage people and processes – improve decision support and optimise performance towards achieving strategic goals.

Dashboards are graphical by nature, visualising data through graphs and charts rather than traditional text-based report methods. This data visualisation approach has been demonstrated to improve uptake of BA tools utilising dashboards. In a recent industry survey, 79% of respondents rated the influence of data visualisation as 'high/very high' in the context of BA dashboard uptake (Eckerson & Hammond 2011). This helps illustrate the potential for successful implementation of a well-designed BA dashboard. Furthermore, Steele and Schomer (2009) highlight the successful implementation of dashboard-type BA solutions within hospital environments and the potential for the roll out of this functionality across radiology departments.

Performance dashboards have the potential to transform traditional BA from a set of tools used primarily by highly trained power users and systems analysts to a mechanism for delivering customisable information to everyone (Eckerson 2010). This model of data analysis clearly provides a more flexible approach to information analysis and empowers users to manage and interrogate data from their own unique perspectives. Dashboards can relay important organisational information at a glance and have the potential to provide a mechanism to deliver self-service analytics for everyone.

2.4.5 Application of Business Analytics to Radiology

The two primary benefits of implementing a BA solution are: 1) transparency and visibility of information and 2) fact-based decision support (Nagy et al. 2009). Access to and visibility of accurate and timely information gives end users the necessary knowledge to inform strategic decision making within an organisation. This potential is already being realised within radiology departments around the globe.

In the USA, a recently implemented radiology digital dashboard to support radiologist workflow has significantly cut medical image diagnostic reporting turnaround times. By accessing and consolidating data from the hospital's PACS and RIS systems, the dashboard provides alerts to radiologists of reports awaiting signoff, as well as providing access to a digital signoff tool. The initiative has been a major success, with a reduction of up to 24% in the turnaround time from transcription to subsequent signoff (Morgan et al. 2008). Similarly, functionality can be implemented that can display average turnaround times from report transcription to signoff as well as the volume of reports completed per individual radiologist (Honeyman-Buck 2010). Interestingly, the previously discussed Hayes report (HSE 2010), was commissioned by the HSE in Ireland in response to media reports that highlighted a similar problem at the AMNCH in Dublin. There were found to be in excess of 57,000 medical imaging scans within the RIS system that contained no radiologist report. An automated dashboard providing alerts to management within the radiology department could have averted this crisis.

At the Huzhou Central Hospital in China, a BA dashboard was introduced to help assist with radiology work flow management. The software tool mapped the current workflow process and was found to integrate well into the radiology department. It was also well received by radiology staff, delivering visibility and monitoring functionality that had not been previously available (Zhu et al. 2010). Visibility of departmental workflow and associated metric data can help management identify bottlenecks in the process as they occur rather than after the event. Drill down into the underlying data can provide valuable information such as average patient wait time and instances in which average wait times are exceeding performance targets (Honeyman-Buck 2010).

Guidance literature on utilising Open-Source software tools to implement BA solutions for radiology has also been published. Recommendations include the establishment of a data warehouse and the implementation of BA data extract technology (ETL) to gather data from numerous sources into a single repository. Data mining and OLAP technologies are then recommended to aggregate the data and a graphical representation is recommended for visualisation (Prevedello et al. 2010).

BA software tools are also being used in radiology departments to extract and aggregate KPI data from a range of underlying clinical information systems. A study in the US that collected results over a 2-year period suggests that the implementation of a BA reporting system has significantly improved management decision support, productivity, departmental performance and quality of radiology services (Nagy et al. 2009).

Visualisation of radiology KPIs enables radiology staff to make more informed and accurate decisions, to improve patient care, to deliver better efficiencies to referring clinicians and to improve cost effectiveness (Mansoori et al. 2013). Access to up to date KPI information can also help to identify activities that are impacting departmental work processes, quality of service and patient satisfaction levels (Ondategui-Parra et al. 2004). Furthermore, operational performance data and metrics can be further extrapolated to determine departmental cost to assist and inform revenue management.

Return on Investment (ROI) on implementation of BA solutions can also be substantial. A US study that examined the financial benefits of implementing BA across 43 US and European organisations showed a 5 year median ROI of 112% with individual returns ranging from 17% to 2000% (Morris 2003). Clearly, the initial cost investment should not be a barrier to implementation however there can be limitations to implementing this technology within the healthcare domain. These can include poor quality data, a lack of access to information in digital format as well as a lack of standards, which can make it difficult to consolidate data from multiple sources (Olszak & Batko 2012). It should be noted that none of these issues existed at the study site.

Moreover, a number of radiology KPIs have already been identified as part of a previous research exercise (Fotiadou 2013) and a data extract from the PACS, RIS and Patient Administration System (PAS) is available. As a result, there is significant potential to implement a BA dashboard that could be utilised to visualise this KPI data and make it available to decision makers within the medical imaging department.

2.4.6 Potential for Forecasting and Predictive Analysis in Radiology

As well as utilising the more common BA technologies, there is also scope to consider more innovative solutions to assist with demand management and capacity planning within radiology.

Bespoke software applications utilising BA technologies offer the potential to create solutions that can forecast future demand based on historical and current performance data. This allows the determination of how future demand, capacity and backlog is likely to unfold based on previous data trends. Complimenting this is the ability to perform 'What if' analyses of the impact of various scenarios on datasets (Negash & Gray 2008). Implementation of predictive scenario functionality for radiology could enable the determination of future demand and capacity based on a user-defined set of criteria.

As previously outlined in section 2.4.5, there are a number of examples within radiology of BA functionality being utilised to assist decision support and workflow management based on past and present performance; however, there is very little evidence of the utilisation of future predictive analysis to drive decision making.

Resource management within the radiology department at the study site is predominantly reactive and based on historic performance data: a rear-view mirror approach. Forecasting and modelling future demand and capacity data could allow radiology departments to anticipate forthcoming demand variations and plan appropriately. This allows a shift from a reactive 'what should we have done' mentality towards a more proactive 'what can we do' mind-set. It would also allow a movement from resource driven to demand driven wait time management. The ability to anticipate demand and to plan capacity accordingly has already been demonstrated to be successful within the healthcare sector (Jones et al. 2009; Mills et al. 2010; Ong et al. 2009). In addition to this, queuing theory has also been successfully implemented to predict patient wait times (Mehandiratta 2011).

Furthermore, discrete event simulation has been used to successfully model patient data to optimise patient flow (Ashby et al. 2008) and provide near future forecasting for A&E departments (Hoot et al. 2008). A recent study conducted at the A&E department at the University of Kentucky Chandler Hospital in the US successfully implemented a simulation model to identify bottlenecks and determine optimum resourcing (Brenner et al. 2010). The model catered for 'What-If' scenarios and accurately recommended increasing A&E capacity by 3 additional nurses as well implementing a new CT scanner in radiography. The study also noted the potential for this functionality in other departments at the hospital. Clearly there is potential to implement a BA system for radiology that can forecast patient wait times utilising predictive scenarios to facilitate capacity planning.

BA technologies offer the potential to implement a future predictive data model for radiology that can forecast demand and capacity data based on historic trends and 'What-If' scenario analysis. This is an area that will be explored in more detail as part of this study.

2.5 Summary

In this review the impact of patient wait times and contributing factors were explored. Based on these findings, demand and capacity management initiatives were examined for potential application. A requirement for a more accurate alignment of demand and capacity data was identified and an Informatics approach through the usage of BA technologies was proposed.

Healthcare organisations and radiology departments are struggling to leverage their data assets to improve operational efficiencies. In the absence of systems that can extract data, perform relevant analysis and present results in a meaningful way, these organisations will continue to struggle with visibility of supply and demand information and lack the knowledge necessary to inform strategic decision making. The implications of this will continue to be lengthy patient wait times, decreased patient satisfaction levels and sub-optimal levels of performance and productivity, as well as diminished cost effectiveness.

The technology is available to address these problems. BA solutions provide a means to empower radiology departments with the knowledge and decision support necessary to deliver on strategic goals such as improved patient wait times. BA technologies also provide a means to implement innovative solutions. Powerful forecasting and predictive analysis tools have the potential to allow management to anticipate and react to diagnostic demand, thus enabling a more proactive approach to capacity planning. With the advent of self-service Business Analytics and the utilisation of digital dashboards, radiology staff can harness the power of data discovery and analysis, both locally in the hospital environment and remotely utilising mobile devices. Traditional reliance on IT departments can also be mitigated. This is especially relevant within the healthcare sector, where IT resources are limited.

Through an evidence based approach, it has been demonstrated that BA solutions are bringing improved operational efficiencies and management decision support to radiology departments across the globe. Proactive decision support solutions implementing ‘What-If’ scenario forecasting have also shown evidence of benefit within the healthcare domain. To assist with this study, a BA prototype software tool will be built for radiology utilising the technologies identified in this review.

Having identified an appropriate area of research, it is necessary to select the relevant research methods. In the next chapter we will discuss in detail the proposed research methodology that will be utilised to carry out this study.

3 Research Methodology

3.1 Introduction

This section of the document outlines the research methodology utilised and applied in order to answer the research question. The methodology proposed for this study can be described as the design, validation and evaluation of a Business Analytical software prototype to facilitate enhanced demand and capacity management decision support to improve patient wait times within a medical diagnostic imaging department. This requires the design and build of a bespoke BA software tool utilising a number of ICT technologies identified as part of the literature review. On completion and validation of the prototype tool, a qualitative evaluation will be undertaken to determine the perceived level of success of the software tool, by key stakeholders, to answer the research question.

3.2 Research Methods

Creswell (2013) describes research methods as the various forms of data collection, analysis and interpretation that a researcher proposes in order to answer research questions. Multiple phases of data collection and analysis were conducted as part of this study.

3.2.1 Phase 1 - Literature Review

Aveyard (2010) defines a literature review as 'a comprehensive study and interpretation of literature that relates to a particular topic'. In order to focus the review and ensure that all content remained relevant to the research question, an initial high level review of the literature was conducted and a selection of peer-reviewed articles relevant to the objectives were appraised. Based on this appraisal, three primary areas of interest were identified as relevant to the research (see table 3.1).

Table 3-1: Literature review primary areas of interest

Areas of Interest	Key Objectives
Patient wait times	• Investigate the impact of patient wait times in radiology departments worldwide • Look at contributory factors towards waiting list build-up • Identify the impact of future healthcare policy on patient wait times in radiology
Demand and Capacity Management	• Evaluate demand and capacity initiatives currently implemented with a focus on radiology • Identify initiatives that can be utilised to improve current

	business processes and contribute towards improved management of patient wait times within radiology
Business Analytics	• Discuss definitions and dimensions of BA • Identify the benefits of data driven decision support • Highlight the importance and relevance of data visualisation • Provide evidence of the successful application of BA tools within radiology • Evaluate the potential for utilising forecasting and predicative analysis functionality to drive decision support in radiology

A methodology was developed and a detailed literature review was undertaken. The review takes an evidence-based approach, identifying primary literature backed up by real world initiatives across radiology departments worldwide.

3.2.1.1 Inclusion and Exclusion Criteria

A significant amount of literature was identified at the outset of the review. In order to ensure that all items selected were relevant to the areas of interest, a set of inclusion and exclusion criteria was developed. Literature was selected for inclusion as per table 3-2.

Table 3-2: Literature review inclusion criteria

Primary selections	**Inclusion criteria**
Literature content	• Global policy and reimbursement models in the context of patient wait times • Patient wait times within radiology and contributory factors • Demand management and capacity planning initiatives within the healthcare domain with a focus on radiology • Forecasting initiatives within the healthcare domain • BA technologies with potential to improve demand management and capacity planning within Radiology • BA Forecasting and predictive analysis initiatives within the healthcare domain
Literature Type	• Published literature • Government reports • Industry white papers

	• BA vendor website articles • Industry research papers and reports
Language	• English language literature only
Date of publication	• Literature published since 2003 with the exception of key technology definition articles

The author has extensive experience of implementing BA solutions within private sector companies. As a result, it was decided to exclude literature on forecasting and BA initiatives outside of the healthcare domain. This would help focus efforts on identifying implementation examples of which the author did not have previous experience and that could be used to inform potential solutions for radiology. Literature excluded as per the criteria is outlined in table 3-3.

Table 3-3: Literature review exclusion criteria

Primary selections	**Exclusion criteria**
Literature content	• Patient wait times impacting on areas other than radiology • Demand management and capacity planning initiatives outside of the healthcare domain • Forecasting initiatives outside of the healthcare domain • Business Analytics technologies not contributing towards improved operational efficiencies and demand management/capacity planning within Radiology • BA Forecasting and predictive analysis initiatives outside of the healthcare domain
Literature Type	• Unpublished literature • Website discussion articles • Blog entries • Wikipedia
Language	• Non English language literature only
Date of publication	• Literature published pre-2003 with the exception of key technology definition articles

3.2.1.2 Electronic Search Criteria

All literature searches were conducted electronically utilising Google Scholar as well as subject-specific electronic databases including Science Direct, PubMed (US National Library of Medicine National Institutes of Health), the ACM Digital Library and Springer. All databases were accessed via the Trinity College Dublin library website in order to maximise authorisation to and availability of literature sources.

A number of keywords were identified as relevant to the areas of interest being addressed. The sections of the literature review and their corresponding search keywords were broken down as per table 3-4.

Table 3-4: Electronic search criteria

Areas of Interest	Search keywords
Patient wait times	Waiting time, reimbursement models, radiology, wait list, medical imaging, MRI, CT.
Demand and Capacity Management	Planning, productivity, operational efficiencies, demand management, capacity planning, radiology, planning, forecasting, diagnostic imaging, initiatives, efficiency, radiology management, Informatics, MRI, CT.
Business Analytics	Business intelligence, business analytics, healthcare, radiology, MRI, CT, BI, BA, data collection, data mining, planning, predictive analysis, data extraction, forecasting, knowledge management, OLAP, data discovery, self-service BI, embedded BI, extract transform load (ETL), reporting, ad-hoc query, data driven decision making, decision support, dashboards, data visualisation, What-if analysis, forecasting.

Various combinations of keywords for each of the above areas were entered into the selected electronic databases and articles were selected for review as per the inclusion/exclusion criteria described. Critical appraisal was conducted on the identified literature and all items selected for inclusion were stored electronically using the Zotero citation manager software tool[12].

A significant number of items were found for combinations of the patient wait time and demand management keywords; however, the initial keywords identified for reviewing Business Analytics returned a small number of relevant articles. Initial searches were conducted requesting exact matches on “Business Analytics” and “radiology” for literature post 2007. This returned a total of 91 articles, of which 12 were deemed relevant to the study.

To address this, BA search keywords were further extended to include ‘dashboards’, ‘data mining’ and ‘data visualisation’ and literature was searched back to 2003 rather than the initial

[12] http://www.zotero.org/

selection of 2007. Due to inconsistencies in nomenclature of BI and BA articles, the use of 'dashboards' as a keyword produced over 500 documents for review. In addition to this, the use of 'data visualisation' also highlighted a number of BA relevant articles.

There was an evident lack of literature relating to the use of predictive scenario analysis forecasting tools within radiology. The initial search returned zero articles, so literature dates were extended back to 2003 and a broader search was conducted selecting 'healthcare' rather than 'radiology' and using the term 'What-If'. Five hundred and eighty articles were returned and a number of healthcare forecasting and simulation articles, particularly relating to A&E, were discovered, including the application of queuing theory and discrete event simulation for optimising patient flow. These were included for selection within the literature review. It appears that there is very little literature currently available on the usage of predictive scenario forecasting tools to improve operational efficiencies within radiology.

3.2.2 Phase 2 - Requirements Gathering

This phase of the study identified a set of user requirements to inform the building of the prototype software tool. In-depth semi-structured interviews were conducted at the study site with the three key stakeholders from within the radiology department. A consent form (appendix B.1) plus an interview information sheet (appendix B.2) were issued one week in advance of the agreed interview dates. A set of interview questions was also provided to the participants in advance of the interview to allow any prior content queries to be addressed.

To assist with data collection, an interview protocol was developed that included an introduction and overview, a set of questions (including probes) and a final wrap up/thank you for the interviewees (appendix B.3). The interview questions were broken into two sections, one addressing current KPI requirements and the second focusing on forecasting and predictive analysis requirements. A number of prototype screens were developed in order to assist and inform user interface requirements and to act as probes to extract additional information (appendix B.4). The interviews were recorded and later transcribed and ranged in time from 22 minutes to 35 minutes. Transcription data was subsequently utilised to document prototype requirements and inform the software build.

3.2.3 Phase 3 - Prototype Software Evaluation

A prototype BA software tool was built based on the requirements identified during the requirements gathering phase of the study. On completion of prototype validation, the software was deployed on a server accessible over the hospital network via the internet. The author gave a demonstration and provided training to each of the evaluation participants; this was followed by the participant evaluating the prototype tool for a number of hours over a period of one week. The author was available to address any queries and provide assistance during the software evaluation period.

3.2.3.1 Qualitative Data Analysis

After completion of the user software evaluation, face to face qualitative semi-structured interviews were conducted at the study site by the author with the three key stakeholders. A participant consent form (appendix B.1) and an interview information sheet (appendix B.5) were issued one week in advance of the agreed interview date. A set of interview questions was also given to the participant in advance of the interview to allow any prior content queries to be addressed. To assist with data collection, an interview protocol was developed which included an introduction and overview, a set of questions (including probes) and a final wrap up/thank you for the interviewees (appendix B.6).

The interview questions were used to gather feedback on the individual's experience of using the prototype tool to visualise demand/capacity and radiology KPIs. They were also used to determine perceived benefit with regard to how the tool can improve decision making through the analysis of historic and current data, as well as the modelling of future demand and capacity data via predictive scenarios. Interview content was recorded and transcribed and notes were taken on body language and tone as well as general observations of the behaviour of the interviewees. Thematic content analysis was conducted on the data. To assist with this, the data was transcribed and then categorised and coded to identify themes which were used to inform research findings.

3.3 Ethical Considerations

Due to the requirement for human participation in this study, ethical approval was sought from the research ethics committee at the School of Computer Science and Statistics (SCSS) at Trinity College, Dublin. Ethical approval was granted to proceed with the study in December 2013 (appendix C.1).

As there are no patients involved in this research, there was no requirement for hospital ethical approval; confirmation of this was received from the research ethics committee at the study site (appendix C.2). Hospital management consent was provided by the clinical director (appendix C.3) and approval to undertake the research study was also received from the Risk and Legal Office at the study site (appendix C.4).

A non-patient specific dataset was provided by the hospital IT department to facilitate the prototype build and validation. No individual patient, radiographer or radiologist data was collected for the purposes of this study. All data collection, storage and analysis complied with the Data Protection (& Amendment) Acts and current best practice in scientific research.

3.4 Summary

This chapter outlined the proposed research methodology that will be utilised to answer the research question. Ethical considerations were also discussed.

The next chapter will discuss the development methodology used for building the software prototype tool as well as the requirements gathering process and prototype design.

4 Software Prototype Requirements and Application Design

4.1 Introduction

In order to attempt to answer the research question, a BA software prototype application was implemented. This involved the design, build and validation of a prototype software tool. Once the prototype tool became available, it was evaluated by the key project stakeholders.

This chapter will discuss the development methodology proposed, the steps taken during the requirements gathering phase and the subsequent design of the prototype software application based on the requirements elicited from the key stakeholders.

4.2 Development Methodology

The software development methodology chosen was predominantly based on the waterfall lifecycle model first introduced by Royce (1970). This process model proposes a linear development cycle from initial conception through to requirements, system design, software build and subsequent validation. Despite assertions that the traditional waterfall model for software development is declining in favour of more modern methods, this has been demonstrated to not be the case (Laplante & Neill 2004).

Whilst agile development methodologies utilising iterative and incremental development approaches are widely used (Larman & Basili 2003), it was decided that these implementation methodologies would not be conducive to building the application within the timeframe allocated and based on the limited resources available at the study site.

4.3 Requirements Gathering

The term 'requirements gathering' is commonly used to refer to the initial phase of software development and is primarily concerned with understanding the business problem rather than solving the business problem (Davis 1988).

At the outset of the project, an initial meeting was held with the clinical director at the study site in order to get a high level overview of current business problems within the department and to discuss potential solutions. The primary area of concern was the current lack of visibility of orders being placed on the radiology department (demand data) as well as a lack of understanding of existing capacity to manage this demand. Consequently, a lack of decision support data was resulting in significant operation inefficiencies and mismanagement of patient backlog.

A number of potential research studies were identified and, after further discussion, it was agreed that the area of most benefit to the medical imaging department would be the introduction of Business Analytical software. This could potentially allow the extraction and visualisation of meaningful information from the vast amounts of existing radiology data. Previous research conducted at the study site had identified a number of KPIs that were determined to be of benefit to the operation of the medical imaging department (Fotiadou 2013). It was agreed to implement functionality that would build on this knowledge and to investigate potential innovative solutions for demand management and capacity planning.

After further deliberation, it was decided to build an application that would provide analysis of radiology data across all time horizons: historic KPI performance data, current waiting list information plus scenario modelling of future forecasted demand and capacity data. Based on these high level requirements, two categories of functionality emerged for inclusion as per table 4-1.

Table 4-1: Requirements categories

Category	Description	High Level Functionality Requirements
C_01	Predictive Scenario Analysis	• Allow creation of multiple predictive scenarios • Provide facility to maintain baseline modality data • Visualise forecast backlog for each predictive scenario • Visualise forecast demand for each predictive scenario • Visualise forecast Inpatient/Outpatient optimum mix percentages • Cater for all modalities
C_02	KPI Data	• Provide a dashboard to visualise radiology KPIs • Cater for multiple selection criteria for KPI data • Provide ability to edit chart dimension data • Provide drill down functionality • Option to display raw data behind each chart • Cater for all modalities

4.3.1 Approach

Once the main categories of functionality had been defined, a detailed set of requirements questions were created and semi-structured interviews were arranged with key team members. See section 3.2.2 for a detailed description of the approach used.

One of the most challenging areas of requirements gathering is assisting users in understanding what they need rather than what they want (Young 2002). In a minor deviation from the standard waterfall lifecycle model, a selection of prototype screens was developed based on the initial high level requirements outlined in table 4-1 (see appendix B.4).

Prototyping of initial screens provides an effective mechanism to help illustrate proposed functionality as well as helping users to visualise an application's user interface (Young 2002). A significant number of the screens within the application contain graph data and the prototypes provided a method to discuss how the data would be calculated and subsequently displayed. The prototype screens were also used as probes to glean additional information during requirements gathering.

4.3.2 User Requirements

A requirement can be defined as a statement that is used to identify a characteristic or capability of a system (Young 2001). In order to elicit the necessary requirements information, semi-structured interviews were carried out with the three project stakeholders. A list of interview questions were prepared in advance based on the high level requirements identified in table 4-1 (see appendix B.3). All interview data was recorded and transcribed and the transcription detail was then used to document application requirements.

Industry experience has shown that customers and system developers should jointly evaluate stated requirements to ensure that each is a verified need (Young 2002). For this reason, a subsequent meeting was held with the clinical director during which requirements were finalised and, where necessary, refactored.

Each finalised requirement was broken down into one of three classifications (see table 4-2).

Table 4-2: Requirement classifications

Classification	Description
Functional	A requirement that will affect system functionality - something that the system must do
Non-Functional	An attribute of a system requirement such as system performance, system usability and intuitiveness
Constraint	A limitation placed on the system such as must be web-based or must use a Microsoft database

4.3.2.1 Functional System Requirements

Functional requirements form the basis of understanding on which the system is built. They detail the stakeholder's expectations of the end product and describe how it should operate as well as what it should look like. Forty-four predictive scenario analysis and KPI data functional requirements were identified during the requirements gathering phase. A full list of all functional requirements is provided in appendix D.1 and D.2.

4.3.2.2 Non-Functional System Requirements

Non-functional requirements apply to the whole system and are often used to gauge the effective operation of the system. Nine non-functional requirements were identified; a full list is provided in appendix D.3.

4.3.2.3 Constraints

Three system constraints were specified for the application. Whilst a constraint can be deemed a technical limitation that can restrict the scope of the solution design, it should be viewed as a mechanism to ensure that the application software is implemented on time with reduced risk. A full list of constraints is provided in appendix D.4.

4.4 Application Design

On completion of the requirements gathering phase of the study, a complete set of user requirements was documented and made available. Having achieved a firm understanding of the business problem and the scope of the work involved, a system design was implemented for a proposed solution.

The system can be broken down into two distinct modules, the first module providing a dashboard to visualise historic and current radiology KPIs, and the second module providing predictive analysis functionality and a dashboard to visualise future forecasted demand, capacity and backlog data.

4.4.1 KPI Dashboard

The KPI dashboard will be designed based on a set of previously defined radiology KPIs that are of most relevance to the medical imaging department at the study site (Fotiadou 2013). Additional KPIs identified during the requirements gathering exercise will also be included. A commercially available BA software tool will be utilised to implement a dashboard to visualise the KPI data. The BA tool will also provide the necessary OLAP functionality to allow various combinations of selections to filter the data as well as drill-up and drill-down functionality.

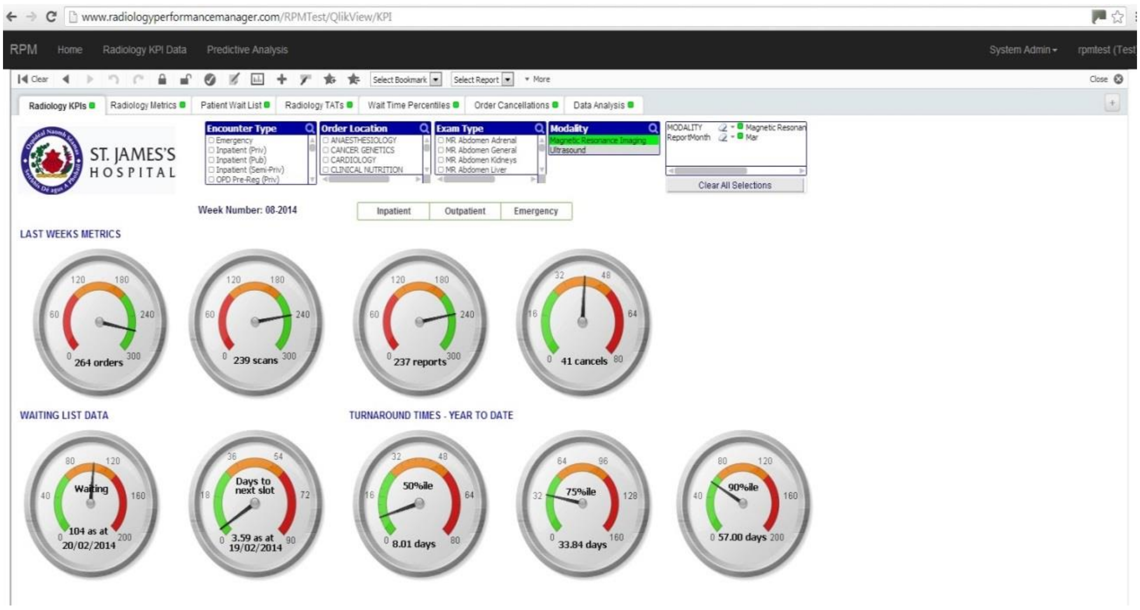

Figure 4-1: KPI summary tab on the KPI dashboard

Figure 4-1 illustrates how the dashboard will be displayed. Various data filters will be provided through list boxes and the dashboard is visualised across a number of tabs. Each tab can be selected by simply clicking on it. The initial tab displays a set of KPIs at a high level with subsequent tabs providing lower level detail on the various figures. For example, by clicking on the ‘Radiology Metrics’ tab, the metric data can be visualised to a lower level of detail, as illustrated in figure 4-2.

Figure 4-2: Radiology metric data

4.4.2 Predictive Analysis Functionality

The second module of the system will be a combination of a bespoke software application and the selected BA software tool. The bespoke functionality will be used to implement maintenance of predictive scenarios as well as to provide forecast algorithms that can be used to generate forecast data. That data can then be visualised on a dashboard using the BA software tool.

4.4.2.1 Predictive Scenarios

The system will be designed to allow users to create and maintain predictive scenarios unique to each modality. Implementation of predictive scenario functionality provides a powerful and flexible tool for modelling and analysis of multiple unique radiology scenarios. Each scenario can be defined by the user to cater for numerous future eventualities.

During the requirements phase of the study, each stakeholder was asked to specify three scenarios that would be of most benefit to model in order to assist with their specific roles. A number of scenarios were identified for inclusion (see table 4-3).

Table 4-3: User requested predictive scenarios

Scenario	Description
Adjustment in scans	Ability to add in or remove a quantity of scans at inpatient or outpatient level. This would allow analysis of the implications of taking additional backlog from other hospitals as well as the ability to model the outsourcing of a quantity of scans to other locations.
Available devices	Ability to model the benefits of implementing additional devices within the radiology department. Also provide the ability to analyse the effect of the removal of devices from within the department.
Device downtime	Ability to model the implications of device downtime, this could be for scheduled maintenance or for periods of de-commissioning.
Radiographer hours	A facility to visualise the impact of an increase in radiographer hours. For example, bring extra radiographers in on weekends to manage backlog. Similarly, the ability to model a reduction in radiographer hours (sick leave, maternity/paternity leave)
Average scan time	Ability to analyse the impact on patient backlog of increases or decreases in average scan time.
Mix allocation	Facility to visualise optimum mix of inpatient/outpatient allocation of departmental capacity based on expected demand. This is currently done manually and is very much based on departmental experience rather than any scientific calculations.

A function will be provided to allow entry of the various requested scenario details (see figure 4-3). Scenarios will be held at modality level with scenario adjustments allowed to week number level. Once the scenario details are entered to the system, they can be maintained on an on-going basis. A Forecast function will cater for the generation of forecast demand, capacity and backlog data using the scenarios entered based on actual historic performance data within the radiology department.

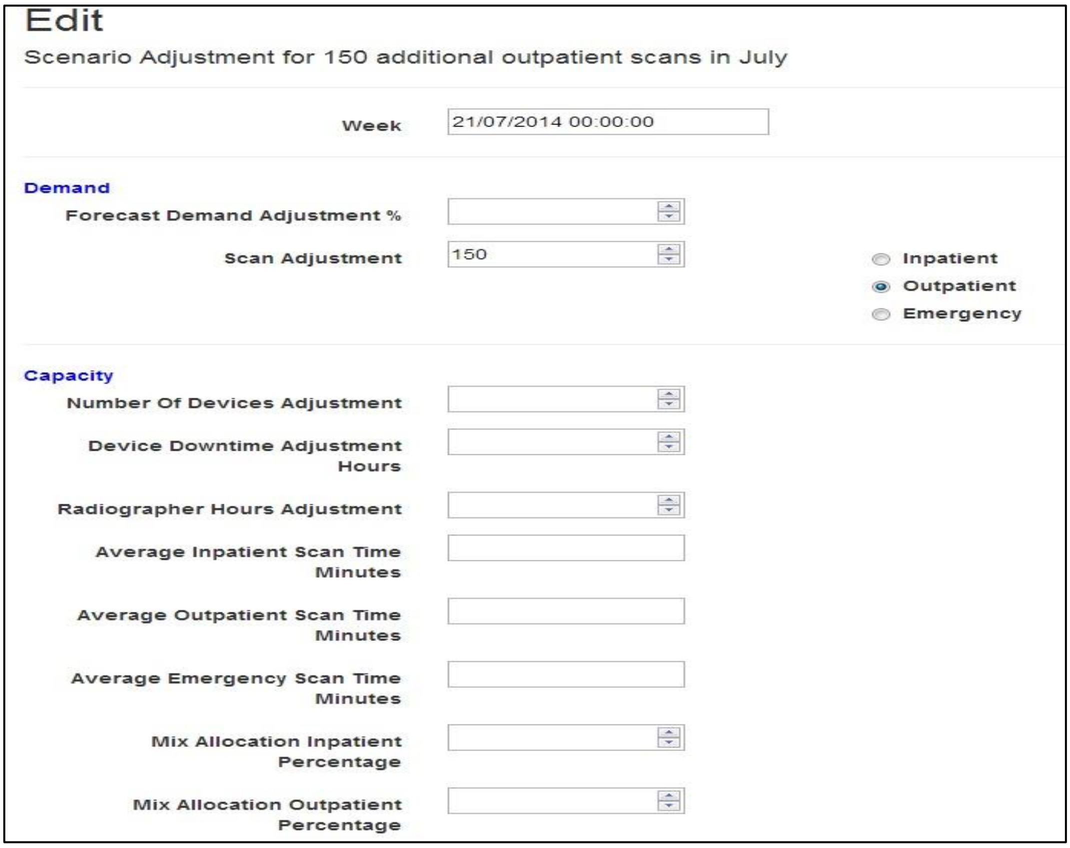

Figure 4-3: Predictive scenario maintenance

Figure 4-3 provides an example in which a scenario is created that allows for an additional 150 outpatient scans for a specific week in July. The user enters the date when the adjustment is expected to occur as well as the number of scans and the specific encounter type. Once this data is updated to the system, the Forecast can be refreshed to include the new scenario. This data can then be visualised.

4.4.2.2 Predictive Analysis Dashboard

The forecast data generated for each scenario will be visualised using a number of graphs on a dashboard, providing predictive analysis of demand, capacity, backlog and optimum mix.

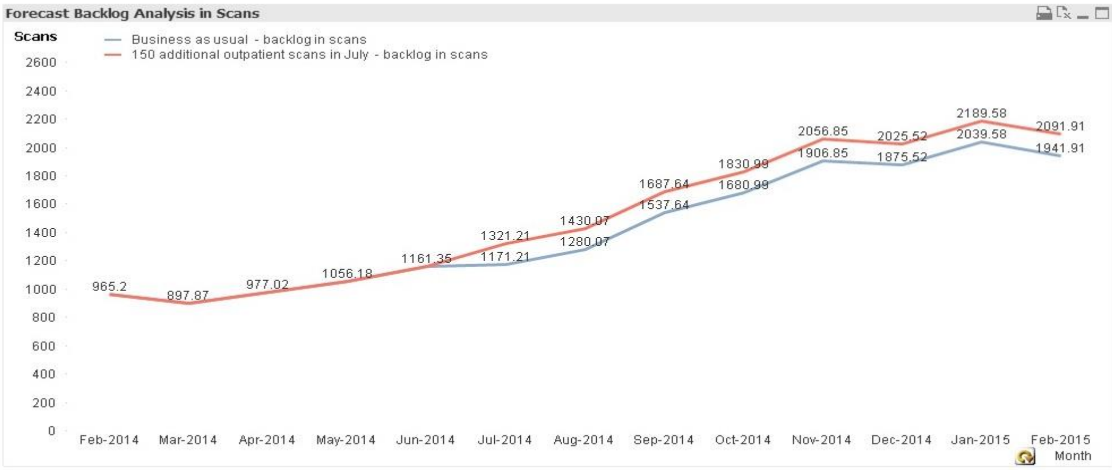

Figure 4-4: Predictive backlog analysis

Figure 4-4 illustrates the way in which the backlog analysis will be graphed. A 'Business as usual' scenario (blue line) will display baseline backlog: i.e. no predictive scenario adjustments. A drop down list box will allow selection of a specific scenario (red line) for comparison analysis. In figure 4-4, the scenario created in figure 4-3 whereby 150 additional outpatient scans in July were requested is displayed against the business as usual scenario. As illustrated, we can see the impact of this scenario through a divergence between the two scenarios in July; the additional 150 scans result in an increase in backlog through to the end of the forecast year. Again, OLAP functionality within the BA graphing tool provides selection and filtering of the data with drill-up and drill down functionality to week or month level. All forecast data will be displayed in either hours or scans depending on user selection.

This predictive scenario functionality allows for any combination of adjustment data to be entered against each user-created scenario. There are no limits on the number of scenarios that can be created; the only restriction is the way in which the user wishes to model the data within the application. This unique functionality provides for powerful user-defined predictive modelling and analysis of future forecasted radiology data.

4.5 Summary

This section discussed the approach to user requirements gathering and the subsequent design decisions taken based on the functional and non-functional requirements as well as system constraints. An overview of the proposed system design was also discussed.

The next chapter will discuss the steps taken to implementation and the validation methods utilised to ensure the accuracy and validity of the application's dataset.

5 Prototype Implementation

5.1 Introduction

Swanson (1988) refers to the system implementation phase as the stages within the systems development lifecycle between system design and use. It is the realisation of a system design based on a set of user requirements and the phase during which the proposed software system is coded, validated and signed off as accepted by its end users.

This chapter will discuss the ways in which the prototype application was implemented in the radiology department at the study site. An overview of the functionality and workflow will be provided as well as the challenges that needed to be addressed during the build. The chapter will also discuss the validation process that was used to ensure the accuracy of the data presented by the system.

5.2 Selection of Development Tools

The initial stage of the design phase involved identifying the development toolset necessary to build the system to the required specification. There were a number of factors that influenced the decision on which technologies to use, which included:

1) Study site IT infrastructure - the study site has invested heavily in Microsoft technology, from desktop applications through to underlying systems architecture and database implementation.
2) Mobile computing – the ability to provide access to KPI data over mobile notepads and smartphones was a key requirement. This is to facilitate clinician access to waiting list data over mobile devices from within the hospital wards.
3) Browser-based application – the preference was to implement a browser-based application as users were familiar with this particular user interface. The application was required to be optimised for Microsoft Internet Explorer 10.

5.3 Selection of Business Analytic Software

A number of analytical technologies were identified during the literature review. Based on these findings and the requirements identified at the study site, a checklist for evaluation was drawn up (see table 5-1).

Three BA software tools, all previously utilised by the author, were evaluated based on the checklist: IBM Cognos[13], Qlikview[14] and Birst[15]. All three solutions adequately satisfied the selection criteria; however, Qlikview proved the strongest with regard to provision of self-service BI functionality and data discovery, which were areas that the author deemed would be of significant benefit to the study site.

Table 5-1: BA software evaluation criteria

Functionality	Description
OLAP	Drill down, aggregation and slicing and dicing of the dataset.
Self-service BI (SSBI)	Capability to create analytic visualisations independent of IT departments.
Data discovery	Interactive exploration and analysis of data.
Mobile functionality	Optimisation and visualisation of analytic data for mobile devices such as phones and tablets.
Embedded BI	Ability to embed existing BA functionality into bespoke software solutions.

It was also discovered during the evaluation that the study site had already purchased a number of Qlikview licenses to assist with the HSE proposed 'money follows the patient' model (DOHC 2012). This provides significant scope to implement the proposed solution for use at the study site going forward, should it be deemed to be of value to the radiology department. For these reasons, Qlikview was selected as the most appropriate BA software tool for use in this study.

5.3.1 Qlikview

Gartner, a US based information technology research and advisory firm, describes Qlikview as a BA market leader with an intuitive user interface and strong data discovery capabilities based on an in-memory associative architecture. They also describe the software as having better than average implementation costs. In its quarterly published magic quadrant report, Qlikview is acknowledged as one of the top Analytics solutions currently available on the market (see figure 5-1).

[13] http://www-01.ibm.com/software/ie/analytics/cognos/
[14] http://www.qlik.com/
[15] http://www.birst.com/

Figure 5-1: Qlik acknowledged as a leading Analytics solution from (Gartner 2014)

Qlik, the providers of Qlikview, describe the associative model as one of its primary differentiators (Qlik 2011). This functionality allows users to define and access data any way that they choose and removes the requirement for pre-defined drill paths (see figure 5-2). This associative technology and the functionality it provides will be factored into the design of the application.

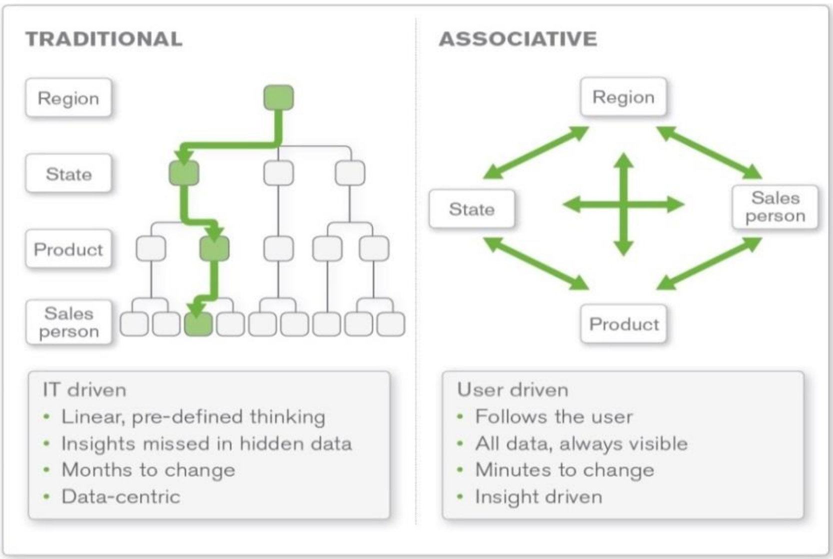

Figure 5-2: Qlikview associative technology from (Qlik 2011)

5.4 Technical Toolset

Having identified the criteria for selecting the development toolset and the BA software solution, the technical specification for the prototype application was finalised as per table 5-2.

Table 5-2: Technical specification details

Item	Description
Environment	Microsoft Visual Studio 2013 (VS2013) for Web, Interactive Development Environment (IDE) – available to download free of charge[16]
Framework	Microsoft ASP.NET MVC 5 – open source model-view-controller web development framework, included as part of VS2013. Facilitates implementation of browser based applications. Benefits of utilising MVC include: • Presentation of a consistent user interface regardless of platform • Centralised deployment across a web server ensures all users are running a single version of the software • Simplified upgrade process • Consistent implementation environment • Facilitates mobile friendly web applications – allows coding of a single user view that can be shared across desktops, tablets and smartphones or any connected device with a browser.
Database	Microsoft SQL Server 2012 Express – a free to download version of the Microsoft SQL server relational database system[17]
Language	Microsoft Visual C# (C sharp) – included as part of VS2013 and based on the ECMA/ISO specification of the C# language
Source Control	All source code was stored in Microsoft Team Foundation server, a source code management tool optimised for usage with VS2013[18].

5.5 Development Environment

The first step in the systems implementation process was to establish a suitable development environment. A number of options were evaluated at the outset; these included a dedicated development desktop, a portable development laptop and a virtual desktop utilising a server in the cloud. A number of factors were considered and the decision was made to implement a virtual desktop utilising Amazon Web Services (AWS)[19].

[16] http://www.visualstudio.com/en-ie/products/visual-studio-express-vs.aspx
[17] http://www.microsoft.com/en-ie/download/details.aspx?id=29062
[18] http://msdn.microsoft.com/en-us/vstudio/ff637362.aspx
[19] http://aws.amazon.com/

The Association for Computing Machinery (ACM) describes cloud computing as a technology to move IT services, computation and data to a location-transparent centralised facility (ACM 2009). Complimenting this is the availability of virtual desktop technology, which provides a means to deliver on-demand desktops from servers in the cloud to users at any location using any device (Deboosere et al. 2012). This format of desktop delivery is often referred to as Desktop-as-a-Service (DaaS). Over the course of the study, a number of benefits were realised through implementation of a cloud based virtual desktop; these are outlined in table 5-3.

Table 5-3: Benefits of a virtual desktop development environment

Benefit	**Description**
'On the Go' computing	Remote access to the development environment from any connected device at any location. This proved very useful as the author was able to develop the application whilst away from home both in Ireland and abroad. The only prerequisite requirement was a WI-FI connection.
Data Loss	Due to the application being stored in the cloud there was a significantly reduced risk of data loss through theft or loss of a computing device.
Data Backup	All application data was backed up regularly and automatically in the cloud at no additional cost.
User acceptance testing and evaluation	Due to the application being stored in the cloud this provided a single point of access for user testing and system evaluation.

There was a small cost in provisioning the AWS server for the length of the study; however, this was deemed justifiable due to the savings in time and efficiency as well as much improved levels of productivity. Once the server was provisioned, the technology toolset outlined in section 5.4 was subsequently downloaded and installed.

It is important to note that a virtual desktop was provisioned purely for the purposes of building a prototype tool for the study. Should the prototype be implemented at the study site, it is not envisaged that a cloud based solution would be utilised, primarily due to data security concerns. Any implemented solution would be installed on-premises utilising the hospital network.

5.6 Application Overview

The software prototype is a standalone bespoke web application that utilises embedded BA functionality to access and display Qlikview data models. The intention at the outset was to provide a business quality application. This can be measured by how well the system conforms to user functional requirements as well as how the system adheres to structural non-functional requirements such as robustness and maintainability. The technical toolset utilised will also help ensure the implementation of a 'best of breed' BA software application that is fit for purpose and conforms to the highest industry standards. The underlying technical architecture, as outlined in table 5-2, will ensure conformance with software development best practice and system reliability. Implementation of a web-based, mobile-friendly application will also ensure future proofing of the prototype application.

The prototype design is a combination of a bespoke web application and Qlikview data models. The application includes two Qlikview models, each developed independently, one displaying a dashboard of KPI data and a second displaying a dashboard of predictive data. Each model was developed within the Qlikview application and deployed to the Qlikview server as a URL that could subsequently be accessed from within the prototype application; figure 5-3 provides an overview of the prototype design.

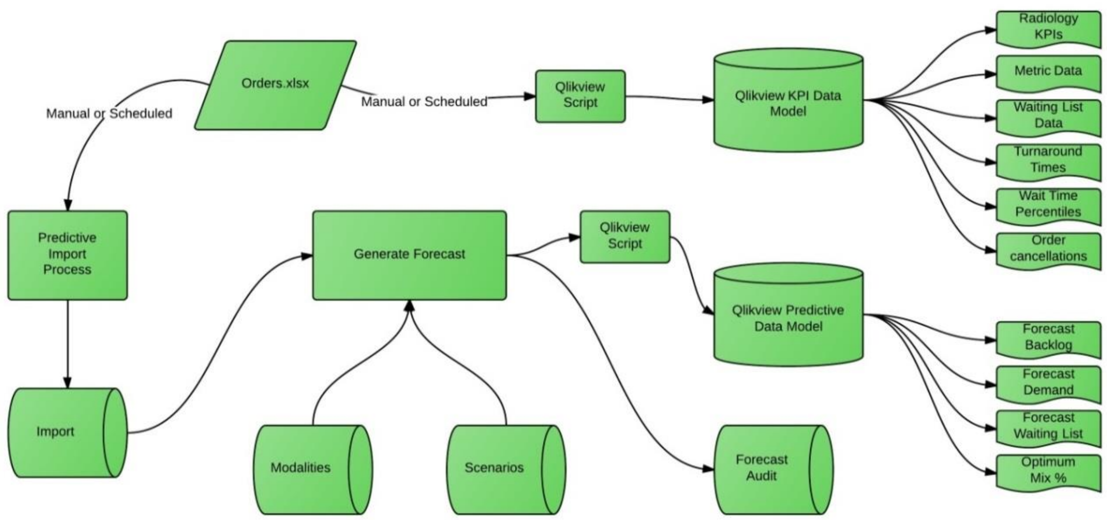

Figure 5-3: Prototype design overview

In order to visualise KPI data, an extract of MRI, Ultrasound and CT patient order data from the EPR, RIS and PACS systems (orders.xlsx table) was generated and then imported into the Qlikview KPI data model. The same extracted data table, orders.xlsx, is also used to populate the Import table within the predictive module of the application. The imported data is then used in conjunction with modality and scenario data to generate the forecast that subsequently loads the Qlikview predictive data model. The implementation of the two Qlikview data models also facilitates a modular design approach to the prototype application. All data models created within Qlikview are allocated a unique web address or URL. This allows the two data dashboards (KPI and predictive) to be accessed from within the prototype application or separately across the hospital intranet or mobile devices connected to the hospital network.

5.6.1 Application Security

Both the prototype application and the Qlikview data models utilise Windows authentication and active directory. Once users are set up on the hospital network, they may use their existing credentials to access the application. Qlikview also provides 'out of the box' security down to document level within a dashboard. Users can be authorised to specific documents within a dashboard; once they sign in, they will only have visibility of the documents that they are authorised to view.

5.6.2 Application Database Design

The application's underlying SQL Express relational database consists of a number of entities with associated relationships, as illustrated in figure 5-4.

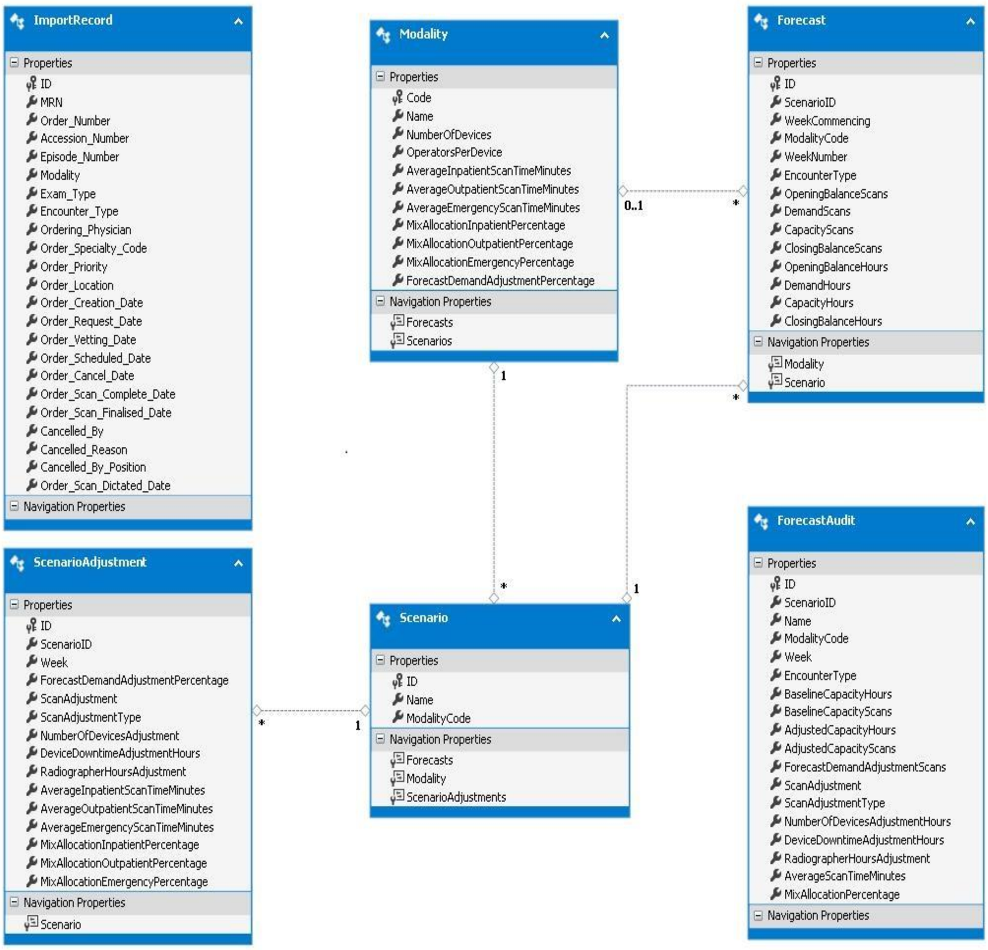

Figure 5-4: Prototype entity relationship diagram

The import record table is used to import the Excel data extract file into the database. Each field on the table is associated with a column on the Excel spreadsheet. The forecast audit table is used to keep a detailed audit trail of all demand and capacity adjustments applied when a forecast is generated. This provides a lower level of detail to the predictive data visualised from the Qlikview predictive data model. As illustrated, scenarios are associated with a modality and scenario adjustments are linked to an individual scenario. The forecast table is generated at modality/scenario level with forecast information stored for each encounter type (inpatient, outpatient or emergency) for each scenario selected.

5.7 Radiology Performance Manager

Radiology Performance Manager (RPM) is the implemented prototype software tool for monitoring and predicting radiology throughput performance. It is a standalone bespoke software application that facilitates the importing, aggregation and analysis of MRI, Ultrasound and CT scan data from the EPR, RIS and PACS computer systems at the study site.

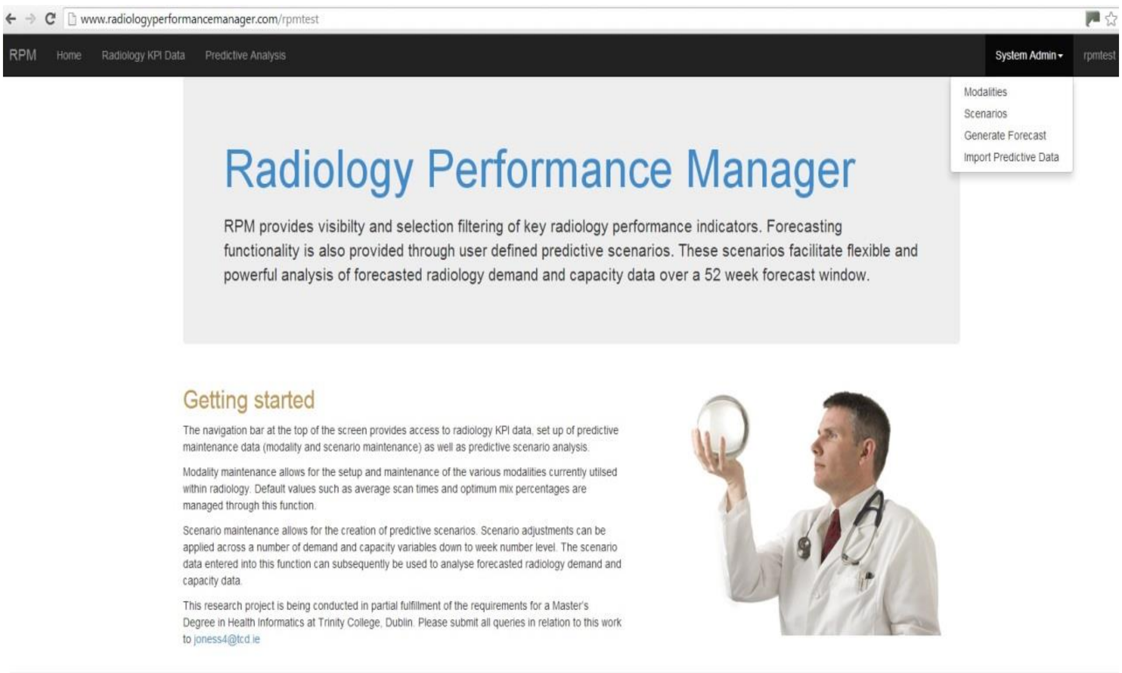

Figure 5-5: RPM home screen

The prototype application is accessible through a range of web browsers (Internet Explorer, Chrome or Firefox). The home screen (see figure 5-5) provides an introduction as well as instructions on how to access the various functions. Stipulation that the application is a prototype study being conducted in partial fulfilment of the requirements for a Master's Degree in Health Informatics as well as contact details for the author are also provided. A dropdown menu provides a clear and hierarchical view of all main sections on the page and the various subsections contained within them; see table 5-4 for an overview.

Table 5-4: Prototype application menu options

Menu option	**Description**
Home	Accesses the application home page
Radiology KPI data	Provides access to the Qlikview KPI data model
Predictive Analysis	Provides access to the Qlikview Predictive Analysis model
System Admin	Drop down menu providing access to the following predictive analysis system maintenance functions: • Modalities – Setup and maintenance of modalities for inclusion within the predictive analysis module. • Scenarios – Setup and maintenance of predictive scenarios for inclusion within the predictive analysis module. • Generate Forecast – Manually creates system forecast data. • Import Predictive Data – Manually import the dataset that predictive forecast data will be based upon.

The system can be logically broken down into two modules. The first module allows the import and analysis of historical and current KPI data from back end hospital systems; appendix E.1 gives a detailed description of the various functions. The second module implements the application's predictive analysis modelling and visualisation functionality; see appendix E.2 for a detailed description of the predictive analysis functions. A short video presentation has been created by the author in order to give an overview of the application's functionality. URL details and logon credentials to access the presentation are as follows:

URL: **https://tcd.wistia.com/medias/ck5nzar9au**

Email: **joness4@tcd.ie**

Password: **Radi0l0gy (case sensitive, zeros replacing 'o's)**

5.8 Challenges

A number of challenges had to be overcome whilst building both the KPI data module and the predictive analysis module of the system.

5.8.1 KPI Data Model

5.8.1.1 Point in Time Reporting

The Excel data file provided by IT contained a single data record per scan. In order to provide point in time analysis for waiting list data, it was necessary to explode out the data in the model to contain a record for every day that an order was active. This was achieved by creating a calendar table within the Qlikview load script and joining the order to the calendar table to create a record for every day that the order was active: i.e., from order creation date through to order finalised date. Whilst this resulted in a bigger data model due to multiple records existing per scan order, it also allowed point in time reporting of metric data, turnaround times and waiting list data. This functionality allowed drill down of all metric data to a specific day as well as aggregation of metric data up to week/month/quarter and year level.

5.8.1.2 Order Finalised Process

An issue existed within the backend systems at the study site whereby if multiple orders were placed for the same patient at the same time then subsequent finalisation of these orders only resulted in one of the multiple orders being flagged as finalised. A problem was highlighted during the validation phase whereby finalised orders were being excluded as they had not been flagged correctly.

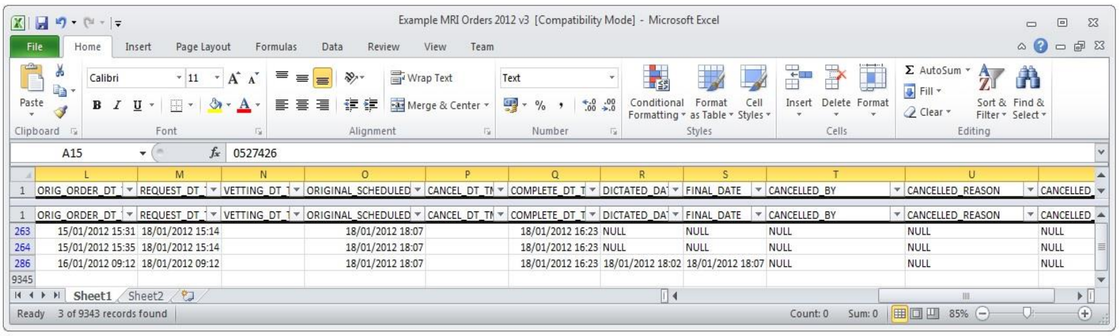

Figure 5-6: Finalised issue with the extracted data

Figure 5-6 illustrates the issue. In the example above, 3 orders are displayed for the same patient. All 3 orders have a complete date entered for the same date and time; however, only one order has a finalised date. In order to address this issue, the Qlikview load script was modified to update the finalised flag correctly. The criterion used to identify these scans was firstly to check if there was a scan already finalised for a patient. If any other scans existed for the same patient with a completed date within 3 hours of the first scan, then the finalised date from the first exam was used to update the finalised date for all other selected scans. This resolved the issue.

5.8.1.3 Date Format Issues

A number of dates on the order import file (orders.xlsx) were stored as either blank or with the value 'NULL'. This caused a number of errors when trying to import the data into the Qlikview model. In order to address this, the load script was modified to put out a null value where import file cells contained either '0' or 'NULL'.

5.8.2 Predictive Analysis Model

5.8.2.1 Forecast Algorithm

Significant time and effort was spent ensuring that the forecast algorithm was applying all of the necessary business rules currently utilised within the radiology department at the study site. This required a number of iterations to deliver accurate forecast numbers. It also involved significant time being spent by staff at the study site, alongside the author, ensuring forecast accuracy.

5.8.2.2 Graphing of Predictive Backlog Analysis to Month Level

All forecasted data is generated within the application at week number level. As backlog is a point in time snapshot, it is not possible to aggregate week data to month level. In order to allow display of backlog data to month level, it was necessary to take the last week of the month's position as the month figure. This required a number of changes to the Qlikview script and the predictive analysis data model.

5.8.2.3 Predictive Model Refresh

One of the consequences of utilising bespoke software tools with off the shelf BA applications can be a disjointed user experience. It is necessary to give the end user a sense of a seamless integration of technologies. When users enter predictive scenario data and generate a new forecast, it is necessary to have the Qlikview predictive model refresh automatically. This is not easily achieved from within the bespoke software application.

In order to address this, the 'Generate Forecast' function creates a simple text file in a specified directory. A batch process continuously runs in the background, monitoring for the existence of this text file. Once found, it executes a command to refresh the Qlikview predictive data model and deletes the text file from the appropriate directory. This simple solution proved very effective when users update scenarios and regenerate the forecast. The graph data is updated instantaneously, which gives the impression of the forecast function performing the model refresh.

5.9 System Validation

Development and implementation of software systems comes with its own unique set of risks. It is therefore necessary to implement a risk management strategy to assist with identifying problems in the software system and to help formulate solutions (Boehm & DeMarco 1997). This is especially relevant within the healthcare sector, where access to accurate and up to date data is necessary for the delivery of quality healthcare, research, strategic planning and effective management of healthcare services (HIQA 2012b).

To assist with validation of the implemented RPM system, a number of steps were identified that would help validate and verify that the software performed as per the original system requirements (see table 5-5).

Table 5-5: Software validation and verification procedures

Validation procedure	Description	Responsibility
Stakeholder commitment	Ensure that all key stakeholders were committed to the implementation of a validated software system.	All stakeholders
Test environment	Ensure that a suitable test environment was implemented to assist with user acceptance testing and system verification.	Author
User acceptance testing	Assess system functionality to ensure conformance with system requirements. Put in place a change management system to assess user feedback and implement changes appropriately.	Clinical director/Medical physicist/Senior data analyst
Data verification	Identify and utilise a representative dataset to assist with system verification and to ensure that all areas of system functionality were addressed.	Author/Medical physicist/Senior data analyst
Parallel data testing	Implement procedures whereby key stakeholders can compare RPM data outputs with existing system data outputs	Senior data analyst/Medical physicist

Each of the validation steps were implemented as part of an overall risk management plan and responsibilities were assigned appropriately.

5.9.1 Stakeholder Commitment

At the outset of the validation phase, a meeting was held with the clinical director and a medical physicist. Stakeholder buy-in was confirmed and a strategy was agreed for system validation. Milestone dates and deliverables were agreed and forwarded on to all stakeholders.

5.9.2 RPM Test Environment

At the commencement of the implementation phase, a development environment was established utilising a virtual desktop on a server in the cloud (see section 5.5). Due to the complexity and time-consuming nature of installing the RPM application on the hospital network, it was agreed by all key stakeholders that this environment would be utilised for system validation and verification. This also helped to allay the concerns in relation to hospital network security expressed by the IT department at the study site.

The RPM system is designed as a web-based application accessible using any standard internet browser. The application was deployed on the cloud-based development server, which allowed stakeholders to access the application over the hospital's network. A domain name was purchased for a nominal fee (www.radiologyperformancemanager.com) and configured to redirect requests to this URL to the development server in the cloud. The result provided seamless access to the application from within the hospital with no impact on the hospital network performance or compromises to network security. It also allowed for rapid implementation and deployment of change management requests during the validation phase.

5.9.3 User Acceptance Testing (UAT)

Once the application was ready for testing, it was immediately made available to the key stakeholders for user acceptance testing. The primary focus of UAT was to ensure that the functionality requested during the requirements phase had been delivered in the final application. A change management process was put in place to address the items identified during UAT. Modifications were requested to a small number of areas of functionality and changes were requested regarding a number of assumptions being made within the application. Altogether there were three iterations of the software over a period of four weeks before signoff was finally achieved on UAT.

5.9.4 Data Verification

There were two areas of data verification necessary, the first to ensure that all KPI data was being displayed accurately and the second to ensure that predictive forecasting data was being calculated correctly. In order to facilitate this, a verification dataset of 100 MRI orders representing a cross section of exam types, encounter types and scan dates were selected. This selection was done in conjunction with a data analyst at the study site to ensure the data subset represented an appropriate selection of radiology orders and was indicative of the ratio of encounter types processed within any given year.

5.9.4.1 KPI Verification

Each of the various KPIs selected for display were individually tested for accuracy as per the data verification subset. Particular attention was paid to non-standard functionality such as the exploding of the radiology source data into point in time snapshots. Checks completed are listed in table 5-6.

Table 5-6: KPI verification checks

KPI	Test completed
Radiology Metrics	Ensure number of orders, patients scanned, patients reported and orders cancelled are displayed as per the verification dataset.
Patient wait list	Ensure number of patients waiting for scan and waiting for report is displayed as per the verification dataset. Additional checks were completed on point in time snapshots to ensure that wait list data for a selection of dates was correct.
Radiology TATs	Ensure radiology turnaround times to scan, report and total times are displayed as per the verification dataset.
Wait time percentiles	Ensure wait time percentiles are calculated and are displayed as per the verification dataset. 50^{th}, 75^{th} and 90^{th} percentiles were all checked ensuring a broad range of compliance.
Order cancellations	Ensure that all orders are being totalled correctly as per the verification dataset and based on the order location where the order was originally placed.
Gauge KPIs	Each gauge chart KPI (previous weeks metrics, numbers of patients waiting, time to next scan, YTD radiology TATs) was verified to ensure calculations were correct.
Data filtering	Ensure that the correct orders are selected from the verification dataset based on the selection filter criteria

5.9.4.2 *Predictive Analysis Verification*

The predictive module of the system required the validation of two specific areas: the accuracy of the forecasting algorithm and the visualisation of the forecast data.

In order to test the forecast generation, five predictive scenarios were created with various demand and capacity adjustments entered against each. A forecast was executed and 15 separate forecasts were generated as expected, one for each encounter type for each scenario. Adjustments for each forecast were then verified using the forecast audit trail table (see section 5.6.2). For each week of the forecast, expected forecast adjustment values were compared to actual values to ensure accuracy. Table 5-7 highlights the checks performed for each forecast.

Table 5-7: Predictive forecast verification checks

Forecast Value	**Test completed**
Opening Balance	For week 1 ensure this is the current number of patients waiting, for all other weeks ensure it is the previous weeks closing balance
Total Demand	Ensure demand scans is calculating based on previous years actuals and that demand adjustments are correctly applied. Ensure totals are correct in both hours and scans
Total Capacity	Ensure capacity is calculated based on current departmental capacity and that capacity adjustments are correctly applied. Ensure totals are correct in both hours and scans.
Closing Balance	Ensure closing balance equals opening balance plus demand minus capacity adjustments

Once the forecast data was verified as being correct, the graph data was validated to ensure that the information was being visualised correctly. Table 5-8 lists the various checks completed.

Table 5-8: Predictive analysis graph verification checks

Forecast Value	Test completed
Predictive Backlog	Ensure closing balance as per table 5-7 is being visualised correctly. Confirm drill up/down to week number/month is totalled correctly and that toggle between hours and scans is displayed correctly.
Predictive Demand	Ensure total demand as per table 5-7 is being visualised correctly. Confirm drill up/down to week number/month is totalled correctly and that toggle between hours and scans is displayed correctly.
Predictive Capacity	Ensure total capacity as per table 5-7 is being visualised correctly. Confirm drill up/down to week number/month is totalled correctly and that toggle between hours and scans is displayed correctly.
Closing Balance	Ensure closing balance as per table 5-7 is being visualised correctly. Confirm drill up/down to week number/month is totalled correctly and that toggle between hours and scans is displayed correctly.

5.9.5 Parallel Testing

The radiology department at the study site had previously utilised Microsoft Excel[20] to graph various sets of radiology data. A number of graphs and reports already existed and this information was used by key stakeholders to verify the accuracy of the KPI data output from the RPM system. Some minor anomalies were found in outpatient figures; however, this was later discovered to be a result of 'OPD' encounter types not being included in outpatient numbers. Parallel testing in conjunction with data verification provided a double validation of the RPM application's data outputs. This was an essential component in stakeholders achieving the necessary confidence levels in the accuracy and data integrity of the RPM application.

5.10 Summary

This section looked at the implementation of the RPM application's functionality as identified during the requirements gathering phase as well as the various technical decisions taken to deliver on the vision. A number of technical challenges encountered during the build were discussed. The validation and verification steps taken with the key stakeholders to ensure the integrity and accuracy of the application's data outputs were also outlined.

The next chapter will discuss the evaluation phase of the project.

[20] http://office.microsoft.com/en-ie/excel

6 Prototype Evaluation and Discussion

6.1 Introduction

The primary objective of this study was to determine whether key stakeholders perceive that a BA software tool built for radiology has the potential to enhance decision support and improve patient wait times. In order to achieve this objective, a prototype BA software tool was built and evaluation interviews were conducted with three key stakeholders: the Clinical Director (CD), the Business Manager (BM) and a Medical Physicist (MP). Feedback was gathered based on a two-week evaluation of the application.

On completion of the prototype evaluation interviews, the data collected was transcribed and analysed and emergent themes were identified (see figure 6-1). In addition to helping to answer the research question, the evaluation interviews provided a useful insight into the potential benefits, barriers to implementation and overall acceptance levels of the prototype tool.

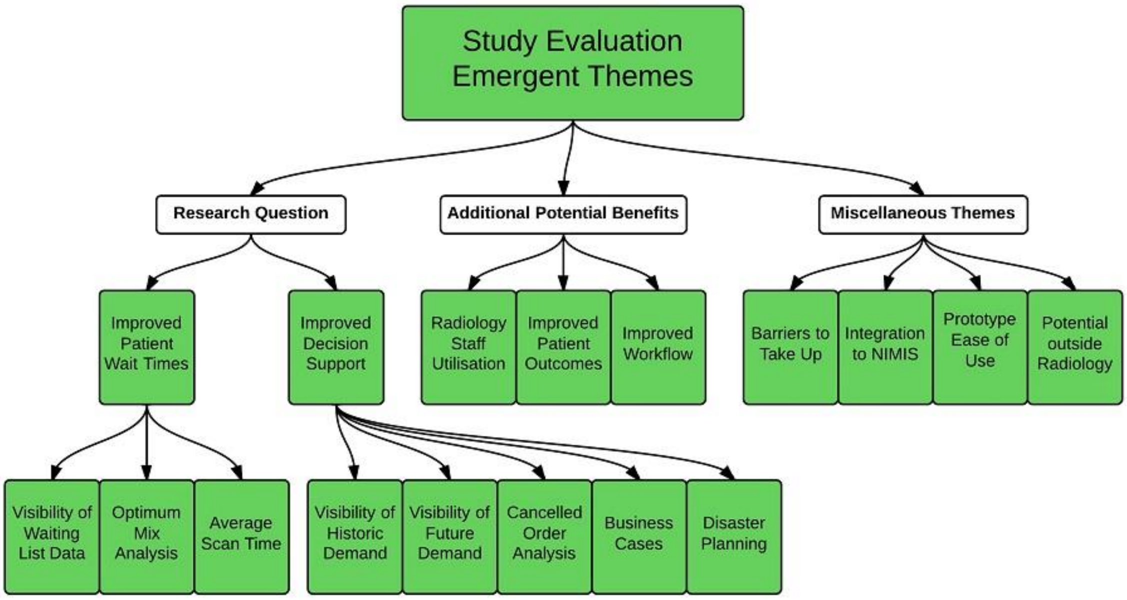

Figure 6-1: Evaluation Interview Themes

This chapter will look at the themes that emerged that address the research question (section 6.2). This will be followed by themes relating to other potential benefits (section 6.3) before a discussion of remaining miscellaneous themes that came to light during the evaluation process (section 6.4). The chapter will conclude with a discussion of the limitations of the work as well as possible future work relating to the study.

6.2 Research Question Themes

6.2.1 Improved Patient Wait Times

A number of areas of functionality within the prototype were seen to have the potential to contribute towards improved patient wait times.

6.2.1.1 Visibility of Waiting List Data

Visibility of existing patient wait times was acknowledged as being a significant step forward in improving overall wait times. The MP noted that, before the tool, ***"we never knew how long patients were waiting and we didn't really get a sense of what the distribution was, so going forward we can now see how we are reducing patient waiting times"***. This further emphasises the need to be able to measure something in order to effectively manage it, as previously discussed in section 2.3. The CD also commented that ***"in terms of wait times, it tells you what they are and it tells you where your department's activities are focused"*** and it was felt that this was *"**very helpful in managing demand and activity and trying to balance those two things out".***

It was also noted by the MP that providing clinicians with visibility of the various modality scan turnaround times would help them to place more informed scan orders, especially for inpatients. This functionality could be used to ***"inform them as to whether they would go with an Ultrasound rather than an MRI because they know the turnaround time is shorter".*** The CD also commented that the tool could be used to give clinicians outside of radiology ***"an idea of where our pressure points are, when they could expect a long wait and whether they should order a different test".*** Evidence of benefit of implementing a single centralised point of access for radiology waiting list data has already been highlighted in section 2.3.1. The prototype application is currently mobile enabled and this functionality can be easily rolled out should it be required.

6.2.1.2 Optimum Mix Analysis

The BM noted that the optimum mix allocation percentage for inpatient and outpatient capacity was especially useful in determining whether ***"we are giving too much percentage to one and not the other".*** This current process of allocation is very much based on departmental experience rather than on any scientific basis and currently contributes towards increased wait times. The BM commented that a ***"mix allocation graph alone would be a big help with getting the balance correct there".***

6.2.1.3 Average Scan Time

During initial testing of the prototype, the average scan time (AST) was deemed to be 21 minutes; however, based on this all backlog was clearing within 13 weeks. On further examination, the actual AST was found to be 46 minutes. What was deduced from this was the significant impact that a change in AST can have on backlog. Even very small changes were shown to have a major impact on wait times. The MP noted that ***"if you can save 2 or 3 minutes per patient by streamlining workflow then that makes a huge difference and that's what the predictive scenario shows you".*** As previously discussed in section 2.3.1, there is significant scope for rolling out Lean initiatives within radiology departments. Application of Lean concepts and techniques to scan workflow could deliver reductions in AST resulting in significant improvements in overall wait times. This is an area that the radiology department intends to explore further.

6.2.2 Improved Decision support

All interviewees were in agreement that the prototype tool provided improved decision support to the medical imaging department. The benefits provided could be broken down into a number of specific areas.

6.2.2.1 Visibility of Historic Demand

In terms of the historic KPI data, it was noted that, through visualisation of scan volumes, the tool gave advance warnings of where problems may be occurring. The MP interviewed had a specific interest in this area and noted that ***"the application helps us know where our real problems are and gives us a sense of what we need to do to plan for addressing these problems".*** *The MP also commented that* ***"we saw that the numbers of patients went from 6000 up to 9000 and then up to 11,000 over three years, you see this huge increase. What this gives us is a bit of ammunition going into the CEO's office to say we need a bit more money for additional devices or extra radiographers, so I think that's very good".***

The BM also expressed similar sentiments with regard to managing continuous increases in volumes of scans, commenting that ***"It's having those increases visualised monthly or quarterly that you can go and say look at the increases that we have got here, we are going to get to a stage that we are in trouble".***

The CD also noted that having the historic data visualised on an interactive dashboard is ***"really useful"***, as currently ***"that information is available but you have to dig for it"***. It was also acknowledged that having historic data readily available **"for planning meetings is gold"**, as attendees are often commenting based on experiences rather than fact based analysis. The CD noted that typical comments are ***"we are much busier than we used to be, that sort of stuff"***.

6.2.2.2 Visibility of Future Demand

The predictive scenario forecasting functionality was also found to be very useful, providing proactive decision support based on future forecasted data. The ability to display future demand was useful for planning; the MP noted that ***"We have this tool that shows you our scans are going to double in the next year and what are we doing to address it, if we don't do anything then this time next year our TATs are probably going to be terrible".***

It was also noted by the CD that all departmental decision support is currently reactive and that the prototype tool provided assistance with proactive demand planning. The CD commented that ***"I think the tool is useful, we haven't had a tool that looks forward so that is a unique aspect of it"***. The CD also felt the visibility of future forecasted demand would help with managing staffing levels, commenting that ***"I think even just in terms of an easy way of generating numbers based on pre-existing demand increases, that's very useful in terms of looking for how many staff you need".***

The BM also felt that visibility of future forecasted demand was particularly useful for management of radiology resources. Due to the reactive nature of current decision making, it is often too late to manage problem areas. The BM commented that **"*What happens is firefighting, it's too late, it's already happened. With this tool you can see what can happen 6/8 months down the road Very useful to be able to flag that to the Chief Operations Officer to say that we are in trouble and we need to sort it".***

6.2.2.3 Order Cancellation Analysis

The order cancellation functionality was noted by the BM to be ***"very, very useful"*** and ***"not something that you would even look at or think about until you see it there".*** Significant numbers of orders are placed on radiology and subsequently cancelled. The BM commented that ***"you would never think that surgery are cancelling this amount of scans"***; however, once this data is available, then it is possible to ***"feed that back to the team and say this is a problem and why is it happening as it can really have an impact on the department".*** Whilst the tool does not solve the problem by visualising the data, it allows management to ask the question. This is a good example of the data discovery functionality that was discussed in section 2.4.2.

6.2.2.4 Business Cases

The predictive scenarios also helped the department with building business cases to justify future expenditure. The CD noted that ***"We generally have to make business cases here if we wish to hire new members of staff, to get new pieces of equipment and a tool like this is very useful in assisting you with that process".***

The BM expressed similar sentiments, noting that it was very helpful to be able *to* ***"see how an extra body, an extra machine or an extra radiographer would impact on wait times".*** The BM also mentioned that this information is not currently available and that ***"knowing what the benefits could be is all guesswork".***

The BM also felt that the tool could be very beneficial for the radiographic services manager with regard to justifying additional radiology staff. There is currently a high turnover of staff and, as a result of budget cutbacks, there is a reluctance to fill some of these posts. The BM felt that the tool could be used to model the impact of reduced radiographer hours and then make a business case for the additional resources. Similarly, the ability to be able to model sick leave as well as maternity and paternity leave was acknowledged as very useful.

6.2.2.5 Disaster Planning

The predictive scenarios also allow for modelling of various disaster scenarios. It was noted the MP that *"**if you have a disaster scenario where all of a sudden something shuts down somewhere and we get lumped with extra scans, I think it's a very useful tool for looking at that"***. The CD also mentioned the Letterkenny hospital example, whereby flooding resulted in a shutdown of the radiology department for over 3 months. It was felt that the tool could be used to ***"easily model device downtime for a lengthy period"*** and visualise the impact of this on backlog. Similarly, there is also the facility to model the impact of additional scans being placed on the department, as was the case for the hospitals that took on the responsibility for managing Letterkenny diagnostic imaging demand during hospital closure.

6.3 Other Potential Benefits Themes

6.3.1 Radiology Staff Utilisation

Improved staff utilisation was also identified as a benefit. The MP interviewed also has responsibility for providing radiology statistical data to the CD and had previously utilised the MATLAB tool[21] to graph sample data. It was noted that the prototype's interactive dashboard

[21] http://www.mathworks.co.uk/products/matlab/

provided significant functionality enhancements and had a more efficient workflow. The MP commented that the prototype tool was ***"very good at organising and pulling out data, from that point of view that saves me an awful lot of time".***

The BM also acknowledged the prototype tool's dashboard functionality, noting that ***"for smaller projects, being able to drill down that easily, to me it is a huge time saver"***. In addition, staff members that produce statistics for the BM were also identified for potential savings; the BM noted that ***"I think that would take a lot of time off what they do".***

Improved staff utilisation has the potential to provide significant financial savings within the radiology department.

6.3.2 Improved Patient Care Outcomes

Whilst there is understandably a focus on various cost and financial models within the hospital, it is also important not to lose sight of patient care. The MP felt that if the prototype was implemented and there was a level of confidence in the data being provided, then saved time could be better utilised towards ***"affecting some sort of change such as improved quality of care".***

The CD also commented that the tool has the functionality to provide ***"early warnings in areas where we are falling down"***. A couple of examples cited included a time lag between a scan being completed and reported as well as a buildup of unreported studies. The latter example has already occurred in Ireland (discussed in section 2.4.5), wherein 57,000 medical imaging scans within the RIS system at AMNCH hospital in Dublin were found to contain no radiologist report. It was noted by the CD that ***"with a tool like this you can get the information straight away which is very useful"***.

It was also acknowledged that the tool had the potential to assist in reducing length of stay (LOS) for inpatients. The tool was used to perform an analysis of MRI inpatient turnaround times over a period of time. The MP noted that ***"now that we can track to see how our turnaround times are doing we can infer that by reducing these times we are effectively helping in a reduction in length of stay"***. This was acknowledged as having significant potential to contribute towards improved patient care and satisfaction levels. Furthermore, it was also noted that reduced TATs would ***"ultimately save the hospital money in the long run".*** The MP commented that the data provided from this type of analysis was ***"something***

we would not have known about before". The medical imaging department is planning to import Ultrasound and CT data into the prototype tool and perform similar studies.

6.3.3 Workflow Process Improvement

There were a number of examples of potential workflow improvements that could be made within radiology as a result of the study. During the validation phase, it became apparent that the 'time to report' KPI was slowly increasing for some exam types. This was found to be a result of the radiologist reports not being flagged as completed on the backend hospital systems, an important step in the overall process. As the MP commented, ***"their report times are rubbish as a result"***.

Scan cancellations were also perceived to be high and raised the question of how scan orders were being raised. The MP asked ***"do orthopedics automatically raise an MRI as soon as patients are admitted and if so that is clogging up our system".*** The CD further expanded on this, noting that ***"this whole process has highlighted a whole bunch of things that we are doing probably incorrectly in terms of the way we deal with patients".***

Current strategies for improving wait times primarily involve increases in capacity through additional devices or increased allocation of staff hours. However, reduction in wait times can also be achieved through the removal of inappropriate scan requests. There is clearly potential to improve on departmental workflow processes and the prototype tool can have a role to play in assisting with this.

6.4 Additional Miscellaneous Themes

6.4.1 Barriers to Implementation

Three main barriers to implementation were identified during the evaluation interviews.

The primary barrier is the cost of the Qlikview software. It was decided at the outset to utilise Qlikview as the software had already been purchased by the HSE; however, the CD noted that ***"the frustration that we have had with this particular product is that it has been purchased by the HSE but internally we can't figure out a way to pay for it".***

Another barrier described by the MP is software support. Whilst IT would take ownership, access to Qlikview expertise would be required.

Finally, trust in the data was highlighted as a potential concern. The MP asked if ***"would we become too reliant on it?".*** The CD also noted that ***"disadvantages are trust in the data".*** This is a common concern during the initial implementation phase of BA systems. Once users build confidence in the application, these concerns generally diminish; however, it is always prudent to keep asking questions of the data.

6.4.2 Integration to NIMIS

During the evaluation, the potential for integrating with Ireland's national imaging system (NIMIS) was discussed on a number of occasions. The primary advantage would be the ability to get a nationwide view of radiology KPI data as well as an understanding of how each hospital is performing at a national level.

The MP noted that ***"most people want to know where they are in comparison to other hospitals"***. The CD similarly noted that ***"if you were able to apply it across a larger system, for example the NIMIS system, where you have a whole bunch of hospitals feeding in then you would get a better vision"***.

Given the small dataset used as part of this study, it should be possible to extract a similar dataset from NIMIS and import that into the prototype model. Visibility of imaging orders at a national level would enable the management of patient backlog, through the sharing of imaging devices, across multiple healthcare organisations. As discussed in section 2.2.1, this is a key recommendation put forward by HIQA in relation to diagnostic services (HIQA 2012a).

6.4.3 Prototype Intuitiveness and Ease of Use

The feeling amongst all evaluation interviewees was that the prototype was generally easy to use. The BM commented that ***"very little training"*** was required, and felt that ***"even if you didn't touch it for month, you could go back into it and be straight back on to it".***

The CD also noted that it was ***"very easy to use"*** and mentioned that a colleague within the department had used the tool to access data and ***"just began using it and found the information he was looking for".*** The CD also acknowledged that it would require a bit more time to ***"sit down and understand how it the data model was built up"*** within the application. For many users this is not necessary; however, for power users building dashboards and graphs, this is a necessary requirement.

6.4.4 Potential Outside of Radiology

Whilst this study was specific to radiology, there is no reason why this tool cannot be rolled out to other areas within the hospital. As the BM commented, ***"we are all based on the same***

stuff, whether it's scans, scopes, outpatient clinics, labs, it's all waiting list driven". Similarly, the CD noted that ***"all we are is supply and demand, anyone who has got a waiting list - outpatient cardiology, respiratory etc. all could benefit from a tool like this"***.

Every department within the hospital that places and completes orders needs to be looking at turnaround times in order to drive efficiencies. Similarly, predictive analysis functionality can allow modelling of future forecast data to assist with decision support across the hospital. As the BM commented, ***"at a hospital level it's all predictive analysis driven, trying to predict where we are going to be".***

6.5 Impact

On completion of prototype evaluation by the CD, there was a willingness to implement the system within radiology. A presentation was made to both IT and radiology with a view to obtaining an existing HSE Qlikview license in order to roll out the tool. The presentation was well received and buy-in was achieved from all of the key decision makers. Currently, the only obstacle to implementation is obtaining the necessary licenses from the HSE. Whilst it has been confirmed that licenses are available and not in use, there is currently no mechanism to charge the study site for usage of these licenses. Understandably, there is frustration with this within radiology; however, it is hoped that this can be resolved in the short term.

The study has also been presented at hospital level at the request of the Informatics Director. All attendees were very enthusiastic and keen to know how the functionality could be applied to other departments. It was acknowledged afterwards that the study has helped to raise awareness within the hospital of what can be done utilising Business Analytics technologies. The Informatics Director has requested that a presentation be made to the Chief Executive Officer (CEO), Chief Information Officer (CIO) and the Chief Financial Officer (CFO) after completion of this study.

The research has also been presented internationally. The radiology department requested that the author produce an abstract of the study in order to submit the work to the Institute of Physics and Engineering in Medicine (IPEM) 2014 conference. The abstract was submitted (appendix F.1) and the author was subsequently invited to present the work (appendix F.2). The presentation was well received and the attendees were very enthusiastic, requesting a presentation of the software at the end of the conference. The author has since been contacted by the Northern Centre for Cancer Care in Newcastle-upon-Tyne for a further demonstration for staff members who were not in attendance at the conference (appendix

F.3). Approval was sought from the CD and a demonstration was given using Webex web conferencing software[22].

The radiology department at the study site has also submitted the work for presentation at the Radiology Society of North America's (RSNA) conference in Chicago in December 2014.

6.6 Research Question

The research question asked "Can a Business Analytics Software Tool Facilitate Decision Support towards Improving Patient Wait Times within a Major Diagnostic Medical Imaging Department in a Public Hospital in Ireland?" Based on the evaluation feedback discussed in the previous sections, it is possible to deduce that the prototype tool can have a significant role to play in assisting with management decision support and contributing towards improving patient wait times within the medical imaging department at the study site.

6.7 Limitations of the Research

There were a number of limitations to the research conducted in this study. These include:

1. The system evaluation was based on the feedback of three people. Ideally, a larger cohort would have participated in the evaluation phase of the prototype application.
2. The dataset used within the predictive module of the application was focussed primarily on MRI. The application has been designed to cater for multiple modalities however this data was not available for the predictive module at the time of the study.
3. The prototype application was not deployed during the study. This resulted in the key stakeholder evaluation being based on perceived benefits rather than evidence-based benefits.

6.8 Future Work

Recommendations for future work can be divided into application features and future research.

6.8.1 Application Features

The following features were highlighted as potential improvements to the application:

1. Automation of data imports – currently manual.

[22] http://www.webex.com/

2. Copy function for adjustments – it was noted that this would be useful for setting up new predictive scenarios.
3. Wait list reporting – the BM requested 3 new KPIs visualising numbers of patients waiting more than 30 days, more than 60 days and more than 90 days.
4. Capacity to device level – currently held at modality level.
5. Number of working days per modality – ability to capture this data to improve accuracy of capacity forecasting.
6. Predictive scenario selection – allow selection of more than one scenario per graph.
7. Forecast regeneration at scenario level – currently done for all scenarios.
8. Mobile deployment of the KPI dashboard – this would be used to inform hospital clinicians of current modality turnaround times.

6.8.2 Future Research

A number of areas were identified as having potential for future research.

6.8.2.1 Average Scan Times

There is significant scope for conducting research into calculating accurate average scan times for each modality. This data is currently calculated manually based on numbers of patients scanned and available capacity. There are a number of factors influencing AST, such as scan type, age and condition of the patient, as well as the workflow process for the various modalities. All of these factors need to be considered when determining AST. Once AST can be calculated accurately, there is significant scope for improving the time taken for each of the various steps during the scan process. Application of Lean concepts and techniques also has potential to improve overall scan times. As demonstrated in this study, even small improvements to overall scan times can result in significant improvements in radiology throughput performance.

6.8.2.2 Demand Uplift Percentage

Demand uplift is currently manually entered to the tool; however, further research could be undertaken to establish more accurately the demand uplift percentage for each modality based on previous years' demand plus other influencing factors. During the study, it was observed that a number of factors influence demand. These can include items such as outbreaks of strains of influenza, inclement weather, air quality and area deprivation indexes.

It would be a beneficial exercise to explore the potential for creating an algorithm that could weight and score various demand factors in order to determine a more accurate forecasted uplift percentage for each of the various radiology modalities.

6.8.2.3 Prototype Evaluation

This study only evaluated perceived potential to improve management efficiencies and patient wait times. A further study is required to determine the actual benefit delivered by the application over a period of time. In order to conduct a study of this nature, it would be necessary to have the prototype system in use for a sufficient period of time. Qualitative and quantitative research could then be conducted to determine whether wait times and management efficiencies were actually improved.

Quantitative measures of wait times pre- and post-implementation would help identify evidence of benefit. Similarly, a more detailed quantitative study comparing forecasted patient backlog to actual backlog across a range of predictive scenarios would help determine accuracy and provide evidence of benefit of the predictive analysis functionality.

Furthermore, qualitative evaluation through sporadic interviews of users of the system to determine insights that they gained as well as efficiencies realised would also contribute towards determining actual benefit.

6.9 Summary

This chapter identified and discussed the key emergent themes from the qualitative analysis of the interview data. Limitations to the research were highlighted and potential future work relevant to the study was identified.

The next chapter will discuss key findings of the study as well as contribution to the research.

7 Conclusion

This study looked at the potential for implementing a Business Analytics software tool within a medical imaging department to assist with management decision support and to reduce patient wait times.

To achieve the aims of the study, a set of requirements were identified through semi-structured interviews with key stakeholders and a prototype software tool was built. Prototype evaluation interviews were conducted and feedback was grouped into themes which were subsequently analysed and examined to answer the research question.

7.1 Key Findings

BA software tools combined with bespoke software applications can provide visibility of radiology data across all time horizons. Historic KPI data provides retrospective analysis which can be used to inform and create predictive scenarios. These scenarios can then be utilised to generate and visualise future predictive demand and capacity data. Visualisation of historic and future forecasted radiology data has the potential to enhance decision support to deliver improved operational efficiencies and wait times within medical imaging departments.

In addition to improving decision support and wait times, the following potential benefits were also highlighted during the prototype evaluation:

- Improved patient care as a result of early warning triggers, reduced inpatient LOS and better staff utilisation.
- Improved radiology workflow through better management of scan cancellations, requests for non-essential scan orders and flagging of completed reports.
- Financial benefits through reduced inpatient LOS and more efficient staff utilisation.
- High acceptance levels for automated dashboards within radiology.
- Significant potential to roll out prototype functionality to other departments within the hospital.

In addition to implementation at local level, there is also potential, with some minor changes, to utilise the prototype tool at a national level. The NIMIS initiative allows the sharing of patient imaging data based on a centralised data access model. This national dataset can be modelled in a similar way to visualise hospital performance data in isolation, as part of larger hospital groups or at a country level.

7.2 Personal Observations

A number of observations were made by the author based on personal experience and knowledge gained over the course of the study.

It is the author's opinion that the current HSE ICT model is not conducive to embracing innovation. Whilst there is huge appetite for technology and innovation at the study site, this is not supported at a national level. BA is a disruptive innovation; such innovations tend to sneak in from below through individuals keen to introduce quick wins for their departments. This bottom-up rollout of technology very often leads to widespread adoption. Disruptive innovations have the potential to introduce fundamental changes within the healthcare sector. It is imperative that these innovations are encouraged, supported and rewarded. National policy needs to open up to disruptive technologies and business models that challenge the status quo and have the potential to improve the quality of healthcare delivery nationwide.

Furthermore, there is significant potential to improve on the current model of ICT delivery within the Irish healthcare system. Bottom-up rollout of ICT systems driven by small agile teams of IT experts and hospital clinicians can deliver best of breed software solutions that address bespoke hospital requirements. By removing the burden of reliance on the larger healthcare software vendors, these highly specialised teams could quickly implement healthcare applications that are fit for purpose and embrace the latest ICT standards and technologies.

Consideration should also be given to the establishment of ICT-focused centres of excellence within the healthcare domain that can deliver on-demand business and technical expertise in niche areas. Analytics centres of excellence have already been successfully deployed within private sector organisations and are helping companies to generate new insights from their data (IBM 2012).

There is also a lack of adequate investment in ICT within the Irish public healthcare sector. From a total annual health spend of €13,404 million in 2013 (HSE 2013), only 0.85% was allocated to ICT spend (DOHC 2013). The recently published eHealth Strategy for Ireland proposes to increase ICT healthcare funding to the European average of 2-3%; however, this has not yet been realised. ICT is a critical component in driving healthcare reform and requires sufficient funding. Investment in proven technologies will deliver a significant return on investment. Analytics technologies are being rolled out extensively across the private sector in recognition of the improvements delivered in operational efficiencies and decision support. As a consequence, significant returns on investment are being realised (see section 2.4.5). This study has highlighted the ways in which BA technologies can also deliver these benefits within the healthcare domain.

7.3 Contribution to the Research

This study has demonstrated the numerous potential benefits of implementing BA technologies within medical imaging departments as well as the potential for a wider deployment at both hospital and national level. More significantly, it has demonstrated the effectiveness of implementing innovative predictive scenario forecasting, an area which, to the best of the author's knowledge, has not been previously explored within radiology.

7.4 Final Thoughts

Investment in multiple hospital software systems to streamline existing processes has led to a significant increase in the volume of available data; however, despite this, public healthcare agencies remain predominantly data rich and information poor. The focus must now shift to the leveraging of these data assets in order to analyse and present key information to decision makers in a meaningful way. BA software tools deliver such functionality, enabling healthcare organisations to gain foresight and insight that can transform medical data into clinical knowledge. Access to this information can assist with more effective decision making, thus driving increased performance.

There is currently a lack of any computerised data analysis and visualisation software within the radiology department at the study site. Based on comments received during prototype evaluation, feedback from hospital presentations and the IPEM conference in the UK, this tool has significant potential for implementation. The only barrier to implementation is the HSE making the necessary Qlikview licenses available.

Healthcare reform is high on the agenda of all public healthcare agencies. By making analytics software available across radiology departments, this study has demonstrated the potential to deliver reform through improved patient wait times, better staff utilisation, reduced inpatient length of stay and increased quality of care.

Private sector companies are embracing analytic technologies throughout their organisations; it is time for our public healthcare agencies to engage on a similar level.

8 References

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Appendix A – Healthstat

A.1 - Healthstat Metrics

ACCESS	INTEGRATION / APPROPRIATENESS	RESOURCES
11. Hospital Wait Time for Electives and Emergency Department *(monthly)* -NTPF elective wait time by time waiting -Collated by PMU from NTPF -ED Traffic Lights and associated detail on wait time -Collated by PMU from WI **12. Routine GP to Hospital Referral Wait Time *(monthly)*** -GP request to hospital time to next appointment for: oX-Ray oUltrasound oPhysio oOPD By Consultant *-Collected by hospital*	**6. Average Length of Stay (ALOS) *(Monthly)*** -Gross and adjusted ALOS for total hospital and by select procedures (varies by hospital type), e.g.: oMI oTonsils oDiabetes oAsthma oCOPD oAppendectomy oCataract oHip -Calculated by Casemix from monthly hospital HIPE returns **7. Hospital Day Case Rates *(Monthly)*** -Overall hospital day case rate by public / private for overall and by select procedures (varies by hospital type), e.g: oVaricose veins oCataract oInguinal hernia oTonsillectomy -Calculated by Casemix from monthly hospital HIPE returns **8. Delayed Discharges *(Monthly)*** -Hospital Delayed Discharges by Type -Collected by PMU **9. Day Of Surgery Admissions *(Monthly)*** -Overall rate of patients being admitted on their day of surgery -Calculated by Casemix from monthly hospital HIPE returns **10. Appropriate Use of Beds *(Baseline then repeat)*** -% of admissions and inpatients on day of care by hospital -Baseline from Acute Hospital Bed Review and updated on repeat	**1. Service Plan Aggregate Statistics *(Monthly)*** -Comparison of YTD summary hospital actual spend versus plan -Collected by CPCP from Service Plan -Comparison of key hospital level performance statistics, such as cost per bed, cost per patient, patients per bed **-2. Detailed Hospital Financials *(Monthly)*** -Breakdown of YTD then monthly hospital operating costs by Non Payroll and Payroll (by Overtime, Agency and Locum) -Collected by Finance **3. Hospital Staffing (Quarterly) and Absentees *(Monthly)*** -Breakdown of quarterly WTEs for: oRadiographers oUlstrasonographers oPhysios oOTs oSocial Workers -Collected from Staff Census -Breakdown of monthly WTEs for Consultants per specialty & junior doctors per specialty -Breakdown of YTD then monthly hospital absentee rates by grade (short term and long term) *-Collected by hospital* **4. Hospital Activity *(Monthly)*** -Breakdown of YTD and monthly hospital activity by new and repeat: oPhysio patients oOT patients oSocial Workers patients -Break of YTD and monthly hospital diagnostic activity for: oXray oPlain films oUltrasound oCT Scan oMRI oInterventional -Breakdown of YTD and monthly hospital OPT Consultant led clinics per Consultant (coded) per speciality by new patient, return and DNA *-Collected by hospital* **5. Public Private Mix and Casemix Base Price *(Monthly)*** -Number of public and private discharges per hospital by specialty, elective/non-elective and inpatient/day case -Collected by PMU -Casemix adjusted base price per hospital

Appendix B – Participant Information

B.1 - Informed Consent (Phases 1 and 3)

Lead Researcher:	Stephen Jones (Trinity College, Dublin – student number 12328069)
Title of study:	A Business Analytics Software Tool for Monitoring and Predicting Radiology Throughput Performance
Research Duration:	December 2013 – May 2014

Individual results will be aggregated anonymously and research reported on aggregate results.

DECLARATION:

- I am 18 years or older and am competent to provide consent.
- I have read, or had read to me, a document providing information about this research and this consent form. I have had the opportunity to ask questions, and all my questions have been answered to my satisfaction and I understand the description of the research that is being provided to me.
- I agree that my data is used for scientific purposes and I have no objection that my data is published in scientific publications or presentations in a way that does not reveal my identity.
- I understand that my interview will be audio recorded however I have the option to request not to be recorded, in which case manual notes will be taken instead.
- I understand that any audio recordings will not be identifiable and will only be used for the purpose of making notes of the interview.
- I understand that no audio recordings will be replayed in any public forum or made available to any audience other than the current researchers/research team.
- I understand that if I make illicit activities known, these will be reported, to appropriate authorities.
- I freely and voluntarily agree to be part of this research study, though without prejudice to my legal and ethical rights.
- I understand that I may refuse to answer any question and that I may withdraw at any time without penalty.
- I understand any direct quotes will be clarified with me before including them in the final report.
- I have received a copy of this agreement.

PARTICIPANT'S NAME: (please print)

PARTICIPANT'S SIGNATURE: **DATE:**

Statement of investigator's responsibility: I have explained the nature and purpose of this research study, the procedures to be undertaken and any risks that may be involved. I have offered to answer any questions and have fully answered such questions. I believe that the participant understands my explanation and has freely given informed consent.

RESEARCHER'S CONTACT DETAILS:

Stephen Jones (Trinity College Dublin student number 12328069),
Email: joness4@tcd.ie, Tel: 087 2544372

RESEARCHER'S SIGNATURE: **DATE:**

B.2: System Requirements Information Sheet for Participants

LEAD RESEARCHER: Stephen Jones (Trinity College Dublin student number – 12328069)

BACKGROUND OF RESEARCH:
Reduction in patient wait times as well as timely patient access to radiology resources are key drivers towards improving operational efficiencies and patient satisfaction levels within Diagnostic Medical Imaging departments.

Current poor visibility of patient demand, within the radiology department at a major academic teaching hospital, is resulting in an inability to adequately plan and effectively manage the usage of radiology staff and resources.

The purpose of this research is to evaluate how a Business Analytics software tool could facilitate decision support towards improving patient wait times in a large diagnostic medical imaging department within a public hospital in Ireland.

WHY ARE YOU BEING ASKED TO PARTICIPATE?
The researcher attended an initial meeting with the Clinical Director of Radiology. The Clinical director was keen for the Radiology department to participate in this study in order to achieve the potential benefits for the Radiology service at the hospital.

The Clinical Director nominated yourself, two of your colleagues and himself as key relevant stakeholders. Nomination was based on domain expertise and knowledge of the business problems associated with the day to day management of the Radiology department at the hospital. The Clinical Director provided your email address and indicated that he would notify you of your nomination in advance of the commencement of the study.

PROCEDURES OF THIS PHASE OF THE STUDY:
As an identified key stakeholder, your input is valuable towards defining a set of requirements for the building of a predictive analysis software prototype tool. In addition, your domain expertise can also provide valuable input towards identifying predictive decision support scenarios within radiology. These scenarios can then be modelled using the software tool with the subsequent data utilised to evaluate the tool.

Should you agree to participate then you will be contacted to agree a suitable time for you to participate in a semi-structured interview. The duration time of the interview will be approximately 45 minutes. A list of interview questions will be provided in advance of the interview to allow for any necessary clarification of the interview content. Informed consent for participation will be required prior to commencement of the interview.

DECLARATIONS:

- Please be advised that this research is being conducted by an employee of a company that supplies business analytical products and services.
- The research conducted by the author is in partial fulfillment of the requirements for a Master's Degree in Health Informatics at Trinity College, Dublin.
- All participation in this is study is voluntary, though without prejudice to legal and ethical rights. Participants have the right to withdraw and omit responses without penalty.

- It is the intention of the researcher to audio record the interview for the sole purpose of facilitating transcription. If you would prefer not to be recorded please state so and manual notes will be taken during the interview instead.
- The electronic recordings can be stopped by the participant at any time, and may at any time, even subsequent to interview participation be destroyed.
- No audio recordings will be made available to anyone other than the researcher, nor will any such recordings be replayed in any public forum or presentation of the research. All audio recordings will be deleted upon transcription and there will be no video recording in this study.
- Participants will be given the opportunity to ask questions on the research at any point.
- There are no expected risks to the participant. There are benefits to be achieved by having an input into prototype software tool design phase and towards helping to identify decision support scenarios that are of most benefit to the radiology department at the hospital.
- There may be some follow up required based on the content of the interviews however this will be kept to a minimum.
- Preservation of participant anonymity will be ensured during any analysis, publication and presentation of resulting data and findings.
- It is an obligation of the researcher to report any inadvertent discovery of illicit behavior to appropriate authorities.
- Provision for verifying any direct quotations and their contextual appropriateness will be made available before any subsequent publication or presentations of study material.
- The data will be used for scientific purposes only and may be published in scientific publications.
- All data collection, storage and analysis will comply with the Data Protection (& Amendment) Acts and current Best Practice in Scientific Research. Individual results will be aggregated anonymously and research will be reported on aggregate results. No individual patient data will be collected for the purposes of this study.
- Ethical approval for the commencement of this study was granted on 13/12/2013 by the Research Ethics Committee of the School of Computer Science and Statistics (SCSS) at the University of Dublin, Trinity College.
- In the event that further clarification, assistance or advice is required in relation to this study please contact Stephen Jones by email: joness4@tcd.ie or by phone: 087 2544372. I will be happy to help with any of your queries.

B.3: System Requirements – Interview Protocol

Introduction
Hello, my name is Stephen Jones and I am currently studying for my MSc in Health Informatics at Trinity College in Dublin. Thank you for taking the time to meet with me today.

The objective of this study is to evaluate how a forecasting and predictive analysis software tool could facilitate decision support towards improving patient wait times in a large Diagnostic Medical Imaging Department within a public hospital in Ireland.

This interview is for the purposes of identifying a set of requirements for developing a forecasting and predictive analysis software tool.

I would like to request your permission to record the audio from our interview today. The recording will be used for transcription purposes only and all audio will be destroyed upon completion of transcription. A copy of the transcription can be provided should you wish to review the content.

Our interview should last no longer than 45 minutes and please feel free to ask any questions regarding the study at any point during the interview. All participation is voluntary and the interview can be terminated by you at any point.

A copy of the participant information sheet has already been issued however a further copy is available on request today, should it be necessary.

A copy of the signed informed consent form is required before the interview commences.

Software Tool Overview
There are two separate elements to our proposed radiology software tool:

- Forecasting and predictive analysis
- Radiology Metrics based on historic performance data

The interview format is divided into two parts in order to address each of these elements appropriately.

Part 1 - Forecasting and predictive analysis functionality
I would like to give you a brief overview of how forecasting and predictive analysis functionality of the proposed software tool will operate (Describe the forecasting element of the tool and how it provides the ability to perform predictive analysis through What-If scenario modeling).

I would also like to give you some prototype screens to help you visualise the proposed functionality (Talk through the basic functionality provided).

Questions for the Interviewee
1. What are your thoughts on the benefits of performing predictive analysis on radiology capacity, demand, backlog and patient wait times?

2. Should the predictive scenarios be user defined or fixed? (If user-defined should they be maintainable? What period of time should user defined scenarios allow entry of variables by? (Weekly or Monthly?))

3. Is it of benefit to display predictive scenarios (plus any related data) by modality?

4. What period of time should forecast data be displayed by? (Weekly or Monthly).

5. Bearing in mind that future forecasted data and subsequent predictive analysis of that data needs to be displayed over a meaningful period of time, what future time period would you recommend that the forecast window visualise? (3, 6 or 12 months)

6. Forecasted Demand will be calculated by converting scan orders (current plus future forecasted) to a unit of time (based on an average scan time). Do you have any thoughts on this?

7. Forecasted capacity will be maintained for a 12 month window by week number/modality and Radiographer hours, do you think this is feasible?

8. Forecasted backlog will be calculated by subtracting forecasted capacity time from the forecasted demand time to come up with a plus or minus adjustment to backlog. For example, where average capacity is greater than average demand we are reducing the backlog and vice versa. Do you have any thoughts on this?

9. Forecasted Demand, Capacity, Backlog and patient wait times will be displayed as per the prototype model, should this be displayed in minutes, hours or days?

10. Is there a one to one relationship between radiographer hours and devices, i.e. does it always take one radiographer to operate one device? (If not how do we handle this?)

11. Where a change is made to the number of devices this will be converted to radiographer hours to reflect additional or reduced capacity, i.e. 39 hours per week per device. In the event of an increase in devices the assumption will be that the radiographers are available to operate the device. Do you agree with this assumption?

12. Average scan time (AST) adjustment will be catered for to modality level, is there a requirement to go to a lower level, i.e. to be able to adjust the AST for an MRI brain scan rather than an MRI scan? If so how would you see this working?

13. Is it of benefit to display forecasted patient wait times by encounter type, i.e. inpatient, outpatient and emergency?

14. It is acknowledged that between 5-15% of all Medical Imaging orders (the percentage varying based on modality and encounter types) are never completed for various reasons, how do you propose we handle this?

15. How should scheduled orders be treated in relation to forecast data?

16. I am currently investigating the feasibility of suggesting an optimum % mix for allocation of radiology resources based on calculated demand. Do you think this would be of benefit? (If so is there a formula that could be applied?

17. Can you please identify two decision support scenarios that you feel would be of benefit to model and display within the prototype tool? (Prompt with a couple of examples)

18. What are the audiences for this functionality?

19. Are there any additional functionality requirements that would be applicable to your role?

20. Additional questions will also be asked in the areas of graph selection criteria, graph visualisation and graph dimension data.

Part 2 - Radiology Metrics functionality

For the second part of our interview, I would like to give you a brief overview of how the proposed radiology metrics functionality could operate (Describe how this data is calculated/displayed based on historic data as well as where the data is sourced from).

I would also like to give you some prototype graphs to help you visualise the proposed functionality (Talk through the basic functionality provided).

Questions for the Interviewee

1. The graphs provided are based on the Key Performance Indicators (KPIs) identified as part of previous research conducted as well as current reported metrics within the radiology department. They are as follows:
    - The absolute number of people on the waiting list
    - Average patient wait time
    - Time to X percentile (X being variable based on modality)
    - Turnaround time to scan
    - Turnaround time to reporting
    - Order trending - number of orders raised/completed/finalised and cancelled

2. Do these KPIs reflect all of the necessary radiology metrics that are relevant to you? (If not then elaborate on the detail)

3. Is there a requirement to display a 'Time to next slot' KPI? (If so what is the best way to calculate this? are there scheduling considerations, e.g. when are knees done?)

4. What period of time should radiology metric data be displayed across? (Weekly or Monthly)

5. Is it of benefit to display Metrics by modality and encounter type?

6. How should scheduled orders be treated in relation to metrics data?

7. How should cancelled orders be treated in relation to metrics data?

8. What are the audiences for this functionality?

9. Additional questions will also be asked in the areas of graph selection criteria, graph visualisation and graph dimension data.

Closing Comments
What are your overall thoughts on the proposed software tool?

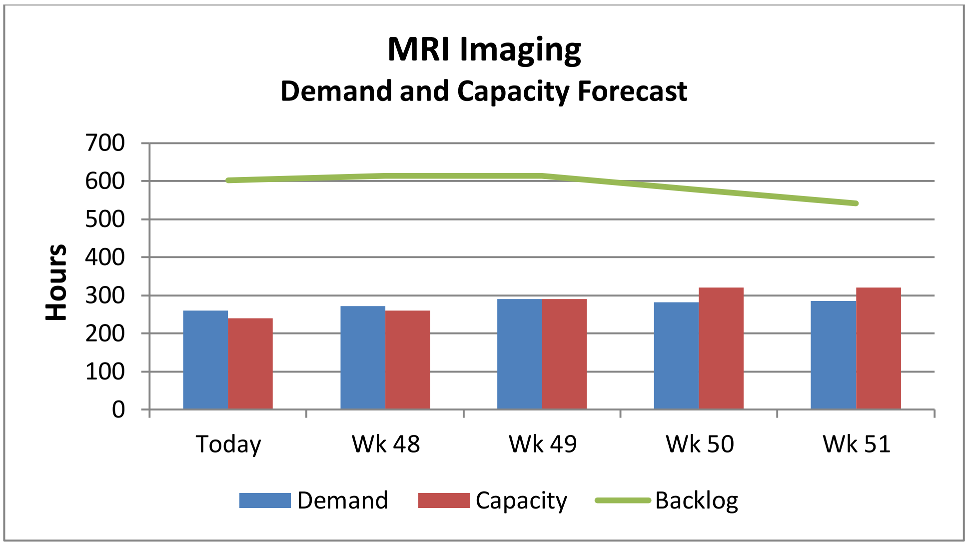
Do you have any suggestions/thoughts on how the proposed tool could be improved?

Do you have any additional comments that you would like to add before we finish?

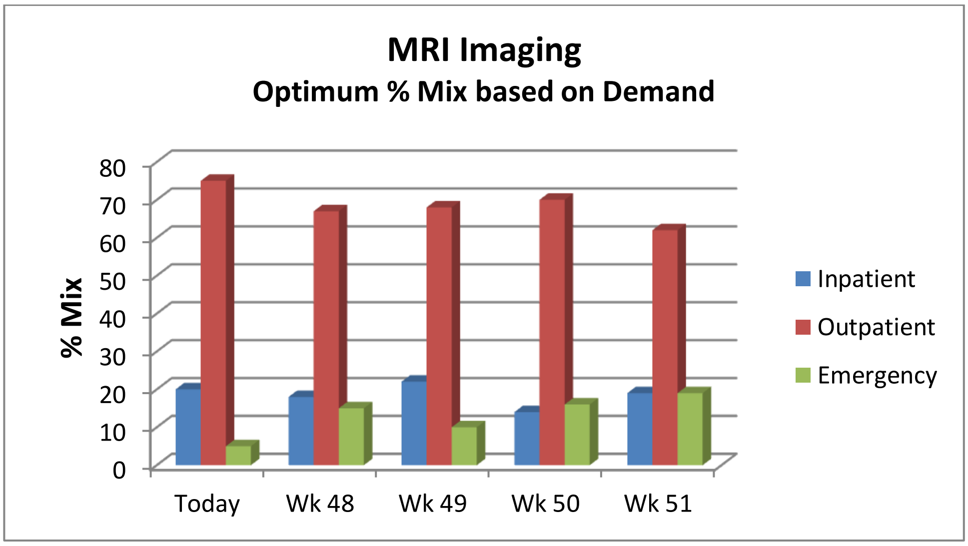
Interview wrap up
A copy of the final report will be provided to you on completion of the study and you will have the opportunity to revise any areas of the report relevant to this interview.

Thank you once again for your time, courtesy and contribution.

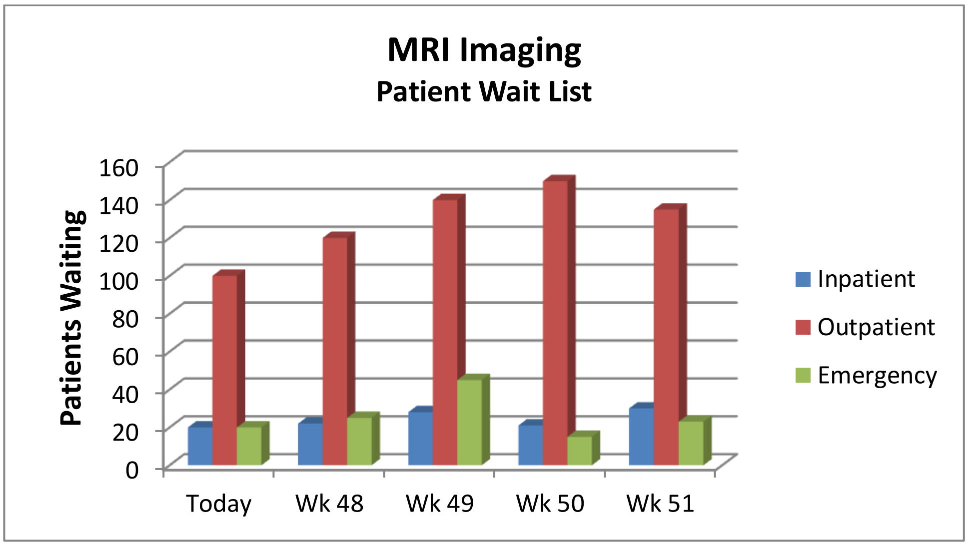
B.4: Prototype Screens



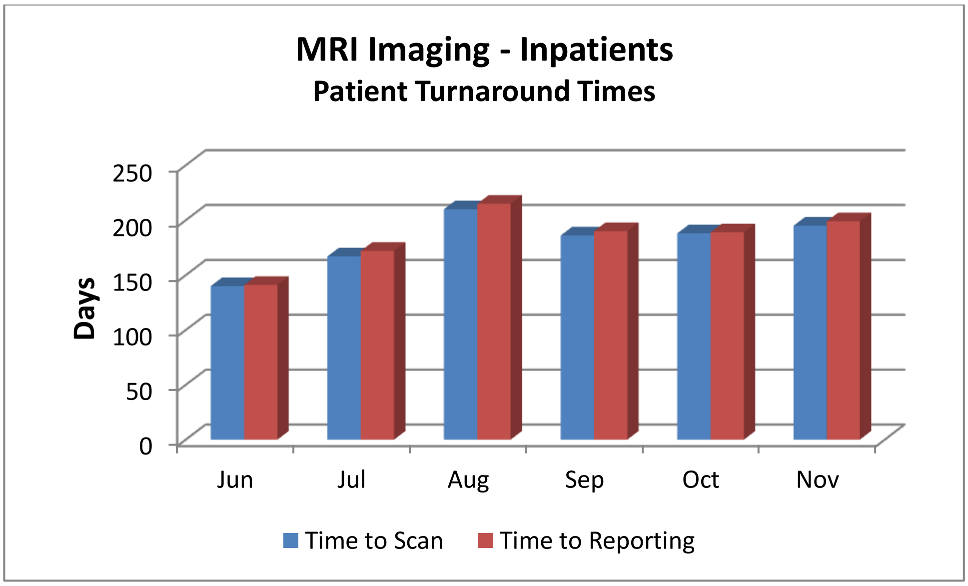
Screen 1 – Forecast demand, capacity and backlog



Screen 2 – Forecast optimum mix %



Screen 3 - Patient waiting list



Screen 4 – Patient turnaround times

B.5: System Evaluation – Information Sheet for Participants

LEAD RESEARCHER: Stephen Jones (Trinity College Dublin student number – 12328069)

BACKGROUND OF RESEARCH:
Reduction in patient wait times as well as timely patient access to radiology resources are key drivers towards improving operational efficiencies and patient satisfaction levels within Diagnostic Medical Imaging departments.

Current poor visibility of patient demand, within the radiology department at a major academic teaching hospital, is resulting in an inability to adequately plan and effectively manage the usage of radiology staff and resources.

The purpose of this research is to evaluate how a forecasting and predictive analysis software tool could facilitate decision support towards improving patient wait times in a large diagnostic medical imaging department within a public hospital in Ireland.

WHY ARE YOU BEING ASKED TO PARTICIPATE?
The researcher attended an initial meeting with the Clinical Director of Radiology. The Clinical director was keen for the Radiology department to participate in this study in order to achieve the potential benefits for the Radiology service at the hospital.

The Clinical Director nominated yourself, two of your colleagues and himself as key relevant stakeholders. Nomination was based on domain expertise and knowledge of the business problems associated with the day to day management of the Radiology department at the hospital. The Clinical Director provided your email address and indicated that he would notify you of your nomination in advance of the commencement of the study.

PROCEDURES OF THIS PHASE OF THE STUDY:
As an identified key stakeholder, your input is valuable towards the evaluation of the prototype predictive analysis software tool. The prototype tool has been built based on the functionality identified during the requirements gathering phase of the study.

Should you agree to participate then you will be given basic training in the usage of the tool in advance of evaluation. An evaluation period of two weeks has been allocated for you to use the software. You will also be contacted to agree a suitable time for you to participate in a semi-structured interview.

The duration time of the interview will be approximately 45 minutes. A list of interview questions will be provided in advance of the interview to allow for any necessary clarification of the interview content. Informed consent for participation will be required prior to commencement of the interview.

DECLARATIONS:

- Please be advised that this research is being conducted by an employee of a company that supplies business analytical products and services.
- The research conducted by the author is in partial fulfillment of the requirements for a Master's Degree in Health Informatics at Trinity College, Dublin.
- All participation in this is study is voluntary, though without prejudice to legal and ethical rights. Participants have the right to withdraw and omit responses without penalty.

- It is the intention of the researcher to audio record the interview for the sole purpose of facilitating transcription. If you would prefer not to be recorded please state so and manual notes will be taken during the interview instead.
- The electronic recordings can be stopped by the participant at any time, and may at any time, even subsequent to interview participation be destroyed.
- No audio recordings will be made available to anyone other than the researcher, nor will any such recordings be replayed in any public forum or presentation of the research. All audio recordings will be deleted upon transcription and there will be no video recording in this study.
- Participants will be given the opportunity to ask questions on the research at any point.
- There are no expected risks to the participant. There are benefits to be achieved by having an input into the evaluation of the prototype software tool. This feedback received from the evaluation interviews may be used to inform any future implementation of the software.
- There may be some follow up required based on the content of the interviews however this will be kept to a minimum.
- Preservation of participant anonymity will be ensured during any analysis, publication and presentation of resulting data and findings.
- It is an obligation of the researcher to report any inadvertent discovery of illicit behavior to appropriate authorities.
- Provision for verifying any direct quotations and their contextual appropriateness will be made available before any subsequent publication or presentations of study material.
- The data will be used for scientific purposes only and may be published in scientific publications.
- All data collection, storage and analysis will comply with the Data Protection (& Amendment) Acts and current Best Practice in Scientific Research. Individual results will be aggregated anonymously and research will be reported on aggregate results. No individual patient data will be collected for the purposes of this study.
- Ethical approval for the commencement of this study was granted on 13/12/2013 by the Research Ethics Committee of the School of Computer Science and Statistics (SCSS) at the University of Dublin, Trinity College.
- In the event that further clarification, assistance or advice is required in relation to this study please contact Stephen Jones by email: joness4@tcd.ie or by phone: 087 2544372. I will be happy to help with any of your queries.

B.6: System Evaluation – Interview Protocol

Introduction
Hello, my name is Stephen Jones and I am currently studying for my MSc in Health Informatics at Trinity College in Dublin. Thank you for taking the time to meet with me today.

The objective of this study is to evaluate how a forecasting and predictive analysis software tool could facilitate decision support towards improving patient wait times in a large Diagnostic Medical Imaging Department within a public hospital in Ireland.

This interview is for the purposes of evaluating the prototype predictive analysis software tool. Three decision support scenarios were defined at the requirements gathering phase and it is intended to evaluate the tools ability to model these scenarios as well and to evaluate functionality and KPI visualisation. It is also intended to gather feedback on potential advantages/disadvantages to subsequent implementation.

I would like to request your permission to record the audio from our interview today. The recording will be used for transcription purposes only and all audio will be destroyed upon completion of transcription. A copy of the transcription can be provided should you wish to review the content.

Our interview should last no longer than 45 minutes and please feel free to ask any questions regarding the study at any point during the interview. All participation is voluntary and the interview can be terminated by you at any stage.

Initial training has been given in the usage of the tool and the software has been available to you for the past two weeks to assist with evaluation. A copy of the participant information sheet has already been issued however a further copy is available on request today, should it be necessary.

A copy of the signed informed consent form is required before the interview commences.

Prototype Software Tool Overview
A prototype software tool has been developed based on the previously identified requirements set. In order to evaluate the success of the software tool we will be evaluating the tools ability to visualise radiology KPIs as well as modelling and analysing data based on the predictive scenarios identified during the requirements gathering phase of the project.

Questions for the Interviewee

1. What area of your role does this application assist with / address?

2. What management decision support role (proactive or otherwise) do you believe that the prototype tool could potentially play within the radiology department?

3. Do you believe that the application has the potential to assist with reducing patient wait times within radiology? (If so then how? Who will use it?)

4. What do you believe are the potential benefits of implementing the prototype tool within radiology? (Improved patient care? Financial benefits?)

5. What do you believe would be the disadvantages of implementing the prototype tool within radiology? (Are there any potential barriers to implementation?)

6. What are your thoughts on the predictive scenario functionality within the application? (What scenarios would you envisage using? when and how often?)

7. Do you believe that the predictive scenario functionality assists with departmental decision support?

8. Do you believe that the visualisation of existing radiology KPIs assists with departmental decision support?

9. Some questions relating to the application:
    a. Do you find the tool intuitive and easy to use?
    b. Is the data displayed in meaningful way?
    c. Do you have confidence in the accuracy of the data?
    d. Do you have any thoughts on the user interface?

10. In what areas do you believe the application can be improved?

11. Do you believe that the tool has a potential role outside of radiology?

12. Do you have any final thoughts or general feedback on the tool?

<u>Interview wrap up</u>
A copy of the final report will be provided to you on completion of the study and you will have the opportunity to revise any areas of the report relevant to this interview.

Thank you once again for your time, courtesy and contribution.

Appendix C – Ethics Application

C.1: Trinity College Dublin SCSS Research Ethics Approval

MYZONE Trinity College Dublin

Stephen Jones <joness4@tcd.ie>

RE: Research ethics application - E023/14

Tricia Fowler <Tricia.Fowler@scss.tcd.ie> 13 December 2013 11:24
Reply-To: Tricia.Fowler@scss.tcd.ie
To: Stephen Jones <joness4@tcd.ie>
Cc: Research Ethics <research-ethics@scss.tcd.ie>

Hi Stephen

Many thanks for this revision. You may now proceed with this study.

We wish you success in your research.

Kind Regards

Tricia

Tricia Fowler

Executive Officer – Research Unit

School of Computer Science & Statistics

O'Reilly Institute

Trinity College

Dublin 2

Tel: + 353 1 896 1445

C.2: Joint SJH/AMNCH Research Ethics Committee Consent

MYZONE Trinity College Dublin

Stephen Jones <joness4@tcd.ie>

Research proposal

Stephen Jones <joness4@tcd.ie> 4 December 2013 12:52
Draft To: stephen.jones@reiteach.ie

From: **David Willow** <David.Willow@amnch.ie>
Date: 4 December 2013 10:52
Subject: RE: Research proposal
To: Stephen Jones <joness4@tcd.ie>

Stephen, thanks for your query. Based on information below this is undoubtedly a service improvement project and has no ethical implications with regard to patient participation, therefore not a concern for the St James'/Tallaght REC. Good luck with the work, regards, Dave Willow

---

From: Stephen Jones [mailto:joness4@tcd.ie]
Sent: 03 December 2013 17:12
To: David Willow
Subject: Research proposal

Hi David,

Hope you are well.

I am student at Trinity College Dublin currently undertaking a research study at St. James Hospital in partial fulfillment of my Masters Degree in Health Informatics.

I am currently working with Niall Sheehy and Seán Cournane in the Radiology department and am proposing to develop a dashboard to display various Radiology key performance indicators (KPIs) based on a patient anonymised data extract.

The data set proposed will not include any patient specific data and only relates to medical imaging orders placed within the radiology department.

I am writing to you to confirm whether there is an issue for the ethics committee at St. James in relation to my research. I would be grateful if you could let me know at your earliest convenience.

Look forward to hearing from you soon.

Thanks and regards,
Stephen.

Notice from AMNCH Email System: This e-mail from joness4@tcd.ie on 12/03/13 @ 17:12:02 was encrypted in transit from the sender to the hospital.

C.3: Hospital Management Information Sheet and Consent

Management Information Sheet

PROECT TITLE: A Business Analytics Software Tool for Monitoring and Predicting Radiology Throughput Performance
LEAD RESEARCHER: Stephen Jones (Trinity College Dublin student number – 12328069)

Background of Research:
Reduction in patient wait times as well as timely patient access to radiology resources are key drivers towards improving operational efficiencies and patient satisfaction levels within Diagnostic Medical Imaging departments. Current poor visibility of patient demand, within the radiology department at a major academic teaching hospital, is resulting in an inability to adequately plan and effectively manage the usage of radiology staff and resources. The purpose of this research is to evaluate how a forecasting and predictive analysis software tool could facilitate decision support towards improving patient wait times in a large diagnostic medical imaging department within a public hospital in Ireland.

This study is in partial fulfilment of my MSc in Health Informatics, which I am currently undertaking at Trinity College Dublin. The aims of the study are:

- To scope and build a forecasting and predictive analysis software tool for radiology which will enhance decision support towards improving patient wait time management.
- To evaluate the ability of the prototype tool to facilitate decision support towards improving patient wait times within a diagnostic medical imaging department.

Study Location and Participants
The study will require participation from staff with various levels of responsibility within the radiology department. The total number of radiology staff required to participate will be four (Clinical Director, Business Manager, Medical Physics and Bioengineering and a senior Radiologist). The study is being carried out in a large academic teaching hospital. All research work will be conducted within the Radiology department at the hospital.

Research Approach
Following on from a literature review semi-structured in-depth interviews will be conducted with four stakeholders in order to determine prototype software tool functionality requirements as well as appropriate KPI's to be selected for display as part of the user interface. In addition, a number of predictive scenarios relevant to demand and capacity management within radiology will be identified for inclusion.

A working prototype will be built to provide visibility of demand and capacity (via a dashboard) as per the requirements identified. Predictive scenario modelling, based on 3 identified scenarios, will be provided as well as visualisation of each scenarios impact on the agreed KPI's. A patient anonymised dataset extracted from the PACS, RIS and EPR hospital systems will be used to validate the software tool. In addition, manual calculation of forecast data will be undertaken and compared to calculated figures from the software tool.

Semi-structured in-depth interviews will be conducted with four key decision makers within the radiology department. These interviews will be used to gather feedback on evidence of benefit with regard to how the tool can improve decision making through data modelling of KPI data and the predictive decision support scenarios identified during the requirements gathering phase.

Data Collection
The data collection procedures of the study will involve two sets of semi-structured interviews for prototype tool requirements gathering as well as subsequent evaluation. Prototype tool validation will utilise a patient anonymised data extract from the PACS, RIS and EPR hospital systems.

All data collection, storage and analysis will comply with the Data Protection (& Amendment) Acts and current Best Practice in Scientific Research. Individual results will be aggregated anonymously and research will be reported on aggregate results. No individual patient data will be collected for the purposes of this study. Research findings will be presented in a manner ensuring that the study site and participants will not be identifiable. A patient anonymised data extract file will be transferred on an encrypted USB stick and stored on a password protected PC.

Risks
All participation in this study is voluntary, though without prejudice to legal and ethical rights. Participants have the right to withdraw and omit responses without penalty. There are no expected risks to the participants. It is an obligation of the researcher to report any inadvertent discovery of illicit behaviour to appropriate authorities. Provision for verifying any direct quotations and their contextual appropriateness will be made available before any subsequent publication or presentations of study material. The data will be used for scientific purposes only and may be published in scientific publications. Please be advised that this research is being conducted by an employee of a company that supplies business analytical products and services.

Hospital Approval
I have received approval to undertake the study from the Risk and Legal Office at St. James hospital. I have been informed by the Joint SJH/AMNCH Research Ethics Committee that the study does not require hospital ethical approval as there are no patients involved; however, the study will undergo approval by the Trinity College Ethics Committee prior to commencement.

Potential Benefits for Radiology
The researcher hopes that the results of this study will enable improved management decision making with regard to the management of patient wait times and scheduling of radiology resources.

Summary
This study is due for completion by the end of June 2014. Copies of the full research proposal as well as requirements gathering and prototype tool evaluation interviews have been provided. If you require any further information please let me know. Your permission and support would be greatly appreciated. I would also welcome any suggestions that you wish to make with regard to this study.

Consent Form

Lead Researcher: Stephen Jones (Trinity College – student number 12328069)
Supervisor: Assistant Professor Lucy Hederman

Title of study: A Forecasting and Predictive Analysis Tool for Management of Patient Wait Times in Radiology

Research Duration: December 2013 – May 2014

DECLARATION:

- I have read, or had read to me, a document providing information about this research and this consent form. I have had the opportunity to ask questions, and all my questions have been answered to my satisfaction and I understand the description of the research that is being provided to me.
- I agree that data may be used for scientific purposes and may be published in scientific publications.
- I understand that participant and site confidentiality and anonymity will be maintained at all times.
- I have been assured all data collection, storage and analysis will comply with the Data Protection (& Amendment) Acts and current best practice in Scientific Research
- I have received a copy of this consent agreement.

APPROVAL
I hereby grant you permission and approval as Clinical Director of Radiology to carry out this research study as outlined per the attached information sheet.

APPROVERS NAME: Niall Sheehy (Clinical Director of Radiology)

SIGNATURE: Niall

DATE: 11/12/13

Statement of researcher's responsibility: I have explained the nature and purpose of this research study, the procedures to be undertaken and any risks that may be involved. I have offered to answer any questions and have fully answered such questions. I believe that the individual understands my explanation and has freely given informed consent.

RESEARCHER'S CONTACT DETAILS:
Stephen Jones (Trinity College – student number 12328069)
Email: joness4@tcd.ie
Tel: 087 2544372

RESEARCHER'S SIGNATURE:

DATE: 10/12/2013

3

C.4: SJH Designated Research Activity Hospital Approval

8. **INDEMNIFICATION**

In general, where a sponsoring agent is involved, it is necessary for that agent to provide indemnification cover to the hospital. The HSE indemnification documentation should be submitted in the standard Hospital format with this approval form. The research activity may not proceed in the absence of this indemnity.

9. **RESEARCH ETHICS COMMITTEE APPROVAL**

Please attach evidence of formal approval from the relevant Research Ethics Committee for the proposed Research Activity.

YES ☐ **NO** ☐ **N/A** ☑

10. **IRISH MEDICINES BOARD APPROVAL**

Please attach evidence of formal approval from the Irish Medicines Board, if relevant.

YES ☐ **NO** ☐ **N/A** ☑

11. **DECLARATION**

I confirm that the information provided herein and attached is accurate and discloses the complete resource implications and grants/funding provisions applicable to the specified proposed research activity.

Applicant and Principal Investigator 4TH DECEMBER 2013 **Date**

12. **APPROVAL**

SIGNED: Muireann O Briain
~~**Deputy CEO/Operations Manager**~~
Legal/Insurance Manager

DATE: 4 December 2013
Date

Risk & Legal Dept. SJH. 2007 7

Appendix D – Complete Set of User Requirements

D.1: Category C_01 (Predictive Scenario Analysis) Functional Requirements

Requirement	Description of Functionality
C_01_FR001	Allow creation and maintenance of user defined predictive scenarios at modality and week number level
C_01_FR002	Cater for the following demand predictive scenarios: 1. Year on year forecast demand adjustment % 2. Increase in demand for scans (Inpatient/Outpatient/Emergency) 3. Reduction in demand for scans (Inpatient/Outpatient/Emergency)
C_01_FR003	Cater for the following capacity predictive scenarios: 1. Increase in the number of available devices 2. Decrease in the number of available devices 3. Device downtime adjustment in hours 4. Increase in the number of available radiographer hours 5. Decrease in the number of available radiographer hours 6. Increase in average scan time (Inpatient/Outpatient/Emergency) 7. Decrease in average scant time (Inpatient/Outpatient/Emergency) 8. Facility to enter various combinations of mix allocation (Inpatient/Outpatient/Emergency)
C_01_FR004	Provide a filtering mechanism to select and display predictive scenarios associated with a modality
C_01_FR005	Provide a facility to record baseline modality information including: 1. Number of available devices 2. Number of operators per device 3. Average scan times (Inpatient/Outpatient/Emergency) Capacity mix allocation % (Inpatient/Outpatient/Emergency)
C_01_FR006	Average scan times will to be stored at modality level , there will be no provision to store at a lower level (such as scan type)
C_01_FR007	Visualise forecast demand and backlog data across a 12 month forecast window
C_01_FR008	Allow drop down list selection of predictive scenarios for visualisation (to be filtered by modality, if selected)
C_01_FR009	Visualise forecast demand and backlog data simultaneously for baseline values (Business as usual) plus a selected predictive scenario

C_01_FR010	Provide facility to display forecast demand and capacity data across multiple dimensions, to include: 1. By week number 2. By month
C_01_FR011	When displaying forecast backlog data by month the system must take the backlog position as per the last week of the month.
C_01_FR012	When displaying forecast demand data by month the system must accumulate the demand data for all weeks within each month.
C_01_FR013	Provide facility to display forecast demand and backlog data from multiple viewpoints, to include: 1. Forecast data in scans 2. Forecast data in hours
C_01_FR014	Provide selection filtering on forecast demand and backlog data, to include: 1. Month 2. Week number 3. Modality 4. Encounter Type (Inpatient/Outpatient/Emergency)
C_01_FR015	Allow multiple simultaneous combinations of selection filters.
C_01_FR016	Encounter Type selection filters should be calculated as follows: 1. Inpatient – Include all orders beginning with 'Inpat' 2. Emergency – Include all orders beginning with 'Emerg' 3. Outpatient – All other orders
C_01_FR017	The starting point for forecasting backlog data must be the based on live waiting list data as per the forecast start date.
C_01_FR018	Once a starting position is calculated, Backlog data should be calculated on a weekly basis. This is will be achieved by subtracting forecast capacity from forecast demand to come up with a plus or minus adjustment to forecast backlog.
C_01_FR019	Should forecast backlog become negative at any point then forecast backlog will be set to zero.
C_01_FR020	Forecast capacity must cater for multiple radiographers operating a device.
C_01_FR021	Forecast demand for a particular week should be based on a weekly average calculated from the week start date from 1 year earlier plus 28 days. This average will help smooth out peaks and troughs in the data.
C_01_FR022	Increases to the number of devices available will assume availability of radiographers to operate the devices.
C_01_FR023	Provide a facility to exclude cancelled orders from forecast data

C_01_FR024	Provide a facility to store the number of standard working hours per week
C_01_FR025	Due to a lack of scheduled scan data, all scheduled order data should be ignored within the application
C_01_FR026	Provide a facility to calculate optimum mix allocation percentages for Inpatient/Outpatient/Emergency based on forecast demand
C_01_FR027	Visualise optimum mix % for all encounter types side by side on the one graph
C_01_FR028	Provide a facility to manually import predictive datasets into the application. This is to allow for modelling of forecasts on various historic datasets
C_01_FR029	Cater for import datasets in Excel format
C_01_FR030	Provide a facility to manually re-generate forecast data once scenarios have been updated.
C_01_FR031	Automatically refresh the demand, backlog and optimum mix graphs on completion of a re-generate forecast.
C_01_FR032	Provide drill down from graph level to data level
C_02_FR033	Although initially designed for MRI data, the application should cater for all modalities
C_01_FR034	Provide a facility to include additional capacity from St Lukes for outpatient forecasts (extra 40 hours per week after the 15th April 2013)

D.2: Category C_02 (KPI Data) Functional Requirements

Requirement	Description of Functionality
C_02_FR001	Provide a dashboard to visualise the following radiology KPIs: 1. Radiology metrics – orders raised, patients scanned, patients reported, orders cancelled. 2. Patient waiting list – patients waiting for scan, patients waiting for report. 3. Median turnaround times – Exam turnaround time, report turnaround time, total turnaround time. 4. Time to X percentiles (TTX%) – facility to display percentile total turnaround times ranging from 5%ile to 95%ile. 5. Order cancellation analysis – display top 10 locations at the study site that are raising and subsequently cancelling radiology scan orders.
C_02_FR002	Provide selection filtering on KPI data, to include: 1. Year 2. Quarter 3. Month

	4. Week number 5. Day 6. Modality 7. Order location 8. Exam Type 9. Physician
C_02_FR003	Allow multiple simultaneous combinations of selection filters.
C_02_FR004	Provide mechanism to update chart dimension data.
C_02_FR005	Encounter Type selection filters to be calculated as follows: 1. Inpatient – Include all orders beginning with 'Inpat' 2. Emergency – Include all orders beginning with 'Emerg' 3. Outpatient – All other orders
C_02_FR006	Provide drill down/up dimension functionality as follows: Year->Quarter->Month->Week->Day
C_02_FR007	Although initially designed for MRI data, the application should cater for all modalities
C_02_FR008	Provide ability to drill down from chart level to data level
C_02_FR009	Provide a summary tab on the dashboard to capture the following KPIs: 1. Previous weeks metrics - orders raised, patients scanned, patients reported, orders cancelled. 2. Number of patients waiting as per last working day 3. Estimated time to next slot 4. Turnaround times year to date – 50%ile, 75%ile, 90%ile.
C_02_FR010	Application should be accessible across multiple mobile devices including tablets and smartphones. This is to facilitate potential roll out of functionality to clinicians on the wards.

D.3: Non Functional Requirements

Requirement	Description
NF001	The application must provide an audit trail of updates to forecast data.
NF002	Application data should be backed up on a nightly basis.
NF003	The application will be stand alone and operated by radiology. There are no interoperability requirements with other hospital systems.

NF004	The application will be handling large volumes of data and should be designed to optimise performance and user response times.
NF005	The application should be scalable to allow for inclusion of additional modality data.
NF006	Sufficient network bandwidth will be required.
NF007	The application will utilise windows authentication for security management.
NF008	Application data must reside on the hospital network in order to utilise existing security protocols and to ensure data privacy.
NF009	The application will be required to automatically load data on a daily basis

D.4: Constraints

Constraint	**Description**
CN001	The application will be browser based
CN002	The application will run on the Windows platform
CN003	The application will utilise a Microsoft SQL express database

Appendix E – Prototype Detailed Functionality

E.1: RPM KPI Data Functionality

The radiology KPI data model is built using Qlikview and is accessed from the 'Radiology KPI Data' option on the home page drop down menu. The data model provides access to a number of documents that display various radiology performance indicators. Each document is accessed via tabs on a dashboard.

E.1.1: KPI Data Import Process

All data is imported into Qlikview from an Excel file using the tools scripting technology. A Qlikview script is a segment of code written in a SQL like language that is used to control the extraction of data from databases as well as the import of data from extract files in numerous formats. Qlikview scripting also provides the ability to transform raw imported data into aggregated information through various calculation functions and field manipulation. All script data is entered into the Qlikview application in a tabular format for organisational purposes, see figure E-1 for a sample of the Qlikview script used.

```
///Stab Excel
MRN_Data_Temp:
LOAD
    MRN & Date(DayStart(COMPLETE_DT_TM)) as UniqueID,
    MRN,
    ORDER_ID,
    ACCESSION,
    EPISODE_NO,
    MODALITY,
    EXAM,
    ENCOUNTER_TYPE,
    ORDER_PHYSICIAN_FULL_FORMATTED,
    ORDERING_SPECIALTY_CODE,
    PRIORITY,
    LOCATION,
    REQUEST_DT_TM,
    ORIGINAL_SCHEDULED_DATE,
    DICTATED_DATE,

//    ORIG_ORDER_DT_TM,
    Date(DayStart(ORIG_ORDER_DT_TM)) as OrderDate,
    Day(ORIG_ORDER_DT_TM) as OrderDay,
    Month(ORIG_ORDER_DT_TM) as OrderMonth,
    Year(ORIG_ORDER_DT_TM) as OrderYear,
    Week(ORIG_ORDER_DT_TM) as OrderWeek,

//    Calculate current previous last week number
    Week(Today()+ 16)&'-'&Year(ORIG_ORDER_DT_TM) as LastWeekYear,

   If (FINAL_DATE <> 'NULL',Date(DayStart(FINAL_DATE)), 0) as FinalDate,

// Date and Time for TAT calculation
   Timestamp(FINAL_DATE) as FinalDateTime,
   Timestamp(ORIG_ORDER_DT_TM) as OrderDateTime,
   Timestamp(COMPLETE_DT_TM) as CompleteDateTime,

   FROM [$(vLoadPath)\$(vMRIFileName)]
   (biff, embedded labels, table is [Sheet1$]) WHERE not wildmatch(EXAM,'*CAMI*');
```

Figure E-1: A sample of the Qlikview script

Execution of the Qlikview script generates the data model. The scripting tool uses dimensional modelling techniques to create a single associative data model (potentially from many data sources) which can subsequently be used by the Qlikview application to rapidly access, sort and display imported data to the end user.

The KPI data model implemented for RPM utilised a fixed format Excel file to import the necessary data. The Excel file was extracted by the IT department at the study site and contained MRI, CT and Ultrasound scan data from January 2010 to February 2014. A formula was applied, by a data analyst at the study site, to the MRN and physician fields on the Excel file to ensure this data was anonymised before it was imported into the application. Whilst the data is currently manually imported into the KPI data model, provision has also been made for setup of an automated process to perform this update on a nightly basis. The agreed extract file format is contained in table E-1.

Table E-1: KPI data Excel file format

Field	Description
MRN	Unique patient identifier number
ORDER_ID	Unique order identifier
ACCESSION	Accession number e.g. MR-12-0000081, details the modality for which the order is placed (MR), the year of the order ('13), and the position of the order, it is the 81st MRI order in 2013.
EPISODE_NO	Unique examination session number, where multiple different specific examination types can be carried out in one session.
MODALITY	Modality e.g. MRI, CT, ultrasound
EXAM	Specific exam type e.g. Brain general, Pelvis general
ENCOUNTER_TYPE	Patient type: Inpatient, Outpatient, Emergency.
ORDER_PHYSICIAN_FULL_FORMATTED	Full name of lead physician/consultant placing order
ORDERING_SPECIALTY_CODE	Speciality placing the order, e.g. Radiology, Urology, Vascular..etc
PRIORITY	Urgency of exam e.g. Routine, urgent..etc
LOCATION	Location where the order is raised
ORIG_ORDER_DT_TM	The initial date that the order is raised
REQUEST_DT_TM	Requested date of exam
VETTING_DT_TM	Date of vetting if carried out
ORIGINAL_SCHEDULED_DATE	Date for which the order is scheduled
CANCEL_DT_TM	Date exam cancelled, if cancelled
COMPLETE_DT_TM	Date of completed exam (scan)
DICTATED_DATE	Date of dictation carried out by radiologist
FINAL_DATE	Date exam results are finalised by radiologist
CANCELLED_BY	Name of person who cancelled exam
CANCELLED_REASON	Reason for cancellation
CANCELLED_BY_POSITION	Position of person who cancelled exam

Once the data is imported into the application it is possible to visualise the information through various graphs and charts. The application's OLAP functionality and associative technology can also be used to slice and dice the data to filter and select various views to enable users to access the required information.

E.1.2: Dashboard Template

A standard screen template was designed for use by each screen within the dashboard. The template contained all of the various requested selection criteria necessary to display the data in the required formats as defined at the requirements gathering stage.

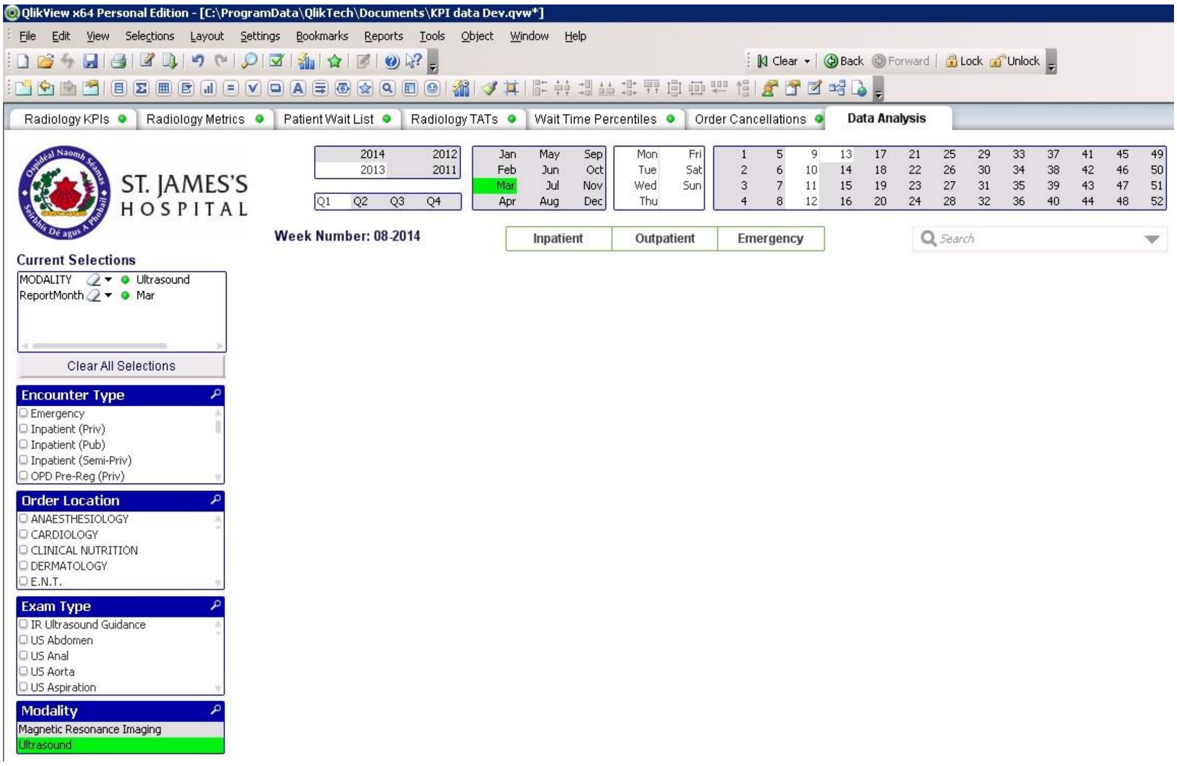


Figure E-2: KPI model template screen

Figure E-2 illustrates all of the various selection criteria. Selection criteria are implemented using list boxes and each list box contains all values held for the particular data item within the model. Simply clicking on any of the items in the various list boxes will filter graph data by the selected values. A list box (towards the top left of the screen) is also used to display current selection criteria and a button below this allows clearing of all current selection data. A search box is provided which allows selection of any data element within the model, once a data element is selected then the model is filtered to display the requested data. Three buttons are also included which allow selection of data by inpatient, outpatient or emergency. Any combinations of selection criteria as well as multiple simultaneous selections are permitted within the data model. Table E-2 describes the various selection criteria available.

Table E-2: KPI data model selection criteria

Selection	Description
Year	Select a single year or multiple years.
Quarter	Allows selection of a single quarter or a range of quarters.
Month	Select a month or a range of months.
Week Number	Select a week or a range of weeks.
Day	Select a single day or a range of days.
Encounter Type	Select a single or multiple encounter types. Whilst the encounter type buttons allow selection of all Inpatient/Outpatient and Emergency the list box allows a lower level of selection such as Inpatient public/Inpatient private etc.
Order Location	Select a single or multiple locations where orders are placed, e.g. Cardiology, Oncology.
Exam Type	Select a specific exam type or multiple exam types, e.g. MRI heart, Ultrasound Abdomen
Modality	Select the modality for which the data should be displayed for, e.g. MRI, Ultrasound, CT

E.1.3: KPI Dashboard

As discussed in the literature review a dashboard is a performance management tool which provides a mechanism for visualising and interpreting complex data. Based on evidence of benefit identified in the literature review it was decided to implement a dashboard with separate tabs for the various KPIs. The standard template as outlined in section E.1.2 was used as a starting point for the design of each screen with graph data implemented appropriately. All graphs within the application allow printing of graph data as well as exporting of data to Excel. The next six sections will describe the functionality of the implemented KPI dashboard.

E.1.3.1: Radiology KPIs

The KPI screen, figure E-3, displays a current snapshot of various radiology KPI data. This information is visualised utilising gauge charts built from the underlying data model. As the various KPI’s are date driven (previous week, waiting list data and YTD turnaround times) the date selections were removed from the template screen however all other selection criteria were retained. This initial tab provides a summary overview of radiology performance with subsequent tabs allowing lower level analysis of the KPI data.

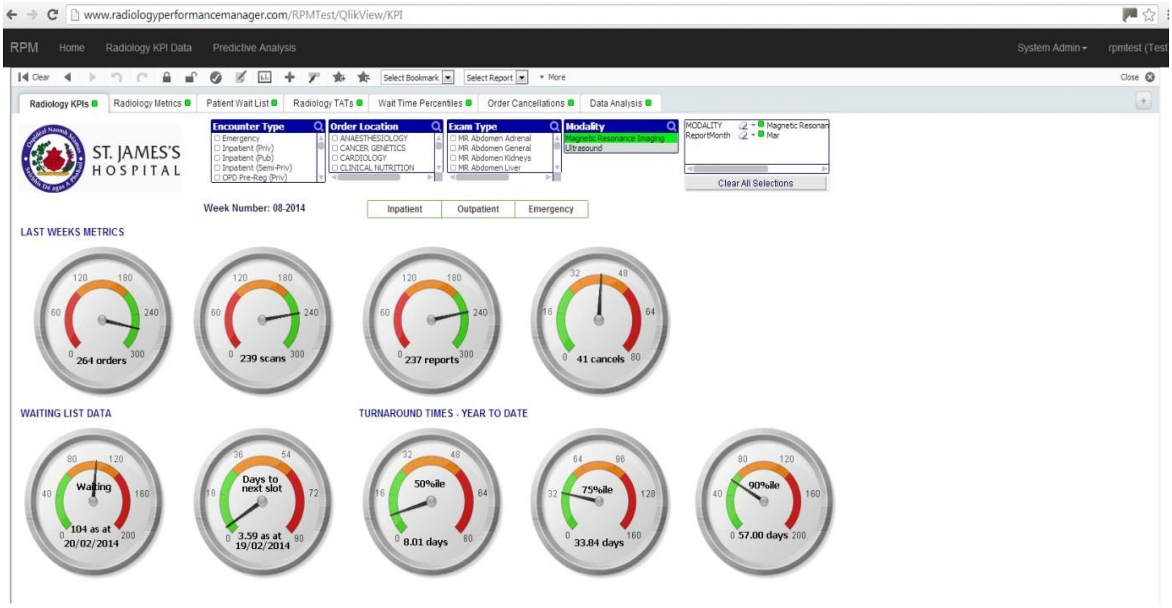


Figure E-3: Radiology KPIs

The KPIs displayed are calculated as per table E-3. The ranges and colour scales associated with each gauge chart were decided by a senior data analyst in the radiology department. The Qlikview tool allows easy maintenance of these variables, simply right clicking on a gauge brings the user to a properties screen where gauge colours bands and number ranges can be edited.

Table E-3: KPI descriptions

Key Performance Indicator	Description
Orders placed last week	The number of orders placed on the radiology department for the previous working week
Patients scanned last week	The number of patients that were scanned within the radiology department during the previous working week
Patients finalised last week	The number of patients that had their scans reported by radiologists during the previous working week.
Orders cancelled last week	The number of orders cancelled for the previous working week
Patients waiting	The numbers of patients waiting as per the last working day, i.e. if it is a Monday then we are displaying the numbers for the previous Friday.
Days to next scan	The number of estimated days to the next available scan slot. There is currently no agreed formula to work out this figure however an

	indicative calculation was agreed based on the number of patients waiting on the last working day divided by the number of patients scanned on the same day.
Turnaround time YTD – 50th percentile	The 50th percentile turnaround time (TAT) or median TAT for the current year to date. Turnaround time represents the time taken from when an order is placed to when the order is scanned and reported. The 50th percentile gives the value below which 50% of all selected TATs fall.
Turnaround time YTD – 75th percentile	The 75th percentile TAT for the current year to date. The 75th percentile gives the value below which 75% of all selected TATs fall.
Turnaround time YTD – 90th percentile	The 90th percentile TAT for the current year to date. The 90th percentile gives the value below which 90% of all selected TATs fall.

E.1.3.2 Radiology Metrics

The metrics tab, figure E-4, displays the various KPI metrics measured and analysed within the diagnostic imaging department. Metric data includes orders raised, patients scanned, patients reported and orders cancelled. Data is visualised using a single bar chart with multiple bars for each KPI. All selection criteria is available as per the template screen. A drill up/down button, at the bottom right hand corner of the screen, was also provided which allows analysis of metrics at year/quarter/month/week and day level.

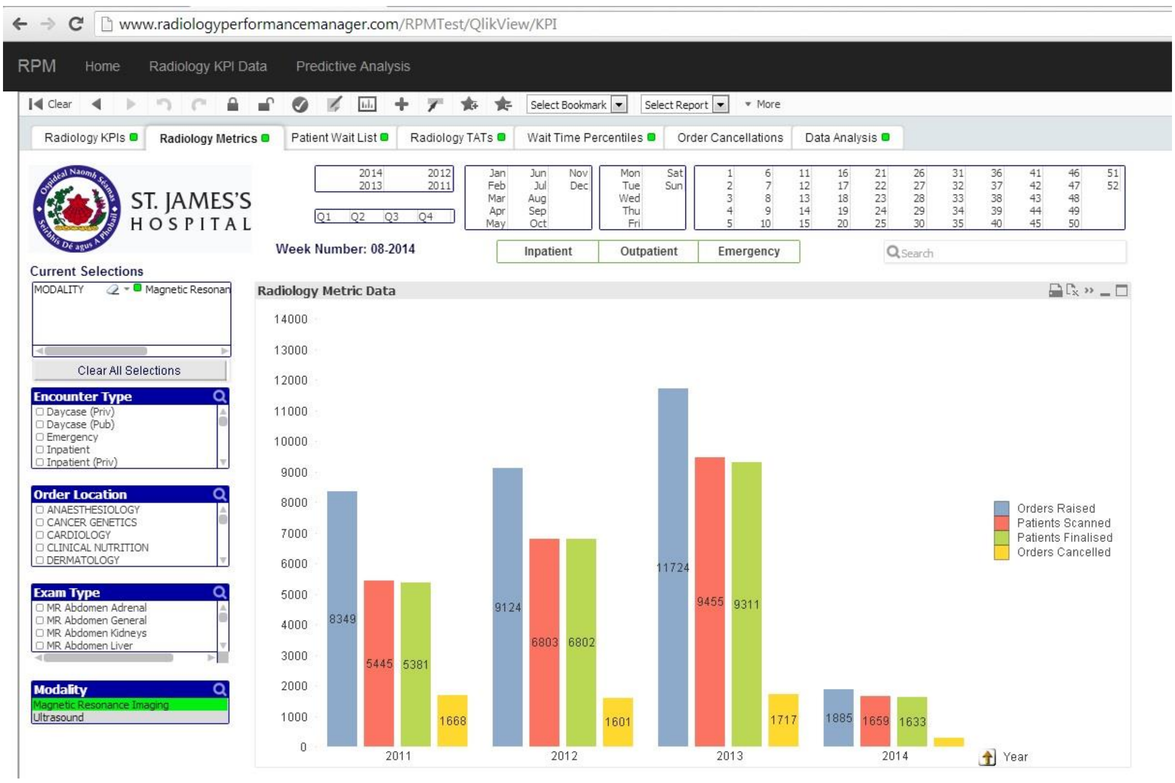


Figure E-4: Radiology metrics

E.1.3.3: Patient Wait List

The patient wait list, figure E-5, is a point in time snapshot of patient wait data. As a result, patient wait data cannot be accumulated over a period of time as the same patient may be waiting over a number of days which would result in them being aggregated multiple times. Thus the patient wait list is displayed by week number and for a selected day of the week. A bar chart is used to visualise patient wait data with both the number of patients waiting for scan and the number of patients waiting for report displayed side by side. This functionality gives management a view of patient waiting list data at any historic point; similarly it can be displayed for the current point in time. As discussed in the literature review (see section 2.4.5), the ability to analyse the number of patients waiting for radiologist reports will help to mitigate the reporting problems that occurred at the AMNCH hospital in Dublin and highlighted in the 2010 HSE commissioned Hayes report (HSE 2010).

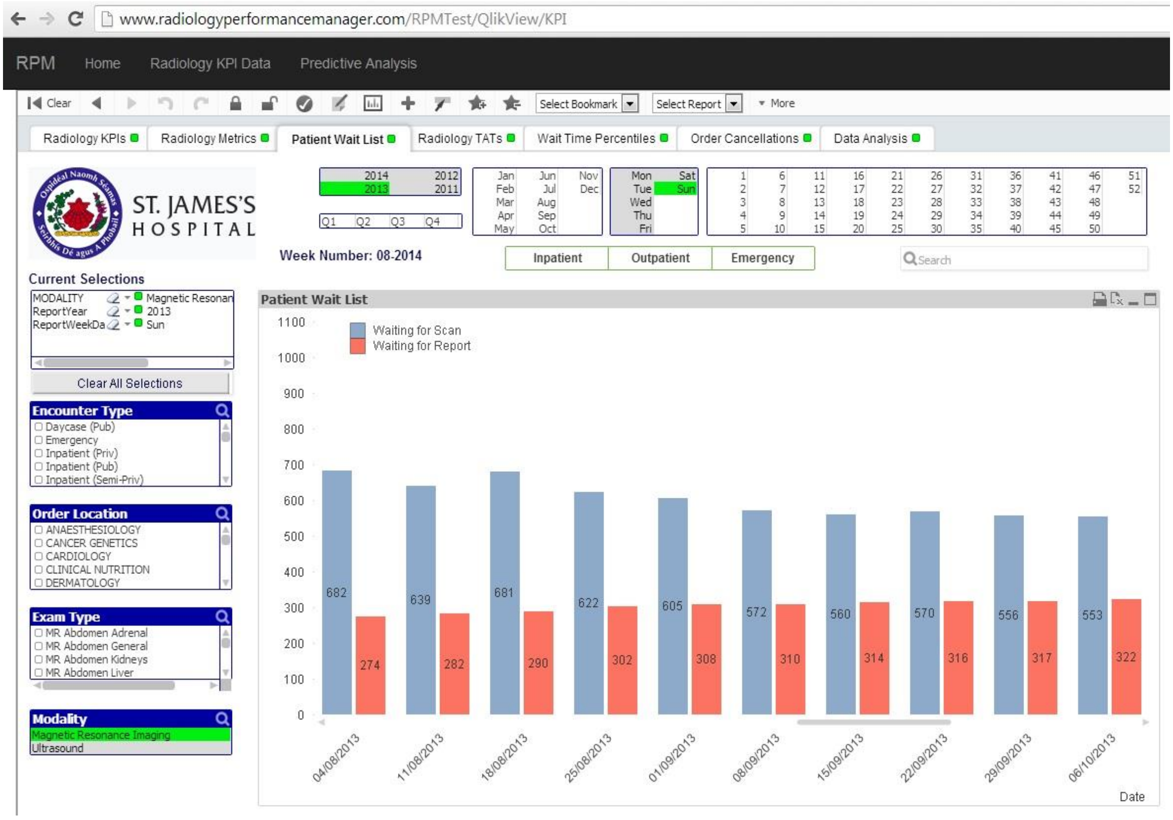


Figure E-5: KPI data model - Patient wait list

E.1.3.4: Radiology Turnaround Times

Radiology turnaround times (TATs), figure E-6, are visualised using a bar chart with data displayed for exam TATs, report TATs and total TATs, see table E-4 for a description of each calculation. The median value (50th percentile) in days is displayed for the selected dataset. The median value was selected because it is more indicative of turnaround times than a calculated average.

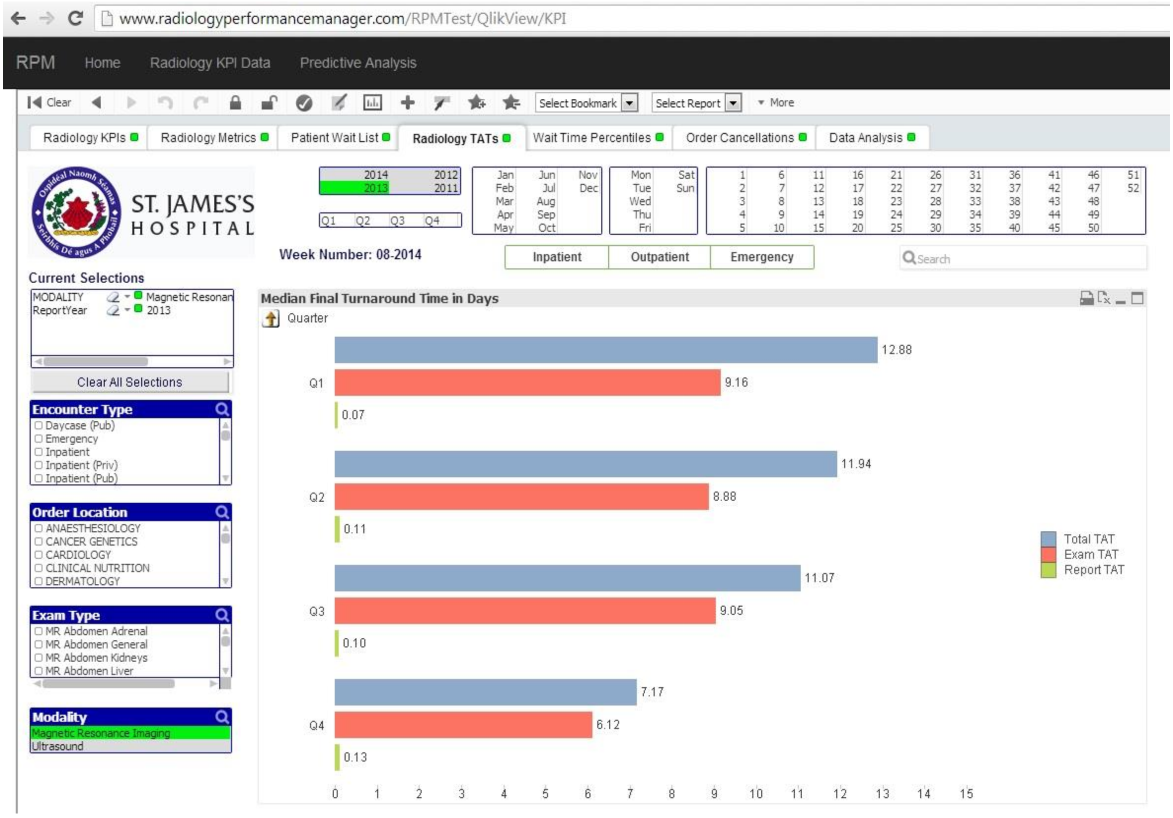


Figure E-6: KPI data model - Radiology turnaround times

Table E-4: Radiology turnaround time calculations

Radiology TAT	**Calculation**
Exam TAT	Turnaround time from when a scan is ordered to when a scan is completed.
Report TAT	Turnaround time from when a scan is completed to when a scan is reported.
Total TAT	Turnaround time from when a scan is ordered to when a scan is reported.

All TAT data is grouped by week number based on the completed/reported week number of the order rather than the order creation week number. All selection criteria are as per the template layout.

E.1.3.5: Wait Time Percentiles

Radiology wait time percentiles, figure E-7, are displayed using a combination line and bar chart. The time to 90th percentile calculation is the wait time KPI most commonly used at the study site however it is useful to get a sense for how other percentiles are performing, particularly the 50th and 75th. To facilitate this on the graph, the 90th percentile is visualised as a line and a bar is used to cater for a variable percentile figure. A slider above the graph allows the user to select the variable percentile value to be compared to the 90th percentile. Once a value is selected on the slider then the bar on the chart is adjusted accordingly. Selection criteria are provided as per the template layout.

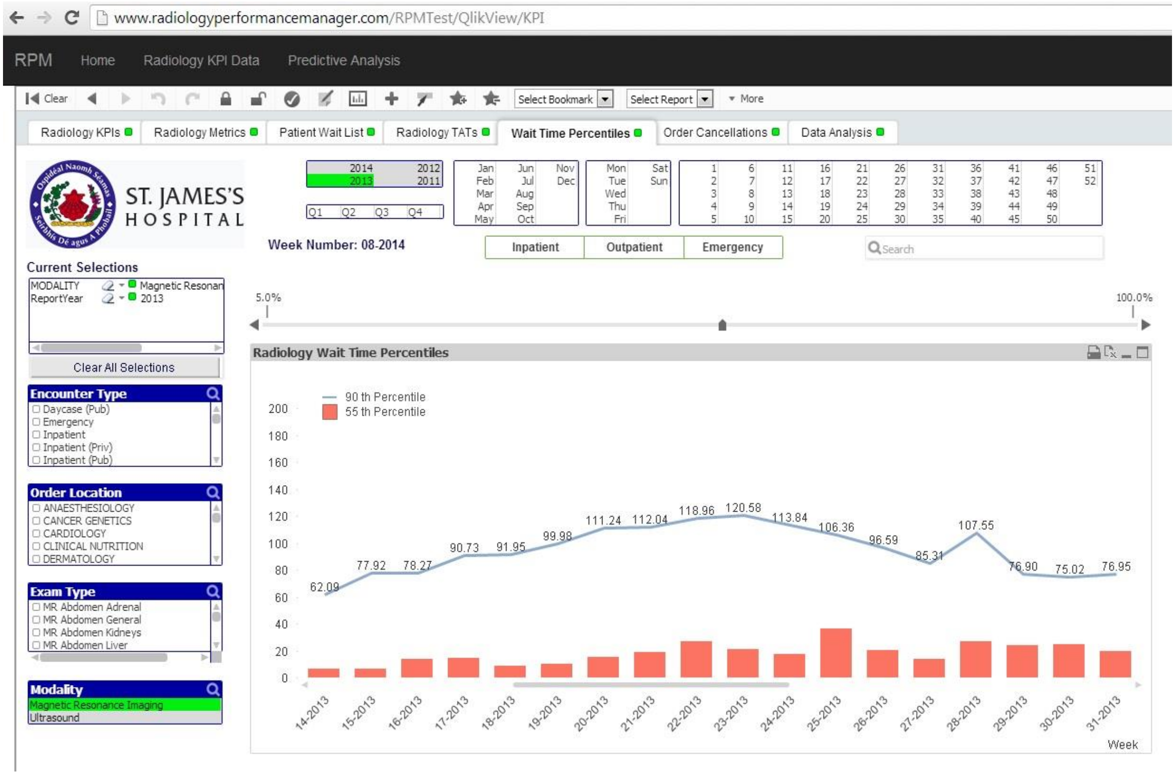


Figure E-7: KPI data model - Wait time percentiles

E.1.3.6: Order Cancellation Analysis

Analysis of cancelled orders (i.e. orders raised with the radiology department that are subsequently cancelled) is visualised utilising a bar chart, figure E-8. The top 9 order locations that are cancelling orders for the selected dataset are displayed. The data is displayed initially by quarter with drill up/down capability to month and week number level. Selection criteria are provided as per the template layout.

This is a useful analysis tool for the imaging department as orders raised and cancelled are included in metric and TAT data for the period of time that they are active. This graph provides the necessary information to address the problem with the various departments that are placing the orders on radiology.

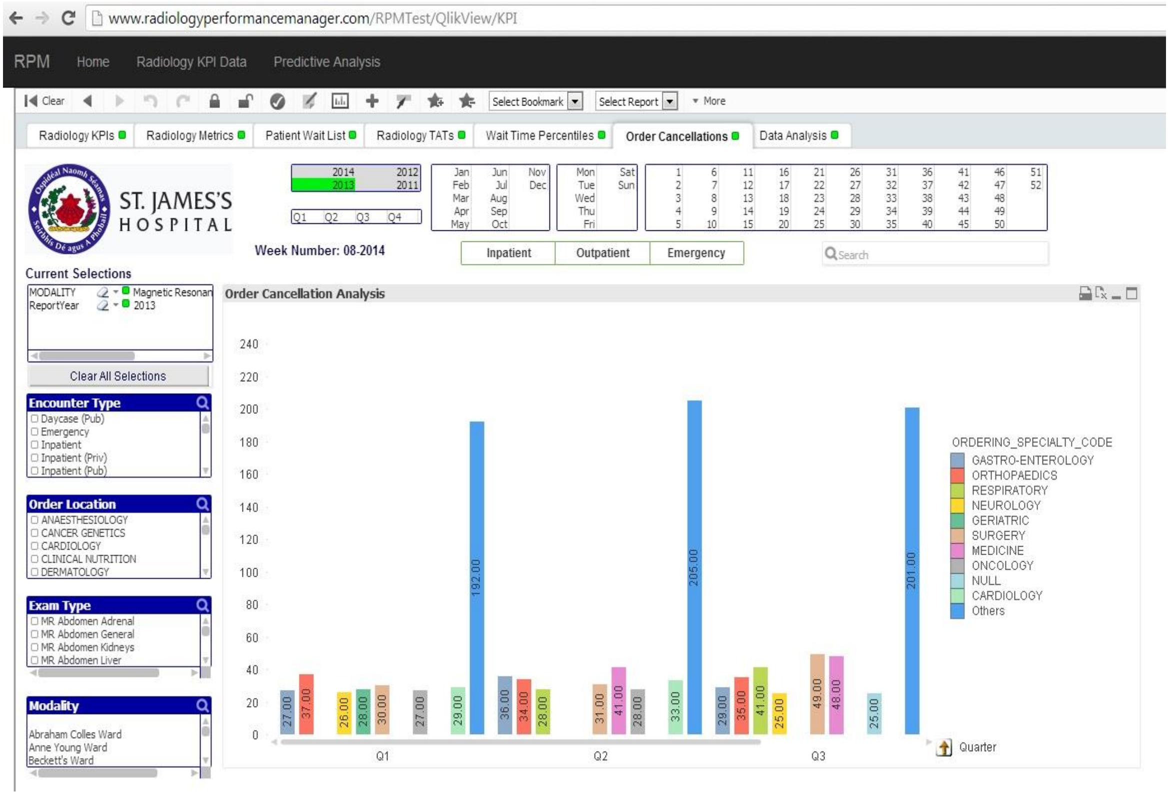


Figure E-8: KPI data model - Order cancellation analysis

E.1.3.7: Data Analysis

Analysis of the underlying data for any of the graphs on the KPI dashbaord is also provided, figure E-9. This allows users to display data to MRN number level for further analysis and reconciliation.

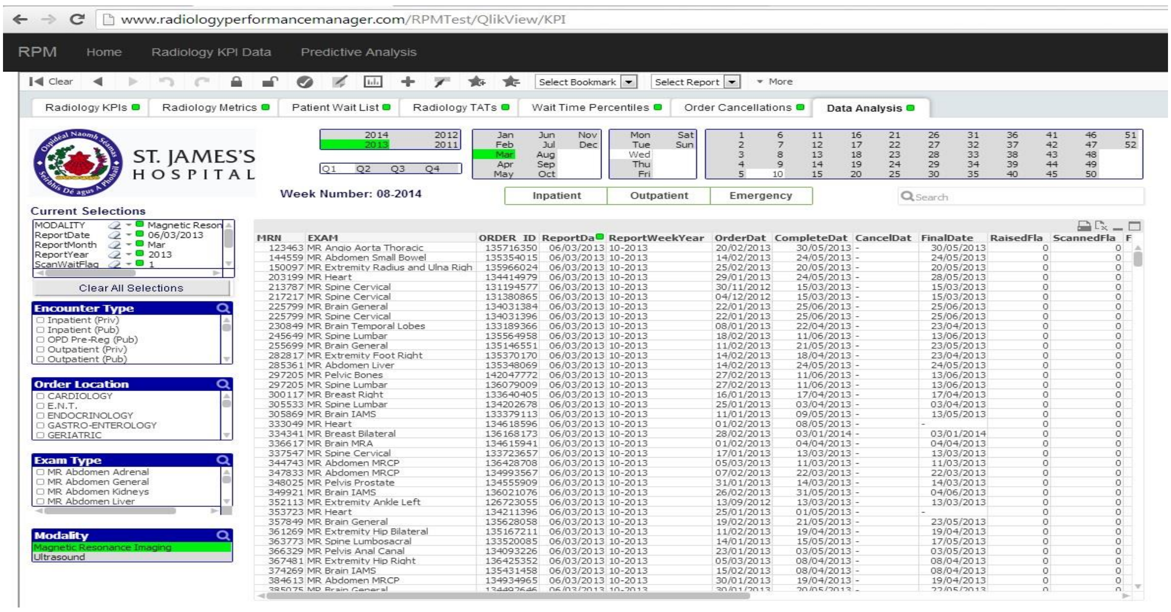


Figure E-9: KPI data model - Data analysis

E.2: KPM Predictive Scenario Functionality

The predictive module of the prototype application is accessed from the 'Predictive Analysis' option on the home page drop-down menu. The application is primarily built utilising MVC5 and C# and connects to a SQL Express database. The application uses information stored in the user defined predictive scenarios to update forecast data and Qlikview is then used to graph this data directly from the application database. A number of maintenance functions allow users to define modalities and predictive scenarios. A facility is also provided to import predictive forecast data as well as an option to generate a forecast based on scenario data.

As illustrated in the literature review there are a number of predictive application's implemented within the healthcare sector. Whilst many have implemented 'What-If' analysis, no evidence could be found of the usage of user defined predictive scenarios to forecast radiology demand and capacity data. Through RPM these scenarios facilitate flexible and powerful analysis of forecasted radiology demand and capacity data over a 52 week forecast window.

We will now examine each of the functions within the predictive scenario module.

E.2.1: Modalities

The modalities function, figure E-10, is accessed from the 'System Admin' drop down menu and allows maintenance of radiology modalities for inclusion for predictive scenario modelling.

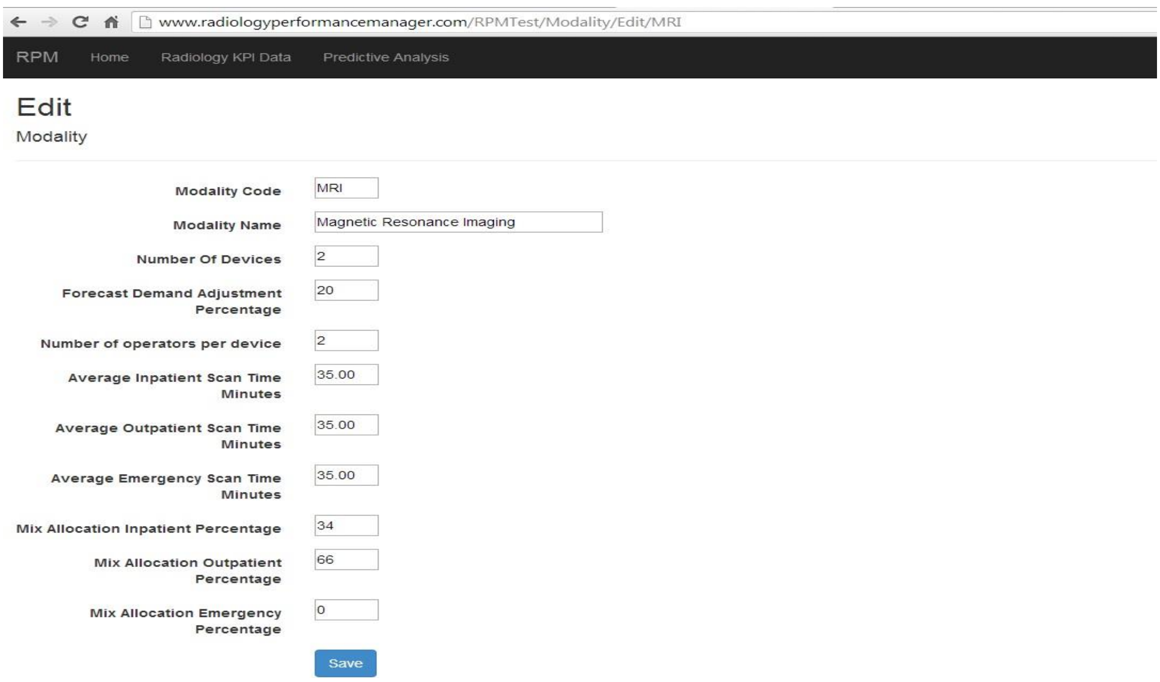


Figure E-10: Modality maintenance

Baseline demand and capacity data is also held at modality level and is used for generating business as usual forecasts. These are forecasts that are based on capacity data remaining as is plus no demand adjustments over the duration of the 12 month forecast window. Modality data fields are described in detail in table E-5.

Table E-5: Modality table data fields

Data Field	Description
Modality	A unique code identifying a modality
Modality Name	A description of the modality
Number of Devices	The number of devices available for this modality
Number of operators per device	The number of operators required to operate a device for this modality
Average scan time in minutes – inpatient	The average scan time per individual inpatient scan for this modality
Average scan time in minutes – outpatient	The average scan time per individual outpatient scan for this modality
Average scan time in minutes – emergency	The average scan time per individual emergency scan for this modality
Mix allocation inpatient percentage	The percentage of total capacity available for this modality to be allocated to Inpatient scans
Mix allocation outpatient percentage	The percentage of total capacity available for this modality to be allocated to Inpatient scans
Mix allocation emergency percentage	The percentage of total capacity available for this modality to be allocated to Emergency scans

Accuracy of average scan times is essential to calculating total available capacity. Significant time and effort was spent by staff in the radiology department at the study site to ensure that these values were correct.

E.2.2: Predictive Scenarios

The predictive scenario function allows the set up and maintenance of user-defined scenarios that can be used to generate forecast demand and capacity data. The function can be accessed from the 'System Admin' drop down menu on the home page. Predictive scenarios are initially created for a specific modality (see figure E-11) after which specific adjustments can be entered against the scenario.

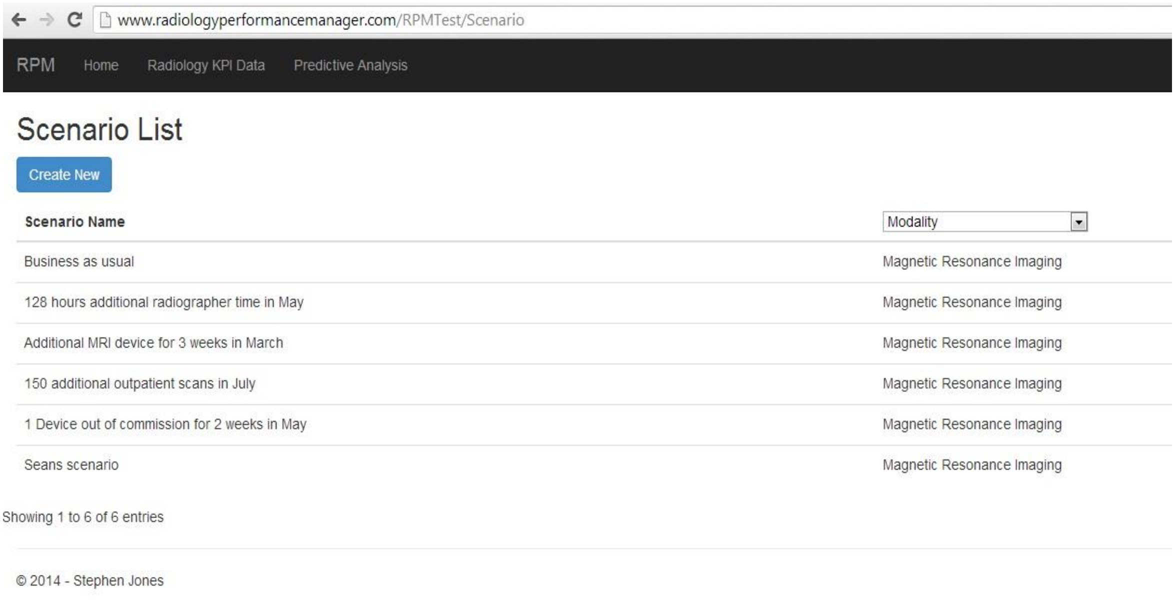


Figure E-11: Predictive scenario filter list

Adjustments are entered for specific weeks across the forecast window, see figure E-12. There is no restriction on the number of scenarios that can be created and a modality selection filter is provided to select scenarios for a specified modality. Table E-6 describes scenario adjustment data fields in detail as well as their corresponding adjustment types.

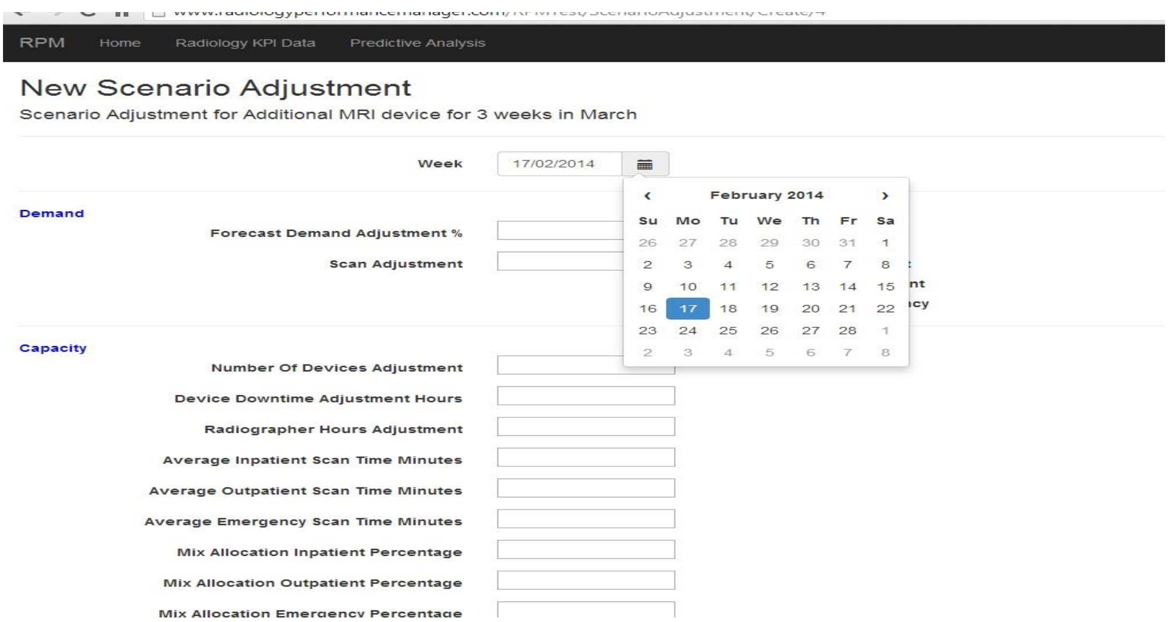


Figure E-12: Predictive scenario adjustments

When a forecast is generated within the application, an individual forecast is created for each predictive scenario for each encounter type (Inpatient, Outpatient and Emergency). Baseline values (from the scenarios modality data) are used during scenario forecast creation however for each adjustment created against a scenario, see figure E-12, the adjustment data values are used to override the baseline values. Each forecast scenario can be thought of as a baseline forecast plus or minus all of the scenario's adjustments.

Table E-6: Predictive scenario adjustment data fields

Data Field	Description	Adjustment Type
Week number	Week number the adjustment is to be entered for	N/A
Demand adjustment %	The demand adjustment % used for determining forecast demand data. Typically year on year demand would increase at a set level, this field allows control of the adjustment with plus or minus % values.	Demand
Scan adjustment	This allows entry of a number of scans to be included in the forecast demand data. For example the radiology department may wish to take an order for 100 additional outpatient scans from another hospital. A number of scans can be entered and an encounter type (inpatient, outpatient or emergency) must also be specified.	Demand
Number of devices	A facility to enter an increase or decrease in the number of available devices for the scenarios modality.	Capacity
Device downtime	Device downtime hours allow entry of a number of hours that devices are unavailable for the scenarios modality. This caters for device maintenance down as well as out of commission time.	Capacity
Radiographer hours	This allows the entry of an increase or decrease in radiology hours for the selected scenario. This could be used to model the impact of additional radiographer hours over weekends or maternity/paternity leave.	Capacity
Average scan time in minutes – inpatient	This provides a facility to override the baseline average scan time per individual inpatient scan as entered at modality level. This allows modelling of an increase or decrease in average scan time.	Capacity
Average scan time in minutes – outpatient	This provides a facility to override the baseline average scan time per individual outpatient scan as entered at modality level. This allows modelling of an increase or decrease in average scan time.	Capacity
Average scan time in minutes – emergency	This provides a facility to override the baseline average scan time per individual emergency scan as entered at modality level. This allows modelling of an increase or decrease in average scan time.	Capacity

Mix allocation inpatient percentage	This provides a facility to override the baseline mix allocation inpatient percentage as entered at modality level. This can be used to model adjustments to standard mix allocation percentages.	Capacity
Mix allocation outpatient percentage	This provides a facility to override the baseline mix allocation outpatient percentage as entered at modality level. This can be used to model adjustments to standard mix allocation percentages.	Capacity
Mix allocation emergency percentage	This provides a facility to override the baseline mix allocation emergency percentage as entered at modality level. This can be used to model adjustments to standard mix allocation percentages.	Capacity

E.2.3: Predictive Data Import Process

Forecasting of demand data, from the forecast commencement date, is based on the previous 12 months actual order data. As a result it is necessary to keep a table of data used for forecasting demand. An import file function is provided from the 'System Admin' drop down menu whereby the user can select the Excel file to be used for the forecast data. The file imported is in the same format as the order import table, see table E-1.

Typically this functionality would be performed automatically at agreed intervals. As a result, provision has been made for an automated import process on a nightly basis.

E.2.4: Generate Forecast

The 'Generate Forecast' function is the heart of the predictive analysis module. It consolidates all of the entered modality and predictive scenario data in order to derive forecasted demand, capacity and backlog data at scenario/encounter type level. Figure 5-3 gives a design overview of the predictive analysis functionality. The function can be accessed from the 'System Admin' drop down menu on the home page.

For each scenario on the predictive scenario table, a forecast is generated at inpatient, outpatient and emergency level. The forecast table generated (see figure 5-4 for an entity relationship diagram and detailed table layout information) holds data at scenario/week number level, in both scans and hours, as follows:

- Backlog Opening Balance – For forecast week 1 this is calculated as all orders, as of today, that are on the system and not yet scanned or cancelled. For all other weeks it contains the previous weeks closing balance.

- Forecast Demand – The demand based on last year's demand for the same week number (taking a 28 day weekly average) plus any demand adjustments.
- Forecast Capacity – The capacity based on the radiology department's current resources (number of devices on modality table by the number of standard working hours per week) plus any capacity adjustments.
- Backlog Closing Balance – This is calculated as backlog opening balance plus forecast demand minus forecast capacity. Where backlog closing balance is negative it is set to zero as unused capacity for a specific week cannot be carried forward.

E.2.4.1: Forecast Demand and Capacity Algorithm

The forecast generation process applies a number of business rules in order to determine forecast demand and capacity. For each predictive scenario forecast being generated, forecast demand and forecast capacity data for each week of the 52 week forecast window is calculated as follows:

1) <u>Determine forecast demand</u>

   - Calculate demand based on week number

     - For forecast week 1 total all scans, as of today, that are on the system and not yet scanned or cancelled. Determine day of week and forecast from this day to end of week (based on a 5 day working week) excluding cancelled orders.
     - For all other weeks get the corresponding week commencement date from last year, total all scans not cancelled for the next 28 days and divide total by 4 to get a weekly average.

   - Apply all scenario demand adjustments in scans for the week being processed (see table E-6).
   - Convert demand scans to hours using average scan time (if adjustment average scan time entered for week number being processed then use this otherwise use average scan time for the modality).

2) <u>Determine forecast capacity</u>

   - Retrieve standard working hours per week from system parameters table

- Calculate standard weekly capacity in hours (calculated as standard working hours per week multiplied by the number of devices available for the scenarios modality as per the modality table)
- Apply all scenario capacity adjustments in hours for week being processed (see table E-6).
- Convert capacity hours to scans using average scan time (if adjustment average scan time is entered for week number being processed then use this otherwise use average scan time for the modality)
- Apply mix percentage for the encounter type (if adjustment mix % is entered for week number being processed then use this otherwise use mix % for the modality)

E.2.5: Dashboard Template

In order to visualise the forecast data, a second standard screen template was designed for use by each screen within the predictive analysis dashboard. Again, the template contained all of the various requested selection criteria. The template differed from the KPI model template in that there was a much reduced set of selection criteria due to forecast data being at a higher level.

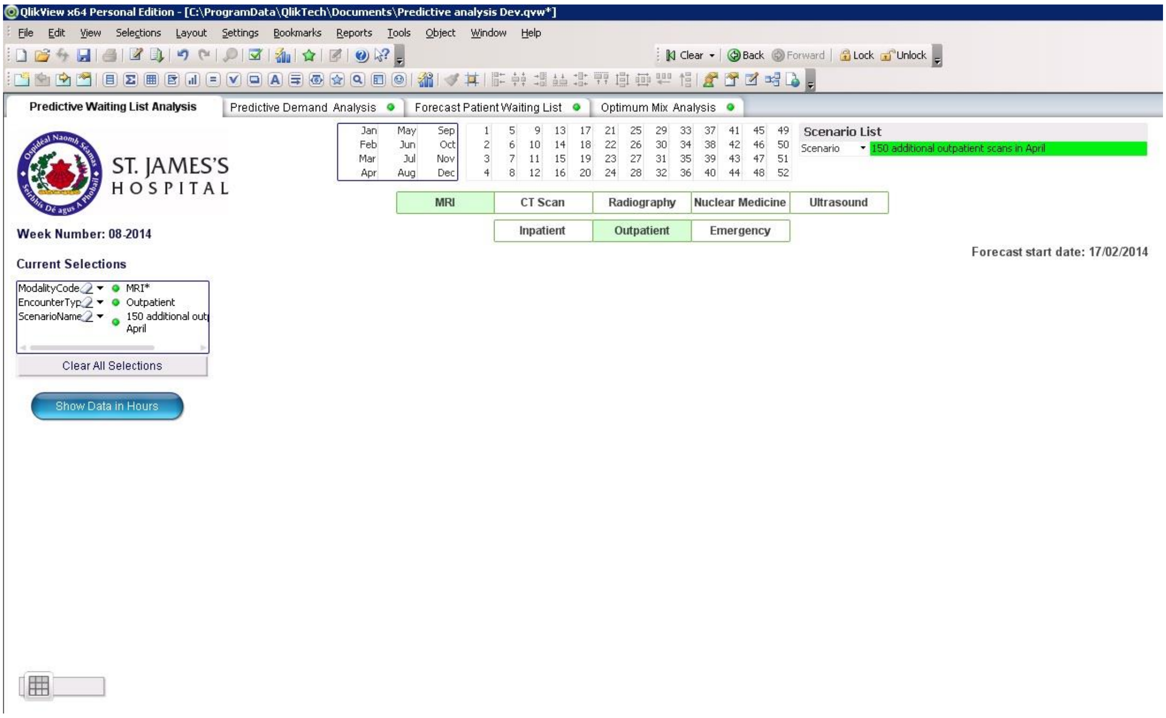


Figure E-13: Predictive analysis model template screen

Figure E-13 illustrates all of the various selection criteria. An additional drop down list box was included to allow selection of a specific scenario to display associated forecast data. Any combination of selection criteria is permitted within the data model.

E.2.6: Predictive Analysis Dashboard

Once the forecast has been generated, the data from the forecast table (see figure 5-4 for a table layout) is loaded into the predictive Qlikview model through execution of a Qlikview script. Once the data is loaded, it is visualised using a dashboard containing multiple tabs to display the various sets of predictive data. The next four sections will discuss each of the predictive analysis graphs in more detail.

E.2.6.1: Predictive Waiting List Analysis

This screen displays a graph of forecasted backlog for a selected scenario and compares this to a business as usual scenario. The business as usual scenario is a forecast of backlog based on current radiology capacity and standard demand, i.e. no demand or capacity adjustments applied.

The information is visualised utilising a line chart and a button allows display of the graph data in either hours or scans. Selections are based on the dashboard template layout. The business as usual scenario is always displayed (blue line) whilst a drop down list box allows selection of a specific scenario (red line), this is loaded from the scenario table discussed in section E.2.2, for comparison analysis. In figure E-14 a scenario is selected for a device out of commission for two weeks in May, this is then displayed alongside the business as usual scenario. As illustrated we can see the impact of this scenario through a divergence between the two scenarios in May, the device downtime results in an increase in backlog through to the end of the forecast year.

This data can further analysed to encounter type level (inpatient, outpatient or emergency) and a button allows the user to switch the graph data from backlog in hours to backlog in scans. A toggle button at the bottom right of the screen also allows drill up/down analysis of the data to week number/month level.

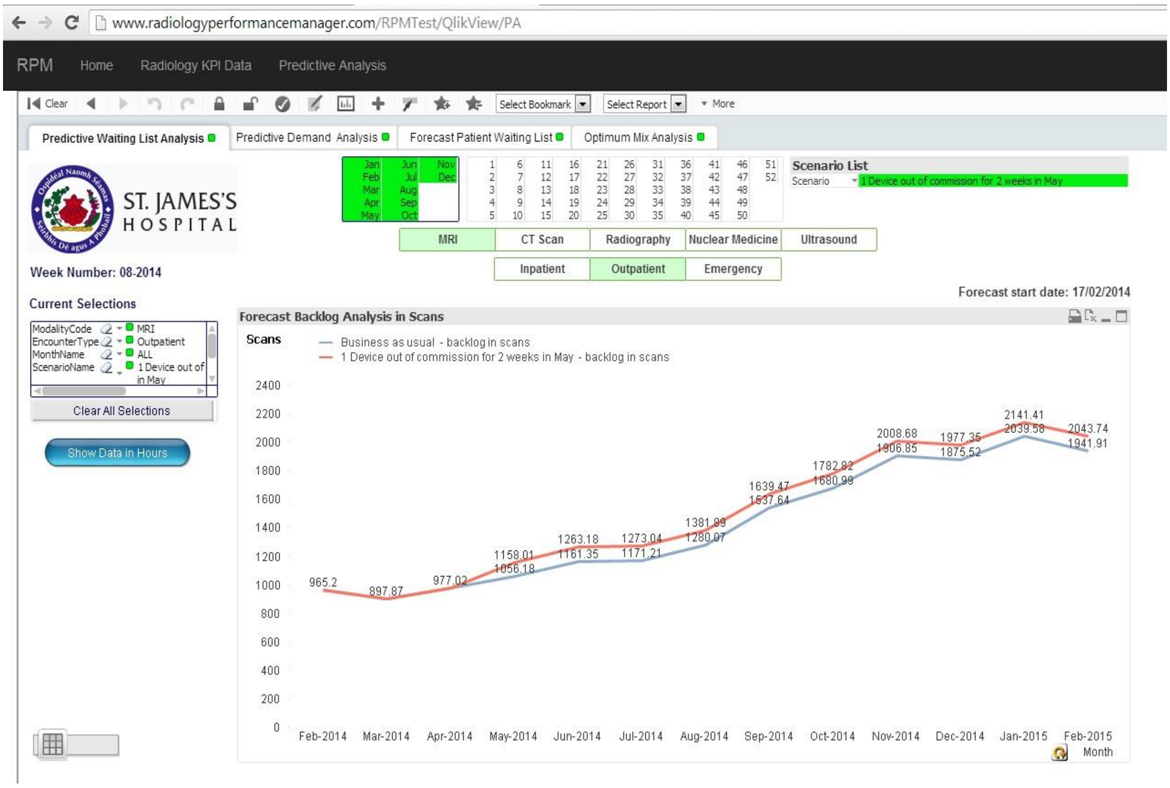


Figure E-14: Predictive model - Waiting list analysis

E.2.6.2: Predictive Demand Analysis

This bar graph, figure E-15, allows analysis of forecasted demand for a single selected scenario and displays the calculated forecasted demand at month level. Again, a button allows users to toggle demand analysis between hours and scans and a button at the bottom right of the screen allows drill up/down analysis to week number/month level. Forecast demand can be further analysed to encounter type level. This chart provides useful analysis of peaks and troughs in radiology demand over the coming 12 month period.

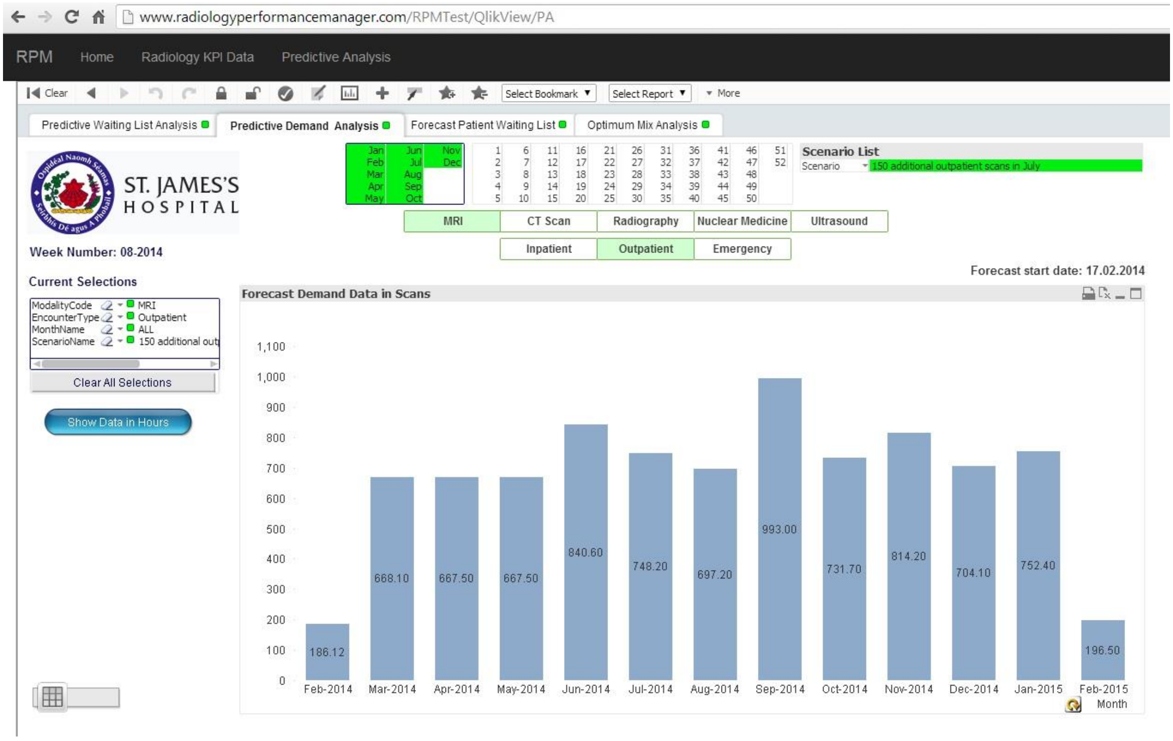


Figure E-15: Predictive model - Forecast demand

E.2.6.3: Forecast Patient Waiting List

This tab displays the forecasted patient waiting list, figure E-16, for both inpatient and outpatient based on a selected scenario. Analysis is provided to week number level and a scenario can be selected. A bar graph is used to visualise inpatient and outpatient data side by side.

Figure E-16: Predictive Model - Forecast patient waiting list

The graph displays expected trends in patient wait times for the coming year based on the selected scenarios forecast demand and capacity data.

E.2.6.4: Forecast Optimum Mix Analysis

This tab displays a bar graph with forecasted optimum mix percentages for both inpatients and outpatients for the selected scenario. Both encounter types are displayed side by side for comparison purposes and mix percentage is calculated based on the available forecast capacity for the specific week.

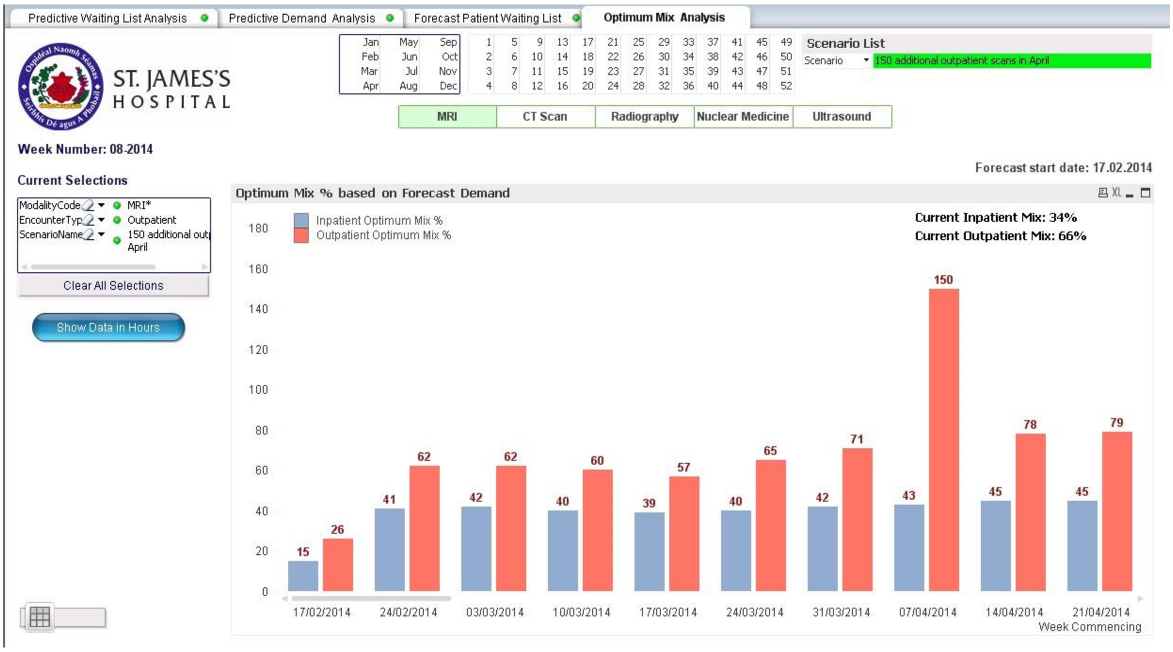


Figure E-17: Predictive Model - Forecast optimum mix analysis

Taking week commencing 24th February 2014 as an example, the graph in figure E-17 is stating that based on the available forecast capacity for that week, 41% of total available capacity is required to address forecast inpatient demand. Similarly, a 62% allocation of forecasted capacity will be required to meet forecasted outpatient demand. We can also see the spike in outpatient capacity required for week commencing 17th April as a result of 150 additional outpatient scans being added per the selected scenario (top right of screen). Whilst these figures are an indicative forecast the graph does help give a sense for the mix allocation required going forward. The ability to model mix allocation scenarios (by adjusting the mix allocation percentage) allows for analysis of various combinations of inpatient and outpatient capacity allocation.

Appendix F – IPEM Conference

F.1: IPEM Conference Submission Abstract

A BUSINESS ANALYTICS SOFTWARE TOOL FOR MONITORING AND PREDICTING RADIOLOGY THROUGHPUT PERFORMANCE

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Background: A primary cause for the build-up of patient wait times in radiology departments is a mismatch between capacity and demand. Lack of understanding of this mismatch as well as inefficient management of radiology resources contributes to inadequate capacity planning [5]. Business Intelligence (BI) software systems combine data gathering, storage and knowledge management with analytical software tools that analyse and present complex data to planners and decision makers [3]. Business Analytics (BA) also encompasses statistical analysis, predictive modelling and forecasting systems and is used as an umbrella term for decision support and Business Intelligence systems [1]. BA functionality is being utilised as a driver for decision support based on past performance [2,4]; however, there is little evidence of the utilisation of future predictive analysis to drive decision making in radiology departments. The objective of the study was to implement a software tool combining data from the Electronic Patient Record (EPR), Radiology Information System (RIS) and Picture Archiving and Communications System (PACS) in order to display existing radiology Key Performance Indicators (KPIs) and provide functionality that allows the forecasting and modelling of future demand and capacity data through predictive scenarios.

Methods: MRI, US and CT time (times of orders raised, cancelled, completed and finalised) and patient data (Modality, encounter type, speciality) from January 2010 to February 2014 was extracted from the EPR, RIS and PACS and imported into Qlikview, a commercially available BA software package. Radiology KPIs including patient waiting lists, backlog and 90th, 75th and 50th percentile turnaround times were calculated and visualised via a specially designed dashboard. Bespoke functionality allowed the entry of various radiology predictive scenarios. Predictive demand and capacity data was then generated based on the inputted scenario data and visualised utilising the Qlikview software tool.

Results: Historic and current KPI data provides the information necessary to analyse radiology patterns and trends. Predictive analysis via user-defined scenarios can be used to visualise future demand and capacity data as well as calculating optimum mix of inpatient versus outpatient capacity allocation.

Conclusion: BA software tools combined with bespoke software applications can provide visibility of radiology data across all time horizons. Historic data provides retrospective analysis which can be used to inform and create predictive scenarios. These scenarios can then be utilised to generate and visualise future predictive demand and capacity data enabling proactive decision support to deliver improved operational efficiencies within radiology departments.

Key references:

[1] Cosic et al. *Proceedings of the 23rd Australasian Conf. on Information Systems 2012*. 1–11.
[2] Nagy et al. *Radiographics*. 29, 7 (2009), 1897–1906.
[3] Negash *Communications of the Association for Information Systems*. 13, 1 (2004), 177–195.
[4] Prevedello et al. *Journal of Digital Imaging*. 23, 2 (2010), 133–141.
[5] Silvester et al. *Clinician in Management*. 12, 3 (2004), 105–111.

F.2: IPEM 'Workflow: It's not just DICOM' Conference Proceedings

IPEM conferences

WORKFLOW: IT'S NOT JUST DICOM

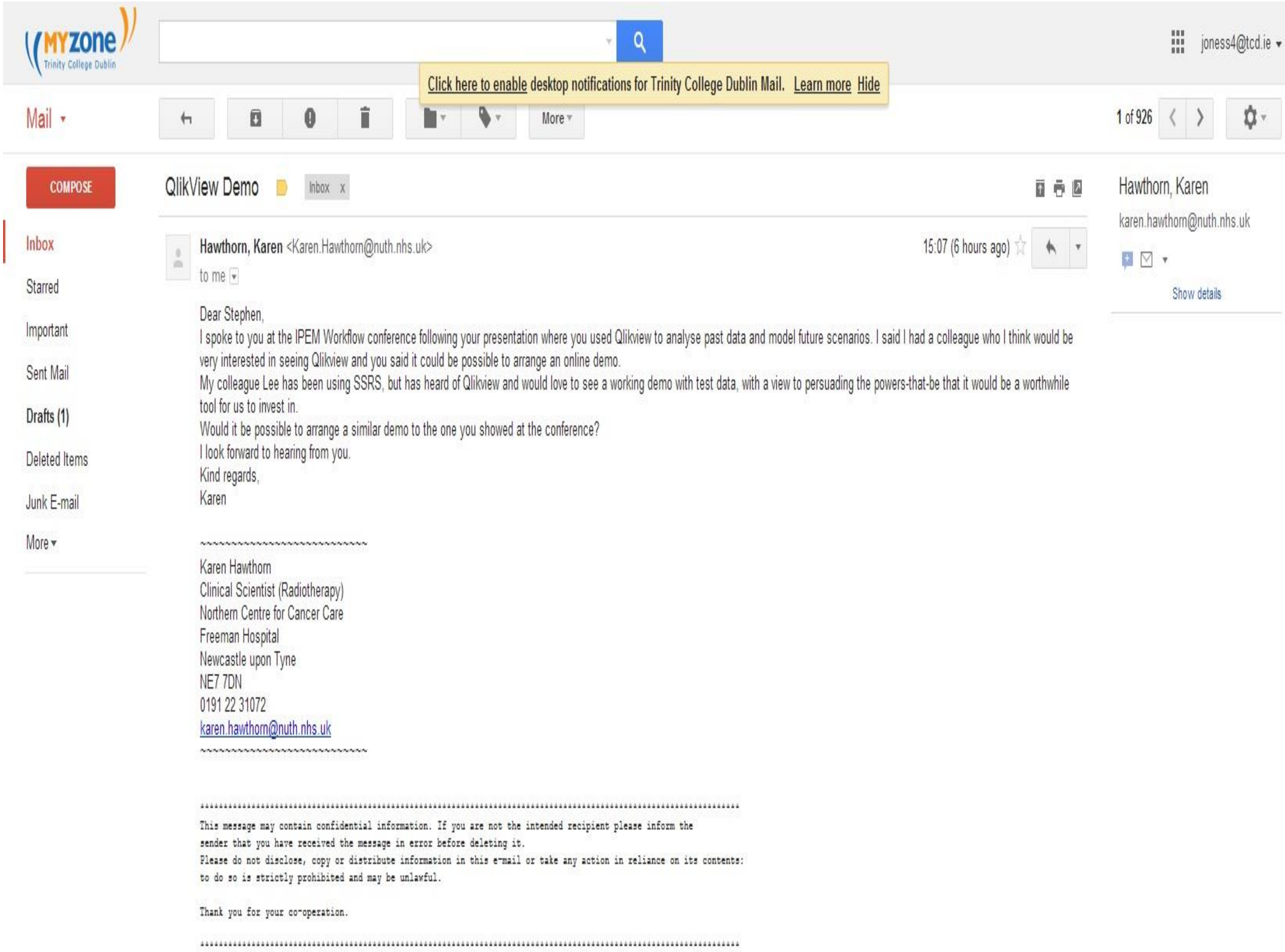
Monday 28th April 2014, London

PROVISIONAL PROGRAMME

09:00 – 09:55	**Coffee and registration**
09:55 – 10:00	**Introduction**
	Chair: Patrick Downes
10:00 – 10:30	**What is IHE and what's its role in modern healthcare?** Invited Speaker: Niall Monaghan, Radiation Consultancy Services Ltd
10:30 – 10:50	**A business analytics software tool for monitoring and predicting radiology throughput performance** Stephen Jones, Trinity College Dublin
10:50 – 11:20	**Coffee**
	Chair: Padraig Looney
11:20 – 11:40	**Collation and presentation of multi-source clinical data to inform and support the radiation oncology service** Bob Wheller, Leeds Teaching Hospitals NHS Trust
11:40 – 12:00	**Development of a pre-treatment worklist, to fit in with current clinical practice** Martin Green, The Clatterbridge Cancer Centre
12:00 – 12:20	**Software for the multidisciplinary management of breast cancer; a private sector perspective** Tim Cross, HCA International
12:20 – 12:30	**Questions**
12:30 – 13:30	**Lunch**
	Chair: Patrick Downes
13:30 – 13:50	**Clinical decision support systems: a consistent way to guide the prescription of care or, like a 'broken clock', only right twice a day** Steve Lake, Royal Liverpool & Broadgreen University Hospitals NHS Trust
13:50 – 14:10	**Electronic check-in and process workflow for outpatient clinics** David Jones, Sheffield Teaching Hospitals
14:10 – 14:30	**On the development of an electronic patient referral system for radiotherapy** David Spendley, Brighton and Sussex University Hospitals NHS Trust
14:30 – 14:50	**Questions**
14:50 – 15:15	**Coffee**
	Chair: Padraig Looney
15:15 – 15:35	**Combining different hospital system datasets to examine the influence of MRI inpatient turnaround times on outcome and hospital length of stay** Sean Cournane, St. James's Hospital, Dublin
15:35 – 15:50	**Siemens CT scanner workflow** Patrick Downes, Velindre Cancer Centre, Cardiff
15:50 – 16:20	**Questions/discussion**
16:20	**Close**

Organised by the IPEM Informatics & Computing Special Interest Group

F.3: IPEM Feedback



QlikView Demo

Hawthorn, Karen <Karen.Hawthorn@nuth.nhs.uk>
to me

15:07 (6 hours ago)

Dear Stephen,
I spoke to you at the IPEM Workflow conference following your presentation where you used Qlikview to analyse past data and model future scenarios. I said I had a colleague who I think would be very interested in seeing Qlikview and you said it could be possible to arrange an online demo.
My colleague Lee has been using SSRS, but has heard of Qlikview and would love to see a working demo with test data, with a view to persuading the powers-that-be that it would be a worthwhile tool for us to invest in.
Would it be possible to arrange a similar demo to the one you showed at the conference?
I look forward to hearing from you.
Kind regards,
Karen

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Thank you for your co-operation.