Using Economic Evaluation and Preference Elicitation Methods to Inform Decisions about How Best to Reorganise Services: A Case Study of the Redesign of Emergency Medical Services

A thesis submitted for the degree of Doctor of Philosophy

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August 2018

Abstract

The aim of this thesis was to evaluate the centralisation of emergency medical services (EMS) in different local hospitals into a single specialised emergency care hospital in terms of costs and quality of care. It also aimed to investigate preferences and trade-offs that individuals' were willing to make to receive treatment at the centralised specialised emergency hospital.

The economic evaluation method builds upon a systematic review of economic evaluation methods and types of economic evaluation that have been used to assess the performance of centralised healthcare specialities.

A discrete choice experiment (DCE) was used to investigate preferences for centralised EMS and the trade-offs individuals were willing to make to receive treatment at the centralised hospital. The DCE identified preferences for: shorter travel times to the hospital; shorter waiting times; fewer days in hospital; low risk of death; low risk of readmission; and outpatient follow-up care in local hospitals. However, people were willing to trade-off increased travel time and waiting time for higher quality of specialised emergency medical care in the centralised hospital.

A Markov model was developed to evaluate the costs and effectiveness of centralisation of EMS compared with non-centralised care. Multiple sensitivity analyses were carried out to assess whether centralisation had an impact on cost, quality and cost-effectiveness over the short and longer term. The incremental cost per QALY at one year (deterministic estimate £1,004 per QALY) and 10 years (deterministic estimate £636 per QALY) were both well below the threshold used by the National Institute for Health and Care Health Excellence (£20,000-£30,000 per QALY). There were fewer deaths in the centralised EMS compared with non-centralised services (deterministic estimate: 31.47 fewer deaths at 1 year, 31.57 fewer deaths at 10 years). Discounting the costs and outcomes at different rates did not alter conclusions.

The economic evaluation suggested that centralisation of EMS into fewer more specialised units could be cost-effective, although cost-effectiveness may vary in specific population sub-groups. Sub-group analyses suggest that centralised EMS would be more cost-effective for elderly patients, the most economically deprived patients and those presenting with diseases of the circulatory system. These findings

support the recommendations to centralise urgent and EMS in England. However, a cost benefit analysis that incorporated the results of the DCE into the economic evaluation suggested that centralised EMS could have negative societal value when compared with services provided in local hospitals.

The implications of these findings, potential limitations of the methods used in this thesis and recommendations for future research are discussed.

Acknowledgements

I would like to thank my supervisors Professor Luke Vale, Dr Peter McMeekin and Dr Chris Price for the valuable guidance throughout this PhD. I would particularly like to thank you Luke for spending several hours reading my thesis Chapters and extensively commenting on my work, even in the out of office hours and in the weekends. This thesis would not have completed without your support and encouragement; many thanks Luke.

I would like to thank Professor Helen Rodgers, Dr Laura Ternent and Dr Heather Brown for their roles as assessors.

I wish to acknowledge the funding support from the Health Foundation London to undertake this PhD project. I would also like to thank Healthwatch Northumberland and Northumbria Health Care NHS Foundation Trust for their help in running the surveys needed in this project.

I would like to thank my friend Vijay GC at The University of York for being there whenever I needed help in R scripts, especially while building up the economic evaluation model. Being at a similar stage in the PhD process meant that all the informal discussions with you were valuable.

I would like to thank members of the Health Economics Group for your help whenever needed and for creating a vibrant learning environment. Special thanks to Janice Legge for sorting out all the admin issues.

I would like to thank my parents and my grandmother for their unconditional support and encouragement throughout. I owe to my wife Muna for her encouragement, support and patience throughout this PhD without which I would have never completed this thesis. Last but not the least, my thanks and love to my son Yug for making me smile and giving me happiness after long and tiring days at work.

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Abbreviations

A&E	Accident and Emergency
ACA	Adaptive Conjoint Analysis
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BWS	Best Worst Scaling
CA	Conjoint Analysis
CBA	Cost Benefit Analysis
CCA	Cost-consequence Analysis
CEA	Cost-effectiveness Analysis
CEAC	Cost-effectiveness Acceptability Curve
CHEERS	Consolidated Health Economic Evaluation Reporting Standards
CUA	Cost-utility Analysis
CV	Contingent Valuation
DAM	Decision Analytic Modelling
DCE	Discrete Choice Experiment
DES	Discrete Event Simulation
EMBASE	Excerpta Medica Database
EMS	Emergency Medical Services
ENBS	Expected Net Benefit of Sampling
EVPI	Expected Value of Perfect Information
EVPPI	Expected Value of Perfect Parameter Information
EVSI	Expected Value of Sample Information
GDP	Gross Domestic Product
GMNL	Generalised Multinomial Logit

GP	General Practitioner
HEED	Health Economic Evaluation Database
HES	Hospital Episode Statistics
HRQoL	Health Related Quality of Life
ICD	International Classification of Disease
ICER	Incremental Cost-effectiveness Ratio
MNL	Multinomial Logit
MRS	Marginal Rates of Substitution
MWT	Marginal Willingness to Travel
MWW	Marginal Willingness to Wait
MXL	Mixed Multinomial Logit
NHCT	Northumbria Healthcare NHS Foundation Trust
NHS	National Health Services
NHS EED	NHS Economic Evaluation Database
NICE	National Institute for Health and Care Excellence
PhD	Doctor of Philosophy
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSA	Probabilistic sensitivity analysis
QALY	Quality Adjusted Life Year
RCT	Randomised Controlled Trial
RUT	Random Utility Theory
SG	Standard Gamble
TTO	Time Trade Off
UK	United Kingdom
US	United States

VAS	Visual Analogue Scale
VOI	Value of Information
WTA	Willingness to Accept
WTP	Willingness to Pay

Dissemination

Publications

The following publication is based on Chapter 2.

Bhattarai N,McMeekin P, Price C, et al.Economic evaluations on centralisation of specialised healthcare services: a systematic review of methods. BMJ Open 2016;6:e011214. doi:10.1136/bmjopen-2016-011214

Note: All authors conceived the study. The author of this thesis designed and executed the search strategy; reviewed and assessed the studies for inclusion; appraised and extracted information from the included studies; and wrote the manuscript for this systematic review. All other authors contributed to the critical revision of the manuscript and provided critical comments. All authors read and approved the final manuscript.

Poster Presentations

Bhattarai N, McMeekin P, Price C, Vale L. Eliciting public preferences for the provision of emergency medical care-a discrete choice experiment. European Health Economics Association (EuHEA) conference, July 2016, Hamburg, Germany

Note: All authors conceived the study. The author of this thesis designed and executed the discrete choice experiment survey; conducted the analysis and prepared the poster for presentation. The thesis supervisors contributed to the poster by providing critical comments.

Chapter 1. Introduction

1.1 Background

The National Health Services (NHS) was launched in 1948 with a fundamental principle that high quality health care should be available to all on the basis of clinical need and regardless of their ability to pay. Since its inception, it has provided universal health care services free at the point of use in the United Kingdom (UK), apart from some prescription fees in England and optical and dental services (National Health Services, 2016). The NHS has faced a rapid and consistent rise in the expenditure since it was launched. In 1948, the expenditure in NHS England was £437 million (today's value roughly equivalent to £15 billion) and by 2015/2016 it was around £116.4 billion (National Health Services, 2016). In 2017/2018 the spending was around £125 billion (Full Fact, 2018). The NHS faces increasing pressure because of the increasing demand for health care services. Increasing demand is mainly due to the increasing strain of the changing population profile, the rise of long-term chronic conditions and multimorbidity, increasing public/patient expectations, increasing costs of providing care and constrained financial and human resources. Taken together these pressure threaten the sustainability and financial stability of the NHS (NHS England, 2013c). The reasons driving the increasing demand for healthcare services in the NHS are described in the following sub-sections.

1.1.1 Changing population profile

The UK population was about 50 million (Office for National Statistics, 2014b) in the year 1948 when the NHS was launched and it now increased to about 66 million in 2017 (Office for National Statistics, 2018b) and projected to continue rising to 73.3 million by the year 2037 (Office for National Statistics, 2014a). Furthermore, the increasing ageing population aggravates the pressure on the NHS. There were nearly 12 million people aged 65 years and over (18.2% of the UK population) in 2017 (Office for National Statistics, 2018b). The ageing of the UK population is projected to continue over the next few decades, with the fastest population increases in the numbers of those aged 85 and over (Office for National Statistics, 2012). The population of those over 85 was estimated at 1.4 million in 2012 and is projected to be 3.1 million in 2032, more than doubling over a 20 year time period

(Office for National Statistics, 2014a). This growth has been the result of improved nutrition, housing, social welfare and health care services have meant that people are living longer than before and it is a matter to celebrate. However, an ageing population has implications in terms of demand and use of health and social care services. An analysis shows that in the past 20 years hospital admissions have increased much more rapidly in comparison to the increase in population and the increase is much higher and notable in those over 85 years (Ham *et al.*, 2012). Age is one of the important factors associated with the bed occupancy in hospital emergencies. Patients under the age of 65 use only about 0.2 hospital emergency bed days whereas those over 85 use more than 5 bed days in an average year (Imison *et al.*, 2012). The average length of stay of an emergency admission also varies with age. Older people are more likely to be ill and account for the majority of the inpatient admissions (Cornwell *et al.*, 2012) and tend to stay longer in hospitals. An analysis of 2009/2010 data shows that average length of stay was approximately 3 days in patients under 65 years of age, but 9 days for those above aged 65 and 11 days for those above age 85 (Imison *et al.*, 2012). These figures need to be interpreted with caution as it is not clear whether they were adjusted for severity of illness in the elderly. It is possible that the observed length of stay is due to the severity of illness with the increasing age, rather than age alone. Older patients are more likely to be readmitted to the hospital within month of discharge from the hospital and among the elderly the fastest rise in readmissions was observed in people older than 75 years in the past 20 years (Cornwell *et al.*, 2012). In 2009-2010, emergency readmissions to hospital within 28 days of discharge from hospital were 5.1% higher for people over 75 when compared to those between 16-74 years of age (Lawrie and Battye, 2012). In the decade between 2000/2001 and 2009/2010, emergency readmissions within 28 days of discharge from hospital rose 3.9% for people over 75 years compared to 2.5% in those in 16-74 age group (Lawrie and Battye, 2012). However, as statistical tests were not conducted it is unclear if this is a real difference or just an artefact of the data (Lawrie and Battye, 2012).

1.1.2 Long-term chronic conditions and multi-morbidity

Multi-morbidity increases substantially with age (Barnett *et al.*, 2012). In England, 14 % of the population under 40 years of age report having a long-term condition whereas 58% of those aged 60 and over report having a long-term condition, with

25% of over 60 years having two or more long-term conditions which include heart disease, stroke, cancer, diabetes, arthritis, and or dementia (Department of Health, 2012; Melzer *et al.*, May 2012, selected graphs updated August 2013). People with long-term conditions are extensive users of health care services and the average health care costs incurred by those with long-term conditions are much higher than those without (Department of Health, 2012). Among those with long-term conditions, patients with more than one long-term conditions have more health care needs and cost more than those with single conditions (Department of Health, 2012). The population of patients with multiple long-term conditions was 1.9 million in 2008 and was predicted to rise to 2.9 million in 2018 (Department of Health, 2012). Dementia often complicates multimorbidity and it is estimated to incur more costs than the combined costs of heart disease, stroke and cancer (Oliver *et al.*, 2014) and costs associated with dementia are far higher than costs of all other mental health conditions put together (McCrone *et al.*, 2008). Dementia is increasingly common in old age. There were 815,827 people with dementia in the UK in 2013; a majority of them (773,502 people) were over 65 years of age (Prince *et al.*, 2014). By 2025, the number of population with dementia in the UK is forecast to be 1,142,677; a 40% increase from 2013 (Prince *et al.*, 2014). The estimated cost of dementia to the English NHS, local authorities and families in 2014 was £26.3 billion a year , which is set to rise with the increase in dementia in the ageing population (Prince *et al.*, 2014).

1.1.3 Increasing costs and public expectations

Development of new and more sophisticated technologies and extensive treatment procedures that could ever have been expected when the NHS was first launched is another reason behind increasing costs of the health care service (NHS England, 2013c). New technologies and treatment methods which cost more and are hopefully more effective, are replacing the older and (hopefully) less effective ones. Increasing health seeking behaviour and changing public expectation may also be influence in the increase in healthcare demand and costs. The NHS is struggling to match the supply of funding with the increasing health care demand (NHS Confederation, 2013b), indeed since its inception, costs in healthcare have increased at a higher rate than the costs in the economy and spending in the NHS has outpaced the growth in gross domestic product (GDP) (Appleby, 2013). An analysis by NHS England predicts that continuing with the current model of health care will lead to a

funding gap of around thirty billion pounds between 2013/2014 and 2020/21 in England (NHS England, 2013c).

1.1.4 Human resource constraint

The increasingly constrained human resources is another issue pressurising the NHS. The European Working Time Directives has restricted the maximum hours that doctors and trainee doctors are allowed to work to 48 hours a week, unless the individual opts out (Independent working time regulations taskforce, 2014). While this time restriction has beneficial impact on patient safety by preventing doctors from working long hours, it has stretched the already limited number of human resources in the NHS (Institute for Public Policy Research, 2006). The reduction in hours that doctors' work comes at a time when healthcare demand is continuously increasing and this has further exacerbated the human resource constraint in certain specialities. The presence of consultants in the specialised acute services is vital for the delivery of high quality care and efficient processes (Geelhoed and Geelhoed, 2008; White *et al.*, 2010; Fielding *et al.*, 2013), however there is a growing concern about the number of consultants available (College of Emergency Medicine, 2010; Higginson *et al.*, 2013). The number of doctors choosing to specialise in emergency medicine has been insufficient to meet the growing need as assessed by NHS England and this poses a serious threat in future supply of consultants in emergency medicine and the sustainability of emergency care (NHS England, 2013b). The current staffing levels in most of the emergency department in England are not considered adequate (Higginson *et al.*, 2013) and as of 2010 estimates, the total number of whole time equivalent emergency medicine consultants available in England were 852, which was far less than the required 2222 for the Emergency Department attendance levels then (College of Emergency Medicine, 2010). This shows a clear shortage of consultants, which may compromise the ability to provide high quality care and maintain the safety of patients. Shortage of consultants in the emergency departments across UK has led to the increasingly heavy reliance on locum doctors (Hassan *et al.*, 2013), which in turn has increased expenditure despite other pressures on the NHS to reduce the costs (HCL Workforce Solutions, 2013). It will be harder for small and rural hospitals to recruit and retain enough emergency consultants providing round the clock acute care services and expensive locum cover will result in severe financial implications (NHS Confederation, 2013a).

1.2 Centralisation of Specialised Health Services

Over the past decade, the benefits of reconfiguration of certain specialised health services in the NHS have been a subject of debate (Meadows *et al.*, 2011). There is increasing evidence that centralisation offers the opportunity to make more intensive use of the services, which may offer economies and provide one stimulus to quality by concentrating and enhancing expertise. Simpson and colleagues report the increased quality of outcomes in terms of improved services, increase specialist presence and speedy access to the hospital beds for the seriously ill and injured patients after the centralisation of accident and emergency departments of three different hospitals (Simpson *et al.*, 2001). Lord Darzi's report recommended reorganisation of stroke and major trauma services in London into specialised services centralised in fewer high volume units catering to large populations with high-tech facilities and comprehensive consultant presence (Darzi, 2007). Lord Darzi's and The National Stroke Strategy (Department of Health, 2007) recommendations led to the publication of London specific stroke strategy (Healthcare for London, 2008), which made the most significant recommendation to consolidate of stroke services into fewer specialised units to provide high quality stroke care and better patient outcomes. A study which assessed and compared the costs and outcomes before and after consolidation of stroke services in London, concluded that consolidating acute stroke services into fewer specialised units improves clinical outcomes while also being cost-effective (Hunter *et al.*, 2013). Another model based study showed that redirection of stroke patients away from localised acute services to regional services improved outcome with small additional costs (McMeekin *et al.*, 2013). A recent study investigating the impact of centralising acute stroke services in English metropolitan areas concluded that centralisation can reduce mortality and length of hospital stay (Morris *et al.*, 2014). There is also an increasing evidence of improved outcomes achieved by the centralisation and increased volume of specific specialised healthcare services such as cleft care (Fitzsimons *et al.*, 2012), cancer care (van Gijn *et al.*, 2010; Woo *et al.*, 2012; Brusselaers *et al.*, 2014; Ravi *et al.*, 2014), cardiovascular care (Fosbol *et al.*, 2013), vascular surgery (Holt *et al.*, 2007; Young *et al.*) and major trauma care (Gabbe *et al.*, 2012; Metcalfe *et al.*, 2014), showing a link between the volume of activity and the clinical outcomes. Evidence also supports that integrating emergency care services within departments of the same hospital also results in reduced mortality and better quality of care (Boyle *et al.*, 2012).

While the study on consolidation of stroke services in London (Hunter *et al.*, 2013) was of good overall quality, it does not mention whether it considered the viability of local hospitals after removal of acute stroke services. There are increasing concerns that centralisation will threaten the viability of local hospitals because of the reduced volume of patients' attendance when some specialised services are moved away. Studies (McMeekin *et al.*, 2013; Morris *et al.*, 2014) show improved outcomes however, it should be noted that spillovers (effects of an intervention on population other than those targeted), possibly because of increased patients to the specialised centralised hospital from the surrounding areas, who would otherwise have been treated in their own local hospitals, may have biased the results in favour of centralisation.

While evidence demonstrates better outcomes and economic benefits (Hunter *et al.*, 2013; Eichler *et al.*, 2014) of reorganisation of hospitals or specialities, there are also some concerns whether centralisation offers economies of scale and whether it is cost-effective (Ke *et al.*, 2012). Another important concern is the impact of centralisation on access to healthcare services. Healthcare services may be less accessible and may reduce quality of health outcomes as journey time increases after centralisation (Kelly *et al.*, 2016). Specialised emergency centres may not be closer to peoples home and the better quality and specialised health care services may come only at the cost of increased travel times to the point of care. Populations living in rural areas already have poor access to the healthcare compared to those living in urban areas and there are concerns that centralisation may only benefit the urban majority and will further widen the urban-rural inequality of healthcare access (Baird and Wright, 2006). Increases in journey distances between home and hospital where the patient is admitted may also be associated with increased mortality (Nicholl *et al.*, 2007; Wei *et al.*, 2008). It is suggested that an increase of 10km in straight-line distance is associated with around one percent absolute increase in mortality (Nicholl *et al.*, 2007). However, this may not always be the case. A study found that longer distances arising out of hospital centralisation were not associated with increased inpatient mortality in a range of time-sensitive conditions (Hsia *et al.*, 2012). In the UK, a vast majority of population live within 20km of their nearest Accident and Emergency (A&E); closing or downgrading the A&E in some cases will double the distance from home to hospital for emergency admissions and this may

have a large impact on local population (Roberts *et al.*, 2014). In practice, time to appropriate treatment of emergencies is more important than the geographical distance and the effect of increased distance may be offset by better road networks and improved ambulance services. It is not known whether centralisation delays the time to get appropriate care. Furthermore, ambulance paramedics services can increasingly provide appropriate treatment in some cases and the availability of specialised team in a centralised emergency services may improve access and reduce the in house delay in getting appropriate clinical treatment; this may compensate for the increased journey time to arrival (Spurgeon *et al.*, 2010).

Centralisation of services is thought to have implications in access to care and is a matter which cannot be ignored when redesigning services (Mungall, 2005; Stitzenberg *et al.*, 2009); a trade-off exists between increased travel times and improved clinical outcome and patient safety. There are also fears of distance decay effect; where the utilisation of healthcare services decreases with the increase in travel distance to the healthcare facility (Turnbull *et al.*, 2008; Raknes *et al.*, 2013). Decreased health service utilisation may have an effect in the population health and wellbeing.

Another concern with centralisation of specialised services is patient preferences. It has not been formally examined what choice society is likely to make in the trade-offs between perceived advantages and disadvantages of current services compared with centralised services (Barratt and Raine, 2012). Some early studies whose findings were based on conjoint analysis (Shackley *et al.*, 2001) and standard gamble (Finlayson *et al.*, 1999) techniques of preference elicitation, showed that majority of patients prefer local treatment to the centralised one despite the higher mortality and morbidity in the local services. Contrary to these finding, more recent studies which generated preferences using a modified standard gamble technique (Landau *et al.*, 2013) and using questionnaires covering a number of discrete service attributes (Holt *et al.*, 2010), concluded that patients are willing to travel longer distances to receive better quality of care in a specialised unit. A possibility that preferences were incorrectly estimated in these studies cannot be ignored because their findings were based on preference elicitation techniques other than a discrete choice experiment

(DCE) (Ryan *et al.*, 2008). DCEs offer strong and useful results (van Helvoort-Postulart *et al.*, 2009) with a better understanding of how people make choices (Louviere *et al.*, 2010) and they are favoured over other preference elicitation techniques. It is also possible that the differences between results of these studies may be due to the differences in population profiles which consequently may differ in perception of scale of adverse events and their impact. In Great Britain people already travel 30% longer for other trips such as work, shopping and leisure than the average distance they need to travel to emergency hospitals from their homes (Roberts *et al.*, 2014), then why people would not be willing to travel a bit longer distances to get quality health care? It may be suggested that people may value the proximity of local NHS services, but may prefer to travel longer distances depending on the seriousness of the condition when specialised expertise and better quality of care is needed. However, there is paucity of evidence.

The possible social impact of centralisation of specialised health care cannot be ignored (Meadows *et al.*, 2011). Getting specialised healthcare may become stressful and unpleasant to the patients and families because of the likelihood of reduced choice and increased travel time and costs. There may be strong social attachment to the local healthcare services and local people may protest against the closure, downgrading or moving away of local services to elsewhere.

1.3 Emergency Medical Services

The increase in demand and costs of health care services is set to continue with the increase in ageing population with increasingly complex and often multiple, long-term conditions. A radical and transformative change is essential for the NHS to survive without compromising on safety and quality of health care services. While efforts to reduce waste (i.e. eliminate activities that incur costs but with no reductions in quality) are important, the NHS must respond to the increasing demand and will need to consider tough choices, some of which may reduce the quality of care for some patients. While all areas of health care face unprecedented challenges and major changes in healthcare service provision, the challenges faced by acute hospitals are larger because they spend a major proportion of the healthcare budget. One area where commissioners and policy makers have to make tough choice is in Emergency

Medical Services (EMS). EMS are struggling to cope with the increasing demand and extra pressures on resources described above from the ageing population with high levels of dementia and changing patterns of disease (Fahy et al., 2011).

While there exists some disease specific evidence that centralisation of specialised services yields better clinical outcomes with financial savings, there are arguments against centralisation in terms of poor patient access, increased travel time and costs, and patient preferences. In NHS England, emergency medical services are typically provided by district general hospitals (local hospitals) and there is pressure to consolidate these services in fewer more specialised emergency medical service units that cover larger populations. Consolidation of specialised medical care is one of the new care models envisaged by the NHS “Five year forward view” (NHS England, 2014). The review by Sir Bruce Keogh recommends reconfiguration of emergency care and the development of centralised and more specialised emergency units that benefits patients with more serious and life threatening conditions by providing more expertise and potentially better quality of care (NHS England, 2013a). Therefore, emergency medical service provided in district general hospitals within the English NHS are expected to continue to centralise into fewer, more specialised, emergency units. Centralisation of services is only one option however, and there are alternative ways that such services could be reconfigured, e.g. shifting the balance of care by enhancing the role of the ambulance service, shifting some of the health care services from local hospitals to the community much closer to patients home, increasing the role of telehealth and telemedicine, enhancements to the NHS 111 service (NHS England, 2014). In each different model of service provision there are groups of patients who could benefit and groups that could lose out. Little is known about implications of different service configurations or about societal preferences relating to equity of access and overall outcome about how emergency medical services could be reorganised.

1.4 Objectives

The discussion in earlier sections of this Chapter warrants the aim and objectives of this thesis. Whilst it would have been valuable to assess and compare the implications of various alternative configurations of emergency medical services, it

was not feasible to carry out all of these in terms of time and resource limitations of this thesis. Hence, the case of centralisation of emergency medical services is the only focus of this thesis. The aim of this thesis is to analyse the costs and quality implications of centralisation of emergency medical services.

The thesis addresses the following questions:

i. What is the methodological quality of existing economic evaluations considering centralisation of specialised healthcare services and are these sufficient to inform judgements on the cost-effectiveness of centralisation?
ii. What are the preferences for emergency medical services and what trade-offs society would be willing to make if emergency medical services were centralised?
iii. What are the short and long term implications in terms of cost and quality after centralisation of emergency medical services and which configuration approach (provided from local hospitals or provided from centralised specialised hospital) offers the best utilisation of available resources?
iv. Which emergency medical service configuration provides the best value for money spent?

1.5 Structure of rest of the thesis

The remaining thesis is structured into Chapters as follows.

Chapter 2 addresses the first question and presents the systematic review of economic evaluations on centralisation of specialised healthcare services and reports the methodological quality of existing studies. It also describes why it was important in this thesis to carry out a systematic review of existing economic evaluations considering centralisation of specialised healthcare services.

Chapter 3 provides an overview of preference elicitation techniques that are used in healthcare and justifies the importance of eliciting preferences in healthcare. Along with this, it also highlights why a discrete choice experiment was the most

appropriate preference elicitation technique to use to address the issues focused on within this thesis.

Chapter 4 addresses the second research question. It reports the development of the discrete choice experiment which explored the public preferences of emergency medical services and quantifies the strength preferences towards different emergency medical care service configurations (local versus distant location of emergency services). It examines how individuals weigh up and trade-off between attributes of emergency medical service. The results from this Chapter are also utilised to inform the economic evaluation model in Chapter 6.

Chapter 5 provides a robust methodological background to the economic evaluation methods used in Chapter 6. It describes the methodological development of an economic evaluation model with the focus on decision analytic model framework. The Chapter demonstrates methods of assessing and presenting the uncertainties in cost-effectiveness estimates.

Chapter 6 addresses the third and fourth research questions. It describes the economic evaluation of centralised specialised emergency medical service compared with those provided at local hospitals using data from a UK setting. It first describes the use of the decision analytic framework to conduct the economic evaluation of centralised provision of emergency medical care compared with the local provision and then presents the summary of the results. The Chapter also incorporates the results of the discrete choice experiments described in Chapter 4 into the economic evaluation.

Chapter 7 provides an overview and discussion of the main findings (reported in Chapter 2, Chapter 4, and Chapter 6) of this thesis. It highlights the main contributions of the thesis and policy implications followed by the outline of major strengths and limitations. It also suggests areas for further research. Finally, Chapter 7 provides an overall conclusion of the work focussed in this thesis.

The next Chapter presents the systematic review of economic evaluations on the centralisation of specialised healthcare services and reports the methodological quality of existing studies.

Chapter 2. Economic Evaluations on Centralisation of Specialised Healthcare Services

2.1 Introduction

Chapter 1 provided an overview of centralisation of specialised healthcare services and provided an outline for this thesis. The aim of the work described in this Chapter is to systematically review and critically appraise the methodological quality of economic evaluations considering centralisation of specialised healthcare services to ensure that the development of economic evaluation described in Chapter 6 is informed by strong methodology. A journal paper based on this Chapter has been published (Bhattarai *et al.*, 2016). This Chapter addresses the first research question set out in Chapter 1.

The Chapter is structured as follows: section 2.2 provides a brief overview of the importance of systematic review of economic evaluation methods used in centralisation of specialised healthcare services, section 2.3 describes commonly used economic evaluation methods, section 2.4 describes the methods used in the systematic review, section 2.5 presents the results of the systematic review, section 2.6 discusses the findings before the concluding the Chapter in section 2.7.

2.2 Importance of Systematic Review of Economic Evaluation Methods in Centralisation

Centralisation of specialised healthcare services is typically characterised by reorganisation of healthcare services into fewer specialised units serving a higher volume of patients and aims to improve patient outcomes and efficiency. As outlined in Chapter 1, Lord Darzi's 2007 report (Darzi, 2007) recommended the reorganisation of London stroke and major trauma services into specialised centralised higher volume units catering for large populations with high-tech facilities and senior medical continuity. A number of studies suggest that reconfiguring healthcare services into fewer consolidated units will lead to increase in high quality care and better patient outcomes (Simpson *et al.*, 2001; Fitzsimons *et al.*, 2012; Gabbe *et al.*, 2012; Woo *et al.*, 2012; Fosbol *et al.*, 2013; Metcalfe *et al.*, 2014; Morris *et al.*, 2014; Ravi *et al.*, 2014). Cost savings arguably resulting from the economies of scale is also one of the

driving force behind centralisation of healthcare services (Posnett, 1999; Imison *et al.*, 2014). However, redistribution of limited resources could have secondary or unpredictable effects such as increased costs of access for patient and their carer. Increased journey distance to hospital may reduce healthcare utilisation particularly in some groups of population such as the elderly, those with poor socio-economic status and those with poor access to transport (Posnett, 1999; Mungall, 2005; Lee *et al.*, 2007; Turnbull *et al.*, 2008). Increased journey distance may also lead to increased risk of mortality in patients with life threatening medical emergencies whereas in some cases the benefits of specialised care in centralised healthcare services may outweigh the detriments of increased travel times (Nicholl *et al.*, 2007). Thus, it is important to understand the trade-off between the quality of care and cost of centralisation. Economic evaluation methods can be used to explore this trade-off and inform decisions as to whether the resources required or redistributed to centralise services are “worth” the health outcomes achieved.

Economic evaluations are increasingly used in decision-making (Eddama and Coast, 2008; Simoens, 2010; Gray and Wilkinson, 2016) but the methodological rigour varies and this can lead to erroneous conclusions being drawn. Therefore, when considering the economic evidence on centralisation of healthcare services it is important to systematically identify relevant economic evidence and to appraise the methodological quality. Such a review has not hitherto been published. It was also important that the development of economic evaluation, described in Chapter 6 of this thesis, is informed by studies using strong methodological quality.

2.3 What are Common Economic Evaluation Methods?

Economic evaluations compare the costs and consequences of two or more competing healthcare interventions to identify which makes best use of limited resources. On the basis of the consequences measured and valued, the full economic evaluations techniques are commonly classified as cost-effectiveness analysis (CEA), cost consequence analysis (CCA), cost-benefit analysis (CBA) and cost-utility analysis (CUA) and can be based on primary empirical studies such as trials, decision analytic modelling or a combination of the two approaches (Drummond *et al.*, 2005).

In CEA, costs are related to single, common effect that may differ in magnitude between the alternatives compared, for example life years gained, premature births averted, discharge from hospital. CEA is often useful to decision-makers in situations where costs per disease/condition specific outcomes are important, for example cost per discharge from the hospital. However, different diseases/conditions are presented on different outcomes posing a problem in comparison between diseases/conditions. This makes CEA inappropriate for cases where decision-makers have to assess opportunity cost (i.e. benefits forgone) of selecting one program over another (Drummond *et al.*, 2005).

CUA is essentially a variant of CEA where the outcome is presented in terms of a generic measure of health gain, usually the Quality Adjusted Life Years (QALYs). CUA allows comparison between competing healthcare programmes on a single outcome measure such as cost per QALY.

CBA allows the monetary valuation of health outcomes that can be interpreted alongside costs of the programme. The results of CBA are either stated as the ratio of costs to benefits or in terms of net benefit of one programme over another (Drummond *et al.*, 2005). Where functioning markets exist, monetary valuation of the outcomes is undertaken using prices revealed in the market. But, where no such markets exist outcomes are monetised using techniques of willingness to pay (WTP) (Drummond *et al.*, 2005). CBA is useful in resource allocation decisions across sectors of economy.

In CCA, costs are presented alongside a number of outcomes. The costs and outcomes are not formally combined in a CCA but it allows decision-makers to make their opinion of the importance of those health outcomes and costs of a healthcare programme in their context. CCA is particularly useful when little is known about the programme/intervention under evaluation and it is difficult to identify an appropriate outcome measure to use CEA.

2.4 Methods

2.4.1 Search strategy

A comprehensive and systematic literature search in the database of PubMed, NHS Economic Evaluation Database (NHS EED), Health Economic Evaluation Database (HEED), and Excerpta Medica database (EMBASE) was first undertaken in January 2015 to identify studies on economic evaluation of centralisation of any health care services. The search was updated on 10th March 2016 to check for any new publications. However, HEED and NHS EED ceased their searches in December 2014, so 31st December 2014 is the date of last search of HEED and NHS EED. In addition, the reference lists of the retrieved articles from the search were also manually searched for relevant publications. Google was also used to check for relevant articles. The search was performed using an extensive search strategy using keywords and free text for each of the databases, with no restrictions on date and year of publication. A detailed search strategy is shown in Table A1 in Appendix A. The Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) guidelines were closely followed to during this review (Moher *et al.*, 2009).

2.4.2 Selection criteria

Inclusion/ exclusion criteria were used to select studies. Studies were included in the review according to the following criteria:

1. Full economic evaluations comparing costs and consequences of at least two alternatives were included i.e. those using the following methodologies: CCA, CEA, CUA, or CBA, were included. Partial economic evaluations i.e. those not involving comparison between alternatives or not relating costs to benefits or those studies which only considered costs analysis / comparison / description were excluded.

2. All relevant health economic evaluations were considered, including those alongside high quality randomised trials, modelling studies based on a meta-analysis of data from high quality randomized trials or utilising secondary data from literature and those based upon observational studies or analysis of large administrative databases.

3. Literature reviews and studies focussing only on methodology were excluded. Reviews, letters, comments, conference abstracts and other general articles which limited the assessment of their methodological quality were also excluded.

4. Only publications in the English language were included.

5. An assessment of centralisation of any specialised healthcare service was included; assessment of institutional/hospital volume of activity as a proxy for centralisation was included but excluded those assessing centralisation on the basis of surgeon/physician volume which measure individual clinician impact rather than the service. It was assumed that the outcomes achieved by a surgeon/physician are mainly driven by the resources provided at the institutional level.

6. Only publications from peer-reviewed journals were included; it is expected that studies published in peer-reviewed journals have already undergone some basic checks on their quality.

2.4.3 Data extraction

Data extraction from the full texts included in the review was focussed on key methodological features such as study objective, population, type of economic evaluation, overall design, economic perspective, time horizon, comparator and intervention, incremental costs and outcomes and handling of uncertainties. The author of this this thesis independently carried out the extensive search and extracted the information from the selected studies, reviewed the evidence and wrote the manuscript while the supervisory team contributed to the critical revision of the manuscript and provided critical comments.

2.4.4 Quality assessment

Studies were assessed for their reporting quality using a template (Appendix A:Table A2) based on the Consolidated Health Economic Evaluation Reporting Standards (CHEERS) (Husereau *et al.*, 2013) and Drummond's (Drummond and Jefferson, 1996) checklists. Scoring systems for quality ratings of included studies were not used, but important aspects of economic evaluations were summarized.

2.5 Results

2.5.1 Literature search

The literature search of the databases initially generated 11,544 hits of potentially relevant articles. Screening of titles and abstracts resulted in 86 articles which appeared to meet the eligibility criteria. After a detailed review of full text of these articles, 27 articles were excluded. The reasons for exclusion of these full text were: not a full economic evaluation (12), only analysing surgeon volume (8), not analysing centralisation aspects (5), not an economic evaluation (1) and not a peer reviewed journal publication (1). References from identified papers were also cross checked and a further five full text articles were identified and included. A total of 64 full text articles met the inclusion criteria and were finally considered in this review (Figure 2.1). A list of studies included in the review is available in Appendix A, Table A3.

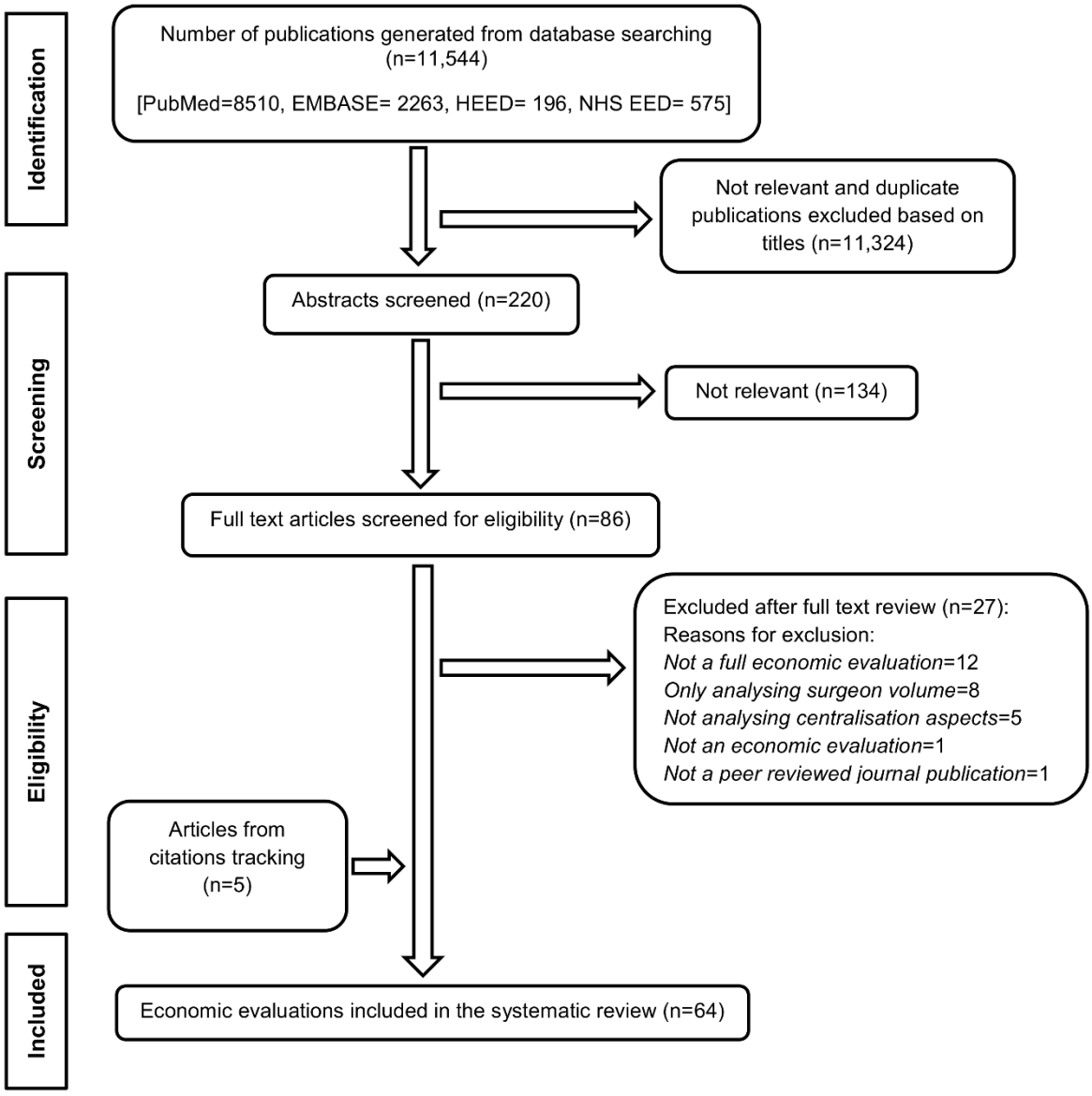

Figure 2.1: PRISMA flow diagram of the study selection

2.5.2 Key characteristics of economic evaluations

An overview of the key characteristics of economic evaluations included in the review is presented in Table 2.1.

Table 2.1: Summary of key characteristics of studies included in the review

Characteristics	**Number of studies**	**Study Reference** (Appendix A, Table A3)
Study Country		
UK	2	10, 31
Germany	1	6
Netherlands	3	7, 11, 55
Canada	1	13
USA	47	1, 2, 3, 4, 5, 8, 9, 12, 14, 17, 18, 19, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 33, 34, 35, 36, 37, 38, 39, 40, 44, 45, 46, 48, 49, 50, 52, 53, 54, 56, 57, 58, 59, 60, 62, 63, 64
Taiwan	4	15, 32, 43, 51
Japan	4	16, 21, 42, 47
South Korea	2	41, 61
Aspect of centralisation		
Hospital Volume	51	1, 2, 3, 4, 6, 8, 9, 12,15,16,17,18,19, 20, 21,22, 24, 25, 26 ,27, 28, 29, 30, 32, 33, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 57, 58, 59, 60, 62, 63, 64
Hospital Location	2	11, 31
Healthcare Specialisation	10	5, 7, 10, 13, 14, 23, 34, 54, 55, 61
Multidisciplinary care	1	56
Study Design		
Decision analytic modelling	11	4, 5, 6, 8,10,11, 12, 27, 54, 55, 60
Cohort	34	1, 2, 3, 7, 8, 13, 14, 15, 17, 18, 19, 23, 24, 25, 26, 29, 32, 35, 36, 39, 42, 43, 44, 47, 51, 52, 53, 56, 57, 58, 59, 62, 63, 64,
Case-control	2	33, 45
Cross-sectional	15	9, 16, 20, 21, 22, 28, 30, 37, 38, 40, 41, 46, 48, 49, 50,
Before-And-After	3	10, 31, 61
Case series	1	34
Economic evaluation type		
Cost Utility Analysis (CUA)	10	4, 5, 6, 10, 11, 13, 14, 27, 54, 55
Cost-effectiveness Analysis (CEA)	4	7, 8, 12, 56
Cost Consequence Analysis (CCA)	50	1, 2, 3, 9, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 57, 58, 59, 60, 61, 62, 63, 64
Economic perspective		
Societal	4	7, 8, 12, 54
Societal & health insurance	1	6
Healthcare	4	10, 13, 58, 63
Third party payer	3	27, 56, 60
Not stated	52	1, 2, 3, 4, 5, 9, 11, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 55, 57, 59, 61, 62, 64
Targeted health services		
Emergency	14	4, 5, 6, 10, 13, 14, 17, 30, 31, 32, 33, 34, 46, 61
Non-emergency	50	1, 2, 3, 7, 8, 9, 11, 12, 15, 16, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 62, 63, 64

It is recommended that studies provide a clear description of the location, setting and other relevant aspects of the healthcare system is reported in studies so that external validity, generalisability and transferability of study results in a different setting can be assessed (Husereau *et al.*, 2013). All included studies have clearly reported their location and setting. Whilst the majority of studies were undertaken in the United States (n=47), two studies were carried out in the UK, one in Canada, four in European countries, and the rest (n=10) in Asian countries. Most (n=51) used hospital volume (defined in terms of activity level) as a proxy for centralisation of healthcare services, however there was a wide variation in the definition of high and low volume hospitals across studies. The variation in definition of volume may further complicate the impact of the findings generated from these studies. Volume alone cannot be a proper measure of quality (Khuri and Henderson, 2005) and the improvement in quality is rather explained by underlying mechanisms of care such as staff expertise, resource availability and specific processes of care correlated with volume (Halm *et al.*, 2002; Mesman *et al.*, 2015). The theme of centralisation assessed was location of health service in two studies, specialisation of healthcare services in nine studies, and multidisciplinary care in one.

It was observed that the majority of the studies followed non-randomised designs including retrospective cohort (n=34) with one (13) also using cross-sectional effectiveness data, cross-sectional (n=15) of which one (9) was repeated cross-sectional, comparative case series (n=1), case control (n=2) of which one (33) was matched case control and before and after studies (n=3). Cross-sectional designs are particularly prone to selection and measurement bias. Uncontrolled before-and-after study designs are generally considered to have poor internal validity because they may fail to account for any prevailing temporal trend which might confound and bias the outcomes of the intervention (Goodacre, 2015; Portela *et al.*, 2015). Only one study (10) which used a before-and-after study design attempted to account for potential confounder and bias by modelling intervention effects before and after centralisation using several independent, population based datasets and by conducting sensitivity analysis. However, this may be insufficient because it has been argued that controlled before-and-after studies should have at least two intervention sites and two control sites to control for site specific confounding effects on the observed differences between intervention and control groups (Effective Practice and

Organisation of Care (EPOC), 2015. Available at: http://epoc.cochrane.org/epoc-specific-resources-review-authors). Altogether 11 studies used some form of modelling approach as their analysis method.

Looking at the economic evaluation methods used in the studies, most of the studies used CCA (n=50) where costs and outcomes such as mortality, length of stay, complications, readmissions were assessed in a disaggregated form. CCA, a variant of CEA, presents a range of outcomes of an intervention in a disaggregated form that decision-makers are likely to use in a trade-off of their importance, however it can be challenging for decision-makers to weigh up different outcomes against each other and compare alternatives (Drummond *et al.*, 2005). CEA is an appropriate economic evaluation method when the outcomes of alternatives can be expressed in common measures such as cost per life years saved, costs per cases averted or costs per readmissions avoided (Drummond *et al.*, 2005). CEA was used in only in four studies. Seven studies (1, 2, 3, 26, 28, 45, 60) which were reported as CEA were in fact CCA. CUA is considered the best approach for decision-making in healthcare because it allows broader comparisons to be made across widely differing alternatives (Robinson, 1993; Drummond *et al.*, 2005), nevertheless it is limited to measuring only health benefits. The results of this review showed that CUA method was used only in ten studies. CBA was not applied by any of the studies.

Studies assessed a wide range of healthcare services or procedures such as stroke, cancers, trauma, accident and emergency services, congestive heart failure, coronary artery bypass grafting, pancreatitis, organ transplantations and other condition specific surgical procedures. A majority of studies (n=50) assessed elective care centralisation issues and the remaining (n=14) focussed around those appearing to be emergency health care need.

2.5.3 Methodological quality of economic evaluations

The results of the methodological quality assessment are presented in Table 2.2 and reflect inconsistency across the studies assessing centralisation of healthcare services.

Table 2.2: Quality assessment criteria for economic evaluations included in the review

Dimension of quality	**Reported** (Study reference in Appendix A, Table A3)	**Not Reported** (Study reference in Appendix A, Table A3)	**Note**
A clear description of the study objective and comparators is provided	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64	52	52- Not clearly stated
Characteristics of target population and subgroups are described and analysed	1, 2, 3, 4, 6, 8, 9, 10, 11, 12, 13, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 27, 28, 29, 30, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64	5, 7, 14, 22, 31	55- reference for target pop given,22- only stated no difference between groups
Setting and location of the study is stated	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64		
Study perspective is clearly stated	6, 7, 8, 10, 12,13, 27, 54, 56, 58, 60, 63	1, 2, 3, 4, 5, 9, 11, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37,38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 55, 57, 59, 61, 62, 64	7 has only health care payer costs; 12-not what is stated, 60- not what is stated
Time horizon of costs and benefits is clear	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 19, 20, 21, 22, 23, 26, 27, 28, 30, 31, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 44, 45, 46, 47, 49, 50, 51, 53, 54, 55, 56, 57, 58, 60, 61, 62, 63, 64	8, 18, 24, 25, 29, 32, 43, 48, 52, 59	
Discount rate is stated or an explanation is given if costs or benefits are not discounted (where applicable)	4, 5, 6, 10, 12, 13, 14, 27, 54, 55	3, 7, 15, 51,	5, 54, 13 benefits only

Table Continued

Table 2.2 continued: Quality assessment criteria for economic evaluations included in the review

Dimension of quality	**Reported** (Study reference in Appendix A, Table A3)	**Not Reported** (Study reference in Appendix A, Table A3)	**Note**
Source and methods used to collect effectiveness data described	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64	8	8-not clear
The primary outcome measure(s) for economic evaluation are clearly stated	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64		
Quantities of resources are reported separately from their unit costs	6, 7, 10, 11, 12, 54, 55, 54, 56,	1, 2, 3, 4, 5, 8, 9, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 57, 58, 59, 60, 61, 62, 63, 64	7 only unit costs reported separately, 55 ref to web table given
Approaches used to estimate resource use and cost is clear	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16, 17, 19, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64	9, 18, 20, 21	
Cost components clear	6, 7, 10,11,12,14, 42, 54, 55, 56	1, 2, 3, 4, 5, 8, 9, 13, 15, 16, 17, 18, 19, 20, 21,22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 57, 58, 59, 60, 61, 62, 63, 64	

Table Continued

Table 2.2 continued: Quality assessment criteria for economic evaluations included in the review

Dimension of quality	**Reported** (Study reference in Appendix A, Table A3)	**Not Reported** (Study reference in Appendix A, Table A3)	**Note**
Currency/price year are explicitly stated	2, 4, 5, 6, 9, 10, 12, 14, 19, 20, 26, 27, 29, 32, 35, 37, 40, 41, 43, 45, 47, 50, 51, 53, 54, 55, 58, 61, 62, 63	1, 3, 7, 8, 11, 13, 15, 16, 17, 18, 21, 22, 23, 24, 25, 28, 30, 31, 34, 33, 36, 38, 39, 42, 44, 46, 48, 49, 52, 56, 57, 59, 60, 64	
Analytic methods supporting the evaluation including methods for dealing with skewed, missing, or censored data, extrapolation methods, methods for pooling data, approaches to validate or make adjustments to a model, methods for handling population heterogeneity and uncertainty described in detail	1, 2, 3, 4, 5, 6, 7, 8, 9, 10,11,12, 15, 16, 17, 18,19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 33, 34, 35, 36, 37, 38 , 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64	7, 13, 14	
Incremental costs and outcomes reported (If applicable incremental cost-effectiveness ratios reported)	2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 26, 41, 48, 54, 55, 56	1, 3, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 49, 50, 51, 52, 53, 57, 58, 59, 60, 61, 62, 63, 64	11-only in graphs
Sensitivity analysis carried out	1, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 27, 33, 42, 45, 54, 55, 57, 60	2, 3, 9, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 28, 29, 30, 31, 32, 34, 35, 36, 37, 38, 39, 40, 41, 43, 44, 46, 47, 48, 49, 50, 51, 52, 53, 56, 58, 59, 61, 62, 63, 64	

Table Continued

Table 2.2 continued: Quality assessment criteria for economic evaluations included in the review

Dimension of quality	Reported (Study reference in Appendix A, Table A3)	Not Reported (Study reference in Appendix A, Table A3)	Note
Limitations clearly discussed	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63	22, 37	Not clearly reported in 22, 37
Generalisability of findings discussed	1, 2, 6, 10, 15, 16, 17, 19, 20, 21, 28, 30, 31, 32, 33, 34, 35, 42, 53, 54, 60, 61	3, 4, 5, 7, 8, 9, 11 ,12, 13, 14, 18, 22, 23, 24, 25, 26, 27, 29, 36, 37, 38, 39, 40, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 55, 56, 57, 58, 59, 62, 63	

2.5.4 Study objectives and comparators

Cost-effectiveness may vary by population characteristics and it is recommended that these studied should be clearly reported (Husereau *et al.*, 2013). It was observed that most of the studies clearly reported their objectives, comparators and description of the target population characteristics, but statement of objective in one study (52) and population characteristics reported by two studies (55, 22) were incomplete; one (55) referred to another study for the characteristics and the other (22) only stated that there was no difference between the two population groups analysed. Five studies (5, 7, 14, 22, 28) did not provide any description and analysis of target populations characteristics.

2.5.5 Perspective of the study

Perspective is the viewpoint from which the costs and outcomes are evaluated and should be clearly stated in an economic evaluations (Husereau *et al.*, 2013). Only 12 studies clearly reported the perspective of the analysis. Among these five (7, 54, 9, 12, 60) reported the use of societal perspective and one (6) reported societal perspective along with statutory health insurance perspective, four (11, 13, 58, 63) reported using healthcare perspective and two (27, 56) reported third party payers

perspective. However, on a closer examination it was clear that three (7, 9, 12) and one (60) of those studies which reported using a societal perspective actually followed a healthcare and payers' perspective respectively.

2.5.6 Effectiveness data

It was observed that the source and methods of effectiveness data were clearly reported in all studies, but one (9). The majority (n=52) of studies analysed the data derived from a single source database. One modelling study (10) utilised information from three different databases. Eight (4, 5, 6, 7, 11, 12, 54, 55) modelling and two (13, 56) observational studies used information from multiple sources including literature review and databases, but one (13) also carried out a cross-sectional survey to derive effectiveness data. A major limitation of eight (4, 5, 6, 7, 12, 54, 55, 13) of these studies which reported using effectiveness estimates from literature review was the failure to report whether a systematic review was conducted; making it unclear whether the best available evidence was used.

2.5.7 Outcomes assessed

The commonly used outcome measures in studies were in-hospital mortality, length of stay in the hospital, readmissions, life years gained or deaths averted, complications, length of stay in the intensive care unit (ICU), long term survival and quality adjusted life years (QALYs). Only 11 studies assessed QALYs as one of their outcome measures. Three studies (21, 43, 61) assessed length of stay in the hospital as the only outcome measure (Appendix A, Table A3).

2.5.8 Costing

The costs resulting from healthcare centralisation can be broadly divided into direct and indirect costs. Direct costs are healthcare related costs that result from inpatient or outpatient healthcare services used to address the health problem, for example costs of surgery, drug treatment, lab tests, staff and equipment. Indirect costs are other types of costs which occur outside the healthcare sector, for example like value of time loss such as productivity/wages lost or leisure time lost, travel costs and costs

associated with other aspects like child care. Direct costs were included in all studies included in this review (Appendix A, Table A3). These were the hospital costs like costs of diagnosis, treatment and surgery associated with the illness, however 18 of the studies used hospital charges and did not report any conversions to actual incurred costs. Eight (1, 6, 10, 11, 12, 13, 14, 54) studies appeared to have considered indirect costs in their analysis (Appendix A, Table A2), however in one of these (11) economic evaluation was restricted to travel costs to hospitals borne by patients, two (1,13) were not clear in what indirect costs were included, one (54) included costs of lost productivity and one (6) included costs of hospital infrastructure and informal carer travel, but explicitly excluded the productivity costs citing an average patient age of 74 years. All studies mentioned how the resource use and costs were estimated and all seem to have used activity based costing method, but three (18, 20, 21) were not clear enough. Only ten (6, 7, 10, 11, 12, 14, 42, 54, 55, 56) of the studies reported the detailed breakdown of components of the total costs assessed. Quantities of resource use and unit costs were reported in eight studies (6, 7, 10, 11, 12, 54, 55, 56), however in two (7, 56) of these studies only unit costs are presented and resource use were not presented separately with one (56) only presenting fee codes.

2.5.9 Adjustments for timing of costs and benefits

It is recommended that the time horizon over which the costs and consequences of an intervention occur and any discount rate used should be stated (Husereau *et al.*, 2013). In this review it appeared that 40 studies had a time horizon of less than a one year. Discounting was not reported nor necessary in these studies with a time horizon shorter than one year. However, it is recommended that analysts should report this as 0% discount rates for clarity (Husereau *et al.*, 2013). Fourteen studies (3, 4, 5, 6, 7, 11, 12, 13, 14, 15, 27, 51, 54, 55) had a time horizon longer than one year, but only seven (4, 6, 11, 12, 14, 27, 55) reported discounting both costs and effects. In three studies (5, 13, 54) the time horizon for costs and effects appeared to be different and effectiveness data only was discounted. Costs in two (13, 54) appeared to have incurred within a year and discounting was not necessary. In the other study (5) the costs were expected for 10 years, but discounting was still not reported. Justification on why costs were not discounted was not provided. It was

difficult to ascertain the time horizon in ten studies (9, 18, 24, 25, 29, 32, 43, 44, 52, 59).

Price changes over time and research settings. Reporting dates, currency and any conversions facilitate comparisons of results from studies carried out at different times and jurisdictions. It is recommended that price year, the currency used and any currency conversions are reported (Husereau *et al.*, 2013). Currency or price dates and conversions were explicitly stated by only 30 studies.

2.5.10 Statistical analysis

All the analytic methods used in the studies must be reported to allow judgement of the appropriateness of the methods and the corresponding results in economic evaluations (Husereau *et al.*, 2013). Single study based economic evaluations should report regression methods that are used in in their analysis (Husereau *et al.*, 2013). The majority of studies (n=53) in this review were primarily single study based economic evaluations and among these only 45 studies explicitly reported the regression methods and other statistical tests used in their analysis. Reporting of statistical analysis in five studies (31, 39, 46, 52, 56) was very limited. Among these one (46) only stated using logistic regression analyses for demographic and clinical variables but nothing was reported on costs. Three studies (31, 52, 56) reported the test of statistical significance in the difference. One (39) of these studies reported the tests of significance but also indicated accounting for clustering effects in groups, one (52) only stated using non parametric analyses in testing continuous variables but failed to explain further, while another one (56) only stated that comparisons between groups were made by ANOVA and did not provide further details. Three studies (7, 13, 14) did not report any statistical methods in analyses of data. Altogether, 24 single empirical studies reported using statistical methods to account for skewed distribution of costs and resource utilisation data, and 14 of them also indicated accounting for potential clustering effects in the groups studied.

Model based economic evaluations should describe and report methods used in estimating parameters used in the model (Husereau *et al.*, 2013). Among the 11 model based economic evaluations in this review, seven studies (4, 6, 10, 11, 27, 54, 55) clearly reported the model parameters estimation methods however in four (27, 54, 55, 60) of these studies there was no indication that any possible heterogeneity effects in parameters was addressed. Three studies (5, 8, 12) reported parameter estimation methods poorly, and reported limited explanation on estimation of transition probabilities, however one (12) study indicated that heterogeneity was addressed. Ignoring heterogeneity effects in parameters may influence the results of an economic evaluation (Grutters *et al.*, 2013). Only two (6, 12) reported half cycle corrections to account for transition events occurring half-way through the cycle. Not incorporating half cycle corrections in states may lead to over or under estimation of economic evaluation outcomes (Siebert *et al.*, 2012). Several methods for analysing healthcare costs and handling patient heterogeneity are currently in practice (Elliott and Payne, 2004; Mihaylova *et al.*, 2011; Grutters *et al.*, 2013). Appropriateness of these methods is dependent on the data used by each study, but is beyond the scope of this review.

2.5.11 Consideration of uncertainty

Effects of uncertainties in parameters arising out of methodological assumptions, sampling variation or structure of analyses should be described in economic evaluations (Husereau *et al.*, 2013). It was observed that analysis in 54 studies were mainly based on patient level data, however only 15 studies presented confidence intervals for both costs and effects results and one presented cost-effectiveness acceptability curves. Some form of sensitivity analysis was included by less than one third of studies (n=19). Among the eight studies (1, 7, 13, 14, 33, 42, 45, 57) which were mainly analysis of patient level data, only seven (1, 7, 13, 14, 33, 42, 57) performed sensitivity analysis: six used one way sensitivity analysis and one (13) used two way sensitivity analysis.

Eleven studies (4, 5, 6, 8, 10, 11, 12, 27, 54, 55, 60) were model based analysis- six (4, 5, 8, 11, 27, 60) performed one way sensitivity analysis although reporting was

limited to thresholds graphs in one (27). In another five (6, 10, 12, 54, 55) one or two way sensitivity analysis was required along with probabilistic sensitivity analysis.

2.5.12 Presentation of results

The recommended practice in economic evaluation studies is to report mean values for the main categories of estimated costs and outcomes of interest as well as the mean differences between the comparator groups and - if applicable - incremental cost-effectiveness ratios (ICERs) (Husereau *et al.*, 2013). Although, all of the studies in this review presented mean values for the estimated costs and major outcomes, it was observed that only 18 studies reported results in terms of incremental costs and outcomes or ICERs. One (11) of these only presented the results graphically and the economic evaluation results were not reported clearly in numerical terms. Study limitations were clearly discussed by all studies but two (32, 37). Generalisability of study findings was discussed only by 22 studies.

2.6 Discussion

The main purpose of this review was to critically appraise the methodological quality of published economic evaluations considering centralisation of specialised healthcare services. The review identified 64 studies undertaking some form of economic evaluation of the centralisation of healthcare services. Considerable variation was observed in the methodological approaches used. The studies reviewed generally did not adhere to current standards for reporting economic evaluations and whilst they might have been sufficient for the purpose they were originally conducted, they provide a very limited evidence base to guide decision-makers in other settings.

Most of the studies in this review used non-experimental designs. It may be impossible or impractical to undertake randomised trials to assess centralisation, therefore quasi-experimental designs such as controlled before-after studies, interrupted time series and repeated measures studies may generate more robust and convincing evidence compared with non-experimental designs (Goodacre, 2015). Modelling is also useful when there is a need to understand the long-term

costs and effects of an intervention, however validity of the modelling results depend on the evidence and assumptions on which they are based upon (Drummond *et al.*, 2005).

The health outcomes assessed in studies were generally appropriate to their objectives. However, QALY which is widely preferred as a summary measure of both quantity and quality of life outcomes in health economics (Kind *et al.*, 2009), was assessed in only 11 studies. Length of stay is widely used both as quality and efficiency measures of healthcare services. It is significantly influenced by several other factors and it has been argued that length of stay alone should not be used as a quality measure to compare healthcare services unless appropriately adjusted (Brasel *et al.*, 2007). Nevertheless, length of stay was the only health outcome measure assessed in three studies (21, 43, 61) in this review. Most of the studies had short-term follow-up and it is possible that their outcomes would have been different if they had considered longer time frame.

It is important to clearly state the perspective of analysis in studies because cost-effectiveness may vary with the perspective and an intervention which is cost-effective from one view point and may not be from another. For example, from the National Health Service (healthcare) perspective which typically includes direct medical costs, centralisation of hospitals may appear cost-effective whilst from a societal perspective which includes broader costs to the society, such as lost productivity and leisure time costs due to additional travel time, costs to family members or caregivers, centralisation may not appear cost-effective. Nevertheless, a large majority (n=52) of studies fail to state their analysis perspective. Studies always did not consider all costs relevant to a particular perspective. One study (6) in this review followed a societal perspective but did not consider the lost productivity costs in the elderly citing their age, however leisure time forgone may however not be valueless to the elderly and not considering it may discriminate against healthcare interventions aimed towards the elderly population. Furthermore, it is also important that the source and methodology used in generating effectiveness are well reported because validity of the estimate of the measure of effectiveness used in the studies depends on the methodology used to generate those estimates.

A number of studies in this review have used hospital charges as costs. But, hospital charges are not considered a good approximation of costs because charges are essentially the list prices which are set to compensate costs such as free or discounted care to the poor, facility costs and other community service costs incurred by any healthcare organisation (Finkler, 1982). In this context, it is possible that the charges set by a centralised or a high volume hospital for a particular treatment is higher than that of a low volume local hospitals to compensate for the better facilities and services it provides to its patients. Alternatively, high volume central hospitals may charge less than small volume local hospitals by spreading out their costs of facilities and equipment over a very large volume of patients they cater to. Therefore, using charges in place of costs to determine if centralisation reduces healthcare costs could lead to unsubstantiated conclusions on healthcare centralisation.

Transparency in the costing methodology and cost components is another important aspect in economic evaluations. Depending on the purpose and the context, there exists variation in estimates of commonly used costing approaches (Chapko *et al.*, 2009), therefore unclear reporting of estimation of resource use and costs may make it hard to judge applicability of estimates in a different healthcare setting. It is recommended that costing approaches and data sources are clearly described in economic evaluations (Husereau *et al.*, 2013). Limited data may lead to biased conclusions but incomplete reporting may make it hard to judge applicability of study results for a different setting. Nevertheless, very few studies (n=10) in this review have presented the cost components clearly.

Centralisation would also be expected to impact on the travel distance to hospitals, resulting in changes in cost to health services and patients as well as potentially health outcomes. The impact on financial and other costs of accessing healthcare caused by centralisation may have equity implications as increases in cost may be disproportionately felt by those less well-off, who coincidently may also be in the greatest need (Stitzenberg *et al.*, 2009). Furthermore, costs generated by the increased distance to hospitals would become a significant component of the total costs of centralisation. Thus, it is important that wider aspects of healthcare centralisation are considered in the estimates of costs and health outcomes.

Notwithstanding the limitations as presented earlier, economic evaluations assessing QALYs as well as other relevant health outcomes and both direct and indirect costs would give a better picture of costs and benefits of healthcare centralisation (Appendix A, Table A2). Sensitivity analysis helps to understand the robustness of their findings by varying the assumptions in the values of major variables.

Many health services are facing an increasing pressure to centralise healthcare services into fewer but more specialised units. The case for greater concentration of some of the specialised health services reflect a relationship between quality of care and patient volume, derived from the greater clinical expertise, more specialised facilities, and greater standards of care in the concentrated services (NHS England, 2014). Whilst it may be attractive and fairly acceptable to transfer findings from one setting to another, healthcare costs and outcomes often have limited transferability across settings because of differences in health and economic systems (Hutubessy *et al.*, 2003). In the light of the methodological limitations and differences, decision-makers should take caution while making decisions on the basis of existing economic evaluation studies on centralisation of healthcare services. Decisions on centralising any health care speciality should be informed by findings from methodologically strong economic evaluation studies considering multifaceted aspects of centralisation. Studies adhering to standard guidelines on economic evaluations and with a clearly reported methodology in terms of cost components, outcomes, analysis perspective, time horizon, robustness of the findings, limitations, and generalisability aspects of the findings would assist decision making.

2.6.1 Strengths and limitations

A number of economic evaluations on centralisation of specialised healthcare services have been conducted, however studies assessing the methodological quality of these economic evaluations are lacking. An earlier review of economic evaluations considering centralisation was narrower and focussed only on specific health issues like cancer (Ke *et al.*, 2012). To the best of my knowledge, this is the first systematic review to comprehensively attempt to assess the methodological quality of economic evaluations assessing centralisation of specialised healthcare services irrespective of their speciality. One of the strength of this review is the use of

a checklist adapted from recommended standard guidelines. Whilst we have adopted rigorous searches, we caution that we may have left out some key search terms and it is possible that we may have missed some relevant English language publications. Databases may be sensitive to different search terms and use of generally similar search terms across databases could have missed key papers. A more substantive limitation is the exclusion of unpublished evaluation, grey literature and non-English language studies. However, it is also likely that unpublished and grey literature may either be of lower methodological quality or be no different compared to the published studies (Higgins JPT and Green S, 2011). Since quality assessment was primarily conducted by only one researcher, the likelihood of bias in quality assessment cannot be ignored. Length of stay, also a surrogate for cost, was assessed as a quality outcome measure in this review, and because of this some of the studies were classified as CCA. Finally, though the checklist used to assess the methodological quality was adapted from standard guidelines it only examines the quality reported by studies. It was not possible to judge the quality of conduct from what was reported by studies, and was beyond the scope of this study. Although arguably complete reporting is a part of good conduct and the safe inference from incomplete reporting is to assume the quality of conduct was poor.

Another important point to note is that, the last search for literature for this systematic review was carried out on 10th March 2016 and did not consider any relevant studies (Lahr *et al.*, 2017; Hunter *et al.*, 2018) published thereafter. It could be argued that the search could be re-run to update the review with any new publications. However, the main objective of the systematic review was to inform the development of economic evaluation conducted in Chapter 6.

Critical appraisal of new publications in this situation may not be beneficial and feasible, nevertheless future studies may benefit from a review of studies published more recently. Therefore, the search strategy was re-run in December 2018 to check if any relevant studies were published after the conduct of the systematic review for this thesis in 2016, which informed the subsequent research reported in later Chapters. Only two additional studies (Lahr *et al.*, 2017; Hunter *et al.*, 2018) meeting the inclusion criteria of this systematic review were identified. One study (Lahr *et al.*,

2017) utilised a discrete-event simulation model to assess the short-term (6 months) costs and effects of centralisation of thrombolysis and optimised care in decentralised stroke care systems in Netherlands. The cost-effectiveness analysis was conducted from the perspective of the policy maker (i.e. healthcare provider). While the other study (Hunter *et al.*, 2018) utilised a Markov model to calculate difference in differences in costs and outcomes before and after the implementation of two major system change strategies in stroke care in London and Greater Manchester, UK. The cost-utility analysis was conducted from the NHS perspective (the healthcare provider).

Whilst Lahr and colleagues assessed the costs and effects for a very short time horizon (6 months) and did not assess the results in terms of incremental costs per QALY gained, both the studies addressed most of the issues that were raised by the systematic review. Wider aspects of costs arising out of centralisation are considered by these two economic evaluations and in both travel time to the centralised service and length of stay in the hospitals were incorporated into the economic evaluation models. Hunter and colleagues went beyond the incremental cost per QALY gained from centralisation and also attempted to use the results as part of a Programme Budgeting and Marginal Analysis (PBMA) exercise to reflect a potential real-world scenario.

In general, the new studies published after the conduct of the systematic review have adhered to the current standards for reporting economic evaluations and are methodologically stronger compared with most of the studies included in the systematic review reported in this Chapter. The methodology used in the UK study (Hunter *et al.*, 2018) is similar to that used in the economic evaluation reported in Chapter 6, however none of the studies assessing centralisation have tried to incorporate peoples' valuation (preferences) into economic models.

2.7 Conclusion

This Chapter demonstrated that economic evaluations on centralisation of specialised healthcare services have limited methodological quality and their results

should be interpreted with caution in other settings. The rationale behind centralisation of specialised healthcare services is the improvement on healthcare quality and its efficiency. However, evidence coming from methodologically poor studies may force decision-makers make uninformed decisions on centralisation. It is important to improve the methodology and reporting of economic evaluations so that decisions to centralise specialised healthcare services are informed by robust evidence of improvements in healthcare quality and efficiency arising out of centralisation. Future economic evaluations of specialised healthcare centralisation should adhere to standard guidelines on economic evaluations. Estimates of costs and health outcomes of specialised healthcare centralisation should consider wider aspects of centralisation. These findings informed the development of economic evaluation described in Chapter 6. Nonetheless, more recent economic evaluations have a stronger methodological quality and have considered a wider perspective for the costs associated with centralisation. They did not however attempt to consider a wider perspective for the benefits of centralisation from the viewpoint of individuals' preferences. The next Chapter describes the preference elicitation techniques used in healthcare.

Chapter 3. Preference Elicitation in Health Care

3.1 Introduction

Chapter 2 demonstrated that economic evaluations on centralisation of specialised healthcare services published up to the end of 2016 have limited methodological quality and their results should be interpreted with caution in other settings. Chapter 3 now provides an overview of preference elicitation techniques that are used in healthcare and justifies the importance of eliciting preferences in healthcare. Along with this, it also highlights why a discrete choice experiment (DCE) was the most appropriate preference elicitation technique to use to address the issues focused on within this PhD. The rest of the Chapter is structured as follows: section 3.2 presents the importance of patient and public preferences in healthcare, section 3.3 presents a short discussion on whose preferences matter, section 3.4 presents the classification of preference elicitation methods commonly used (or that could be used) in healthcare, section 3.5 presents the theoretical framework of DCE and section 3.6 presents the overall summary of the Chapter.

3.2 Importance of Patient and Public Preferences in Healthcare

Patient and public involvement in all levels of healthcare decisions is expected to result in more responsive services leading to improved health outcomes (Florin and Dixon, 2004; Dirksen *et al.*, 2013). Therefore, there have been a strong movement towards the involvement of patients and the public in healthcare policy decisions (Mockford *et al.*, 2012; Ocloo and Matthews, 2016). In the NHS England, it is emphasized that patient preferences should be at the heart of healthcare decisions (Coulter and Collins, 2011). However, patient preferences are often overlooked and inaccurately measured by healthcare providers and decision-makers (Mulley *et al.*, 2012). Inaccurate measurement of patient preferences may risk wrong decisions being made in healthcare. Therefore, it is necessary that healthcare decisions are informed by preferences generated from robust methods underpinned by theory.

3.3 Whose Preferences- Patient or Public?

There is a considerable debate in health economics around whose preferences, patient or public, are more appropriate to inform decision making (Dolan, 1999;

Brazier *et al.*, 2005; Gandjour, 2010; Stamuli, 2011; Mott and Najafzadeh, 2016). The argument for patient preference are based on the fact that patients have real experiences and are better positioned to value their own health condition under evaluation compared to the general public trying to imagine them (Brazier *et al.*, 2005). The general population is not fully informed and do not have accurate expectations of consequences of ill health, and therefore their uninformed preferences can result in sub-optimal public resource allocation (Karimi *et al.*, 2017). Furthermore, it has been put forward that the use of patient preferences is founded in preference-utilitarian theory and welfare economics whereas the use of public preferences has no compelling theoretical basis (Gandjour, 2010). In contrast, others argue that public preferences would be more appropriate in a publicly funded healthcare system like the UK NHS where the fully informed general population should have a say in the allocation of resources (Stamuli, 2011). Moreover, the general public are more likely to have no vested interest and provide an unbiased judgement of values compared to patients (Brazier *et al.*, 2005; Stamuli, 2011). Although there is still no firm consensus on whose preferences is more appropriate, the choice often depends on the decision making context (Stamuli, 2011). For example, it is hard to argue against the use of public preferences in system-level decision making in publicly funded healthcare system such as UK NHS (Mott and Najafzadeh, 2016). Moreover, obtaining public preferences from a general population well informed on patient experiences, adaptations and patient values have also been advocated previously (Brazier *et al.*, 2005).

3.4 Valuation Methods

Preference elicitation methods in health care can be broadly categorised into stated preference elicitation methods and revealed preference methods. Figure 3.1 illustrates the categorisation of preference elicitation methods used. The following sections describe these methods.

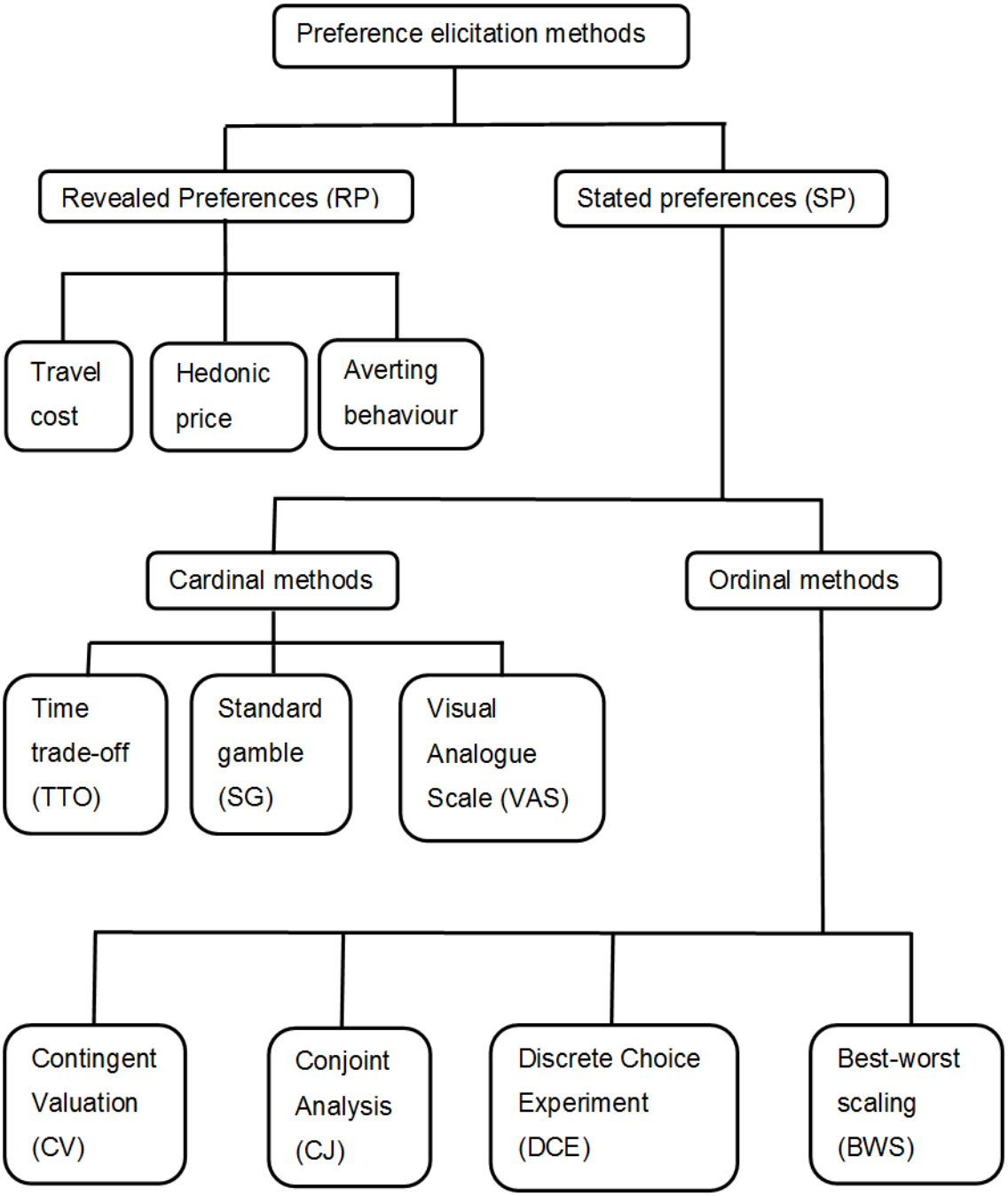

Figure 3.1: Simplified classification of preference elicitation methods

(Adapted from Ali and Ronaldson (2012))

3.4.1 Revealed preferences

Economists have traditionally relied on consumer behaviour in actual market setting to make decisions, and these consumer behaviour observed in actual market setting are known as the revealed preferences (Ali and Ronaldson, 2012). For example,

analysis of data on choice of opticians over a time period may reveal how patients trade-off different attributes of opticians. The advantage of revealed preferences is that it is based on actual decisions which gives revealed preferences a high reliability and face validity (Mark and Swait, 2004). The commonly used revealed preference methods are set out below.

3.4.1.1 Travel cost

Travel cost method is often used to reveal the value of a good or service by taking into account of monetary expenses incurred, such as travel cost, access cost, time cost of travelling, by an individual visiting a service or facility. The travel cost method is used extensively in environmental economics to reveal the recreational value of activities in an environment site such as hiking in a park, fishing at a lake, hunting, and indicated by the trip cost incurred by an individual in reaching that site (Parsons, 2017). Although, use of travel cost method is quite rare in health economics, estimates of willingness to pay for improved access to healthcare services have been derived using this method (Clarke, 2002). However, the travel cost method has been criticised for generating superficial estimates of travel costs as a proxy of value of a good or service and is limited by problems in accurate valuation of time (leisure time) spent travelling, exclusion of costs of equipment such as vehicles that may be involved, lack of consideration of other characteristics of amenities visited and other available choices forgone (Randall, 1994; Hanley and Barbier, 2009).

3.4.1.2 Hedonic pricing

Hedonic pricing is another revealed preferences technique which infers that the price of a marketed good is directly related to its other non-marketed attribute/s (Basu and Sullivan, 2017). Therefore, the value of a particular attribute or combination of attributes of a good is revealed by observing the changes in the price individuals are willing to pay with the change in attribute/s. Hedonic pricing method is often used in valuing environmental characteristics in property prices in housing markets (Taylor, 2017). For example, the monetary trade-offs people are willing to make for a house on a tree lined street which is otherwise similar to other house/s reveals the value people place on trees. This technique has been used in health economics to assess the demand for various health insurance policies and the trade-offs consumers made

between premiums and insurance cover (Jensen and Morrisey, 1990; Robst, 2006). However, market failure in the publicly funded healthcare systems like the UK NHS where consumers do not face the marginal price of consuming healthcare would make the use of hedonic pricing approach difficult to operationalise (Basu and Sullivan, 2017).

3.4.1.3 Averting behaviour

Averting behaviour is a revealed preference method that infers the value of avoiding an adverse effect by observing how much people pay to defend against adverse effects (Dickie, 2017), for example buying bottled water or boiling water prior to drinking to avoid drinking contaminated water (Birol *et al.*, 2006). However, individuals may take more than one form of defensive behaviour in response to an adverse event and therefore, averting behaviour method may fail to explicitly consider all the costs involved (Birol *et al.*, 2006).

A common problem of all the revealed preference techniques is that they are not applicable in new and developing field or policy due to the lack of an established market nor in health care where an actual market situation often does not exist (Lancsar and Louviere, 2008; Ali and Ronaldson, 2012). Nevertheless, even though a market might not exist resources still need to be allocated. Therefore, it would still be important to make judgements about how individual consumers would respond to proposed goods or services. Furthermore, revealed preference is criticised for its inability to estimate non-use values i.e. the values people derive from a good or service without actually consuming it (Lazo *et al.*, 1997). For example, even if there is no observational data on people utilising a primary health care service near their home, these people may still derive value from its availability for others or simply because they know it is there for their own future use. Stated preference methods overcome some of these limitations of revealed preference methods, and hence widely used in the healthcare field (Ali and Ronaldson, 2012).

3.4.2 Stated preferences

In a lot of cases economists observe preferences rather than elicit, but there are limited opportunities in healthcare to do so. In contrast to the revealed preferences, stated preferences involve asking respondents to make a choice between alternatives varying in their characteristics (often hypothetical) and allows assessment of trade-offs that respondents make. Therefore, stated preference methods are particularly useful when no actual market exist or when preferences across hypothetical alternatives need to be evaluated (Ali and Ronaldson, 2012). For example, the valuation of the preferences for a new drug not yet available in the market or the comparison of preferences of two currently available alternative drugs. Stated preference methods can be divided as either cardinal or ordinal methods, though the categorisation is not based on theory in itself. Cardinal stated preference methods generate quantitative preferences from the respondents and provide direct estimates of the degree to which one health state (or health programme) is preferred over another (Ratcliffe *et al.*, 2009). Standard gamble (SG), time trade-off (TTO), visual analogue scale (VAS) are commonly used examples of cardinal methods. Contrary to the cardinal stated preference methods, ordinal stated preference methods do not directly establish the degree preference of one alternative over another (Ratcliffe *et al.*, 2009). Discrete choice experiments (DCE) and ranking exercises are commonly used examples of ordinal methods (Ali and Ronaldson, 2012). These methods of stated preferences are described as follows.

3.4.2.1 Ranking

Ranking is the simplest form of stated preference methods. It involves assessing the preferences by presenting individuals with a set of attributes or alternatives and asking them to order those attributes or alternatives, example from the best to the worst, based on their value (Ali and Ronaldson, 2012; Weernink *et al.*, 2014). Ranking studies are relatively less complex to design and easy to administer and have a reduced cognitive burden posed to the respondents (Ali and Ronaldson, 2012). However, ranking studies are criticised for lack of consideration of the principle of opportunity cost, lack of consideration of marginal context of decision making and failure to provide a measure of strength of preferences (Ryan *et al.*, 2001).

3.4.2.2 Standard gamble

Standard gamble (SG) is the conventional method for measuring utilities and conforms to the axioms of expected utility theory (Torrance and Feeny, 1989). According to the expected utility theory, under conditions of uncertainty any individuals behaving rationally will make decisions that maximise their utility. Therefore, in health care programs or interventions (or health states) individuals should choose the one that increases their survival duration and quality of life.

The SG method involves asking participants to consider the choice between two alternatives A and B, where A is the continuation of current health state (for a given time) with certainty, whereas B is to take a gamble offered with the possibility of perfect health (for a given time) with a probability *P* or immediate death with a probability 1-*P* (Torrance and Feeny, 1989). The application of SG is displayed in Figure 3.2. The value of P is varied until the participant is indifferent to the choice between alternative A and B, at which point *P* is the utility of alternative A (Torrance and Feeny, 1989; Morimoto and Fukui, 2002; Whitehead and Ali, 2010). Therefore, the lower the value of P, the less desirable is the health state A and the greater the risk of death the participant is prepared to accept for a perfect health (Torrance and Feeny, 1989; Whitehead and Ali, 2010).

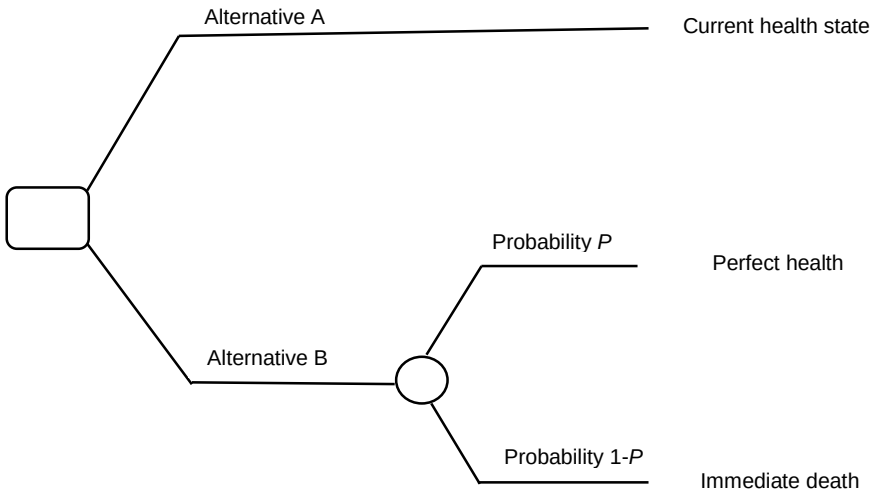

Figure 3.2: Standard gamble method of measuring utilities

(adapted from (Torrance and Feeny, 1989)

However, respondents may find SG cognitively demanding in terms of interpreting the complex risk probabilities involved (Dolan and Iadarola, 2008). Furthermore, SG utility estimates are likely to suffer from upward biases arising from the effect of probability weighting (the tendency of people to process probabilities in a non-linear manner; that is they tend to overweight small probabilities and underweight large probabilities) and loss aversion (tendency to strongly prefer avoiding losses to acquiring gains; losses weigh more heavily in decisions compared to gains) (van Osch *et al.*, 2004) (Bleichrodt, 2002). These concepts have been defined in details by van Osch et al, 2004. In addition, having to rate health states relative to death may make respondents risk averse which in turn will lead to higher utility estimates from SG.

3.4.2.3 Time trade-off

Time trade-off (TTO) is a similar technique to the SG method, however TTO was developed specifically for the use in health care and it is not based on the expected utility theory (Torrance, 1986; Bleichrodt and Johannesson, 1997). It involves asking participants to trade-off the longevity for quality of life (Torrance, 1986; Arnesen and Norheim, 2003). The participant is offered a choice between two alternatives: health state *i* for time *t* followed by death or perfect health for time $x<t$ followed by immediate death. The time *x* is varied until the participant is indifferent between the two alternatives, at which point the preference for health state *i* is x/t (Torrance, 1986). The application of TTO is displayed in Figure 3.3.

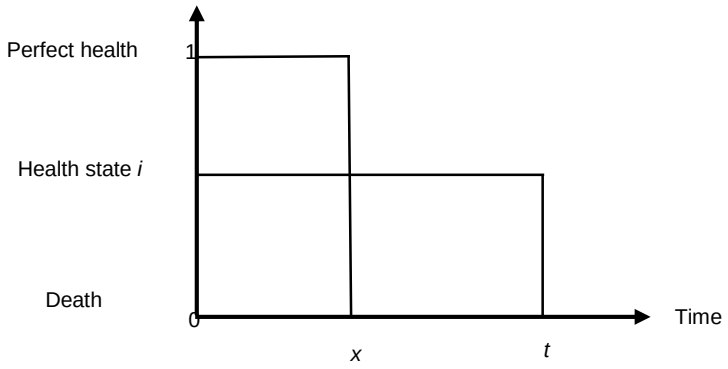

Figure 3.3: The time trade-off method of measuring utilities

(adapted from (Torrance, 1986))

TTO is argued to be less cognitively demanding compared to the SG (Torrance, 1986), however is criticised for problems in valuing health states considered worse than death (Robinson and Spencer, 2006; Devlin *et al.*, 2011). Nevertheless, other modified TTO approaches have been suggested to overcome this limitation (Torrance, 1986; Devlin *et al.*, 2011).

3.4.2.4 Visual analogue scale

Visual analogue scale (VAS), the most common form of rating scales, has long been used in measuring the preferences in health care (Torrance *et al.*, 2001). It involves providing the participant with a linear rating scale often between 0 (worst imaginable health, usually death) and 100 (best imaginable health) and asking them to place preferences for different health states (Torrance *et al.*, 2001; Whitehead and Ali, 2010). An example of a VAS is shown in Figure 3.4. However, this method is criticised for the fact that it involves a rating task which does not involve any trade-offs or choice tasks like SG or TTO (Brazier *et al.*, 1999; Whitehead and Ali, 2010). In addition, a VAS also suffers from scaling bias, as the participant may be reluctant to place their preferences for a health state at the extreme ends of the scale (Weinstein *et al.*, 2009; Whitehead and Ali, 2010). Therefore, VAS as a method of eliciting utility values is generally considered inferior to SG and TTO (Weinstein *et al.*, 2009). Nevertheless, being a simple and quick preference tool, it has been argued that VAS could be best used jointly with other methods (Torrance *et al.*, 2001; Whitehead and Ali, 2010).

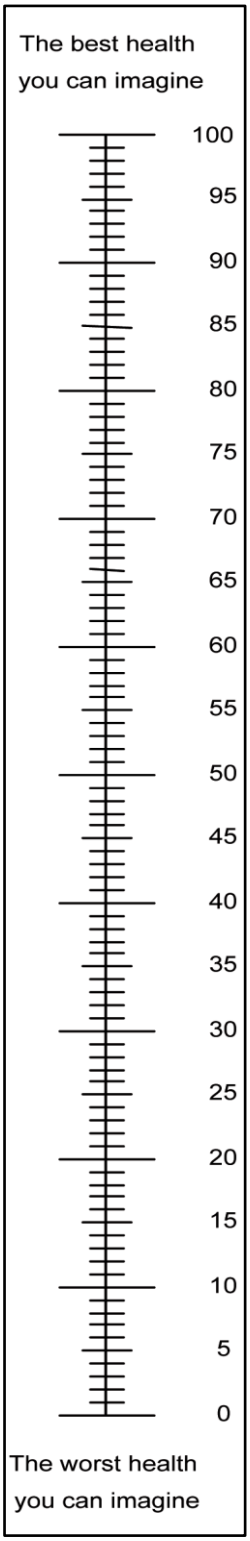

Figure 3.4: Visual Analogue Scale (VAS)

(adapted from EuroQol group www.euroqol.org)

3.4.2.5 Contingent valuation and willingness to pay

Contingent valuation (CV) is trade-off based method used to measure the monetary valuation of a health state or programme (O'Brien and Gafni, 1996; Klose, 1999;

Hanley *et al.*, 2003). It involves presenting participants with hypothetical scenarios, event, goods in healthcare and asking them directly to express their willingness to pay (WTP) or willingness to accept (WTA) compensation for the particular scenario or event through questionnaires/structured interviews. These are helpful in estimating the marginal WTP for a service. Various question techniques such as open-ended CV, bidding game, payment card, and dichotomous choice are used to determine the WTP or WTA (Diener *et al.*, 1998; Klose *et al.*, 2016). The open-ended CV questions directly ask respondents to provide their maximum WTP value for a good or service. For example: “what is the maximum amount you would be willing to pay for the treatment at a specialised hospital?”. The bidding game involves asking respondents “Would you pay £X for a service?” (£X is the starting bid amount). If the respondent answers “Yes”, the starting bid is increased in specified increments until he/she says “No”, but if the respondent answers “No”, the starting bid is lowered until he/she says “Yes”. The payment card method involves asking respondents if they would be willing to pay £X (is one of the amounts from a list) for a service; respondents are shown one amount at a time usually written on a card. A dichotomous choice respondents reply to the question if they would be willing to pay the specified amount the WTP question in “Yes” or “No”.

A higher WTP or WTA value for a given level of income indicates a greater benefit derived by the participant from the scenario or event (or from avoiding the scenario or event in the case of WTA) under consideration. The strength of the CV method lies in its ability to value welfare implications in the absence of market and being less complex and less burdensome to respondents compared with other stated preference methods such as discrete choice experiments, described below (Hanley *et al.*, 2001; Olsen and Smith, 2001). However, the CV method is also criticised in a number of respects (Carson *et al.*, 2001; Murphy *et al.*, 2005; Lusk and Norwood, 2009). First, respondents may find it difficult to place a price value when faced with unfamiliar goods or service, in particular those related to healthcare. Second, the CV method only provides the value of the goods or services as a whole and provides no information on the value of individual attributes that make up the goods or services. Third, the estimates from CV survey may suffer from challenges such as anchoring or framing effects (as there may be a tendency to rely heavily on the first piece of information offered. Depending on the techniques used, the WTP values generated

from CV studies may also suffer from biases such as starting point bias (tendency of the maximum WTP amount be influenced by the starting bid amount), ordering bias (tendency to be affected by the order of questions asked), warm-glow effect (tendency to express a socially desirable attitude rather than the true intention), yea-saying bias (tendency to accept the bid in order to limit cognitive effort) and protest zero bids (tendency to state zero WTP when the respondents actually have a positive WTP value) (van Exel *et al.*, 2006; Grammatikopoulou and Olsen, 2013).

3.4.2.6 Conjoint analysis

Conjoint analysis (CA) is one of the stated preference methods based on trade-off of attributes. The term “conjoint analysis” has been inconsistently used in the literature and often referred to as Discrete Choice Experiments (DCE) (Louviere *et al.*, 2010). The major difference between a CA and DCE is the fact that CA developed out of purely mathematical theory of “Conjoint Measurement” (CM) concerned with the behaviour of number systems but DCE is based on long standing and well tested theory of choice behaviour (Louviere *et al.*, 2010). Therefore, in line with the earlier recommendations from Louviere et.al. (2010), this thesis identifies CA and DCE as different methods.

CA involves asking participants to rate or rank hypothetical alternatives that vary along several attributes (Ryan, 1999; Ratcliffe, 2000). In the ranking approach participants are asked to order alternatives according to their preferences for each alternative, whereas in the rating approach participants are asked not just to order alternatives on the basis of their preferences but also to indicate the strength of their preferences (Ratcliffe, 2000; Boyle *et al.*, 2001). Adaptive conjoint analysis (ACA) is another form of CA method, which involves presenting the ranking or rating task to the respondents and then based on their ranking/rating responses, a set of attributes are selected and again presented asking them to indicate their preferences (Fraenkel, 2010; Adrian *et al.*, 2016). Although, ACA improves the efficiency of CA by focussing on attributes most relevant to respondents, it is limited by the need to administer it using computers or mobile devices, the longer time taken to complete it and a possible increase in cognitive burden (Cunningham *et al.*, 2010; Pieterse *et al.*,

2010). Nevertheless, increasing number of smart phone users worldwide may still make ACA easier to administer.

CA as a method of preference elicitation is criticised for diverging from the neoclassical utility theory based on choice, because ratings and rankings in CA do not straight away translate into a choice (Louviere *et al.*, 2010). Furthermore, ranking and ratings are rarely carried out by individuals in the real world decision-making process (Ryan, 1999). Therefore, inferences drawn from a CA study may not represent the actual behaviour and could be misleading (Louviere *et al.*, 2010).

3.4.2.7 Discrete choice experiment

Discrete choice experiment (DCE) is an ordinal preference elicitation method increasingly used in healthcare research (de Bekker-Grob *et al.*, 2012; Clark *et al.*, 2014). In a DCE, healthcare service/intervention are usually described by their typical features, known as attributes (Reed Johnson *et al.*, 2013). For example, effectiveness of the intervention, mode of administration of the treatment, length of stay in the hospital. Each attribute is assigned a range of possible values known as levels (Reed Johnson *et al.*, 2013). For example, the attribute “mode of administration of treatment” could include levels as oral, intravenous, nasal, and the attribute “length of stay in the hospital” could have levels as 1 day, 3 days, 5 days and 7 days. A DCE involves presenting individuals with a series of hypothetical alternative choice sets, usually pair-wise, differing in their attributes and levels, and asking them to indicate their preferred alternative in each set (Ryan *et al.*, 2008; Reed Johnson *et al.*, 2013). Figure 3.5 shows an example of choice set used in a DCE. Based on Lancaster’s consumer theory (Lancaster, 1966), it is assumed that the respondents consider attribute levels of each alternative to choose the alternative with highest utility value for them. Lancaster’s theory is further described in section 3.5.1 of this Chapter. A DCE also allows the quantification of the relative importance of attributes in terms of willingness to pay (WTP) for monetary (cost) attributes and marginal rates of substitution across non-monetary attributes (Ryan *et al.*, 2008). Furthermore, when health states are used as attributes, DCE can be useful in generating preference weights and then utility values for each health state included as attributes (Stolk *et al.*, 2010; Bansback *et al.*, 2012; Brazier *et al.*, 2012). DCE’s

are rooted in a long standing and well-tested neoclassical utility theory of choice- the random utility theory (RUT) (Louviere *et al.*, 2010) and can adequately predict actual behaviour in the public health setting (Salampessy *et al.*, 2015). RUT is further described in section 3.5.2. Therefore, compared to other traditional stated preference elicitation methods described in the earlier sections of this Chapter, DCE offer several advantages for economic evaluation and decision-making (Ali and Ronaldson, 2012; Salampessy *et al.*, 2015).

Hospital characteristics	**Hospital A**	**Hospital B**
Travel time to the hospital	30 minutes	1 hour
Waiting time to be treated	1 hour	30 minutes
Length of stay in the hospital	5 days	2 days
Risk of death while in hospital	3 in 100	5 in 100
Out of pocket expenses	£10	£20
Which hospital would you choose to go?		

Figure 3.5: An example of choice set in a DCE

3.4.2.8 Best-worst scaling

Best-worst scaling (BWS) is an alternative to DCE and is considered more appealing than the DCE for its simplicity and ability to provide additional insights compared to traditional DCE (Flynn *et al.*, 2007; Krucien *et al.*, 2016). There are three types of BWS methods, namely object case (case 1), profile case (case 2) and multi-attribute case (case 3) (Flynn, 2010). Figure 3.6 shows examples of BWS methods. The object case involves asking respondents to choose best and worst attributes (Cheung *et al.*, 2016). In contrast to the object case, the profile case involves asking respondents to choose best and worst attributes with their levels shown (Cheung *et al.*, 2016). Therefore, in the object case and profile case BWS, the choices are made within alternatives not between alternatives. The multi-attribute case closely resembles the DCE but involves respondents making repeated choices of the best and worst set of profiles from the given set of alternatives (at least three), each described by a number of common attributes (Lancsar *et al.*, 2013; Cheung *et al.*, 2016).

Case 1: Object case

Least important	Hospital Characteristics	Most important
	Travel time to the hospital	
	Waiting time to be treated	
	Length of stay in the hospital	
	Risk of death while in hospital	

Case 2: Profile case

Least important	Hospital Characteristics	Most important
	Travel time to the hospital: 30 minutes	
	Waiting time to be treated: 1 hour	
	Length of stay in the hospital: 5 days	
	Risk of death while in hospital: 3 in 100	

Case 3: Multi-profile case

Hospital characteristics	Hospital A	Hospital B	Hospital C
Travel time to the hospital	30 minutes	1 hour	2 hours
Waiting time to be treated	1 hour	30 minutes	1 hour
Length of stay in the hospital	5 days	2 days	7 days
Risk of death while in hospital	3 in 100	5 in 100	1 in 100
Which hospital would be the best for you?			
Which hospital would be the worst for you?			

Figure 3.6: Examples of best-worst scaling methods

The best worst-discrete choice experiment approach (case 3) is recommended as a valuable tool to provide rich preference information in healthcare (Lancsar *et al.*, 2013). However, research suggests no significant differences between the preference weights generated using best worst-discrete choice experiment (case 3) and traditional DCE (Potoglou *et al.*, 2011). Moreover, BWS format is reported to be less definitive compared to a traditional DCE in terms of consistency in the responses and respondent acceptability (Whitty *et al.*, 2014). Furthermore, research comparing the DCE and multi-profile based BWS in eliciting preferences for the EQ-5D-5L, found the DCE more feasible and reliable than BWS (Xie *et al.*, 2014). Another study, suggested that BWS provides lower quality data compared to a DCE and cautioned the use of BWS in measuring health preferences (Krucien *et al.*, 2016). The limitations in DCE have been extensively researched compared to BWS, and a

comprehensive research is suggested before BWS is used as an alternative to DCE (Krucien *et al.*, 2016).

3.5 Theoretical Framework of Discrete Choice Experiments

Both the DCE and BWS are underpinned by the same theoretical foundations. However, the limitations of the BWS discussed in section 3.4.2.8 of this Chapter would suggest that a DCE would be a less risky preference elicitation method compared to BWS (Clark *et al.*, 2014). Furthermore, as discussed in section 3.4.2.7, a DCE offers several advantages over other stated preference elicitation methods such as ranking, rating, CA, CV; as well as the other methods described earlier in this Chapter. This is because attributes in a DCE are traded against each other, it incorporates the concept of opportunity costs and allows the presentation of preference values in the marginal context; both of which are desirable characteristics of a preference elicitation method (Shackley and Ryan, 1995; Ryan *et al.*, 2008). In addition, a DCE is underpinned in the neoclassical utility theory of choice, is considered a reasonable basis for predicting actual choice behaviour in practice (Louviere *et al.*, 2010). Therefore, given the advantages offered by a DCE, it was considered the most appropriate preference elicitation method to predict actual behaviour in health care and was thus used within Chapter 4 to assess preferences for emergency medical services. Other preference elicitation methods are not discussed further in this thesis.

Given the focus on the DCE approach and given that the DCE is underpinned by a number of economic theories of consumer behaviour a brief exposition of the key theories is provided. The two theories that are important in the DCE are Lancaster's theory and the random utility theory which are described in sections 3.5.1 and 3.5.2 respectively.

3.5.1 Lancaster's theory

DCEs in economics are underpinned in the Lancaster's consumer theory (Lancaster, 1966). The essence of Lancaster's consumer theory is stated as follows:

1. *The good, per se, does not give utility to the consumer; it possesses characteristics, and these characteristics give rise to utility.*
2. *In general, a good will possess more than one characteristics, and many characteristics will be shared by more than one good.*
3. *Goods in combination may possess characteristics different from those pertaining to goods separately*.

Lancaster's theory considers a good as a bundle of attributes and consumer's choice of a good is defined over the attribute bundles. Therefore, according to Lancaster's theory, the utility of a healthcare alternative in a DCE is determined by its attributes and any changes in attributes can change the consumer preference from one alternative to another with the most beneficial combination of attributes.

3.5.2 Random utility theory

The DCE also has the theoretical foundations in random utility theory (RUT) which is used to explain uncertainty around predicting consumer and respondent choices. The RUT was originally developed by Thurstone (1927) in psychology, and was substantially developed into economics by McFadden (1974) who applied a conditional logit model consistent with RUT laying the foundation for the modern day DCE (McFadden, 1974). RUT introduces the idea that individuals choice behaviour is essentially probabilistic and at random (Thurstone, 1927). The basic axiom of RUT can be separated into two parts: 1) a systematic (explainable) component that can be observed by the researcher, and 2) a random (unexplainable) component which cannot be observed. The RUT framework assumes that individuals when faced with making a choice between alternatives will act rationally and will choose the alternative that maximises their utility. Therefore, the utility function is specified by the following equation:

$$U_i = V_i + \varepsilon_i \qquad (3.1)$$

where,

U_i is the latent utility of an individual for the alternative i

V_i is the systematic component of utility

ε_i is the random and unobservable component of utility

In a DCE, V_i is defined by the attributes and levels in the alternatives presented. The ε_i is the random error term representing all the unobservable factors influencing the choice decisions made by the individual. This random error implies that a researcher cannot observe the individuals true utility function, therefore a probabilistic utility function is used to estimate the likelihood of an individual choosing a particular alternative from a set of alternatives to choose from. The probability that an individual will choose alternative i over another alternative j is given by the following equation:

$$P_i = Prob(U_i > U_j) = Prob(V_i + \varepsilon_i > V_j + \varepsilon_j) = Prob(V_i - V_j > \varepsilon_i - \varepsilon_j) \quad (3.2)$$

Equation 3.2 shows that higher the probability of choosing alternative i, the larger will be the difference in utility between alternative i and alternative j. With the increase in quality of attributes in alternative i relative to quality of attributes in alternative j (i.e. the difference in estimated utility between alternatives increases) the probability of choosing alternative i converges towards 1. In a DCE, each respondent makes discrete choices in each set of alternatives and the proportion of respondents choosing alternative i is interpreted as the probability of choosing alternative i.

3.6 Conclusion

This Chapter discussed the importance of preferences in healthcare and identified commonly used preference elicitation techniques. Although there is a considerable debate on whose preferences should be used in health care, preferences from the representative general public would be most appropriate in a publicly funded health care system like the UK NHS. The preference elicitation techniques can be broadly categorised into revealed preferences methods and stated preference methods. In the absence of data on revealed preferences through participation in the market, stated preference methods prove useful in healthcare. Furthermore, the stated preferences methods can be also classified either as cardinal or ordinal methods. A DCE is an ordinal preference elicitation method that is well established and increasingly used in healthcare and offers several advantages compared to other preference elicitation techniques. A DCE is rooted in Lancaster's consumer theory and RUT, and it incorporates the concept of opportunity costs. Furthermore, it allows the presentation of preference values in the marginal context, which are desirable characteristics of a preference elicitation method. Therefore, the DCE approach was

considered the most appropriate method in the context of this PhD thesis. Chapter 4, describes application and results of a DCE in eliciting preferences for an emergency medical care context.

Chapter 4. Eliciting Public Preferences for the Provision of Emergency Medical Care

4.1 Introduction

Chapter 3 provided an overview of preference elicitation techniques that are used in healthcare and highlighted the importance of DCE. The aim of this Chapter is to report the development of the DCE which explored the public preferences of emergency medical services and quantified the strength preferences towards different emergency medical care service configurations (local versus distant location of emergency services).The two main objectives of the DCE were: i) to examine how individuals' weigh-up and trade-off between attributes of hospitals in an emergency, as well as the influence of their individual characteristics' upon their choice ii) to utilise the utility coefficients of hospital attributes from this study to inform an economic evaluation model of centralisation of emergency medical services in Chapter 6. The Chapter addresses the second research question set out in Chapter 1. The Chapter is structured into the following sections: section 4.2 presents the background to the importance of preferences in healthcare centralisation, section 4.3 describes the methods and process of DCE design including the samples, attributes and levels, survey design and analytical methods used, section 4.4 presents the results of the DCE using different analytical methods and models, section 4.5 presents the discussion of the results, implications of the findings, strengths and potential limitations of the experiment and finally the Chapter ends with section 4.6 summarising the Chapter.

4.2 Importance of Preferences in Healthcare Centralisation

Public preferences regarding the location and nature of healthcare providers have become an important influence upon policy and many European countries have incorporated patient preferences into decisions about their healthcare systems (Beckert *et al.*, 2012). Promoting patient choice is suggested to result in quality improvement and efficiency gains (Dixon *et al.*, 2010b). While designing and evaluating healthcare programmes in the context of limited resources, it is important to understand how users of the healthcare might respond to healthcare reforms and what elements they are prepared to exchange for improvement in one aspect of care compared with other aspects.

Centralisation of emergency healthcare services is one of the areas where patients may face alternatives with different consequences for different populations. This is because the activity of local district hospitals is transferred to fewer more specialised emergency units providing specialised review and technology services to patients (NHS England, 2013a). The expected quality of care at the specialised emergency units however may come only at a price of increased travel times, some delay in initial assessment and challenges for repatriation and continuity of care. Patients may have strong preferences towards local healthcare services and depending upon the nature of their illness may value proximity of local services more than the higher quality care provided by centralised services further away. It is also likely that patients may trade-off increased travel time, inconvenience and possibly greater fragmentation of care for improved quality of outcomes and other proposed benefits of centralised healthcare services, such as the availability of specialised teams and investigations.

Patient experience has been a core aspect in reformation of emergency medical services in the UK NHS (Fernandes, 2011; Department of Health, 2010) and it is important that patient preferences continue to inform centralisation decisions. Previous research projects in the UK have examined patient preferences towards different hospitals varying in their characteristics, however they did not consider emergency medical services (Ryan *et al.*, 2000; Shackley *et al.*, 2001; Burge *et al.*, 2005; Dixon *et al.*, 2010a). Gerard and Lattimer (Gerard and Lattimer, 2005) have quantified patient preferences for emergency primary care during usual GP surgery hours, but this was limited to healthcare advice and not the comparison between hospital configurations. Incorporating patient preferences in healthcare policy decisions may improve the uptake and efficiency of emergency healthcare services. Thus, it is desirable that the key drivers of choice of hospitals in an emergency are explored and preferences are established and incorporated in the emergency healthcare reforms to enable decision-makers better understand patient preferences and to give patients a greater say in the way how emergency medical services are best organised.

4.3 Methods

4.3.1 Discrete choice experiment

As noted in section 3.4.2.7 of Chapter 3, DCEs are an increasingly popular method for eliciting preferences in healthcare (de Bekker-Grob *et al.*, 2012; Clark *et al.*, 2014). DCEs provide rich data sources for economic evaluation and decision-making and offer several other advantages compared to other traditional stated preference elicitation methods (Ali and Ronaldson, 2012; Salampessy *et al.*, 2015). Chapter 3 provided an overview of preference elicitation techniques used in healthcare, discussed the appropriateness of DCE to address the issue focussed in this thesis and described its theoretical framework. In short, DCEs are rooted in a long standing and well-tested neo-classical utility theory of choice (Louviere *et al.*, 2010) and evidence (Salampessy *et al.*, 2015) has shown that preferences derived from DCEs can adequately predict actual behaviour in the public health setting. DCEs involve presenting individuals with a series of hypothetical choice sets which differ in characteristics and their magnitude or levels, and ask them to choose the alternative they prefer in each set. The choices that individuals make from DCE survey enable researchers to understand the value that individuals place on various levels of healthcare provision characteristics. Therefore, a DCE process was applied to elicit individual's preferences regarding a choice between local and distant hospital during an episode of emergency medical need according to different descriptions of care provision and outcome. The key stages involved in the development of a DCE are described in the next sections.

4.3.2 Defining attribute and levels

The first step when conducting a DCE is to define the variables (attributes) and associated range of values (levels). Several studies (Ryan *et al.*, 2000; Shackley *et al.*, 2001; Burge *et al.*, 2005; Gerard and Lattimer, 2005; Dixon *et al.*, 2010a) reporting patients' preferences and choices in healthcare were reviewed to identify important attributes in emergency medical services from the patient perspective. It was also essential that attributes also reflected the performance measures commonly used in emergency medical services (Sorup *et al.*, 2013) and also the key hospital quality indicators in NHS England (Cameron *et al.*, 2011; The College of Emergency

Medicine, 2011; Roberts *et al.*, 2014). Therefore, it was essential that the attributes balanced the need to identify important attributes with the need to reflect key hospital quality indicators. The identified attributes were assigned levels that were potentially applicable under the existing NHS systems (Acute surveys co-ordination centre for the NHS patient survey programme, 2009).

A number of qualitative research approaches such as focus group discussions, patient interviews and brain-storming could be conducted while developing attributes and levels in healthcare DCEs (Helter and Boehler, 2016). It has been highlighted by Coast and colleagues that if important attributes are excluded, then intuitively and self-evidently the resulting DCE is likely to be biased or useless for policy formation (Coast *et al.*, 2012). A recent publication has also highlighted the importance of qualitative research to inform the development of a DCE (Vass *et al.*, 2017). However, qualitative research exploring the attributes in the DCEs in this case was challenging in terms of time and resource constraints of this PhD. Getting the required sample for the qualitative work within a limited time was difficult. Furthermore, this DCE focussed on considering patient preferences of hospitals based on their key quality indicators.

The number of attributes considered appropriate in a DCE is context specific, but previous studies have used between four and six, with a few using more than ten (Ryan and Gerard, 2003; Marshall *et al.*, 2010; Clark *et al.*, 2014). However, increasing the number of attributes and their levels increases the complexity and the cognitive burden to the respondents in completing the DCE survey (Ryan and Gerard, 2003) which may lead to unreliable responses. Respondents are also likely to ignore attributes with narrow levels because of little difference between the levels (Lancsar and Louviere, 2008). A long list of attributes and their levels were identified from the literature which was then discussed with the expert supervisory team who voted on the relative importance of attributes. This list was then shortened, balancing the need to consider important attributes in this DCE with the need to reflect key hospital quality indicators in NHS England as discussed above. Therefore, only six key attributes (three quality outcomes and three process outcomes) and with a maximum of four reasonably wide levels for each attribute were selected (Table 4.1).

The attributes selected were travel time to hospital, waiting time to be treated, length of stay in the hospital, risk of dying, risk of re-admission to the hospital and outpatient care after emergency treatment. These attributes reflected the key quality indicators used in emergency medical services in the UK (Cameron *et al.*, 2011; The College of Emergency Medicine, 2011; Roberts *et al.*, 2014). The selection of attributes balanced the need to keep the choice set simple with the need to reflect key quality indicators of emergency medical services in the preference data. In addition, the appropriateness of these attributes and their levels were discussed extensively with the thesis supervisory team.

Table 4.1: Attributes and levels used in the DCE

Attributes	**Levels**
Travel time to hospital	Less than 30 min, 1 hour, 1 and half hours, 2 hours or more
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	30 min, 1 hour, 2 and half hours, 4 hours or more
Length of stay at the hospital before going home	1 day or less, 3 days, 5 days, 6 days or more
Risk of dying from the illness	Low (Less than 1 in 100 patients), Mild (3 in 100 patients), Moderate (5 in 100 patients), High (More than 7 in 100 patients)
Risk of being re-admitted to the hospital after going home	Low (Less than 1 in 100 patients), Mild (3 in 100 patients), Moderate (5 in 100 patients), High (More than 7 in 100 patients)
Outpatient care after emergency treatment	At your Local hospital, At a hospital which is about an extra 1 hour travel time from your local hospital

4.3.3 Initial experimental design

In the absence of underlying theory guiding DCE survey design or analysis the choice experiment design depends on the study circumstances (Amaya-Amaya *et al.*, 2008). However, the available guidance (Reed Johnson *et al.*, 2013) for best practice were closely followed in designing the DCE described in this Chapter. The attributes and attribute levels in Table 4.1 were used to develop an initial experimental design of choice scenarios using *Ngene* software version 1.1.1 (ChoiceMetrics, 2012). A full factorial design which incorporates all possible combinations of attributes and levels (Lancsar and Louviere, 2008) would have resulted in 2128 (i.e. $4^5 \times 2^1$) possible scenarios. However, considering numbers of attributes, task complexity and the time/resource constraints in this project a full factorial design was considered too large and thus inappropriate. Therefore, a fractional factorial design was used to reduce the number of choice scenarios to a more manageable number but still enabled the exploration of all main effects (effects of each attribute) of interest (Lancsar and Louviere, 2008). There are various approaches to obtaining a fractional factorial design. An efficient design, which maximises the statistical efficiency of designs by minimizing the predicted standard errors of the parameter estimates (usually the D-error statistic) was used for the initial experimental design (Rose and Bliemer, 2009). The generation of an efficient design requires knowledge of prior coefficient values, which in most instances are not known prior to the model estimation (Rose *et al.*, 2008). It could be expected that people prefer less travel time, less waiting time, fewer days in hospital, low risk of readmission, low risk of mortality and outpatient care in their local hospital; this could have shown the direction of attribute coefficients. However, prior coefficient values for all of the attributes considered in this case were not readily available. In addition, it was not certain whether similar direction of coefficients applied for the case focussed on in this Chapter. Therefore, the prior coefficient values were assumed to be zero for the initial efficient design which was piloted (explained in section 4.3.5). D-efficiency scores were used to ensure that an optimal set of choice scenarios are used in the DCEs survey.

The initial efficient design generated 20 choice sets-a number which may place heavy cognitive burden on respondents. Therefore, to minimise the potential cognitive burden to the respondents, the choice sets were blocked into two, with

each block having 10 choice sets (Reed Johnson *et al.*, 2013). Respondents were randomly assigned one of the blocks of choice sets. The respondents were asked to make a forced choice between the hospitals. Whether or not to include an "opt out" alternative in choice studies has been widely debated. Studies (Dhar and Simonson, 2003; Brazell *et al.*, 2006; Parker and Schrift, 2011; Veldwijk *et al.*, 2014) have shown that presence of 'opt out' alternative in choice sets generates smaller attribute coefficients compared to the coefficients from a forced choice which could have implications in computation of marginal rates of substitution. It has also been argued that including an opt out alternative in choice studies leads to unnecessary loss of efficiency in choice designs if a higher number of respondents choose to opt out (Brazell *et al.*, 2006; Veldwijk *et al.*, 2014). Dual response design, in which respondents are first forced to choose between the available alternatives and then immediately after choosing are again asked to choose between the available alternatives and the opt-out alternative, could have allowed a better estimation of the attribute coefficients (Brazell *et al.*, 2006; Rose and Hess, 2009; Veldwijk *et al.*, 2014). However, dual response design would have increased response burden. Furthermore, considering the nature of decision problem faced by respondents in this case of healthcare emergency considered by this DCE, an opt-out alternative of "no treatment" in a healthcare emergency would have lacked realism.

One choice scenario was repeated in each of the blocks (making 11 choice scenarios in each block) to assess the completeness in the participant responses. The completeness (test-rest reliability) axiom of consumer theory specifies that each individual has a well-defined preference between any two possible alternatives (Lancsar and Louviere, 2006) i.e. if participants prefer A to B in a choice set at any point in a survey then they should again prefer A to B when the choice set is repeated at any subsequent point within the questionnaire (Ryan and San Miguel, 2003).Violation of completeness axiom was considered irrational. Completeness axiom as a test of rationality was used in initial experimental design because it is simple and is more often used in preferences studies compared to other tests used in health economics such as Sen's expansion and contraction and transitivity (Lancsar and Louviere, 2006).

The questions on socio-demographic and general health information are very useful in understanding the characteristics of the population studied. It is also common to use these information as covariates in different analysis models in discrete choice experiments. The socio-demographic questions in the survey included: gender, age-group, partial-postcode location (the first part of the postcode, for example only NE2 for NE2 4AX) and their GP surgery name. The postcode and GP surgery information was used to ensure that any respondent outside of Northumberland region (the study area) was not included. In addition, the survey also included questions on difficulty in completing the choice task and the number of emergency visits in the last 12 months. The data on choice task difficulties was expected to provide insights into the cognitive burden on respondents. The data on number of emergency visits in the last 12 months was expected to inform whether the preferences varied with experience of emergency visits. Person identifiable information such as name, date of birth, full postal address and NHS number were not collected to comply with data governance protocols.

Generic health information is expected to provide insights into the health related quality of life of the respondents. Therefore, the survey also included EQ-5D-5L and EQ-VAS generic health status questions from the EuroQol group (Herdman *et al.*, 2011; Devlin and Brooks, 2017). The EQ-5D-5L describes health on 5 dimensions: mobility, self-care, usual activities, pain/discomfort and anxiety/depression. Each dimensions include five levels ranging from no problems to extreme problems from which the respondents are asked to select the level closely matching to their health state. The descriptive data is commonly converted to utility weight in a scale where 0 is equivalent to dead and 1 is considered full health, but negative values indicating a health state worse than dead is also possible. The utility values for each health state were derived from EQ-5D-5L tariffs for England (Devlin and Shah, 2018). The EQ-VAS is a scale where respondents are asked to indicate their self-rated health ranging between 0 (worst imaginable health state) to 100 (best imaginable health state).

The survey questionnaire had a study information section in the very beginning which included: the aim of the survey, what the participation in the survey would involve, the

estimated time to complete the survey, the description of each of the attributes included in the DCE, clear statement of voluntary participation in the survey and assurance of no person identifiable questions, an example of selection of hospitals in a choice scenario and contact details of the researcher in case of any questions on the survey. This information section was included to ensure that this survey was conducted ethically.

4.3.4 Pre-testing the survey

The paper format of the initial survey design was pretested among six members of the Institute of Health & Society (IHS), Newcastle University. Following the pre-test, the survey questionnaire was revised with some simplification to the wording of survey introduction and choice sets. The pre-test indicated that it would take participants about 12-18 minutes to complete the survey.

4.3.5 Piloting the survey

After the pre-test, the paper format of revised questionnaire was piloted on a sample of 29 purposively selected participants registered with the Healthwatch Northumberland's network. Healthwatch England is a national consumer champion in healthcare and operates through networks in every local authority across England. The survey pilot was run between July 2015 and September 2015. The survey pilot was expected to provide prior coefficients for each attributes to be used in final design of the DCE choice sets (see section 4.3.6). It was also expected to assess whether the wording of the survey was appropriate to the potential respondents and whether they had any difficulties in understanding and completing the survey. Three respondents among the 29 included in the pilot did not fill out the survey correctly and were excluded from the pilot analysis. The majority (58%) of remaining 26 participants reported no difficulty in completing the DCE choice sets and most of them answered all questions correctly. Although 42% reported DCE survey as difficult and two participants did not complete the self-reported health questions, all the 26 participants provided complete responses to the choice questions. The high level of correct and complete responses to survey questions was considered satisfactory. However, among the 26 participants analysed, 8 (30.76%) were not consistent in their choice and failed the completeness axiom/test-retest reliability in

their responses. The pilot study showed that respondents understood the choice task and easily manage the choice questions.

It is well known that DCEs can be cognitively demanding. A high level of complete responses in this DCE was assumed to reflect that the text, attributes and levels used in the survey were appropriate and did not result in cognitive overload for respondents. However, to further ensure the clarity of the survey some of the text were reformatted and simplified. The respondents were reassured by reiteration that no questions will identify them. Some of the text was changed to bold and some underlined to highlight important information about the survey. The paragraph of text following the example choice set was changed to bulleted list form to increase clarity. The font size of the text was also enlarged and only one scenario per page was presented to respondents. An option “Prefer not to say” was added in the question asking about the participant’s gender. In the pilot it was realised that participants disliked the question on their education / qualifications. Therefore, this question was removed from the final survey questionnaire. The pilot also helped to identify the need for a paper format of the survey questionnaires with large font for the visually impaired participants. The characteristics of participants of the pilot test are presented in Table 4.2.

Table 4.2: Characteristics of participants of the pilot test

Characteristics	All
Sample (n)	26
Age groups	
60-64	4(15.3%)
65-69	9(34.6%)
70-74	4(15.3%)
75-79	4(15.3%)
80-84	3(11.5%)
85+	2(7.6%)
Gender	
Male	13 (50%)
Female	13 (50%)
Self-reported health*	
Mean EQ-VAS score (SD)	62.91(23.21)
Mean EQ-5D score(SD)	0.64 (0.29)
Emergency experience	
Yes	6 (23.07%)
No	20 (76.92%)

*Analysis based on only 24 participants who completed self-reported health

The pilot data was used to generate the prior coefficient parameters in Table 4.3 and the pilot results indicated the direction of the attribute preferences. The negative coefficients in each of the attribute indicate that respondents preferred less travel time to the hospital, less waiting time to receive the treatment, fewer number of days in hospital, low risk of death, low risk of readmission, and outpatient follow-up in their local hospitals; the higher the level of the attribute, the higher the level of attribute the individual is less likely to choose that attribute.

Table 4.3: Regression results from the pilot study

Attributes	Coefficients (SE) (Main effects-MNL)
Travel time	-0.01 (0.003)***
Waiting time	-0.007 (0.0013)***
Length of stay	-0.10 (0.04)*
Risk of death	-0.28 (0.05)***
Risk of readmission	-0.16 (0.04)***
Outpatient follow-up	-0.62 (0.17)***

***p<0.001, *p<0.05; SE=Standard Error,

4.3.6 Final discrete choice experiment design and survey questionnaire

The final survey was also designed using *Ngene* software version 1.1.1 (ChoiceMetrics, 2012). In the last 10 years coefficient values estimated from pilot surveys have been used to re-design and improve the level of statistical efficiency of the final survey design (Rose *et al.*, 2008). But, the robustness of these priors used in this DCE design is questionable because they were based on a small and purposive pilot sample. If the priors were mis-specified then the statistical efficiency of the design would be reduced. However, experiments have demonstrated that statistically efficient designs are likely to outperform orthogonal designs, even if the priors used in the construction are incorrectly specified, even up to $\pm$40% deviation (Rose and Bliemer, 2013). Therefore, coefficients generated from the pilot data (Table 4.3) were used as priors to re-design the final survey.

Efficient design with twenty choice sets blocked into two with 10 choice sets in each block were designed. Blocking reduced the number of choice sets answered by respondents and was expected to minimise the potential cognitive burden on them (Reed Johnson *et al.*, 2013). Respondents answered the block randomly assigned to them. New design in *Ngene* meant that the choice sets in the final design differed from those used in the pilot, however the questions on socio-demographic

information and general health remained the same as in the pilot. Both the blocks had the same socio-demographic and general health questions.

DCE results are based on hypothetical scenarios which means that it is important that these results are externally valid i.e. similar results are observed in the real world. However, there is often little scope of tests of external validity of DCE results in the health sector because of lack of market in health care and unavailability of real data on individuals' health (de Bekker-Grob *et al.*, 2012; Clark *et al.*, 2014). Therefore, tests of external validity were considered difficult in this study context and were not applied. It is difficult to establish whether the respondents' stated preferences were consistent with their actual behaviour. Nevertheless, the study attempted to minimize any such differences in the stated and actual choice by offering best possible real world alternatives to choose from.

Internal validity checks were carried out using the tests of theoretical validity and rationality. Theoretical validity was assessed by checking whether the parameters moved in expected direction by looking at the estimated signs of the parameter coefficients. For example, it was expected that shorter travel time to a hospital is preferred over longer travel time duration. The completeness axiom used as rationality tests in initial survey design and the pilot (see section 4.3.3) was dropped in the main study for tests of "transitivity" and "monotonicity". The importance of these tests was realised only after the pilot was conducted. Transitivity was used as the test of the underlying axioms of consumer theory and is considered the more fundamental test of rationality in preference elicitation compared to completeness (Lancsar and Louviere, 2006). A completeness test in addition to transitivity and monotonicity tests would obviously have made investigation of rationality checks stronger but this could have come only at a price of increased cognitive burden and time for respondents caused by the increased number of choice sets in the questionnaire. Another commonly used rationality test is Sen's expansion and contraction which implies that if a respondent prefers A in choice set with three choice options A, B and C, then again when presented with choice set 2 contracted to just two options A and B, the preferred choice should not be B (Lancsar and Louviere, 2006). Sen's expansion and contraction test (which involves at least three

alternatives in original choice set contracted to two alternatives in another choice set or vice-versa) as a rationality test in the two alternative DCE described here in this Chapter would have been difficult and was considered inappropriate.

Transitivity implies if A is preferred to B and B is preferred to C, then A should be preferred to C (Ozdemir *et al.*, 2010). In each of the blocks of questionnaire, choice set number 3 with alternatives as hospital A and hospital B (i.e. from the choice design) was taken as a base for the transitivity test. The transitivity test were spread out as evenly as possible across the choice task. Therefore, another choice set number 6 was manually added keeping hospital B attribute levels the same as in the choice set 3 but with a new alternative, hospital C with completely different attribute levels. Another additional choice set number 9 was manually added taking characteristics of hospital A from the choice set 3 and characteristics of hospital C from choice set 6. In short, the test was structured as follows:

Choice set number 3: Hospital A=A, Hospital B=B

Choice set number 6: Hospital A=B, Hospital B=C

Choice set number 9: Hospital A=A, Hospital B=C

However, in the questionnaire in each of the choice sets the alternatives were named as hospital A and hospital B. So, if the respondent made choices in a cyclic order (prefer A to B and prefer B to C and then prefer C to A; prefer B to A, C to B, and then prefer A to C) the choice was considered intransitive and thus irrational.

Though not essential for rationality, monotonicity, is a desirable axiom of consumer theory and implies that more is preferred to less (Lancsar and Louviere, 2006). Therefore, another choice set number 12 where one hospital alternative was obviously dominant in terms of all attributes was manually added to the choice task as a test of violation of monotonicity axiom. It was assumed that individuals preferred the alternative with shorter travel time, shorter waiting time, low risk of mortality, low risk of readmission, shorter length of stay and outpatient follow-up at their local hospital. Any violation of monotonicity axiom in the respondent choices was considered irrational.

Hence, the final survey consisted of 13 choice sets in each block asking participants to indicate which of the two hypothetical emergency care emergency hospitals varying in terms of the attribute levels they would choose in case of emergency (see Appendix B for a sample block of questionnaire used in the survey). However, the responses to the choice sets number 6, 9 and 12 used as internal validity tests were not included in the final data analysis. The number of choice sets used were considered manageable considering the existing evidence (Clark *et al.*, 2014). It has been suggested that respondents can manage multiple number of choice scenarios (up to 17 in the experiment) without any difficulty (Bech *et al.*, 2011). There are instances where many more scenarios have been used for example 36 choice scenarios in a DCE involving people with glaucoma (Burr *et al.*, 2012). However there will be a tendency for choice variance to increase with the increase in the number of choice sets (Bech *et al.*, 2011).

So, how was violation of validity tests in discrete choice experiments dealt with? Any respondents violating such tests may be deleted and excluded from the main analysis (Ryan and Bate, 2001; San Miguel *et al.*, 2005; Hifinger *et al.*, 2017) however an influential research article (Lancsar and Louviere, 2006) has argued that failure of the test would not necessarily mean the respondent was irrational and deletion of responses that fail the validity tests may result in removal of valid preferences which may lead to biased results. Moreover, random utility theory is expected to be robust to such violations in validity tests (Lancsar and Louviere, 2006). Furthermore, qualitative research (San Miguel *et al.*, 2005; Ryan *et al.*, 2009) in this area also revealed that respondents failing the validity tests had rational reasons for doing so. Therefore, in this choice experiment the choice data was analysed with and without respondents failing the validity tests.

4.3.7 Electronic questionnaire

The paper format of the questionnaire was adapted into an web version of survey using a commercial platform Qualtrics (Qualtrics, 2015). The web version of the survey was purposively tested on five staff from Institute of Health & Society, Newcastle University. There were no reports of technical issues in completing the web version of the survey. Table 4.4 shows an example of the choice set.

Table 4.4: Illustrative example of choice set used in the DCE

Suppose you have an emergency healthcare need which required calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

Characteristics	**Hospital A**	**Hospital B**
Travel time to hospital	1 and half hours	1 hour
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	4 hours or more	Less than 30 minutes
Length of stay at the hospital before going home	3 days	5 days
Risk of dying from the illness (..patients die)	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Outpatient care after emergency treatment	At a hospital which about an extra 1 hour travel time from local hospital	Local hospital
Which hospital would you chose to go in emergency? (Please tick only one box at the right)	☐	☐

4.3.8 Survey sample and data collection

The survey sample was taken from list of individuals over 18 years of age either registered with the healthwatch Northumberland (Healthwatch) network or with a record of emergency healthcare visit in the Northumbria Health Care NHS Foundation Trust (NHCT). The survey was administered to the potential participants

via healthwatch Northumberland and NHCT. The survey was administered between January 2016 and April 2016.

Potential participants with email access were sent an electronic link to the survey using online commercial platform, Qualtrics (Qualtrics, 2015) whereas those without email access were sent a paper format of the survey in post. Participants previously identified with visual impairments and no email access were sent a paper format of the survey questions in large fonts in post. All the participants accessed via NHCT were sent a paper format of the questionnaire in post. An invitation to participate, containing key information explaining the survey, time required and how the responses will be used, were also sent along with the web link to the survey. The web link was provided in case some potential respondents receiving the survey questionnaires in post would prefer to complete the survey online. As explained earlier in section 4.3.6, the survey was blocked into two and the participants were randomly assigned to a block.

4.3.9 Sample size

Sample size estimation methods in healthcare DCE studies are currently developing (de Bekker-Grob *et al.*, 2015). Traditional designs and existing sampling theories do not address the issue of minimum sample size requirements in terms of reliability of parameter estimates produced and assumptions are often employed in computing sample estimates (Rose and Bliemer, 2013; de Bekker-Grob *et al.*, 2015). A range of the range of 100 to 300 respondents used by most of the DCE studies in health care (de Bekker-Grob *et al.*, 2015).The sample size in more recent studies vary, with fewer samples in disease specific population (Shalowitz *et al.*, 2018), higher samples in studies in general population (Nexo *et al.*, 2017) and within the range of 100-300 in others (De Brún *et al.*, 2018). It appears these sample sizes are mainly determined by the rule of thumb or in line existing DCE studies or based on the context.

The sample required for this study was estimated following the rule of thumb suggested by Johnson and Orme (Orme, 1998; de Bekker-Grob *et al.*, 2015; Orme, 2010) using the following equation:

$$N > 500L/TA$$

where N is sample size required, L is the largest number of levels for any of the choice attributes, T is the number of choice sets, and A is the number of alternatives assessed. The required minimum sample was estimated as 100 respondents. However, a much larger sample was targeted to allow for heterogeneity between respondents.

It should be noted that rules of thumb are considered a sub-optimal approach. Even the sample estimate computed using an alternative sample size estimation method (de Bekker-Grob *et al.*, 2015) suggested that this study would only need a minimum 53 respondents to generate adequately powered coefficient estimates; at the same time it should be noted that the estimated minimum sample was increased to above 1000 respondents when risk of death and risk of readmission were recoded into categorical levels. This method requires prior knowledge of the significance level, the statistical power level, the statistical model to be used in the DCE analysis, prior coefficients and the DCE design. Using these information, the sample size is computed by this method using the following equation:

$$N > ((Z_{1-\beta} + Z_{1-\alpha})\sqrt{\sum_{\gamma k}/\delta)}$$

Where, N is the sample size, $1-\beta$ is the power level, α is the confidence level, $\sum\gamma$ is the variance-covariance matrix, δ are the effect sizes. The step by step guideline to estimate the sample size using this method in R programming language is provided by de Bekker-Grob et al (2015).

Hence, a sample of 148 respondents included in the analysis in this DCE was considered adequate.

4.3.10 Data analysis

Discrete choice modelling within a random utility modelling framework was used to analyse the survey data collected. A wide range of logistic regression modelling approaches are available (de Bekker-Grob *et al.*, 2012) and selection depends upon the characteristics of data collected (Amaya-Amaya *et al.*, 2008). Multinomial Logit

(MNL) analyses, also sometimes known as conditional logit analyses, are increasingly popular in analysing choice data in health economics (Clark *et al.*, 2014). A simple MNL analyses was performed and depending upon the characteristics of the data and restrictions of MNL model, estimates from other model specifications such as Mixed Multinomial Logit (MIXL) and Generalised Multinomial Logit (GMNL) were also considered. Although the initial plan was to perform the subgroup analysis, small sample size in the subgroups were considered insufficient to generate meaningful results. However, covariate interactions with the attributes were assessed to see how the results were influenced by the patient characteristics. Both the pilot and final survey data analysis was performed in R (R Core Team, 2016) and were replicated in STATA 13 (StataCorp, 2013).

Model 1A and Model 1B utilised MNL regression on the choice data. Model 1A tested the main effects assuming homogenous choice across all respondents in the sample. Model 1B assessed the significance of attribute interactions with the respondent characteristics to understand how the respondent characteristics influenced the preference estimates. However, the MNL models are based on assumptions of independence of irrelevant alternatives (IIA), independence and identical distribution of error terms (IID) across observations and no heterogeneity across respondents. This may be restrictive and limited in describing human choice behaviour (de Bekker-Grob *et al.*, 2012). Therefore, the MIXL model (Hensher and Greene, 2003; Hess and Train, 2017), a popular extension of the MNL which, while keeping the IID and not making the IIA assumptions eliminates the limitations of MNL by allowing for choice heterogeneity across respondents was considered in Model 1C.

It has been argued that generalised multinomial logit (G-MNL) model allows for the scale heterogeneity by accounting for some respondents who exhibit more random (i.e. relatively insensitive to attributes) and extreme (i.e. near lexicographic- always choosing a particular attribute regardless of others) choices, and thus offers a better fit; outperforming the MIXL model (Fiebig *et al.*, 2010). Therefore, Model 1D was considered utilising the G-MNL model. All these models initially considered all the attribute levels as continuous but were again repeated (except Model 1B) after

recoding risk of readmission, risk of death and outpatient follow-up as categorical variables.

Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used as measures of the model fit. The lower the AIC and BIC measures the more preferred is the model (Hauber *et al.*, 2016).

4.3.11 Marginal rates of substitution

The signs (negative or positive) of coefficients indicate the direction of a particular attribute in terms of utility, however attribute coefficients are not directly comparable against each other because of differences in the scale of measurement in each attribute (Vass *et al.*, 2018). The magnitude of coefficients alone provide a little meaningful information. One of the commonly used approach is to compare the coefficient results is to estimate the marginal rates of substitution (MRS). Therefore, MRS were calculated, across all models, to compare respondent preferences on a common value scale and understand the trade-offs they were willing to make between two attributes. MRS values were estimated as the ratio between coefficients of two attributes i.e. dividing coefficient of one attribute by coefficient of another attribute. Since there was no cost attribute in this choice experiment, willingness to pay (WTP) was not generated. However, time was utilised as the “currency” to derive how much travel time or waiting time respondents were willing to give up to get more of other attributes. Ratios of other selected attributes were also estimated.

4.3.12 Ethical considerations

The DCE survey conducted via Healthwatch was ethically approved by the Newcastle University Faculty of Medical Sciences Ethics Committee (*approval code 00893/2015*) (see Appendix B-B1). The survey via NHCT was administered via the trust patient experience team so there were no data protection issues relating to transfer of names and address. Furthermore, only anonymised data were provided for the analysis. All potential participants were provided brief information about the survey and reassured that personal identifiable information will not be collected. Since this survey was administered using postal and web based electronic methods,

specific written consent of the participants was not obtained. However by participating in the survey, respondents were made aware that they were providing consent for their views to be collected. Participants were also informed that participation in the survey was voluntary and they could stop completion of the survey at any time without providing any reason whatsoever. However once completed, it was not possible to remove their responses as no identifiable information were collected. Participants were provided with the contact details of the researcher to provide them an opportunity to raise any concerns regarding the survey. All data collected from the participants were anonymous.

The survey data and other related materials were handled in accordance with the Newcastle University's rules and regulations in place with strict adherence to *The Data Protection Act 1998* and the *Newcastle University Information Security Guidelines* (http://www.ncl.ac.uk/data.protection/policy.htm).

4.4 Results

4.4.1 Descriptive statistics

The survey was sent through post to a total of 681 potential respondents (181 via Healthwatch and 500 via NHCT). A total of 148 respondents completed the survey: 62 completed the web version and 86 completed the postal version. The response rate in the survey sent through post was 12.62%. It was quite difficult to assess the response rates in the web version of the survey. However, the survey web-link was emailed to 342 individuals (these do not include individuals who were sent the survey through post) and to 301 organizations, 115 parish councils, as well as 67 county councillors requesting them to share the survey web link. The web link to the survey was opened by 101 potential respondents and the response rates in terms of those opening the survey in the web version of the survey was about 61%.

Table 4.5 presents the summary of the key characteristics of the respondents. Most of the respondents were above 55 years of age, close to retirement. There were almost twice the number of female respondents compared with the number of males. About half of the respondents had some form of emergency experience in the

immediate 12 months before the survey. The general health measures (EQ-VAS=75.5, EQ-5D-5L=0.77) suggested the health status of the respondents is rather low compared to UK general population average, however, it was generally similar to the average for those above 55 years of age in the UK general population (Janssen and Szende, 2014). A majority of respondents in this survey were aged more than 55 years suggesting that general health measures could be reasonable reflection of members of the general population of a similar age.

Table 4.5: Summary of respondent characteristics

Characteristics	All
Sample (n)	148
Age groups	
16-29	4 (2.70%)
30-34	6 (4.05%)
35-39	5 (3.37%)
40-44	4 (2.70%)
45-49	9 (6.08%)
50-54	12 (8.10%)
55-59	19 (12.84%)
60-64	21 (14.19%)
65-69	27 (18.24%)
70-74	17 (11.48%)
75-79	9 (6.08%)
80-84	9 (6.08%)
85+	6 (4.05%)
Gender	
Male	49 (33.10%)
Female	98 (66.21%)
Prefer not to reveal	1 (0.67%)
Self-reported health	
Mean EQ-VAS score (SD)	75.50 (20.48)
Mean EQ-5D-5L score(SD)	0.77 (0.22)
Emergency experience	
Yes	78 (52. 70 %)
No	70 (47.30%)

Among the sample, 65 (44%) respondents self-reported some form of difficulty in completing the choice task (Table 4.6). However, only two respondents (one completed the postal version and the other completed the web version of the survey) failed the transitivity test among the two internal validity checks (transitivity and monotonicity) employed.

Table 4.6: Reported choice task difficulty and internal validity failure

Characteristics	Number of respondents (percentage)
Choice task difficulty	
Very Difficult	3 (2.03)
Difficult	9 (6.08)
Somewhat Difficult	53 (35.81)
Neutral	27 (18.24)
Somewhat easy	27 (18.24)
Easy	19 (12.84)
Very Easy	10 (6.76)
Internal validity failure	2 (1.4)

4.4.2 Regression analysis of DCE data

A very small number of respondents (two) failed the validity tests and the initial regression analysis indicated that the coefficient estimates remained similar regardless of whether those respondents failing the validity tests were included or excluded in the analysis. Therefore, all respondents were included in the final analysis. Table 4.7 presents the regression analysis considering all the attributes as continuous, whereas Table 4.8 presents the analysis where the attributes “risk of readmission”, “risk of death” and “outpatient follow-up” were dummy coded as categorical variables. The coefficient generated from each models considered in the analysis (see section 4.3.10) are presented in Tables 4.7 and 4.8. The negative and positive signs in the coefficients indicate preference of a lower level and higher level of an attribute respectively.

In Table 4.7, Model 1A utilised MNL regression (see section 4.3.10) on the choice data to test the main effects and presents the utility coefficients for each attributes used in the choice experiment. The negative signs in the coefficients value in Model 1A indicated that higher the level of these attributes in an alternative, the less likely the individual was to choose the alternative. The coefficients estimates were in line with the priori expectations that individuals would prefer less travel time to the hospital (-0.0086, $p<0.001$), less waiting time to receive the service (-0.0056, $p<0.001$), fewer number of days of length of stay in hospital (-0.0768, $p<0.001$), low risk of death (-0.3258, $p<0.001$), low risk of readmission (-0.1442, $p<0.001$), and outpatient follow-up care after the emergency treatment in their local hospital (-0.9624, $p<0.001$).

Model 1B in Table 4.7 utilised the MNL regression but also assessed the significance of attribute interactions with respondent characteristics. None of the attribute interactions with respondent age and self-reported health measures were significant. This ruled out important differences therefore age and health status were unimportant in this case. Only the interactions (Travel Time* Gender, Waiting Time*Gender, Waiting Time* Survey Mode, Risk of Death* Gender, Risk of Death*Survey Mode, Risk of Readmission* Gender) were significant and were included in the final specification (Table 4.7). Results suggest that men have stronger preferences for less travel time (-0.0049, $p<0.01$), less waiting time (-0.0021, $p<0.05$), lower risk of death (-0.1047, $p<0.01$) and lower risk of readmission (-0.0775, $p<0.01$) compared to women. Respondents completing the web based survey showed stronger preferences for less waiting time (0.0027, $p<0.001$) and lower risk of death (0.0862, $p<0.01$) compared to those completing the survey in paper. Model 1B had lower AIC and offered a better model fit compared to Model 1A. However, it has to be noted the coefficients for travel time and risk of readmission were no longer significant.

Model 1C in Table 4.7 utilises mixed logit (MIXL) model (see section 4.3.10) and takes heterogeneity into account. The significance of attributes remained the same as Model 1A, however, the lower AIC and BIC in Model 1C indicated that it provided a better model fit compared to Model 1A and Model 1B. Furthermore, the statistically significant standard deviations in Model 1C indicates the presence of heterogeneity among respondents, which suggests that the mixed logit models in this case are more appropriate than the multinomial logit models. Coefficient estimates in Model 1D which utilises generalised multinomial logit (G-MNL) model (see section 4.3.10) also retained the signs and significance similar to Model 1A and Model 1C, but had reduced significance.

Table 4.7: Regression results

Attributes	Model 1A (Main effects-MNL)	Model 1B (Including respondent characteristics-MNL)	Model 1C (Main effects-MIXL)		Model 1D (Main effects-GMNL)	
	Coefficients (SE)	Coefficients (SE)	Coefficients (SE)	SD (SE)	Coefficients (SE)	SD (SE)
Travel Time	-0.0086 (0.0009)***	-0.00068 (0.0032)	-0.0125 (0.0020)***	0.0165(0.0024)***	-0.0235 (0.0097)*	0.0254 (0.0091)**
Waiting Time	-0.0056 (0.0005)***	-0.00333(0.0015)*	-0.0077 (0.0008)***	0.0048(0.0009)***	-0.0146 (0.0059)*	0.0078 (0.0028)**
Length of Stay	-0.0768 (0.0152)***	-0.0784(0.0153)***	-0.1217 (0.0262)***	0.1608(0.0395)***	-0.2501 (0.1149)*	0.2668 (0.1264)*
Risk of Death	-0.3258 (0.0202)***	-0.1953(0.0553)***	-0.4623 (0.0425)***	0.2577(0.0434)***	-0.8409 (0.3184)**	0.3930 (0.1478)**
Risk of Readmission	-0.1442 (0.0159)***	-0.0192 (0.0518)	-0.1803 (0.0262)***	0.1384(0.0386)***	-0.3436 (0.1491)*	0.2210 (0.1171)
Outpatient Follow-Up	-0.9624 (0.0776)***	-0.9887(0.0792)***	-1.2442 (0.1424)***	0.7290(0.1826)***	-2.2214 (0.8883)*	1.5190 (0.1478)*
Interaction terms						
Travel Time*Gender	-	-0.0049 (0.0019)**	-	-	-	-
Waiting Time*Gender	-	-0.0021 (0.0009)*	-	-	-	-
Waiting Time*Survey Mode	-	0.0027 (0.0008)***	-	-	-	-
Risk of Death*Gender	-	-0.1047 (0.0327)**	-	-	-	-
Risk of Death*Survey Mode	-	0.0862 (0.0291)**	-	-	-	-
Risk of Readmission*Gender	-	-0.0775(0.0297)**	-	-	-	--
Sample size (Observations)	148(2960)	148(2960)	148(2960)	-	148 (2960)	-
Log Likelihood	-813	-800	-763	-	-757	-
AIC	1640	1623	1522	--	1544	-
BIC	1670	1687	1621	-	1624	-

***p<0.001, **p<0.01, *p<0.05; SE=Standard Error, SD= Standard Deviation; AIC= Akaike information criterion; BIC = Bayesian information criterion

Similar models to those presented in Table 4.7 are presented in Table 4.8, but they do not consider MNL with attribute interactions with respondent characteristics. Model 2A, 2B and 2C are MNL model, MIXL model and G-MNL model respectively. In Table 4.8, the attributes “risk of death”, “risk of readmission” and “outpatient follow-up” which were coded as continuous attributes earlier were recoded into categorical levels. Among Models 2A, Model 2B and Model 2C, the AIC was lowest in Model 2C indicating that it offers the better model fit compared to others. The coefficients of “length of stay” in Model 2A and the level mild of “risk of death” attribute were not significant across all three models (Model 2A, Model 2B, and Model 2C). The non-significant coefficients in the models indicate that it was not sure whether length of stay in the hospital and mild risks of death did really matter to the respondents.

The coefficients increased with the increase in the levels of “risk of death” and “outpatient follow-up”, however coefficients of levels of “risk of readmission” demonstrated non-linearity (Figure 4.1 and Figure 4.2). The coefficient of the level mild of “Risk of Readmission” was not significant.

Table 4.8: Regression results after recoding selected variables as categorical

Attributes	Model 2A (Main effects-MNL)	Model 2B (Main effects-MIXL)		Model 2C (Main effects-GMNL)	
	Coefficients (SE)	Coefficients (SE)	SD (SE)	Coefficients (SE)	SD (SE)
Travel Time	-0.0065 (0.0009)***	-0.0094 (0.0020)***	0.0160 (0.0026)***	-0.0105 (0.0022)***	0.0165(0.0026)***
Waiting Time	-0.0039 (0.0007)***	-0.0051 (0.0010)***	0.0046 (0.0010)***	-0.006 (0.0013)***	0.0049 (0.0010)***
Length of Stay	-0.0277 (0.0168)	-0.0608 (0.0265)*	0.1459 (0.0429)***	-0.0744 (0.0302)*	0.1541 (0.0419)***
Risk of Death					
(Base level: Low (1 in 100))					
Mild (3 in 100)	-0.6103 (0.319)	-0.3169 (0.4903)	0.2563 (0.6952)	-0.6024 (0.5483)	0.2919 (0.3664)
Moderate (5 in 100)	-1.8155 (0.288)***	-2.0607 (0.4388)***	0.3318 (0.5390)	-2.4479 (0.5104)***	0.0473 (0.4896)
High (7 in 100)	-1.5249 (0.161)***	-2.1425 (0.2830)***	1.3199 (0.2785)***	-2.4847 (0.3624)***	1.3312 (0.2726)***
Risk of Readmission					
(Base level: Low (1 in 100))					
Mild (3 in 100)	0.3326 (0.1296)*	0.3297 (0.1864)	0.3266 (0.6027)	0.4436 (0.2119)*	0.5174 (0.2913)
Moderate (5 in 100)^	-	-	-	-	-
High (7 in 100)	-0.7728 (0.1219)***	-0.9753 (0.1986)***	0.7813 (0.2846)**	-1.1345 (0.2297)***	0.8667 (0.2689)***
Outpatient Follow-Up					
(Base level: Local hospital)					
Distant hospital	-0.8455 (0.1027)***	-1.0647 (0.1808)***	0.9440 (0.1821)***	-1.2177 (0.2222)***	1.0642 (0.1940)***
Sample size (Observations)	148(2960)	148(2960)	-	148 (2960)	-
Log Likelihood	-796	-751	-	-747	-
AIC	1612	1539	-	1533	-
BIC	1680	1640	-	1647	-

**p<0.001, **p<0.01, *p<0.05; SE=Standard Error, SD= Standard Deviation; AIC= Akaike information criterion; BIC = Bayesian information criterion, ^ could not be estimated because of collinearity issues

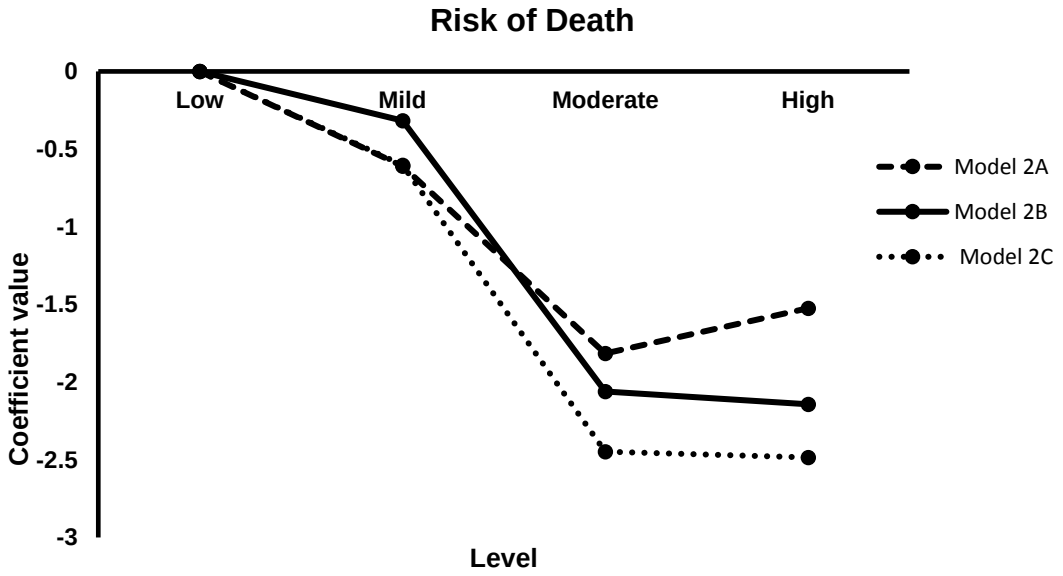

Figure 4.1: Coefficients of levels of Risk of Death across models

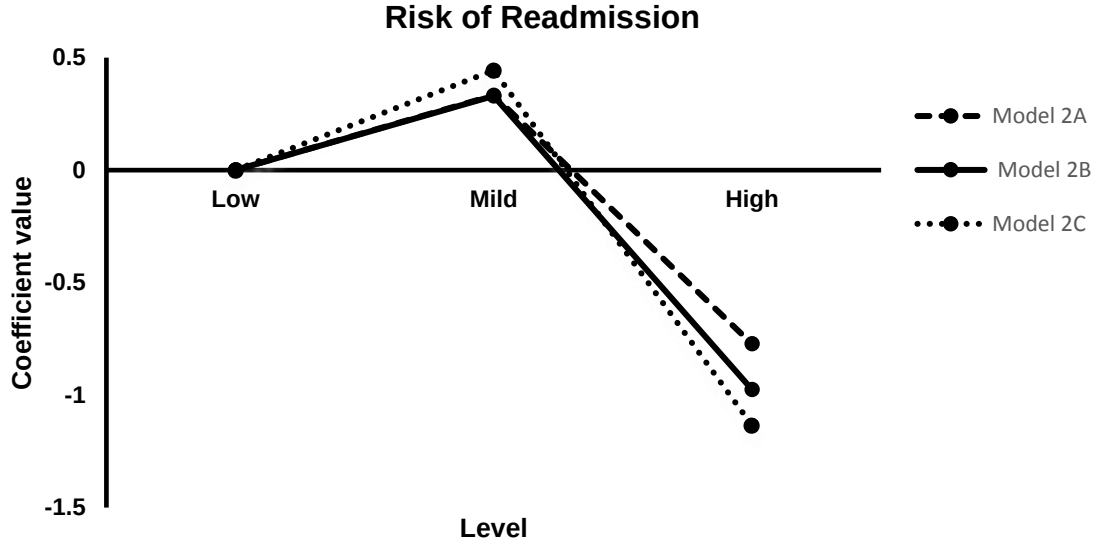

Figure 4.2: Coefficients of levels of Risk of Readmission across models

4.4.3 Marginal rates of substitution

The coefficients generated from each model presented in Table 4.7 were used to calculate the marginal rates of substitution (MRS) and helped to understand the trade-offs the respondents would be willing to make among the attributes. MRS approach is described in section 4.3.11.

For example, the coefficients in Model 1A indicated that individuals would be willing to give up their preferred outpatient follow-up care at their local hospital only if the risk of death was reduced by at least 2.9 % (0.9624/0.325). Similarly, individuals would be willing to give up outpatient follow-up care only if the length of stay in the hospital was reduced by minimum of 12.5 days (0.924/0.0768) and risk of readmission was reduced by minimum 6.7% (0.0924/0.1442). Model 1B, Model 1C and Model 1D showed generally similar ratios, however Model 1B showed different but statistically non-significant ratio of outpatient follow-up care and risk of readmission in model.

Furthermore, the ratios between selected attributes presented in Table 4.9 show how much respondents were willing to travel or willing to wait for an improvement in another attribute. For example, the ratio of coefficients of length of stay and travel time from Model 1A indicated that respondents are willing to travel nine minutes and willing to wait 14 minutes for one day reduction in length of stay in hospital.

In Model 1B (Table 4.7), coefficients of travel time and risk of readmission were not significant, therefore in Table 4.9, the MWT derived across all attributes and MWW derived for attribute risk of readmission were not significant. In terms of both MWT and MWW, across all models (with an exception to Model 1B which had statistically non-significant coefficients) the respondents most valued outpatient follow-up attribute followed by risk of death, risk of readmission and length of stay.

Table 4.9: Marginal rates of substitution in terms of willingness to travel and willingness to wait

Attributes	Marginal rates of substitution								Interpretation
	MWT (in minutes)				**MWW** (in minutes)				
	Model 1A	**Model 1B**	**Model 1C**	**Model 1D**	**Model 1A**	**Model 1B**	**Model 1C**	**Model 1D**	
Length of stay	8.93	115.29	9.74	10.64	13.71	23.54	15.81	17.13	For 1 day reduction in length of stay in hospital
Risk of Death	37.88	287.21	36.98	35.78	58.18	58.65	60.04	57.6	For 1% reduction in risk of death in hospital
Risk of Readmission	16.76	28.24	14.42	14.62	25.75	5.77	23.42	23.53	For 1% reduction in risk of readmission in hospital
Outpatient Follow-Up	111.90	1453.97	99.54	94.53	171.85	296.91	161.58	152.2	For having outpatient follow-up care at their local hospital

MWT- Marginal willingness to travel; MWW- Marginal willingness to wait; Model 1A- Main effects MNL, Model 1B- With interactions MNL, Model 1C- Main effects MIXL, Model 1D- Main effects GMNL

4.5 Discussion

This DCE demonstrated the influence of hospital attributes on the choice of hospitals in an emergency. In line with priori expectations, the results confirmed that people prefer less travel time to hospital, less waiting time, fewer number of days in hospital, low risk of death, low risk of readmission and outpatient follow-up care in their local hospital.

The generation of MRS allowed an understanding of trade-off the respondents were willing to make among attributes. The results highlighted that follow-up outpatient care at their local hospital is more important to the respondents than any other hospital attributes. It was unexpected that participants would value outpatient follow-up care more than the risk of death. But, high valuation of outpatient follow-up in the local hospital may highlight the emotional attachment, sense of belongingness and enormous pride associated with the local hospital (Thomson *et al.*, 2005). However, it is also likely that this study might have suffered from attribute non-attendance, where the participants always chose hospitals providing outpatient follow-up in a local hospital irrespective of other attributes. Issue of attribute non-attendance is described later in section 4.5.3.2. It is also likely that the levels of risk of death used might have been very low and were not perceived to be important by the respondents compared to the outpatient follow-up. Respondents were willing to trade-off increased travel time and waiting time for the lower risk of death, lower risk of readmission, less days in the hospital and follow-up outpatient care in their local hospital which was highly valued. In general, the MRS indicated that people can compromise other attributes for high quality of healthcare provided by hospitals. However, the results also indicated that the specialised hospital should not be too far away (more than two hours of travel time) to be valued.

Gender of the individual influenced the strength of the preference, with results suggesting that men have stronger preferences for less travel time, less waiting time, lower risk of death and lower risk of readmission compared to women. The difference in preferences of men and women could possibly be related to the differences in thinking, problem solving, healthcare perception (Wessels *et al.*, 2010). However, the influence of other individual characteristics such as age, recent experience of

emergency care and current health state of the person on the choice of hospitals were not statistically significant.

4.5.1 Comparison with other studies

This section compares the findings of this DCE with other relevant existing studies. While differences exist between studies in terms of healthcare context, design, attributes and attribute levels used, the findings of this study are in line with other relevant DCE studies. Earlier studies attempting to quantify the strengths of individual preferences for emergency health care available during usual GP service hours have indicated that patients do prefer less waiting times to get a decision on treatment and prefer the services provided closer to their homes (Gerard *et al.*, 2004; Gerard and Lattimer, 2005). A study on Australian public's choice among alternatives of emergency care reported clear preferences for shorter wait times and strong emphasis on quality emergency health care (Harris *et al.*, 2015). In another DCE study patients choice of hospitals for elective health services demonstrated individual preferences for less travel time to the hospital, less waiting time to receive the service, the follow-up care at their home hospital rather than the alternative hospital and high valuation of hospital reputation (Burge *et al.*, 2005). Schwappach and Strasmann revealed that potential patients in Germany were willing to sacrifice longer travel distance and preferred location of care for a highly specialized surgical care provision with short waiting times (Schwappach and Strasmann, 2007). Ryan and colleagues also observed negative utilities for increased travel times to hospital and increased waiting time to receive care in their study assessing trade-offs between location and waiting times to elective surgery (Ryan *et al.*, 2000). A more recent study assessing preferences for centralising specialised cancer services also concluded that patients, health professionals and the public all preferred shorter travel times, lower risks of deaths and complications, and access to specialised centres (Vallejo-Torres *et al.*, 2018).

The findings of this DCE study are also consistent with the findings of other studies assessing choice of healthcare using methods other than DCE. A study examining the choice of hospitals for elective hip replacements amongst patients in England, using the records of hospital episode statistics (HES), identified that people do take

hospital quality in particular low mortality and less waiting time, the Methicillin-Resistant Staphylococcus Aureus (MRSA) infection rate and Care Quality Commission (CQC) ratings into account when choosing hospitals (Beckert *et al.*, 2012). Results of another study assessing patient preference for location of elective abdominal aortic aneurysm surgery indicated that patients would accept increased travel distances for care with reduced risks of perioperative mortality (Landau *et al.*, 2013). A recent study suggested that choice of hospital is influenced by overall health gain not just by the more traditional measures of hospital quality such as risk of death and readmission (Gutacker *et al.*, 2016). Using the data on elective hip replacement patients in the English NHS, Moscelli and colleagues demonstrated that patients value quality while choosing hospitals in particular those with low readmission rates, low mortality risks, less waiting times, closer to their homes (Moscelli *et al.*, 2016).

4.5.2 Implications of the study findings

This study reveals preferences and the trade-offs individuals are willing to make across attributes while choosing hospitals for emergency healthcare and provides valuable insights to the decision-makers in relation to the centralisation of emergency health care services into fewer specialised units. The results of this study indicate people prefer less travel time and waiting times to treatment however, they are willing to travel longer or wait longer for receiving better quality emergency healthcare in terms of lower mortality risk, lower readmission risk and fewer days of stay in hospital. At the same time, the findings also indicated that individuals value outpatient follow-up care at their local hospital more than any other hospital attributes considered. For example, in the context of the hospitals compared in this PhD thesis, individuals are likely to choose to go to the specialised emergency hospital only if it offered lower mortality, lower risk of readmission and fewer days of stay in the hospital compared to their local hospitals even if it meant increased travel time to the hospital and increased waiting time to be seen. If the specialised emergency hospital offers the possibility of outpatient follow-up care at a local hospital, individuals would be willing to travel 1.5 to two hours for the treatment at a specialised hospital. But for the specialised hospital service to be utilised without the provision of outpatient follow-up care at a local hospital, it should provide a very high quality service where the risk of mortality is reduced by 2.9%, length of stay in the hospital is reduced by

12.5 days, and risk of readmission by 6.7% (see section 4.4.3). Furthermore, to ensure the service at specialised hospital is utilised, the geographical location of the hospital should not be more than two hours of travelling time (whether or not it provides high quality care or outpatient follow-up at a local hospital) for the catchment population. Therefore, the results of this DCE would mean that decisions to centralise emergency care into fewer specialised hospitals should not only be justified on clinical grounds and cost savings, but should also be informed by patient preferences. Patients are more likely to use the high quality service at a specialised hospital only if their preferences are valued. Consideration of individual preferences in emergency services centralisation decisions may mean increased value, increased satisfaction across a population and efficiency gains.

If the results of this study hold, then these could have implications for practice. The review by Sir Bruce Keogh recommends reconfiguration of emergency care and the development of centralised and more specialised emergency units that benefits patients with more serious and life threatening condition by providing best expertise and potentially better quality of care (NHS England, 2013a). In addition, consolidation of specialised medical care is one of the new care models envisaged by the NHS "Five year forward view" (NHS England, 2014). However, centralised healthcare may not be closer to people's homes and the specialised healthcare services may come only at the cost of increased travel times to the point of care. Centralisation of hospitals may mean increased travel time to most of the patients and a poor utilisation. There are concerns about distance decay, where the utilisation of healthcare services decreases with the increase in travel distance to the healthcare facilities (Turnbull *et al.*, 2008; Raknes *et al.*, 2013) (see section 1.2, Chapter 1). Contrary to this, the results of the DCE reported in this Chapter suggest that whilst people may place a high value on their local hospital, they may be willing to trade-off the increased journey time with the treatment at a specialised hospital providing better quality of care. The preferences are not influenced by age, health status or previous experience of emergency medical services which suggests that emergency medical services do not necessarily have to be tailored according to age-groups or health status, at least within the range of respondents. However, the results also suggest that the specialised hospital should not be too far away to be valued and should make provisions of outpatient follow-up care in the local hospital (both of

which are highly valued) whenever possible. Overall, the DCE results support the decisions to centralise emergency care in local hospitals into fewer specialised units in the NHS England.

4.5.3 Strengths and limitations

The results of this DCE should be interpreted in the light of several strengths and limitations, the major ones are presented in the following sections.

4.5.3.1 Respondent sample, response rates and survey approach

A wide cross section of the local general population taken from the Healthwatch Northumberland or NHCT were studied. This sample was considered most appropriate to represent the preferences of potential users of a newly built specialised emergency hospital; the focus of this PhD. However, it is likely that some specific population groups from the general population may be under represented, particularly those not registered with the Healthwatch or NHCT (e.g. very old, very young, those with special needs). The EQ-5D-5L and EQ-VAS scores of the respondents included in the survey were lower than those of the general population in England (see section 4.4.1) but consistent with those for the general population of a similar age. Therefore, it is likely that the healthiest groups may have been left out because of not being registered with Healthwatch or NHCT. The study would have benefitted from a larger sample of respondents. The National Institute for Health and Care Excellence (NICE) and the United States (US) Public Health Service's panel on Cost-Effectiveness in Health and Medicine, each recommend that preferences on health outcomes should be estimated from a representative sample of general public (Russell *et al.*, 1996; National Institute for Health and Care Excellence, 2013). However, there is a considerable debate around whose preferences (patient or general public) count when valuing health outcomes in health economics and no firm consensus exists (Dolan, 1999; Brazier *et al.*, 2005; Stamuli, 2011).

The survey response rates were low, for both electronic and paper formats and it is possible that non-response bias which occurs due to systematic differences between respondents and non-respondents might have impacted on the DCE results.

Financial incentives for completing the survey would have provided a higher response rate (Church, 1993; Shaw *et al.*, 2001; Singer and Ye, 2013). However, when a financial incentive is offered, the extent to which individuals complete each survey with sincerity could be questionable, as there is a possibility that respondents might be participating in and completing the survey merely to qualify for the incentive. In this survey, no financial incentive was offered to respondents completing the survey, therefore it is assumed that the results were a representation of genuine preferences of respondents.

The strength of this DCE also exhibited by the fact that it was pre-tested and piloted before finalisation. A high proportion of correct and complete responses in this DCE could mean that the respondents clearly understood the choice sets and the overall survey. However, a high proportion of respondents found the choice tasks difficult to complete which could mean that attributes were not appropriate to them and the choices were arbitrarily made. Furthermore, it was not possible to get the information of respondents attempting to complete the survey but who did not ultimately respond because the survey was too difficult for them to complete. It could be possible that the non-respondents differed in characteristics and had different choices compared to the respondents. Therefore, there remains a concern that this study may not have truly reflected the real preferences of targeted general population.

Another strength of this survey lies in the fact that both survey approaches –web based and postal were used enabling the representation of a wider cross section of population. This might have also introduced a response bias because of the systematic differences between the respondents in each approach. Although, experimenting with the different approaches for survey administration was beyond the scope of this survey, the results indicated that the strength of preferences of less waiting time and low risk of death may be higher in those completing the web version of the survey (see section 4.4.2).

4.5.3.2 Attribute selection, framing and attribute non-attendance

The attributes identified in this survey were taken from the literature and did not involve any qualitative research to identify them which might mean that some other

attributes which were very important to respondents were left out. Therefore, it is likely that the study results might have suffered from the impact of important attributes not included in the choice experiment. However, as explained in section 4.3.2, it could have been challenging to get the representative respondent sample for qualitative research into one place and conduct the qualitative research in the limited time frame and context of this PhD. Nevertheless, the importance of qualitative research in a DCE has been highlighted recently (Vass *et al.*, 2017) and hence should be considered in future DCE studies.

The way the attributes were framed might have influenced the choices the respondents made. The query that remains to be answered is would the choices remain the same, if the attributes were framed in the other way, for example do the preferences differ when one of the attributes "risk of dying" is framed as "chances of survival"? Whilst experimenting with the framing of DCE questions was not the objective of this thesis, several research findings show that attribute framing can influence respondents' choice behaviour (Howard and Salkeld, 2009; Kragt and Bennett, 2012; Veldwijk *et al.*, 2016). Furthermore, presentation of attribute levels in choice tasks only in text formats could have created difficulties for some respondents in understanding the choice sets. Graphics and icons are often superior to text in communicating health information (Tait *et al.*, 2010b; Tait *et al.*, 2010a; McCaffery *et al.*, 2012). However, within a DCE context, independent of educational level and literacy of respondents, words depicting the attribute levels lead to more consistent answer patterns, more accurate attribute level interpretation, and more accurate attribute level estimates (Veldwijk *et al.*, 2015).

The conventional practice for a DCE assumes that respondents choose among alternatives by rationally trading off across all attributes in their choice set. However, emerging evidence suggests that some respondents trade-off only a subset of attributes and ignore one or more attributes while choosing among alternatives (Hensher *et al.*, 2005; Carlsson *et al.*, 2010; Colombo *et al.*, 2013). This phenomenon, which is widely referred to as attribute non-attendance raises a concern on violation of continuity axiom and a departure from compensatory behaviour: a conventional framework underlying choice experiments (Campbell *et al.*,

2008). Failing to account for the attribute non-attendance may lead to biased preference estimates (Hensher and Greene, 2010). It is possible that the coefficient estimates generated in this study could have been influenced by attribute non-attendance, but do not have any evidence for this. A number of methods to identify attribute non-attendance have been proposed in the literature. One of the approach is to ask respondents directly if they ignored any of the attributes (if so which alternatives) while making choice between alternatives (Hole *et al.*, 2013). Another approach is to use econometric models such as the latent class model to estimate the probability of attribute non-attendance (Hensher and Greene, 2010; Campbell *et al.*, 2011; Hole *et al.*, 2013). Another alternative approach to identify the attribute non-attendance is the use of eye tracking technology which records the focus of respondents while making a choice in a computer based survey (Spinks and Mortimer, 2016). However, there is no consensus on which approach to use to identify attribute non-attendance in a DCE.

4.5.3.3 Marginal willingness to pay and cost-benefit analysis

Time was used as the non-monetary metrics to generate marginal willingness to travel (MWT) and marginal willingness to wait (MWW). However, inclusion of a cost attribute in a DCE could have allowed the generation of marginal willingness to pay (MWP) for the potential cost-benefit analysis (Lancsar and Louviere, 2008). The use of a cost attribute was considered, however, it was excluded because framing of a cost attribute is difficult in this context where individuals are not used to out of pocket payments for healthcare at the point of use (Johnson *et al.*, 2011). In a publicly funded healthcare system like the UK NHS, respondents may ignore the cost attribute as it is not borne by them directly (Ratcliffe, 2000). Inclusion of a cost attribute was expected to provoke strong reactions with respondents not trading off between all available attributes and only trading-off against the cost attribute by always choosing the cheapest alternative or not making a choice at all (Pedersen *et al.*, 2011). Therefore, with the inclusion of a cost attribute, the inferences drawn possibly would not have reflected individual's true preferences. Nonetheless, the MWT estimates were converted to MWP to conduct the cost-benefit analysis (see section 6.4.5 in Chapter 6).

4.6 Conclusion

In summary, this Chapter described the development of the DCE, explored and quantified the strength of individual preferences towards different emergency medical care service configurations (local versus distant). The results indicated that people prefer less travel time to hospital, less waiting time, fewer number of days in hospital, low risk of death, low risk of readmission and outpatient follow-up care in their local hospital. However, people were willing to trade-off increased travel time and waiting time for the lower risk of death, lower risk of readmission, fewer number of days in the hospital and follow-up outpatient care in their local hospital which was highly valued. The findings revealed that individuals value outpatient follow-up care at their local hospital more than any other hospital attributes. Any decisions to centralise emergency medical services into specialised hospitals should not only be justified on clinical grounds and cost savings, but should also be informed by preferences of potential users of that service. However, considering the limitations in this study, these findings should be interpreted with caution.

The results of this DCE will be incorporated into the economic evaluation model described in Chapter 6. The next Chapter will provide methodological background to the economic evaluation in Chapter 6.

Chapter 5. Decision Analytic Modelling in Economic Evaluations

5.1 Background

Chapter 4 reported the development of the DCE and quantified the preferences for characteristics of centralised provision of emergency medical services. The role of economic evaluations is to inform decision-making by comparing the expected costs and health outcomes of alternative treatment strategies or healthcare interventions against each other (Drummond *et al.*, 2005). Chapter 2, suggested that the economic evaluations on centralisation of specialised healthcare services is dominated by studies with limited methodological quality and generally not adhering to the current standards for reporting economic evaluations.

Therefore, the aim of this Chapter is to provide a methodological background to the economic evaluation methods used in Chapter 6 of this thesis. It describes the methodological development of an economic evaluation model with the focus on a decision analytic model framework. This Chapter is structured into the following sections: section 5.2 presents a brief description on types of economic evaluations commonly used and their importance in healthcare; section 5.3 provides a justification for the economic evaluation model selected in this thesis; section 5.4 describes the key steps in building a decision analytic model framework; section 5.5 describes the presentation of the economic evaluation results and section 5.6 summarises the Chapter.

5.2 Economic Evaluations in Healthcare

Economic evaluations are increasingly undertaken to inform decisions on global health policy on wide range of topics including healthcare organisation and delivery (Gray and Wilkinson, 2016). For example, economic analysis is highly integrated into the technology appraisals of National Institute for Health and Care Excellence (NICE) in England (Williams I *et al.*, 2008; National Institute for Health and Care Excellence, 2013). Likewise, the Scottish Medicines Consortium (SMC) in Scotland require the assessment of new health care technologies to be well supported by economic evaluations (Scottish Medicines Consortium (SMC), 2017). Similarly, economic evaluations are integral component of regulatory and reimbursement decisions on

technologies and interventions in Australia, Canada and other countries (Hutton *et al.*, 2006; Pharmaceutical Benefits Advisory Committee (PBAC), 2016; Canadian Agency for Drugs and Technologies in Health (CADTH), 2017). Hence, economic evaluations are now a key element of funding decisions in health care (Clement *et al.*, 2013; Cerri *et al.*, 2014; Dakin *et al.*, 2015). Economic evaluations in healthcare can take one of the two approaches: i) conducted as part of a randomised controlled trial (RCT) and conducted using the cost and effectiveness data collected or ii) conducted using data from wide range of sources synthesized into decision analytic models (Sculpher *et al.*, 2006).

RCTs are a common vehicle of data collection for economic evaluations and are often utilised to help make informed decisions on healthcare interventions providing best value for money (Doshi *et al.*, 2006; Petrou and Gray, 2011a). Trials present the opportunity to collect resource utilisation and outcomes data related to the health care under evaluation directly from the trial. Moreover, economic evaluations conducted alongside rigorously designed trials benefit from prospectively collected patient data with high internal validity. The addition of data collection for economic variables is likely to be less costly compared to data collection for stand-alone economic evaluations (O'Sullivan *et al.*, 2005). However, it has been argued that economic evaluations conducted alongside single RCTs do not always form a sufficient basis for decision-making (Ramsey *et al.*, 2015). For example, an economic evaluation based on single trial may fail to incorporate all relevant evidence from other trials, meta-analyses and observational studies and may not compare all available alternatives than the ones considered in the trial or may have inappropriate time horizons which may not capture differences in economic outcomes. All of these may restrict the generalisability of an economic evaluation to other decision-making context (Sculpher *et al.*, 2006; Petrou and Gray, 2011b). In addition, the sample size of a trial are commonly based on primary clinical outcomes alone which could potentially result in inappropriately powered economic evaluations (Ramsey *et al.*, 2015). Considering the limitations of economic evaluations based on a single RCTs, decision analytic modelling are seen as an alternative framework for economic evaluation (Petrou and Gray, 2011b).

Decision analytic modelling (DAM) is extensively used in healthcare economic evaluations to inform decisions regarding optimal allocation of limited resources

(Buxton *et al.*, 1997; Claxton *et al.*, 2002; Petrou and Gray, 2011b). DAM is particularly useful when the intervention under consideration is relatively new and RCTs are difficult to conduct or when the existing economic data is very limited (Buxton *et al.*, 1997). A DAM provides a framework for explicit representation of decision problems under uncertainty by combining evidence from range of sources and facilitates the extrapolation of costs and outcomes over time and across patient groups and health care settings (Claxton *et al.*, 2002). An economic evaluation utilising DAM enables a wide range of costs and effects from various sources to be synthesized within a model framework to generate cost-effectiveness outcomes of an intervention. But, it may not be always possible to include all the consequences/outcomes of an intervention within the modelling framework. Therefore, DAM may not always reflect reality and modellers need to be careful in deciding the pathways, consequences and outcomes considered in the model framework (Briggs *et al.*, 2006). Decision analytic models are often criticised for being heavily relied upon assumptions (Sheldon, 1996) and several concerns have been raised about modelling (Buxton *et al.*, 1997). The first concern is around inappropriate use of clinical data, mainly related to the inadequate attention to the quality of data used in the model. Use of poor quality data in models may mean incorrect estimation of economic benefit. Second is the biases in the observational data used in the model, such as failure to account for the competing risks of outcome under consideration. It can be sometimes very difficult to know the biases present. The third concern is around difficulties in extrapolating the results beyond the end of the trial, for example the differences in extrapolated results and the results of subsequent trials with longer follow-up time. The fourth concern is around transparencies and validity of model. Models may not be fully transparent and it may be sometimes difficult to understand the underlying conceptual basis and there might be difficulties in verifying the model in the absence of similar models. However, despite these limitations, DAM still remains a useful tool to help decision-making under conditions of uncertainties in costs and outcomes. The basic concepts of DAM in healthcare has been extensively covered in the literature (Drummond *et al.*, 2005; Briggs *et al.*, 2006).

5.3 Selection of Economic Evaluation Model

The two broad approaches to economic evaluations described in the previous section each have their own strength (A RCT generates parameters to be utilised for

economic evaluation of a particular intervention/healthcare program whereas a decision analytic model provides economic evaluation framework by incorporating additional supplementary evidence and assumptions) and should be considered as compliments to each other rather than as alternatives (Sculpher *et al.*, 1997; Claxton *et al.*, 2002; Drummond and Sculpher, 2005; Petrou and Gray, 2011b). A mixture of both economic evaluation approaches with 'within trial' economic evaluation supporting wider secondary evidence in a decision analytic model would be more beneficial (Sculpher *et al.*, 2006). However, considering the nature of intervention focused on in this thesis, trials to assess the impact of centralisation of emergency hospitals in this instance would be challenging. Although economic models are essential in healthcare intervention appraisals, it is not essential that those should be trial-based economic models (National Institute for Health and Care Excellence, 2013). This requirement of NICE further justifies the use of DAM in this project. In the instances where RCTs are unworkable or unethical, data coming from quasi-experimental studies (e.g. controlled before-after designs, interrupted time series) or observational studies (e.g. cohort, case-control, cross-sectional) could be used to inform the economic evaluation models (Centre for Review and Dissemination, 2009). Therefore, a decision analytic model was considered the most appropriate economic evaluation approach in this project.

5.4 Decision Analytic Model Framework

A series of steps are involved in building a decision analytic model in economic evaluation (Briggs *et al.*, 2006; Sun and Faunce, 2008; Petrou and Gray, 2011b). Briggs and colleagues have proposed six basic steps in building up a decision analytic model in economic evaluations in health care (Briggs *et al.*, 2006).The first step is to specify the decision problem; the second step involves defining the boundaries of the model i.e. what goes into the model and what does not; the third step is to structure the decision model; the fourth step involves identifying and synthesizing evidence followed by the fifth step dealing with uncertainty and heterogeneity. The final step is to assess the value of additional research. These key steps are now discussed below.

5.4.1 Specifying the decision problem

In line with the objective of the economic evaluation, this step involves clear identification of the questions to be addressed by the analysis. The alternative

interventions or programmes being evaluated and the outcome measures used to compare them should be clearly specified. Additionally, the specific characteristics of the recipient population (e.g. the patients receiving the treatment) and their sub-groups should be clearly defined. Other requirements include clear statement of the perspective of the analysis (e.g. health care provider or societal) and study location (e.g. UK NHS) and setting (e.g. Accident & Emergency Unit or primary care). The perspective is the view point used to determine what costs and outcomes are to be included in the economic evaluation and is determined by whose cost is of interest to the research. For example, the NHS perspective could include only costs of providing the treatment (intervention) along with costs of treating any adverse effects as incurred by the NHS such as later treatment costs, hospital admissions, follow-up visits but it does not include costs falling on the patient such as transportation, time-off from work, or 'over-the-counter' payments. Whereas, the societal perspective includes broader range of costs such as incurred by the patients and their families (example: transportation costs, over the counter payments) and indirect effects to the society (example: productivity losses because of time-off from work).

5.4.2 Defining the boundaries of the model

Defining the boundaries of model is concerned on potential impacts of the options under evaluation and what is relevant and what is not. It will never be possible to include all possible consequences of the options under consideration, therefore choices need to be made about which consequences will be incorporated in the model (Briggs *et al.*, 2006). For example, if the intervention under evaluation is a new drug treatment there could be side effects which may impact the costs and outcomes of the model, or these side effects may be negligible and may not have a large impact on the patient population. Therefore, researchers should be careful in considering what goes into the model and what does not. Important things to consider in an economic evaluation are time horizon and discounting.

Time horizon is the duration over which the costs and outcomes are tracked in a model (Siebert *et al.*, 2012). In the context of decision-making, the time horizon adopted in a model should be large enough to capture all important health effects and costs of the alternatives compared (Siebert *et al.*, 2012). A time horizon shorter

than the expected impact of intervention do not usually provide best costs and effect estimates (National Institute for Health and Care Excellence, 2013). The question to be asked at this stage is what time horizon is appropriate to assess the costs and outcomes of intervention under study? For example is a life-time time horizon required or will a shorter time horizon of one year will be more appropriate to incorporate all the relevant costs and outcomes? Longer time horizons are more applicable to chronic conditions which need to be managed for a long-time (e.g. cancer), whereas shorter time horizons are more appropriate for acute conditions when there are no long-term sequelae where long-term consequences may not be important (e.g. acute infections). NICE recommends a life-time horizon for interventions that could have impact on costs and outcomes over the patient's life time (National Institute for Health and Care Excellence, 2013). However, a time horizon shorter than the patient's life-time could be justified when there are no differential mortality effects or other long-term sequelae between the alternatives compared and the costs and effects relate to the short time period (National Institute for Health and Care Excellence, 2013).

Cost and outcomes at present are valued more than those occurring in the future. Therefore, cost-effectiveness analysis should reflect the present value of costs and outcomes which accrue over the time horizon of the economic evaluation (National Institute for Health and Care Excellence, 2013). Discounting is a method of adjusting the future costs and outcomes to the present value. The question that could be asked is whether both the costs and benefits will be discounted or only costs will be discounted and if so at what rate? NICE recommends that both the costs and QALY be discounted at 3.5% and sensitivity analysis could be carried out using rates of 1.5% (National Institute for Health and Care Excellence, 2013).

5.4.3 Structuring the decision model

The structure of the decision model partly depends on the nature of the decision problem and model boundaries discussed earlier. Briggs and colleagues suggested that the choice of model structure is dependent on the nature of intervention evaluated, natural history of particular condition and the impact of options on that process (Briggs *et al.*, 2006). In addition, Brennan and Akehurst suggested that

determination of the model structure should take practical consideration of decision maker's requirement, the complexity of the intervention and health care system, the population size and often should weigh upon the modeller expertise, data and software availability (Brennan and Akehurst, 2000; Brennan *et al.*, 2006). Although, it has been argued in the literature that the model structure is governed by the issue of data availability (Philips *et al.*, 2006), it is recommended that the model structure be as simple as possible, consistent with the decision problem (Sculpher *et al.*, 2000; Philips *et al.*, 2006). Data availability alone should not determine the model structure (Sonnenberg *et al.*, 1994; Sculpher *et al.*, 2000; Philips *et al.*, 2006). However, data availability may limit or refine the model structure and its scope (Philips *et al.*, 2006). While inappropriate model structure will invalidate study findings, choices made while structuring the model may also influence study conclusions (Peñaloza Ramos *et al.*, 2015) (Brennan *et al.*, 2006). Therefore, it is essential that the choice of the model structure is fit for purpose and is determined by the level of detail required and complexity (Roberts *et al.*, 2012).

Model structures used in economic evaluations in health care can be broadly categorised into aggregate cohort models or individual patient level models (Brennan *et al.*, 2006). Cohort models examine costs and outcomes of an average patient from a population undergoing different events. Whereas, patient level models consider individual patients accounting for variability between patients and follow their progress overtime (Brennan *et al.*, 2006; Briggs A *et al.*, 2006). Depending on the decision problem and boundaries of economic evaluation, these model structures commonly use modelling techniques such as decision trees, Markov models and other alternative modelling approaches such as patient level simulation, discrete event simulations and dynamic models (Cooper *et al.*, 2007a; Petrou and Gray, 2011b).

5.4.3.1 Decision trees

Decision trees are the simplest and most common form of DAM in economic evaluation (Karnon and Brown, 1998; Barton *et al.*, 2004; Petrou and Gray, 2011b). Decision trees are appropriate in decision models with short-time horizon and when the mortality between alternative interventions do not differ (Barton *et al.*, 2004). All

possible patient pathways and their associated probabilities and outcome measures are explicitly shown on decision trees and branches. The key features of decision tree are the decision node (typically represented by a square symbol), also known as “choice node”, which indicates a decision point between alternatives, chance nodes (typically represented by circular symbols) which indicate the point where two or more alternative events are possible. The alternative patient pathways branching out at chance nodes are mutually exclusive events with their individual probabilities summing into one (Petrou and Gray, 2011b). The end points of the pathways are indicated by terminal nodes (typically represented by triangle symbols) where costs and effectiveness are assigned. The costs and effectiveness for each alternative is derived by summing up the costs and effects weighted against probabilities of each pathway. The probabilities for each pathway (also known as joint probability) is estimated by multiplying the probabilities along the pathways (Briggs *et al.*, 2006).

Figure 5.1 shows a hypothetical example of a simplified decision tree model, where a decision has to be made between intervention 1 and intervention 2 represented by the branches coming out of decision node. Each intervention leads to two mutually exclusive events of being dead and alive whose occurrence depends on their underlying probabilities. The total costs and benefits are then estimated for each intervention as the sum of the pathway values weighted by the probabilities in each pathways.

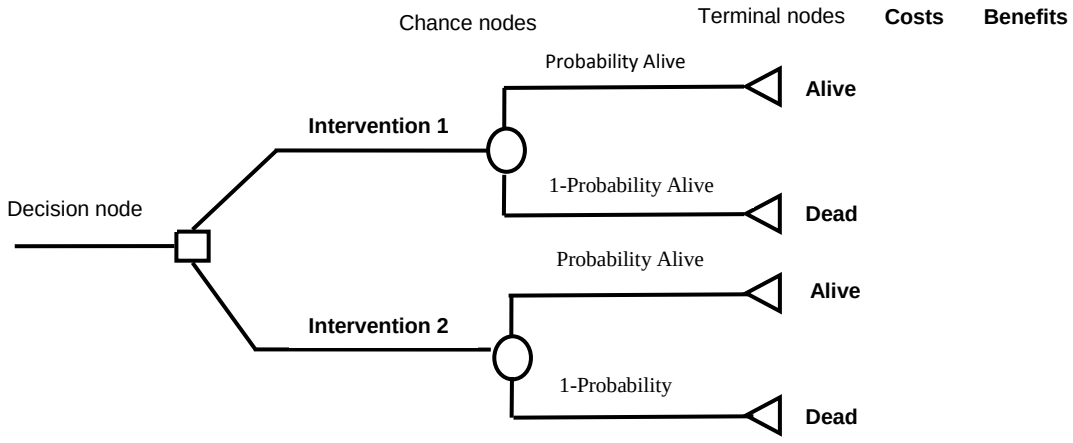

Figure 5.1: Simple representation of decision tree model

However, decision trees may not be suitable in situations such as modelling chronic conditions, where the need to reflect large number of recurring events and consequences over longer time horizon would make them lengthy, unwieldy and complex to programme (Briggs *et al.*, 2006; Petrou and Gray, 2011b). In addition, decision trees are limited by the inability to implicitly account for the progression of time making incorporation of time dependency in model difficult (Karnon and Brown, 1998; Briggs *et al.*, 2006).

5.4.3.2 Markov model

Markov models are useful when an easier representation of complex and repeated set of events over time is necessary (Sonnenberg and Beck, 1993; Brennan *et al.*, 2006). Patient events are modelled to transit from one state to another, over series of discrete time intervals or cycles. The choice of the cycle length in a Markov model depends on the problem being assessed; the remaining life expectancy in patients; and computational efficiency, but the cycle length should be short enough to represent the intervention being assessed (Siebert *et al.*, 2012).

In a Markov model, at any point of time patients are assumed to be one of the finite number of states. A set of transition probabilities determine the movement of patients from one state to another in each cycle (Petrou and Gray, 2011b). Transitions are usually modelled to occur either at the beginning or the end of a cycle, but in reality they may occur half-way through the cycle on an average (Naimark *et al.*, 2008). Therefore, to account for this, a half-cycle correction is applied to the costs and effects in the first cycle and also in the last cycle if life time horizon is not used (Siebert *et al.*, 2012). Costs and effects (typically utility and quality of life weights) are attached to models as mean value per state per cycle, thereby allowing the analyst to estimate expected values as a sum total across cycles (Briggs *et al.*, 2006).

Figure 5.2 provides a hypothetical example of a Markov model, where there are three states (Healthy, Injured and Dead). At the end of the Markov cycle, a cohort in the healthy state can either remain in the healthy state or progress to injured state or dead state depending on the transition probabilities between states. Those in the injured state can either remain injured or recover to be healthy or die. Those dead

cannot be healthy or injured again, therefore cohort can enter the dead state but cannot leave it (this is called an “absorbing state”). The arrows indicate the movement of the cohort.

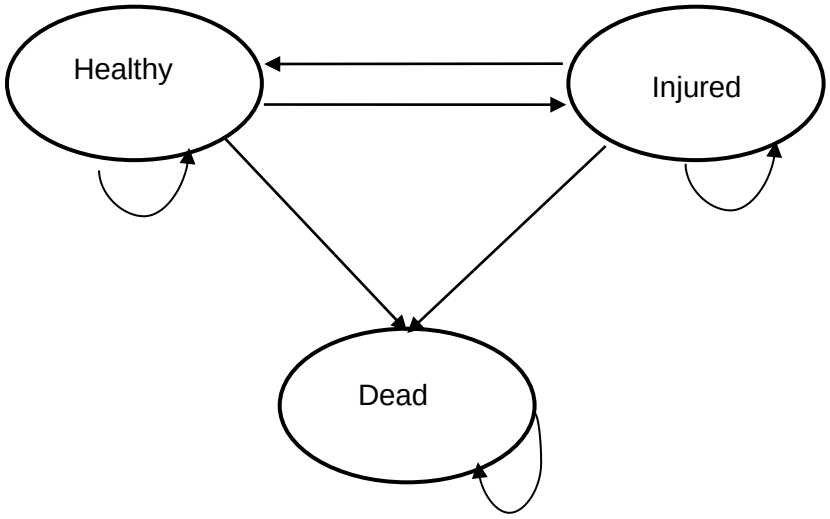

Figure 5.2: A simple Markov model

Markov models are widely used in economic evaluations (Barton *et al.*, 2004), however the main limitation with Markov models is that the probabilities of transitioning from one state to another only depends on the current health state and is independent of historical experience. This is known as the Markov assumption or memoryless feature. The implications of the Markov assumption is that all patients are treated as being homogenous regardless of the time spent in a given state or the previous history (Karnon and Brown, 1998). However, this limitation could be overcome by adding additional states to the model and by incorporating time dependency into transition probabilities (Briggs *et al.*, 2006). However, the addition of states and the incorporation of time dependencies may increase the computational burden and may make the model unmanageable.

5.4.3.3 Other types of decision models

Other type of decision models commonly used in health economic evaluations are patient level simulation, discrete event simulation and dynamic models. Patient level simulation, also known as micro-simulations, models the progression of individuals with potentially heterogeneous characteristics one at a time rather than in cohorts

(Briggs *et al.*, 2006; Petrou and Gray, 2011b). Interaction is not allowed in patient level simulation and individuals progress through the model independently of each other and the environment (Brennan *et al.*, 2006). Unlike Markov models, individuals follow “time to next event” rather than equal time periods for the group(Brennan *et al.*, 1997). Patient level simulation allows accumulation of individual patient history to determine transitions between states, costs and health outcomes (Briggs *et al.*, 2006). However, patient level simulation models are limited by the fact that they can be more demanding of data, have high computational burden and can have less flexibility to assess uncertainty because of that computational burden (Briggs *et al.*, 2006).

A discrete event simulation (DES) is similar to the Markov Model in several aspects, however DES offers advantages over Markov model by not being restricted by the Markov assumption or by the use of equal time to event (Brennan *et al.*, 2006). DES operates at the individual level but unlike the patient simulation models it allows the interactions between individuals for example when resources are limited a particular treatment provision to one individual will affect the treatment given to another (Barton *et al.*, 2004; Petrou and Gray, 2011b). DES is particularly useful for complex models where the patient history, interactions and nonlinear behaviour of individuals in the model need to be taken into account (Cooper *et al.*, 2007a; Roberts *et al.*, 2012). However, the benefits DES offers over Markov model could be outweighed by the far greater time and programming skills required to develop and evaluate the DES model (Karnon, 2003).

Dynamic models are particularly valuable when interactions between groups influence the outcomes, particularly in infectious disease modelling (Barton *et al.*, 2004; Pitman *et al.*, 2012). Interactions between individuals should be accounted for in instances such as modelling infectious diseases where presence of disease in a group at a given point in time will determine the risk of an individual getting infected. A dynamic model is distinguished from other models by its feature that typically captures the interactions between the entire health system or population and outcomes under consideration, for example the effect of herd immunity on the likelihood of infection over time (Petrou and Gray, 2011b; Pitman *et al.*, 2012).

However, dynamic models might become unmanageable when a large number of complex interactions because of more detailed characterisation of the problem under consideration (Roberts *et al.*, 2012).

5.4.4 Identifying and synthesizing evidence

This stage involves systematic approach to identifying, bringing together all relevant evidence from a range of sources and appropriately synthesizing the intervention effect(s) as model input parameters (Briggs *et al.*, 2006). The synthesized effectiveness parameter is combined with other data parameters such as cost and utilities to estimate the costs and benefits of an intervention. Although well conducted RCTs are considered the best source of evidence to evaluate the effectiveness of an intervention, trial data may be unavailable for a number of reasons (practicality, cost etc) (Centre for Review and Dissemination, 2009; Lathyris *et al.*, 2010; Estellat and Ravaud, 2012). In the event of RCTs data not being available for the interventions of interest, evidence will have to be taken from quasi-experimental designs (e.g. controlled before-after designs, interrupted time series) or observational studies (example: cohort, case-control, cross-sectional, case series) (Centre for Review and Dissemination, 2009). The hierarchy and potential biases in the evidence may be dependent on the type of evidence used. The need to combine evidence from range of sources to be used in economic evaluation models could potentially lead to several issues such as differences in the measure of outcomes, differences in follow-up times between sources, heterogeneity in the sample studied. Lack of guidance on the appropriate methodology for the identification of evidence to inform model parameters other than RCTs of clinical effectiveness has been previously reported (Cooper *et al.*, 2007b). However, issues arising out of combination of evidence, mainly related to relative effects and clinical end-points, are increasingly dealt with the use of indirect and mixed treatment comparisons and meta-regression (Lumley, 2002; Lu and Ades, 2004; Donegan *et al.*, 2010; Jansen *et al.*, 2011). Furthermore, time dependency in transition probabilities is an important issue that need to be considered when identifying and utilizing the evidence from secondary sources in Markov models. Time dependency in transition probability is summarised in the following sections.

5.4.4.1 Time dependency in transition probabilities

An important parameter in an economic evaluation model is the transition probability from one state to another, which may be time dependent. Assuming a constant transition probability may not be practical in some of the models, where transition probabilities may change as the model progresses (Briggs *et al.*, 2006). For example the probability of death increases as the cohort ages and probability of transitioning to death state in the second year may be higher than the first year. Probabilities may also change according to the time spent in a particular state in a model. For example the probability of dying from a particular disease may increase with time spent with that disease. A practical problem in Markov models is in identifying and applying transition probabilities obtained from a range of literature where events may be reported as rates rather than probabilities (Sun and Faunce, 2008) or rarely available for the time frame required (Fleurence and Hollenbeak, 2007). Rate is the instantaneous potential for the occurrence of an event and is expressed as per number of persons at risk, whereas probability is the likelihood of occurrence of an event over a specific period of time and reported as a number ranging between 0 and 1 (Briggs *et al.*, 2006). Therefore, the time period used in estimates of event rates may not be equal to the cycle length in the model where they are applied as transition probabilities between states. Simply copying these rates from the literature and applying them in the model could influence the inferences from the model. But it is possible to translate the rates of events into probabilities using the following equation, if the rate is assumed constant over the time period considered:

$$p = 1 - \exp(-rt) \tag{5.1}$$

where p is transition probability, r is the rate of event, and t is the time period of interest (Briggs *et al.*, 2006; Fleurence and Hollenbeak, 2007).

Similarly when transition probabilities will have to be varied according to the model cycles, instantaneous rate of event (r) could be derived from the transition probability (p) for a given time period (t) using the following formula (Briggs A *et al.*, 2006; Fleurence and Hollenbeak, 2007):

$$r = -[\ln(1 - p)]/t \tag{5.2}$$

The calculated instantaneous rate could then be used to generate the transition probability for the time period of interest using equation 5.1.

However, these translation of rates and probabilities only apply to two states model where one state is an absorbing state and a more complex method is recommended for multi-state models with more than two state models (Nicky and Ades, 2005; Fleurence and Hollenbeak, 2007; Jagpreet *et al.*, 2016). Furthermore, these rates and probabilities may not be always readily available in the literature. Hence, time dependent probabilities are commonly derived from patient-level time to event data using survival analysis (Briggs *et al.*, 2006).

5.4.4.2 Using survival analysis to implement time dependency

Survival analysis involves modelling the time to event data and analyses the expected time until the occurrence of the event of interest (for example death, readmission). The main feature of survival analysis is that it allows the censored data (uninformative) to be included in the analysis. Censored data are those individuals lost to follow-up or those with no event until the end of the study follow-up. Briggs et al (2006) provide a detail description and examples of using survival analysis to implement time dependency in transition probabilities used in Markov models (Briggs *et al.*, 2006) but will be briefly considered here.

Standard survival analysis mainly uses three concepts: probability density function, survival function and hazard function. The probability density function ($f(t)$) is the probability of an event occurring at time t, and is associated with cumulative density function $F(t) = P(T \leq t)$ which is the cumulative probability of event up to time t. The survival function, $S(t) = P(T > t) = 1 - F(t)$ indicates the probability of surviving beyond time t. The hazard function is the instantaneous rate of failure (event) at time t, conditional upon the survival (no occurrence of event of interest) until time t and is expressed as the ratio of probability density function and survival function:

$$h(t) = f(t)/S(t)$$

The survival function expressed in terms of cumulative hazard function, $S(t) = \exp(-H(t))$ is central to derive time dependent transition probabilities in Markov models and is of particular interest in economic evaluations (Briggs *et al.*, 2006). However, these hazard functions are rates and need to be translated to probabilities as discussed earlier.

A range of different survival models and distributions can be used in the survival analysis. The most common form of survival analysis is the semiparametric Cox proportional hazard model. However, it does not specify how the risk of an event varies with time and is therefore limited in terms of generating time dependent transition probabilities required in Markov models (Briggs *et al.*, 2006). Alternatively, a parametric survival model may be used for analysing time to event data in economic evaluation. Commonly used distributions in the parametric models are exponential, weibull, gompertz, log-logistic, log-normal and generalised gamma, each having their unique characteristics and vary in their functional forms (Latimer, 2011). However, exponential distributions are only suitable when the transition probabilities are constant over time (Briggs *et al.*, 2006). A variety of approaches are used to assess the suitability of the distributions used in survival models such as visual inspection, Log-cumulative hazard plots and Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC). AIC and BIC are defined in Chapter 4. Further details on survival analysis models, properties of distribution, and their use in economic evaluations will not be described here, but can be available in a report by the NICE Decision Support Unit (Latimer, 2011).

An important issue that researchers need to be careful in survival analysis is "competing risks". A competing risk in a survival analysis is defined an event whose occurrence either precludes the occurrence of another event under examination or fundamentally alters the probability of occurrence of this other event (Gooley *et al.*, 1999), For example, the discharge from the hospital is the event of interest in survival analysis, but if the patient dies while in hospital then there is no chance of discharge from the hospital for that patient. So, death in the hospital is the competing risk in this instance. Common approaches such as Kaplan-Meier method treat any censored observations at equal risk of experiencing the event of interest as non-censored observations. Failure to account for competing risks may lead to biased estimate of the cumulative events of interest (hazard functions) (Brock *et al.*, 2011; Noordzij *et al.*, 2013; Austin *et al.*, 2016) which in turn may bias the transition probabilities derived from them.

However, common statistical programming language such as R facilitates survival analysis in multistate models in presence of competing risks using packages such as "*flexsurv*" which also allows fitting of appropriate survival distributions and takes account of conversion of hazard rates into time dependent transition probabilities (Jackson, 2016).

5.4.5 Dealing with uncertainty and heterogeneity

The economic evaluation is undertaken once the model is populated with point estimates of all parameters required by the model. This form of economic evaluation will estimate the expected costs and outcomes (effects) for each intervention compared and is known as deterministic analysis. However, uncertainty is an unavoidable phenomenon in any decision-making process and should be handled appropriately if decision-makers are to be confident in the results of the decision analytic model (Barton *et al.*, 2004; Briggs *et al.*, 2006). Uncertainties in decision analytic models could arise out of number of reasons, but have been broadly categorised as variability, heterogeneity and uncertainty (Briggs *et al.*, 2006).

Variability, also referred to as first order uncertainty in medical literature (Stinnett and Paltiel, 1997) or Monte Carlo uncertainty (Petrou and Gray, 2011b), is the differences that occur between patients by chance (Briggs *et al.*, 2006). Variability occurs in models due to the modelling process itself because the probability of an event happening or not in a given cycle or run is typically determined by random probability distributions due to which identical individuals will experience different outcomes as they progress through the model (Petrou and Gray, 2011b). This kind of variability cannot be addressed by collection of additional data (Briggs *et al.*, 2006), but has to be eliminated by repeatedly running the model large number of times until a stable estimate of central tendency is observed (Weinstein, 2006). Though there exists no guideline or indication on the number of runs needed (Petrou and Gray, 2011b), it is acceptable to use model iterations higher than 1000 (Briggs *et al.*, 2006), but it could be worth testing the stability of results and computational efficiency of the software used over higher number of iterations.

Heterogeneity relates to differences in individual characteristics such as age, sex and disease specification that can be explained by variations in the sub-group (Briggs *et al.*, 2006). For example, men and women could have differences in their mortality rate. Heterogeneity can be addressed by re-running the model for a specific sub-group of interest. Alternatively, heterogeneity can be addressed by making model parameters the function of patient characteristics, such as incorporating transition probabilities between states in the model according to the age or disease severity (Petrou and Gray, 2011b)

Therefore, rather than variability or heterogeneity, it is uncertainty that models should seek to capture (Briggs *et al.*, 2006). The two most widely reported forms of uncertainties in health economics are structural uncertainty and parameter uncertainty (Briggs *et al.*, 2006). Structural uncertainty arises due to uncertainties around the structure of the model and assumptions in the model framework. For example, whether the model structure and the number of health states used can simulate the disease progression and the possible outcomes (Briggs *et al.*, 2006; Sun and Faunce, 2008; Petrou and Gray, 2011b)? An illustration of this would be a study that investigated the impact of structural uncertainty on cost-effectiveness of the treatment of advanced breast cancer by comparing the results of four common Markov models varying in the number of health states and assumptions considered (Bhattarai *et al.*, 2016).

Structural uncertainty is commonly addressed with deterministic sensitivity analysis or scenario analysis in which the impact of varying one (univariate) or more (multivariate) model assumptions on robustness of results is investigated (Weinstein *et al.*, 2003; Afzali and Karnon, 2015). Alternatively, structural uncertainties could be handled with model averaging techniques (Bojke *et al.*, 2009; Jackson *et al.*, 2009; Jackson *et al.*, 2011), where model results are weighted by model adequacy measures.

Parameter uncertainty, also sometimes known as second order uncertainty (Briggs *et al.*, 2006), relates to the precision around the estimation of value of model parameters such as transition probabilities, costs and utilities (Petrou and Gray,

2011b). For example, a study utilised probabilistic sensitivity analysis to quantify the effect of parameter uncertainty in cost-effectiveness of varicella vaccination by using a range of possible input parameters derived by assigning distributions to the parameters (Brisson and Edmunds, 2006). Parameter uncertainty can be addressed with number of techniques such as univariate, multivariate or probabilistic sensitivity analysis, or analysis of extremes, bootstrapping, or microsimulation, however there is no agreement on appropriate approach to use (Bilcke *et al.*, 2011; Briggs *et al.*, 2012). It has been recommended previously that either deterministic or probabilistic sensitivity analysis can be used in addressing parameter uncertainty, with probabilistic sensitivity analysis more appropriate in case of cohort simulations (Weinstein *et al.*, 2003). Others (Sonnenberg *et al.*, 1994; Sculpher *et al.*, 2000) however have argued that parameter uncertainty is best addressed by using data as distributions rather than point estimates. The National Institute of Health and Care Excellence (NICE) in the UK also requires model parameters to be specified as probability distributions rather than point estimates (National Institute for Health and Care Excellence, 2013), though there could be some exceptions such as discount rates which are point estimates. The advantage of probabilistic sensitivity analysis over deterministic sensitivity analysis is the fact that it provides an assessment of the joint effect of uncertainty over all parameters incorporated in the model (Briggs, 2000). Probabilistic sensitivity analyses involves randomly varying all parameters simultaneously across specified distributions (described later in this Chapter) informed by best available point estimates of sample mean and standard error and are usually executed by repeating this random draw several thousand times estimating costs and effects across repetition for each intervention under comparison (Petrou and Gray, 2011b). The uncertainty is illustrated by plotting incremental costs and effects for each of the iterations on cost effectiveness plane (Briggs, 2000). Cost effectiveness acceptability curves (CEAC) which show the probability that each intervention is cost-effective across a range of assumed monetary thresholds of willingness to pay can also be derived from probabilistic sensitivity analysis (Fenwick *et al.*, 2004). Both the cost-effectiveness plane and the CEAC are described in more detail later in this Chapter. Therefore, probabilistic sensitivity analysis is the most appropriate approach to handle parameter uncertainty in a decision model (Briggs, 2000; Philips *et al.*, 2006).

In making parameters probabilistic, there are numerous forms of distributions which can be fitted across parameters. A distribution in simple terms is the spread of values of a random parameter of interest. However, the choice of these distributions to reflect uncertainty in model parameters is not arbitrary, but rather guided by the type of parameter, type of data and the estimation process (Claxton *et al.*, 2005; Briggs *et al.*, 2006). Briggs and colleagues describe the forms of distribution and their appropriateness into parameters and also provide details including the step by step guideline in estimating these distributions (Briggs *et al.*, 2006), but will be summarised in the following sections.

5.4.5.1 Normal (Gaussian) distribution

It is the most common form of continuous distributions used in capturing parameter uncertainties and represents the sampling distribution of the mean parameter value. A random parameter in a normal distribution can assume any value between negative and positive infinity. The central limit theorem assumes that with a sufficiently large sample size the sampling distribution of the mean will be normally distributed regardless of underlying distribution of the data (Briggs *et al.*, 2006). This would mean that a normal distribution could be used for representing uncertainty in any model parameters as long as the sample size remains sufficient to justify the normal assumption. Usually the mean and the standard deviation from the mean is used to estimate normal distribution of a random parameter.

5.4.5.2 Lognormal distribution

It is a continuous distribution of a random parameter whose logarithm is normally distributed. A lognormal distributed parameter takes only positive real value and therefore ranges from zero to infinity with distributions skewed to the left (Limpert and Stahel, 2017). Lognormal distribution is generally suitable for parameters that are non-negative, highly right skewed or have a multiplicative format such as ratios (Limpert and Stahel, 2011; Limpert and Stahel, 2017). Usually, the mean and the standard deviation from the mean is used to compute the lognormal distribution of a random parameter.

5.4.5.3 Beta (Binomial) distribution

It is also a continuous probability distribution defined on the interval 0-1 and is characterised by two positive shape parameters, typically denoted by α and β. Beta distribution is appropriate in representing uncertainty in binomial data, such as proportions. The α and β are computed as follows:

$$\alpha = \mu[\frac{\mu(1-\mu)}{S^2} - 1] \qquad \beta = [\frac{\mu(1-\mu)}{S^2} - 1 - \alpha]$$

where, μ is the mean of the sample, S^2 is the variance.

5.4.5.4 Dirichlet distribution

It is a continuous multivariate probability distribution parameterised by a vector α of positive counts. It is the multivariate equivalent of the beta distribution (Briggs *et al.*, 2003). It is used to represent numerous categories in a multinomial data, individual proportions of which sum into 1.

5.4.5.5 Gamma distribution

It is another widely used continuous probability distribution and is defined on the scale ranging from zero to infinity and is suitable for data that is right skewed. The gamma distribution is typically denoted by the shape parameter α and scale parameter β. The α and β are computed as follows:

$$\alpha = \frac{\mu^2}{S^2} \qquad \beta = \frac{S^2}{\mu}$$

where, μ is the mean of the sample, S^2 is the variance.

5.4.5.6 Choice of distributions

Even though there exist numerous probability distributions the choice of these distributions should be guided by parameter type and standard statistical methods of estimation, for example beta distributions for binomial data, Dirichlet for multinomial data, gamma or lognormal for right skewed data and lognormal for relative risks or ratios (Claxton *et al.*, 2005; Briggs *et al.*, 2006).

Probability parameters range between zero to one and where these are estimated from proportions the natural choice would be beta distributions. However, if probabilities are estimated from a logistic regression, then a lognormal distribution would be appropriate. On the other hand if there are numerous categories of proportions which sum into 1, then a Dirichlet distribution would be representative of the uncertainty. Uncertainties in disease prevalence and diagnostic test accuracy are commonly represented using beta distributions.

Cost data range from zero to infinity and are non-negative figures based on counts of resource use weighted by resource unit costs. Therefore, it would be appropriate to use gamma or lognormal distribution. However, when the cost estimate is not highly skewed and is from sufficiently large data, then the central limit theory could be applied fitting the normal distribution to the cost estimates.

Theoretically, utilities take the value ranging from zero representing worst health state or death to one representing perfect health. But negative utility scores which indicate a poor health state valued even less than the death is possible from some scoring instruments such as EQ-5D-5L (Devlin and Shah, 2018). Beta distribution is a commonly used to represent uncertainties in utility parameters. However, a beta distribution is not appropriate when negative utility values are possible in instances such as some forms of cancer which are considered worse than death. Therefore, in such situations it will be appropriate to use gamma or lognormal distribution for disutility. Disutility is a simple transformation of utility (disutility=1-utility) that ranges from zero to infinity (Briggs *et al.*, 2006).

5.4.6 Assessing the value of additional research

Probabilistic sensitivity analysis (PSA) assesses uncertainties surrounding model parameters and uncertainties are displayed using cost effectiveness acceptability curves (CEAC) (Fenwick *et al.*, 2004). However, the true values of costs and effects estimates from a decision model are never certain, which implies that there is always a risk of making wrong decisions which may have costs implications to the healthcare system in terms of costs or health benefits forgone (Claxton, 1999). For example, in

Figure 5.4 the CEAC displays a 70% probability that the intervention under consideration would be cost-effective at a willingness to pay threshold of £30,000, which would be an optimal choice. However, the decisions to adopt the intervention may still go wrong 30% of the time which represents the uncertainty in a decision to adopt the intervention. Uncertainty could be reduced with additional information, however it could mean incurring higher costs of conducting additional research and incur the opportunity costs of health benefits of new intervention forgone while waiting for the additional information (Claxton, 1999; Eckermann and Willan, 2007). Therefore, it would be beneficial to assess the value of additional research in reducing decision uncertainty.

Value of information (VOI) analysis is a valuable extension of the probabilistic sensitivity analysis (Felli and Hazen, 1999) and provides information on the consequences of making wrong decisions arising out of uncertainties surrounding costs and effects estimates. The VOI analysis quantifies the value of additional research to reduce the uncertainties in decision-making (Claxton and Posnett, 1996). The VOI technique mainly considers whether the technology or intervention be adopted (rejected) at the current level of evidence and whether additional information is required to support the decision-making (Briggs *et al.*, 2006). The expected cost (value) of uncertainty is commonly generated by combining the cost of making incorrect decision with the probability of making incorrect decision (Oostenbrink *et al.*, 2008; Petrou and Gray, 2011b).

A range of VOI analysis methods could be undertaken to inform decisions. Expected Value of Perfect Information (EVPI), the most common measure used in VOI analysis, is the monetary value of conducting additional research to eliminate uncertainty in all parameters and decision uncertainty (Claxton, 1999). For example, if the objective is to maximise health outcomes under budget constraints, then EVPI is the maximum the decision maker is willing to pay for additional information eliminating all uncertainties (Briggs *et al.*, 2006).

However, it would be useful to indicate parameters whose additional information would be most valuable in reducing uncertainties. Therefore, Expected Value of

Perfect Parameter Information (EVPPI), an extended form of EVPI, guides the focus of the study by identifying those parameters for which additional information would be most valuable (Claxton, 1999; Briggs *et al.*, 2006). EVPPI is simply the difference between the expected value with perfect information for identified parameter(s) and expected value with current information about the parameter(s) (Briggs *et al.*, 2006). Though with the same definition, EVPPI is also denoted as Expected Value of Partial Perfect Information (Ades *et al.*, 2004; Petrou and Gray, 2011b). Understanding what drives the uncertainty is the essence of EVPPI.

Both the EVPI and EVPPI place an upper bound on the potential value of additional research which is a necessary but not a sufficient condition for conducting further research (Claxton, 1999; Briggs *et al.*, 2006). To establish a sufficient condition for value of additional research, marginal benefit and marginal cost of sample information needs to be considered (Claxton, 1999; Briggs *et al.*, 2006; Eckermann and Willan, 2007). Therefore, Expected Value of Sample Information (EVSI) is used to estimate the value of collecting additional sample information (Claxton, 1999; Ades *et al.*, 2004). EVSI focusses on optimal design issues for further studies such as optimal sample size, optimal allocation of study population, appropriate follow-up and outcomes (Ades *et al.*, 2004; Briggs *et al.*, 2006). EVSI is calculated as the difference between the expected value of sample information and the expected value of current information. The Expected Net Benefit of Sampling (ENBS) is the difference between the EVSI and the expected costs of the study and it implies that higher the ENBS the more worthwhile the study is (Ades *et al.*, 2004).

VOI techniques such as EVPI have been increasingly reported in cost-effectiveness analysis, however the reporting of EVSI and ENBS is limited (Steuten *et al.*, 2013; Tuffaha *et al.*, 2014);with few studies being reported that have based their sample size estimate on EVSI or ENBS estimates (Cook *et al.*, 2014). Further details on VOI and the framework for the techniques utilised are described in the literature (Claxton, 1999; Ades *et al.*, 2004; Briggs *et al.*, 2006). The next section of this Chapter will discuss the presentation of results from decision analytic models.

5.5 Presenting Results of Decision Analytic Models

Finally, in a decision model the estimates of costs and effects associated with two or more interventions and cost-effectiveness are presented. The cost-effectiveness is normally summarised in terms of Incremental Cost-Effectiveness Ratio (ICER). An ICER represents the additional costs that will be incurred per unit effect gained by an intervention compared with another (Briggs, 1999). The ICER is calculated as the difference in cost of the intervention under consideration and the comparator (ΔC) divided by the difference in their effects (ΔE) using the following equation:

$$ICER = \frac{C^i - C^c}{E^i - E^c} = \frac{\Delta C}{\Delta E}$$

where C^i and C^c represent mean costs in the intervention and comparator, respectively, E^i and E^c represent effects, ΔC and ΔE represent incremental cost and effects.

A cost-effectiveness plane is used to visually illustrate the differences in costs and effects between the alternatives compared in an economic evaluation (Figure 5.3). A cost-effectiveness plane is divided into four quadrants where the incremental costs (ΔC) are illustrated on the vertical axis and the incremental effectiveness (ΔE) are illustrated on horizontal axis. If the intervention under consideration is more effective but less costly than the control, the cost-effectiveness estimates fall in the South-East (SE) quadrant, and therefore the intervention under consideration dominates the control and the intervention is the cost-effective strategy. Alternatively, if the intervention under consideration is less effective and costs more than the control, the estimates fall into the North-West (NW) quadrant which demonstrates that the control dominates the intervention and thus the control is the recommended strategy. In these circumstances, it is clear that the least costly and more effective intervention should be implemented and a ICER will not be necessary (Briggs *et al.*, 2006). However, a trade-off is involved if the estimates are more effective and more costly (i.e. when they fall into the North-East (NE) quadrant) or less effective and less costly (i.e. when they fall into South-West (SW) quadrants).

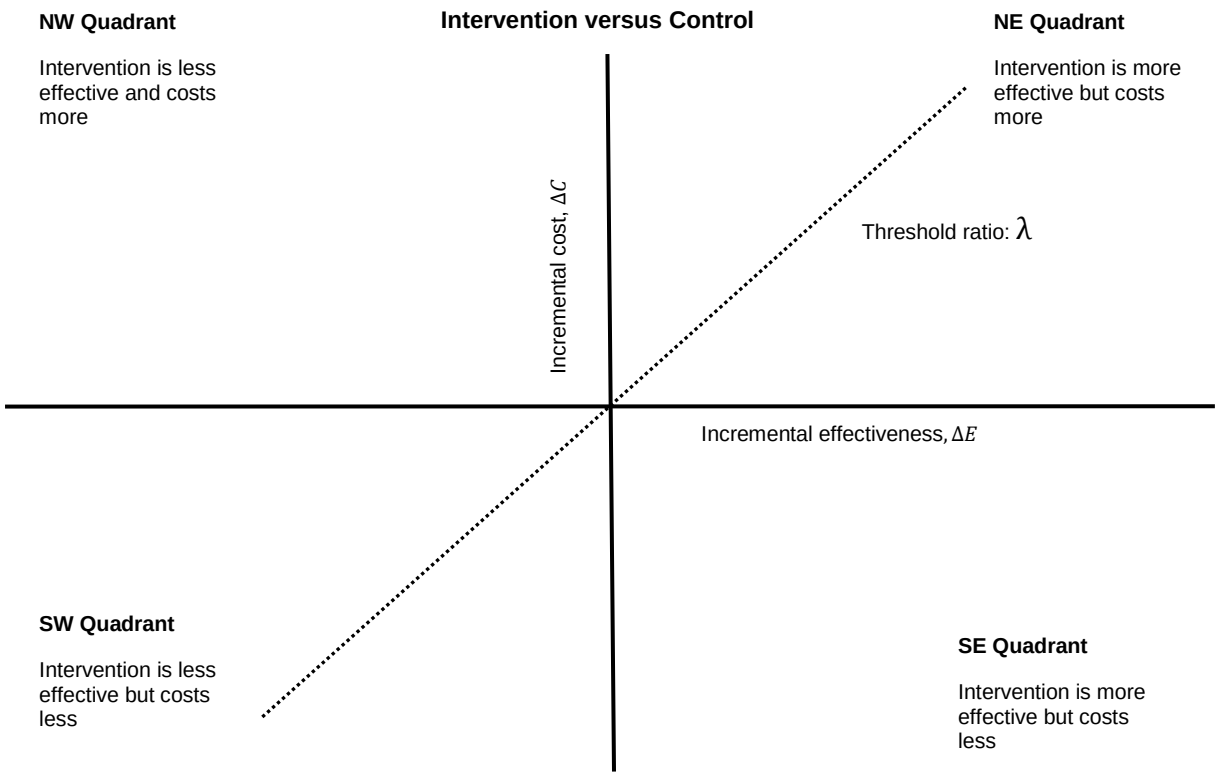

Figure 5.3: Cost-effectiveness plane

In situations where the cost-effectiveness estimates fall into either NE or SW quadrants of the cost-effectiveness plane, decisions on cost-effectiveness of interventions will depend on the decision maker's willingness to pay value. In the Figure 5.3, the willingness to pay threshold (λ), also known as ceiling ratio, is represented by the dotted diagonal line passing crossing through the origin of the cost-effectiveness plane and across the NE and SW quadrants. The intervention is considered cost-effective at a given value of λ, if the incremental values fall below (values fall to the right of the dotted line). Whereas it will not be considered cost-effective if the incremental values fall above (values fall to the left of the dotted line). In other words, the intervention is deemed cost-effective and said to offer a good value for money if the ICER is less than the ceiling ratio λ, otherwise not (Fenwick *et al.*, 2006). The ceiling ratios are generally subjective, however they are also considered to reflect the opportunity costs of implementing the intervention under consideration (McCabe *et al.*, 2008). In the UK, NICE recommends a ceiling ratio in the range of £20,000 to £30,000 per QALY (National Institute for Health and Care Excellence, 2013). A range rather than a fixed amount allows reflection of uncertainties in the ICER estimates and flexibility to use criteria other than cost-

effectiveness in decision-making (Appleby, 2016). ICER's less than £20,000 per QALY are normally considered cost-effective by NICE, however decisions on ICER's above £20,000 per QALY take account of factors such as i) the degree of certainties around the ICER, ii) whether the intervention under consideration is innovative in nature and adds demonstrable and distinctive benefits which may not have been captured by QALYs, iii) whether intervention involves benefits on broader social considerations other than health, iv) whether the QALYs have been adequately captured, v) whether the intervention meets the criteria for special consideration as a "life extending treatment at the end of life" (National Institute for Health and Care Excellence, 2013; Dakin *et al.*, 2015).

In a PSA, a Monte Carlo simulation generates a large number of estimated costs and effects. The average of these estimated costs and effects across simulations, and the resulting ICER represent uncertainties in the decision model. However, another way of illustrating uncertainty is to plot the incremental costs and incremental effects in each of these simulations as a cloud of points in a cost effectiveness plane. In probabilistic analysis where the range of incremental values spread across cost-effectiveness plane quadrants there will be some negative ICERs which do not have a meaningful interpretation (Stinnett and Mullahy, 1998) and there will often be problems in interval estimation of ICER (Briggs *et al.*, 2006). Therefore, to avoid the problem with interpretation of negative ICER, the use of CEAC is recommended (Fenwick *et al.*, 2001; Briggs *et al.*, 2006). Furthermore, the exact value of the CEAC is ceiling ratio λ is not known in practice. However, the probability of cost-effectiveness of an intervention over a range of ceiling ratios can be illustrated in the CEAC. A hypothetical example of CEAC is presented in Figure 5.4 where the intervention and the control both have 50% cost-effectiveness probability at the ceiling ratio of £20,000. But, at the ceiling ratio of £30,000 the cost-effectiveness probability increases to 70% for the intervention and decreases to 25% for the control.

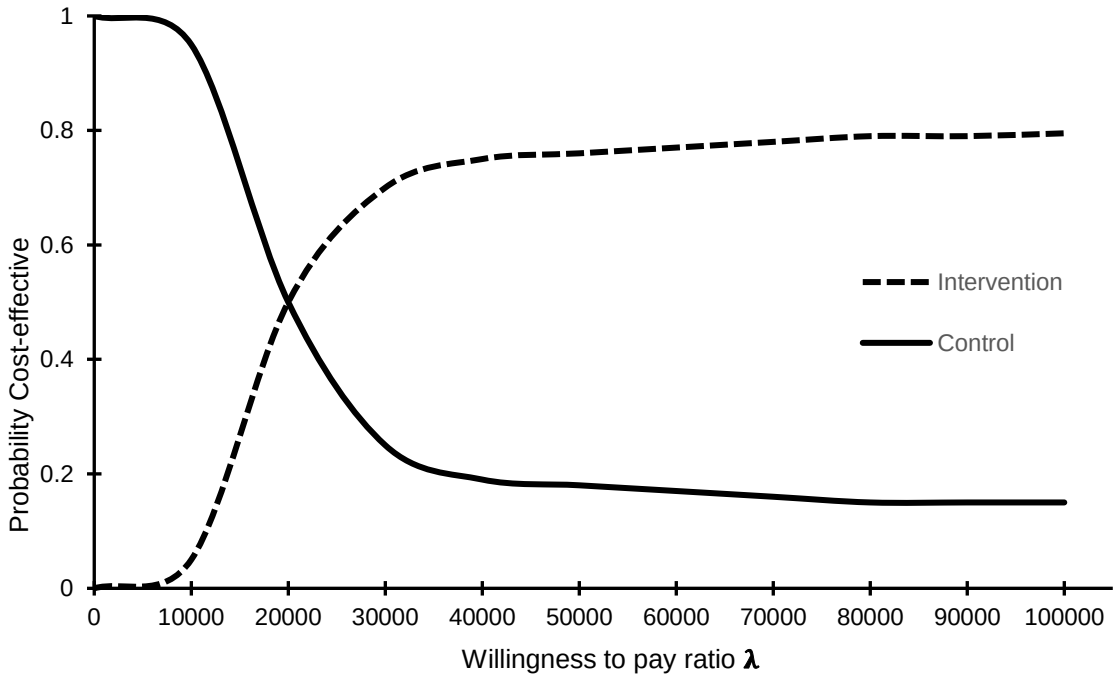

Figure 5.4: A CEAC for intervention versus control

As described earlier for the cost-effectiveness plane in Figure 5.3, the incremental values falling below and to the right of the line representing the maximum willingness to pay (ceiling ratio) illustrates the estimates that are cost-effective. Therefore, CEAC involves calculating the probability of intervention is cost-effective as the proportion of incremental values falling below the threshold line for each of the range of willingness to pay. Then the probability estimates of intervention being cost-effective for the range of ceiling ratio are summarised in the CEAC plot.

Alternatively, incremental net benefit (INB) which is a simple rearrangement of the ICER based on decision rule of cost-effectiveness, is used to overcome problems associated with ICERs explained earlier (Stinnett and Mullahy, 1998; Briggs *et al.*, 2006). The decision rule stated earlier in this section explains that the intervention under consideration should be implemented only if its ICER is lower than the threshold λ, i.e. if $\frac{\Delta C}{\Delta E} < \lambda$. This decision rule can be re-arranged into either cost (monetary) or effect (benefit) scales in the net-benefit framework as follows (Briggs *et al.*, 2006):

$$Net\ Monetary\ Benefit\ (NMB) = \lambda * \Delta E - \Delta C > 0$$

$$Net\ Health\ Benefit\ (NHB) = \Delta E - \frac{\Delta E}{\lambda} > 0$$

According to these decision rules, which are equivalent to the standard rule in the ICER, a positive net benefit indicate that the intervention is cost-effective and good value for money, whereas a negative net benefit is not (Drummond *et al.*, 2005).

5.6 Summary

The economic evaluations on centralisation of specialised healthcare services is dominated by studies with limited methodological quality. This Chapter provided a methodological background to the economic evaluation methods used in this thesis. Considering, the nature of the case considered in the next Chapter, a RCT to assess the impact of centralisation of emergency hospitals in this instance would be challenging. Decision analytic models enable a wide range of costs and effects from various sources to be synthesized within a model framework to generate cost-effectiveness outcomes of an intervention and are particularly useful when RCTs are difficult to conduct or when the existing economic data is very limited. This Chapter described the methodological development of an economic evaluation model with the focus on decision analytic model framework. It demonstrated methods of assessing and presenting uncertainties in the cost-effectiveness estimate. The decision analytic modelling framework will be applied in the next Chapter.

Chapter 6. Application of Decision Analytic Model in Economic Evaluation of Centralised Emergency Medical Care

6.1 Introduction

The aim of this Chapter is to describe the economic evaluation of centralised specialised emergency medical service compared with those provided at local hospitals in a UK setting. The Chapter addresses the third and fourth research questions set out in Chapter 1. Chapter 2 systematically reviewed and discussed the economic evaluation methods used in assessing the centralisation of specialised health care services. Chapter 5 described the development of an economic evaluation model with an emphasis on a decision analytic model framework. Chapters 2 and 5 informed the development and conceptualisation of economic evaluation reported in this Chapter. Many of the approaches described in Chapter 5 are used in this Chapter.

The Chapter first describes the use of the decision analytic framework to conduct the economic evaluation of centralised provision of emergency medical care compared with the local provision and then presents the summary of the results. The rest of the Chapter is structured as follows: section 6.2 describes the economic evaluation model development, section 6.3 describes what additional analysis were considered, section 6.4 presents the results, section 6.5 discusses the findings highlighting some major strengths and limitations of the study and this is followed by the conclusions which are reported in section 6.6.

6.2 Model Development

This section describes the use of economic evaluation techniques to build the model. The model conceptualisation and development adhered to a practical guide to Markov models in decision-making (Sonnenberg and Beck, 1993) and the guidelines and practices outlined by ISPOR-SMDM Task Force on Modelling Good Research Practices (Caro *et al.*, 2012; Roberts *et al.*, 2012; Siebert *et al.*, 2012).

6.2.1 Alternatives compared

The concentration of care into specialised centres is one of the new care models suggested by the “Five year forward view” in NHS England (NHS England, 2014). Furthermore, Sir Bruce Keogh also recommended the centralisation of emergency medical services into specialised units providing efficient and high quality care to those with serious and life threatening conditions (NHS England, 2013a). Grounded on these recommendations, a new specialised emergency care hospital was built at Cramlington in Northumberland, the first of its kind in the UK, with the aim to provide improved quality of care by providing faster access to consultants and diagnostics (O'Neill *et al.*, 2017). Before June 2015, the emergency medical services were provided from the A&E departments at three general hospitals within the area: North Tyneside, Wansbeck and Hexham. All of these hospitals are operated by Northumbria Healthcare NHS Foundation Trust and they accounted for 90% of all A&E visits by the population of Northumberland (O'Neill *et al.*, 2017). The emergency care provided by the three general hospitals was centralised into the new specialised hospital. Although this represents a major system change, the cost and effectiveness of the change was not known. Therefore, the aim of the economic evaluation described in this Chapter is to assess the impact of these changes on A&E service provision in Northumberland. Thus, the emergency medical services provided at centralised specialised emergency hospital is compared to those at the general hospitals. From here on, in this Chapter, emergency medical services provided at the centralised specialised emergency hospital will be referred as “central hospital” (i.e. intervention) and those at the local general hospitals as “local hospital” (i.e. control).

6.2.2 Choice of the model

As stated in Chapter 5, a mixture of economic evaluation approaches with within trial economic evaluation supporting wider secondary evidence in the decision analytic model would be most beneficial (Sculpher *et al.*, 2006). However, considering the nature of centralised care a trial comparing centralisation with non-centralised care would not be feasible. Costs and effectiveness of centralisation of healthcare services is a much debated topic as discussed in Chapter 1 and these are often not known with certainty. As described in Chapter 5, decision analytic models are established framework used to inform decision-making under conditions of uncertainty. Therefore, in the context of uncertainties in costs and outcomes, an

economic evaluation based on a decision analytic model was considered the most appropriate approach in assessing the costs and effects of centralisation of emergency medical services.

Common variations in the decision analytic model structures, their strengths and limitations are described in Chapter 5. Decision trees were not appropriate in assessing centralisation of emergency hospitals because of difficulties in incorporating time dependency and complexity in modelling interventions with shorter cycle lengths over a long time horizon (Briggs *et al.*, 2006; Petrou and Gray, 2011b). The patients attending the emergency hospitals were regarded independent of each other and absence of interaction between patients ruled out the need to use dynamic models or discrete event simulation with interaction. Thus, the decision analytic model alternatives left for the work described in this Chapter were either a Markov (cohort) model or a patient level simulation. Patient level simulation offers several advantages over a Markov model as they allow accumulation of individual patient history to determine transitions between states, costs and health outcomes (Briggs *et al.*, 2006). However, the benefits of a patient level simulation can be outweighed by the parametrisation and computational burden it requires compared to a Markov model. Therefore, given the nature of the decision problem the model is seeking to inform and the relative simplicity and transparency of the Markov model compared to the patient level simulation, a Markov modelling approach was adopted. The choice of Markov model is further supported by existing literature which argue that the substantially increased analytic input for the patient level simulation compared to a Markov model may not have any impact on ultimate decisions (Karnon, 2003; Griffin *et al.*, 2007).

6.2.3 Markov model structure

The Markov model seeks to represent the patient care pathways in emergency healthcare need. The Markov model structure is depicted in Figure 6.1 and consisted of four possible states: Community, A&E, Admission and Dead. These states, defined in Table 6.1, closely represented the pathways of emergency patients in NHS England. In Figure 6.1, the ovals represent the Markov states and the arrows represent the possible transitions from one state to another. The arrows leading to

the state itself indicate the possibility that the patient may remain in the same state in the consecutive cycles. These Markov states are mutually exclusive which means that at a certain time point a patient can be only in one state. A hypothetical cohort of 1000 patients were modelled with changes between states depending on the transition probabilities between the Markov states. In both the central and local hospitals the following transition between states were possible at the end of each Markov cycle:

- Patients in the community state can either transit to A&E state or remain in their current state or die.
- Patients in the A&E state either get discharged back into the community or get admitted or die. Patients were not expected to stay in the A&E at the end of each cycle. This reflected the current provisions in the NHS where patients attending the A&E either get discharged or get admitted or declared dead (if they die in the A&E).
- Patients in the admission state either get discharged or continue to be admitted or die.
- Death is the absorbing state of the model and patients who die remain in the dead state until the model terminates.

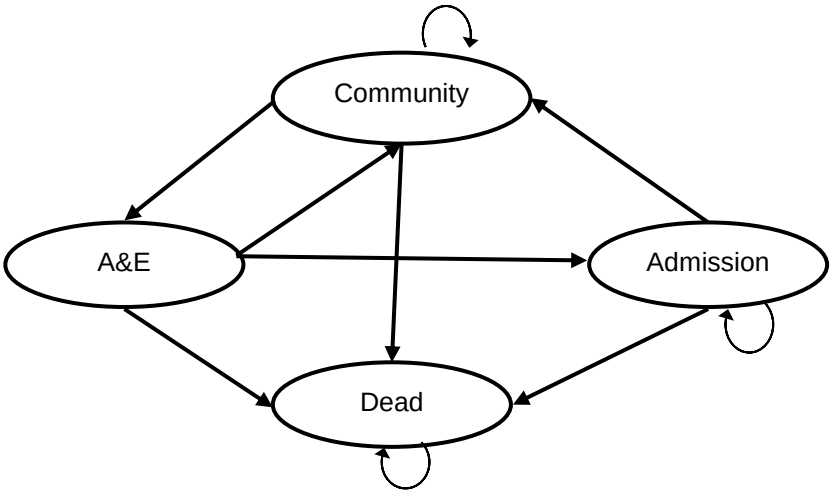

Figure 6.1: The Markov model

Table 6.1: Definition of states in the Markov model

Markov state	Description
Community	This is the usual place of residence of the patients.
A&E	This is the Accident and Emergency (A&E) department of the hospital that patients visit in the event of emergency health care need.
Admission	This is where patients are admitted in the hospital after visiting the A&E department for the treatment.
Dead	This is the dead state and is the absorbing state of the model.

6.2.4 Time horizon

The model employed a 10 year time horizon. However, the cost and outcomes were estimated for three different time points of 30 days, one year and 10 years. The first 30 days was modelled to generate the most precise estimates of the costs and outcomes of centralisation of emergency medical service. One year and 10 years were employed to project the relevant costs and outcomes over a longer period of time. The 10 year time horizon was deemed sufficient to capture the relevant long term costs and outcomes of the two models of emergency hospitals compared in this thesis.

6.2.5 Cycle length

Two different cycle lengths were used. A cycle length of one day was used for the first 30 days of the model. One day cycles were considered to capture better approximate the costs and outcomes occurring within one month. Thereby reflecting the NHS indicator of quality of healthcare service provided by hospitals. For the remainder of the 10 year time horizon cycle length of one-months (i.e. 30 days) were fitted and hence there were 119 monthly cycles in the model. The monthly cycles were used to reduce the complexity of the model that would have resulted had one day cycle lengths been used for the entire 10 years. Nevertheless, the first monthly cycle was accounted for by the costs and outcomes in the 30 days model. The non-homogenous cycle lengths in the entire model was accounted for by adjusting the corresponding model input parameters of transition probabilities and costs. The

proportion of patients in each state at the end of 30 daily cycles were used to populate the model states in the first monthly cycle (i.e. after 30 days).

6.2.6 Model parameters

The parameters used to populate the Markov model were transition probabilities between the Markov states, and the costs and utilities attributed to each Markov state. The transition probabilities used in the local hospital and the central hospital are reported in Appendix C, Tables C1 and C2 respectively. The unit costs considered in both the models are reported in Table 6.3 and the utilities are in Table 6.4. The approaches used to derive these model parameters are described as follows.

6.2.6.1 Transition probabilities

The transition probabilities for both the local and central hospitals were derived from the Hospital Episode Statistics (HES) (Health and Social Care Information Centre, 2015) of consecutive patients attending the emergency department (ED). Caldicott approval was in place for the ethical use of HES patient data (Appendix B-B3 & B4).The cases without a local postcode were removed because it was considered unlikely that they would have had a future chance for a readmission. In addition, patients aged 18 years or younger were removed as it was believed that there would be a different nature of healthcare issues and resource utilisation in this age group. The data for the local hospital comprised 230,669 HES records of patients attending the A&E services of three general hospitals-North Tyneside, Wansbeck and Hexham between 1 January 2010 and 31 May 2015. The data for the central hospital comprised of 52,721 HES records of patients attending the specialised emergency care hospital in Cramlington, Northumberland in between 16 July 2015 and 30 September 2016. All of these hospitals belong to the Northumbria Health Care NHS Foundation Trust (NHCT) in North East England.

The characteristics of patients are presented in Table 6.2.

Table 6.2: Characteristics of patients used to derive transition probabilities in the local and central hospital

Patient Characteristics	Local	Central
Mean Age (SE)	62.12 (0.045)	63.97 (0.087)
Male (%)	43.04	45.54
Female (%)	56.96	54.46
Age groups (%)		
<=29	10.83	7.67
30-64	36.37	36.57
65+	52.80	55.77
IMD Quintiles (%)		
Missing	3.20	4.48
1st (<=8.49)	14.03	13.88
2nd(8.5-13.79)	14.93	15.00
3rd (13.8-21.35)	17.26	17.78
4th (21.36-34.17)	24.07	23.61
5th (>=34.18)	26.51	25.24
CCI (%)		
0	51.54	44.79
1	24.21	25.09
2	9.95	12.14
3	4.42	5.42
>=4	9.88	12.56
Primary Diagnosis (ICD10 Classification) (%)		
Missing Information	0.01	1.23
Certain infectious and parasitic diseases	2.78	3.65
Neoplasms	2.97	3.25
Diseases of blood or blood forming organs	0.92	0.87
Endocrine, nutritional and metabolic disease	2.07	2.48
Mental and behavioural disorders	2.58	2.11
Diseases of the nervous system	3.39	3.56
Diseases of the eye and adnexa	0.23	0.19
Diseases of the ear and mastoid	0.28	0.32
Diseases of the circulatory system	11.02	11.32
Diseases of the respiratory system	11.88	11.89
Diseases of the digestive system	10.14	10.89
Diseases of skin and subcutaneous tissue	2.21	3.45
Diseases of musculo-skeletal system	6.42	7.39
Diseases of genito-urinary system	6.89	6.52
Pregnancy, child birth, puerperium	4.29	0.94
Conditions originating from puerperium	0.00	0.00
Congenital malformations	0.02	0.06
Abnormal clinical laboratory findings	17.42	16.46
Injury, poisoning and certain consequences	14.00	12.91
External causes of morbidity (falls, accidents)	0.00	0.00
Factors influencing health status	0.49	0.50

SE= Standard error; IMD= Index of mean deprivation; CCI= Charlson's comorbidity index

Transition probabilities were derived using survival analysis to model “time to event” where the event was the movement out of a state. Patients were only included in the survival analysis if they had a record of date of A&E attendance and discharge or death. A parametric model with a weibull distribution was used and any competing risks (events) were accounted for. The AIC for weibull distribution indicated a better model fit compared to other distributions that were applicable. Survival analysis, distributions used, approaches for assessing suitability of the distributions and the impact of not accounting for competing risks are described in section 5.4.4 in Chapter 5. Separate survival analysis models were run for community and admission states. In the survival analysis conducted for the community state, the maximum follow-up time for the re-attendance of the A&E department and death in the community was 28 days. Death in the community was the competing event for re-attendance and vice versa. The transition probabilities were then estimated from these data for the first 30 days. The follow-up time of 28 days reflected the indicator of hospital care quality in the NHS. Multiple re-attendances were considered in the survival analysis and the previous discharge was considered the index case for any re-attendance within 28 days of a previous discharge from hospital. In the survival analysis for the admission state, the maximum follow-up time for any discharge from hospital and death in the hospital was 60 days. Death whilst in the hospital was the competing event for discharge back into the community and vice versa. The follow-up time of 60 days was arbitrarily taken. Such an approach of setting a follow-up time in survival analysis for competing events is common in existing literature (Brock *et al.*, 2011).The transition probabilities out of admission state were generated for the first 30 days.

The *flexsurv* package was used as a platform for parametric survival modelling in R (Jackson, 2016; R Core Team, 2016). Transition probabilities were time dependent and varied with the number of days passed in the daily cycles of the Markov model. However, it was assumed that the transition probabilities after the first 30 days (i.e. the monthly cycles) did not change with time. The transition probabilities are reported in Appendix C, Tables C1 and C2.

Survival analysis was not used for the computation of transition probabilities out of A&E state. The patients in the A&E state were discharged or admitted or die on the same day which meant the length of stay in the A&E state was less than one day. Therefore, the proportions were used as transition probabilities of patients moving out of A&E state to community, admission and dead state. Transition probabilities from A&E state were not time dependent.

6.2.6.2 Costs

Each Markov state was assigned a value that reflected the cost of being in that state in each cycle. The perspective of analysis was that of the NHS and therefore did not include any costs falling on the patients. The cost components included in the model were cost of ambulance journey to the hospital, cost of A&E attendance and cost of hospital admission. The costs after discharge from the hospital or death were not considered in the model and were assumed zero. The costs of nursing staff and other healthcare professionals were not accounted for separately, since it was assumed that these costs were included in the unit costs for A&E and admission state. In addition, the cost of additional consultant time was included in the central hospital. However, this assumption of additional consultant costs was investigated in the sensitivity analysis (described later in this Chapter) examining how the results look like if costs of additional specialised consultant was not included in the central hospital. The resource utilisation and the cost components considered in the model were derived as follows:

- Ambulance journey time was considered as the time taken to drive via the fastest route between the patient postcode and hospital postcode. The postcodes were taken from the HES records of patients attending the hospital A&E services. The driving times between the patient and hospital postcodes were computed using the Google Maps *Geocoding API* and *XML* package in R (R Core Team, 2016). The mean travel times were derived for each hospital model from the journey times of HES records of patients used in this Chapter. Journeys for repeated attendances of patients were accounted for in the mean travel time. The cost per minute of ambulance journey obtained from secondary literature (Curtis, 2008) was then applied to the mean travel time for each of the hospital model to

generate the mean cost of ambulance journeys to the hospital. The cost per minute of ambulance journey was reported to account for the overheads and management costs, buildings and land, ambulance and equipment, and ambulance crew salaries and wages (Curtis, 2008).

- Cost of A&E attendance was the cost of one event of A&E attendance and was taken from a secondary source (Curtis, 2010). The cost of mean ambulance journey was added to the cost of A&E attendance to obtain the total cost of A&E state in the model. Only the costs for ambulance travel into the hospital was considered. It was assumed that patient travelled privately after they got discharged from the hospital and no costs of travel after discharge were considered from the NHS perspective.

- Cost of hospital admission was the cost per day of individual stay in the hospital and was taken from a secondary source (Curtis, 2010).

Table 6.3: Cost parameters used in the models

Resource	Unit (95% Confidence Interval)		Reference
	Local hospital	Central hospital	
Mean travel time to the A&E	14.41 min (14.36-14.88)	19.55 min (19.43-19.67)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£117.87 (117.49-118.26)	£159.92 (158.97-160.87)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (90.11-132.8)	£115.01 (90.11-132.8)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (112.64-177.85)	£155.32 (112.64-177.85)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost

Costs derived were considered as per day costs and were applied in the daily cycles of the Markov model. The costs for the 30 day cycles were computed as thirty times the costs in the daily cycles. However, the A&E state costs used in the daily cycles were constant throughout the model because it was expected that patients attend the A&E for less than a day and the time they spent in the A&E state always remained the same.

Costs are expressed in 2016/17 UK sterling (GBP, £). Wherever unit costs were only available from previous years, were inflated to the price year 2016/17 using the hospital and community health services (HCHS) pay and price inflation indices (Curtis and Burns, 2017).

6.2.6.3 Utilities

Health utility weights were attached to each Markov states. The utilities were derived from the published literature (Sullivan *et al.*, 2011; Goodacre *et al.*, 2012). The utilities for A&E state and admission state were assumed to be same. The utility for the dead state was assumed zero. Table 6.4 presents the utility values used in the model.

Table 6.4: Utility values associated with each state in the model

Markov state	Utility value	SE*	Reference
A&E	0.45	0.006	*Goodacre et al 2012*
Admission	0.45	0.006	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

*SE=standard error

Utility estimates were used to generate the Quality Adjusted Life Years (QALY) estimates in each state of the alternatives compared. In the daily cycles, the utility estimates for each state were converted to daily QALYs by dividing the value by 365.25. In the monthly cycles, these daily QALYS were multiplied by 30 to generate the monthly estimates of QALYs (please note that use of 30 days in a month will only

add up as 360 days in a year, a limitation in the calculation but one that affects both comparators). However, in the A&E state the QALYs used in the daily cycles remained the same for the monthly cycles because it was expected that patients attend the A&E for less than a day and the time they spent in the A&E state always remained the same throughout the model.

6.2.7 Model outcomes

The outcomes considered in the model were “cost per QALY gained” and “cost per death averted”. Total QALYs were calculated for each state by multiplying the cohort in each state in each cycle with the respective QALY for each patient in the state. Total costs were calculated in the same way as a product of cohort and costs associated in each state. Total mortality in each cycle was calculated as the number of people who die after the end of the cycle. Separate calculations were conducted for central and local hospital models.

6.3 Analysis

Cost-effectiveness analysis was carried out as the incremental cost per QALY gained and incremental cost per death averted at 30 days, one year and 10 years. These were calculated as the difference in total costs in the central hospital and local hospital divided by the difference in QALYs or death averted. The following approaches were considered in the analysis.

6.3.1 Discounting

The costs and outcomes (QALYs and deaths) after the first year were discounted at 3.5% as recommended by NICE (National Institute for Health and Care Excellence, 2014).

6.3.2 Half cycle correction

It was uncertain when the transitions happen within the cycles in the model. Therefore, a half-cycle correction was employed in the first and final cycle of the model as a recommended best practice (Siebert *et al.*, 2012).

6.3.3 Handling uncertainties and heterogeneity

Assessments of uncertainties and heterogeneity in the model parameters were incorporated in the analysis. The following approaches were considered to assess the impact of uncertainties and heterogeneity on the model outcomes.

6.3.3.1 One-way sensitivity analysis

One way sensitivity analysis was conducted to assess the consequence of not considering an additional costs of consultant service in the central hospital. In addition, one way sensitivity analysis was also conducted to assess the impacts of discounting the costs and outcomes at 1.5% and 5%. NICE recommends conducting a sensitivity analysis on discounting the costs and outcomes at a lower rate of 1.5% (National Institute for Health and Care Excellence, 2014). One-way sensitivity analysis was not considered for utility estimates used in the model because of the negligible standard error figures in the utility data available. Likewise, one-way sensitivity analysis was not considered for the transition probabilities used, as imprecision was captured using PSA as described below.

6.3.3.2 Probabilistic sensitivity analysis

PSA, defined in Chapter 5, was carried out to determine the impact of the uncertainty surrounding the model input parameters i.e. transition probabilities, costs and utilities. Distributions were fitted to all the input parameters of the model and 10,000 simulations were run, with each simulation picking up random values from each distribution and generating the cost-effectiveness results. Transition probabilities were assigned the dirichlet distribution however the transition probabilities of moving out of the A&E state which were derived as proportions were assigned the beta distributions. Utilities were assigned beta distribution and costs the gamma distribution. The cost-effectiveness plane and the CEAC were used to present results of PSA at 30 days, one year and 10 years. The distributions for costs, utility and transition probabilities were estimated using the alpha and beta parameters generated using the formula described in section 5.4.5 of Chapter 5.

6.3.3.3 Value of information analysis

VOI analysis was carried out at 10 years (i.e. at the end of the time horizon set for the cost-effectiveness model) as described in section 5.4.6 in Chapter 5. VOI analysis is expected to establish whether further research is warranted considering the uncertainties surrounding the cost-effectiveness results.

6.3.3.4 Scenario analysis/ modelling heterogeneity

Scenarios analysis was conducted to account for any impact of heterogeneity in the patient characteristics in both the central and local hospitals. Scenario analysis and heterogeneity are described in section 5.4.5 in Chapter 5. The analysis was run repeatedly using the same starting cohort but each time with specific model parameters accounting for each of the patient characteristics. The patient characteristics considered in the scenario analysis were gender (male and female), age (≤ 29 years, 30-64 years, 65+), Charlson's Comorbidity Index (CCI) (CCI=0, CCI≥4), Index of Mean Deprivation (IMD) (least deprived quintile i.e. ≤8.49 and most deprived quintile i.e.≥ 34.18) and according to some ICD 10 primary diagnosis classifications (diseases of the circulatory system, diseases of respiratory system, diseases of the digestive system, abnormal clinical laboratory findings, injury poisoning and certain consequences) with which the patients attended the emergency. These patient sub-groups were considered in the scenario analysis because it was expected that any differences in their characteristics could influence the resource utilisations and ultimately the model outcomes.

The transition probabilities varied with the sub-groups. These transition probabilities for each sub-groups were estimated using the same methods for the base case models described in section 6.2.6.1. The cost parameters were assumed to remain the same across the scenarios. However, the cost of ambulance journey to the A&E varied in each sub-group because of the differences in the mean travel times to the hospital in each sub-group, which in turn led to the differences in the costs used in the A&E state of the model. Where available from secondary sources, the utility values for each state in each of the sub-group models were also varied. However, in the instances where utility estimates were not available for a particular sub-group, these were assumed to be the same as the ones used in the base case models. The

parameters used in the sub-group models are in Appendix C of this thesis. Deterministic estimates of cost-effectiveness were generated for each scenario analysed. PSA was also carried out for each sub-group considered in this economic evaluation and followed the same approach as described in section 6.3.3.2. Multiple CEACs were produced for each sub-group, where the probability of central hospital model being cost-effective was plotted against the willingness to pay (WTP) threshold.

6.3.4 Incorporating DCE results into the economic evaluation

This Chapter also looked into methods of incorporating the results of the DCE described in Chapter 4 into the economic evaluation. Whilst DCEs are widely used in health economics to elicit preferences, the application of these preferences values into economic evaluations is limited (de Bekker-Grob *et al.*, 2015). Terris-Prestholt and colleagues showed that in the absence of observed uptake data DCE can be used in parameterising user uptake in economic evaluations (Terris-Prestholt *et al.*, 2016). Furthermore, in a recent systematic review and meta-analysis DCEs are reported to provide reasonable predictions of health-related behaviours outside of experimental context (Quaife *et al.*, 2018). However, only a few studies have attempted to apply the monetary values in terms of WTP estimates from a DCE within an economic evaluation in the form of cost-benefit analysis (Vale, 2005; Petrou and McIntosh, 2009; van der Pol *et al.*, 2010; Burr *et al.*, 2012; Tinelli *et al.*, 2016). It was not possible to generate the WTP monetary values for the hospital models assessed in this Chapter because cost was not included as an attribute in the DCE for reasons explained in Chapter 4. Nevertheless, the travel time was used as a proxy for costs and marginal willingness to travel were converted to marginal WTP using the average weekly earnings and average weekly hours worked in the UK (Office for National Statistics, 2018a). Hence, a cost-benefit analysis was conducted using the marginal WTP value estimates derived from marginal willingness to travel results from the DCE in Chapter 4.

6.4 Results

6.4.1 Base case analysis

The results of the base-case analysis showed that in all of the time points i.e. 30 days, one year and 10 years assessed the central hospital was more costly and more effective compared to the local hospital. However, at 30 days, both the deterministic (£32,730 per QALY gained) and probabilistic (£31,338 per QALY gained) estimates of ICER were above the £20,000 to £30,000 per QALY gained benchmark used in England and Wales (National Institute for Health and Care Excellence, 2013). Hence, the results at 30 days suggested that the central hospital was on average not a cost-effective alternative to local hospital. Nevertheless, the ICER estimates for one year and 10 years were well below the £20,000 to £30,000 per QALY gained benchmark set by NICE and suggested that the central hospital may be a cost-effective alternative compared to the local hospital. The results also indicated that there were fewer deaths (which were generally consistent over time) in the central hospital compared to the local hospital. Therefore, the results suggested that the central hospital saved lives and produced more QALYs compared to the local hospital. A detail breakdown of the deterministic and probabilistic estimates of incremental costs, incremental QALYs and mortality averted observed in the base case analysis is presented in Table 6.5. The results reflect that the cost-effectiveness of the central hospital increases in the long term and supports any decisions to adopt it from the NHS perspective.

Table 6.5: Results of cost-effectiveness analysis: central hospital minus local hospital

Time Horizon	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
30 days					
Base case (*deterministic*)	51,385	-26.55	1.57	1,935	32,730
Base case (*probabilistic)*	49,201	-26.55	1.57	1,853	31,338
1 year					
Base case (*deterministic*)	310,946	-31.47	310	9,881	1,004
Base case (*probabilistic)*	312,999	-31.43	310	9,959	1,011
10 years					
Base case (*deterministic*)	1,986,329	-31.57	3,123	62,918	636
Base case (*probabilistic)*	2,003,944	-31.60	3,121	63,416	642

Note: Incremental cost, Difference total death and Incremental QALYs expressed as per 1000 people

The overall uncertainty in the base-case analysis is presented in the form of cost-effectiveness plane and CEAC. Figures 6.2, 6.3 and 6.4 show the CE planes at 30 days, one year and 10 years of estimates respectively and the numbers in the cost-effectiveness planes are expressed per 1000 people. These cost-effectiveness planes show the difference in QALYs against the difference in costs (central hospital minus local hospital).

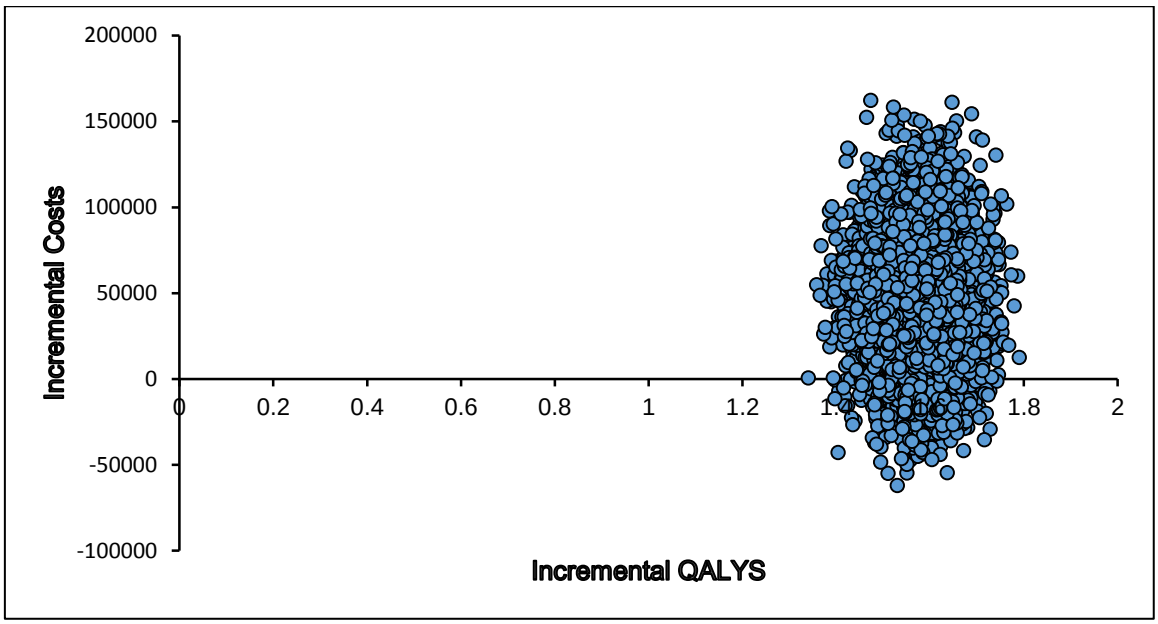

Figure 6.2: Cost-effectiveness plane of central hospital vs local hospital at 30 days (base-case analysis)

These cost-effectiveness planes at 30 days, one year and 10 years show the results from the 10,000 simulations where the majority of the results fall in the north-east quadrant of the plane suggesting that the central hospital is more costly and more effective than the local hospital. However, a smaller portion of the results also fall in the south-east quadrant of the plane which also indicate the possiblity that the central hospital to be less costly and more effective.

The uncertainty in the results at 30 days, one year and 10 years are also represented in the CEAC in Figures 6.5, 6.6 and 6.7 respectively. At 30 days, there is only 28% probability for central hospital being cost-effective at the decision-makers willingness to pay value of £20,000 per QALY. The CEAC in Figure 6.5 shows that both the models have equal probability of being cost-effective at 30 days if the decision maker is willing to pay around £30,000 per QALY. However, at one year and 10 years time, the probability of central hospital being cost-effective increases to 100% at around WTP £4000 per QALY. These CEACs indicated that central hospital is more likely to be cost-effective in the long run.

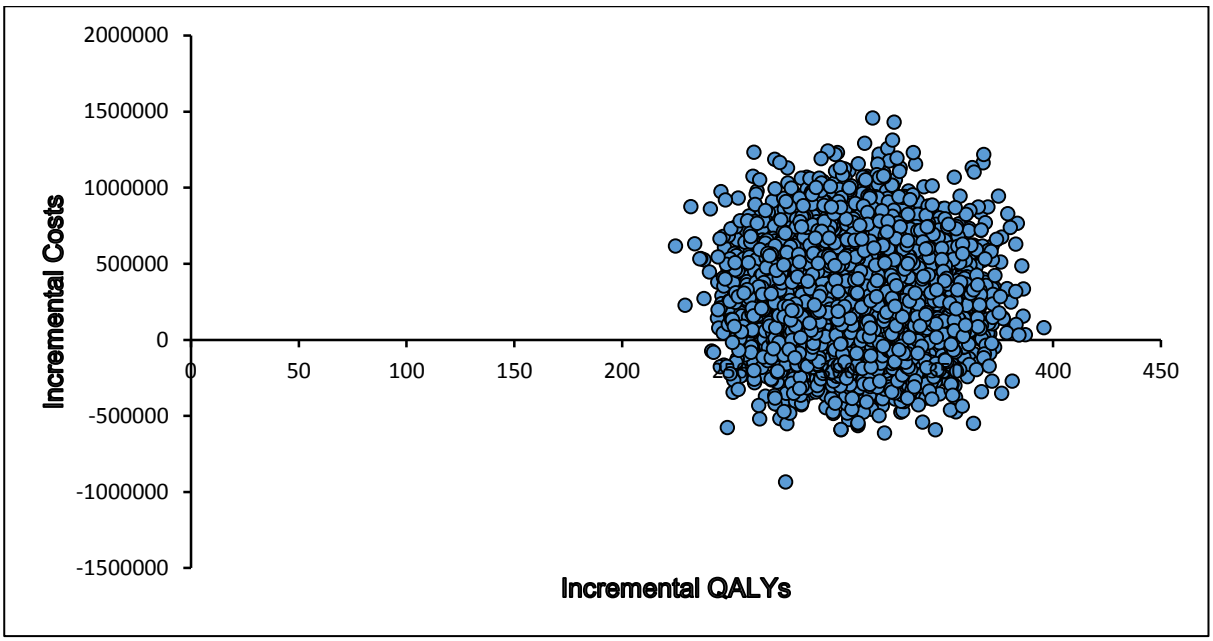

Figure 6.3: Cost-effectiveness plane of central hospital vs local hospital at one year (base-case analysis)

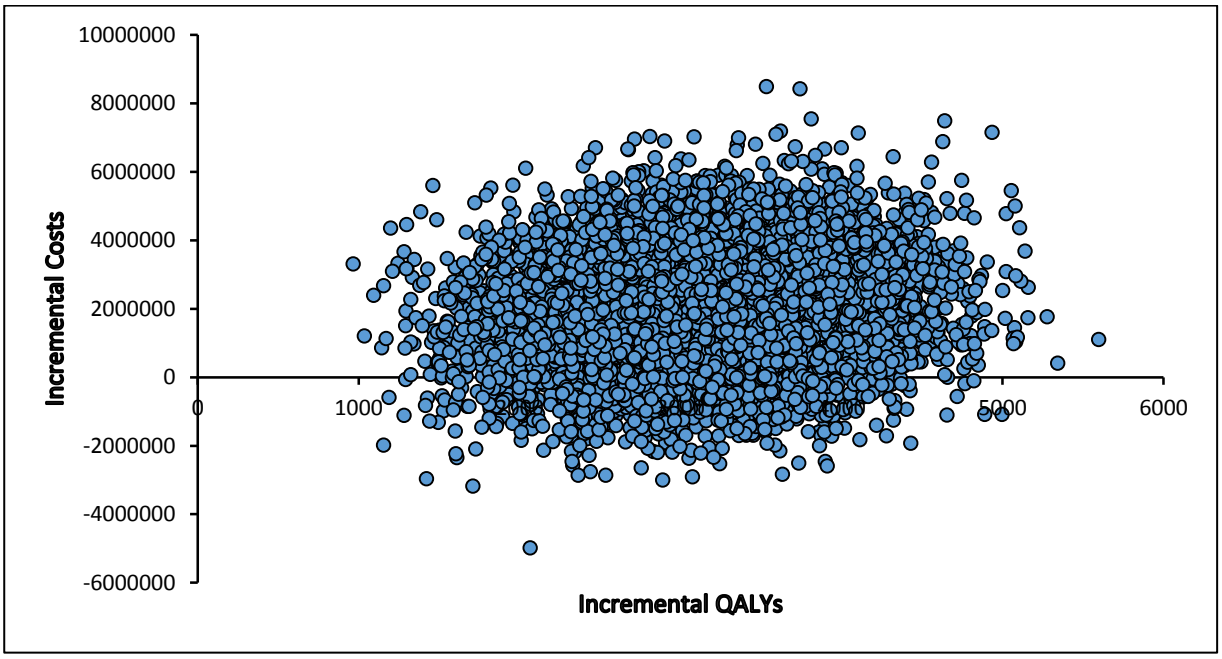

Figure 6.4: Cost-effectiveness plane of central hospital vs local hospital at 10 years (base-case analysis)

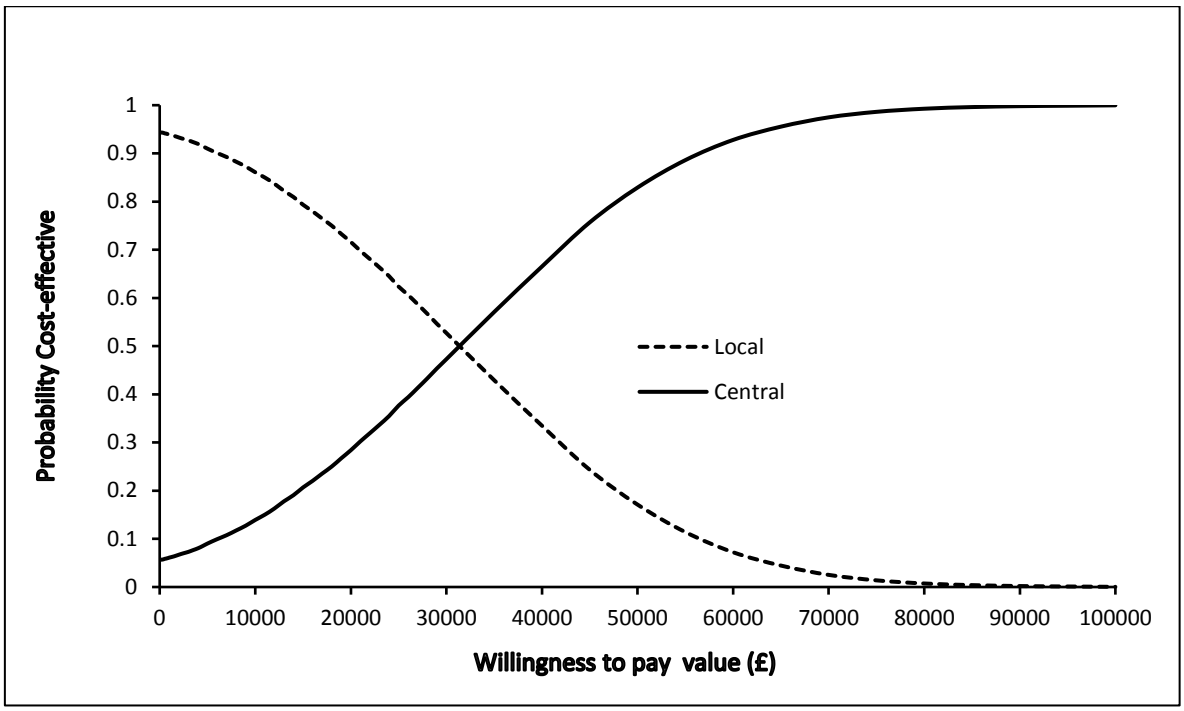

Figure 6.5: Cost-effectiveness acceptability curve for central hospital vs local hospital at 30 days (base-case analysis)

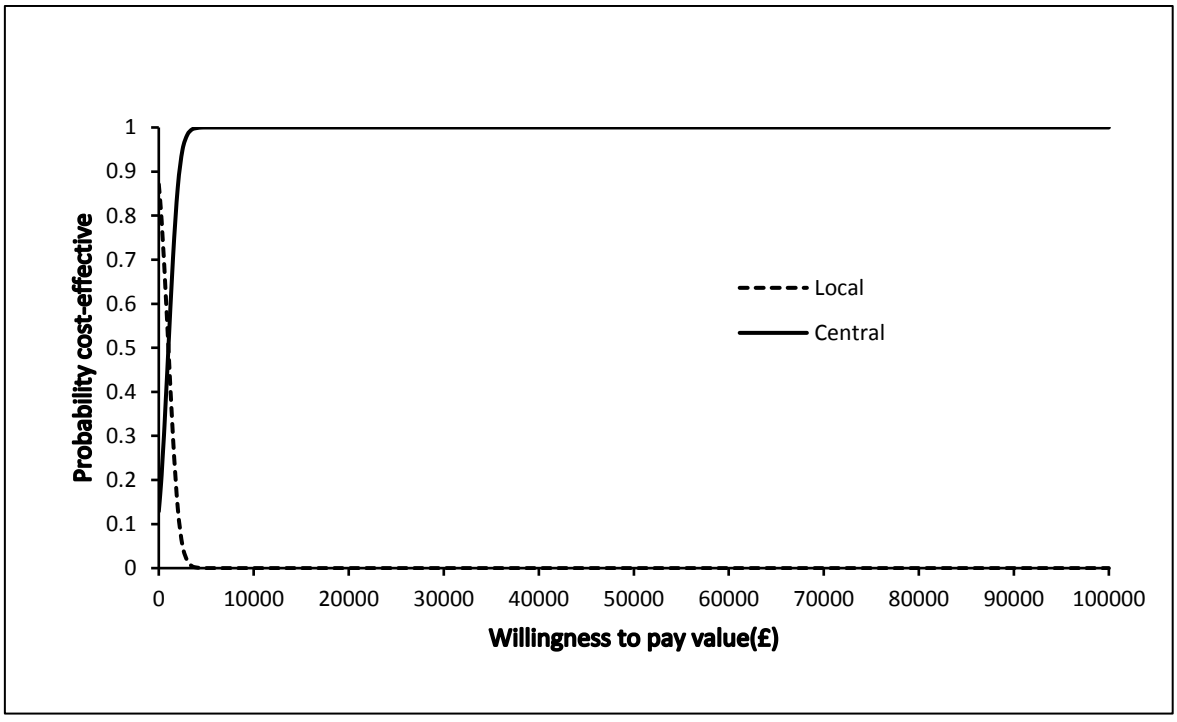

Figure 6.6: Cost-effectiveness acceptability curve for central hospital vs local hospital at one year (base-case analysis)

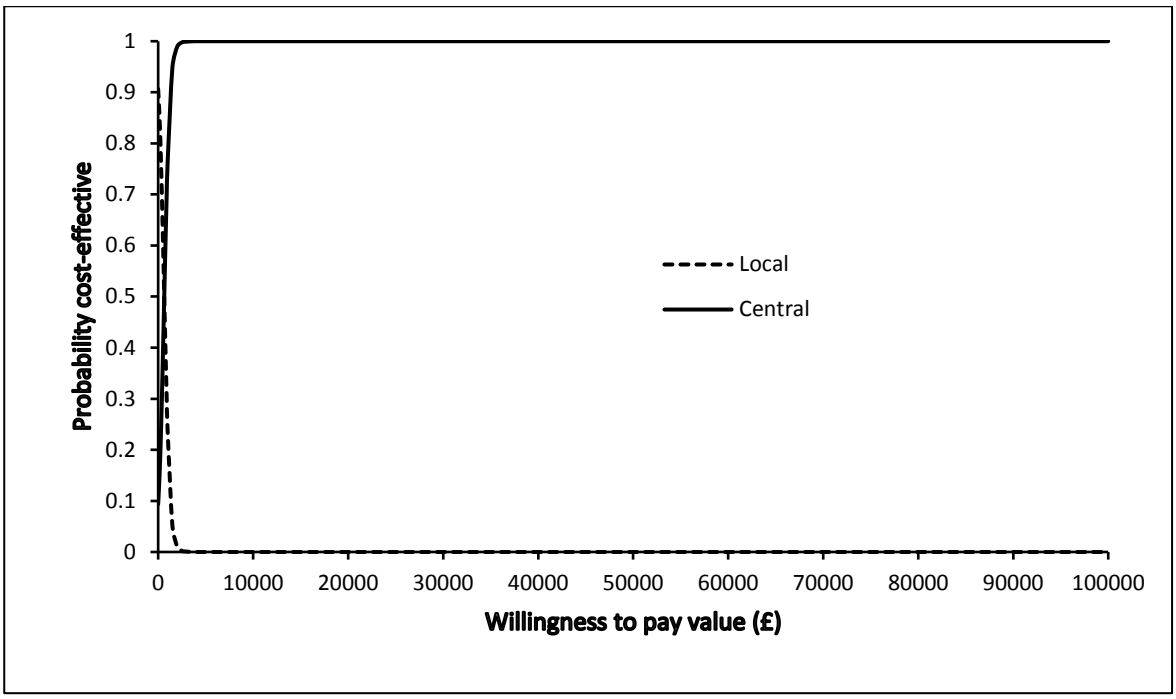

Figure 6.7: Cost-effectiveness acceptability curve for central hospital vs local hospital at 10 years (base-case analysis)

6.4.2 Univariate (one-way) sensitivity analysis

The results of the one-way sensitivity analysis are presented in Table 6.6. Not considering the cost of consultant in the central hospital in the cost-effectiveness analysis, would make it dominant (i.e. cheaper and more effective than the local hospital) at 30 days, one year and 10 years' time horizon. The probabilistic and deterministic estimates of incremental costs, incremental QALYs and mortality averted at were generally similar at each of the time points studied.

At 10 years, discounting the costs and QALYs at 1.5% resulted in the deterministic estimate of ICER of £630 per QALY gained and £67,131 per death averted. When costs and QALYs were discounted at 5% the deterministic ICER was £641 per QALY gained and £60,090 per death averted. The probabilistic and deterministic estimates only differed by a small amount. The use of alternative discount rates also changed the cost-effectiveness results by a small amount. In the sensitivity analysis, the cost-effectiveness results remained the same at 30 days and one year because discounting was applied only after one year time horizon.

Table 6.6: Results of one-way sensitivity analysis: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
30 days					
Not considering the cost of a consultant in the central hospital *(deterministic)*	-24,232	-26.55	1.57	Dominant	Dominant
Not considering the cost of a consultant in the central hospital *(probabilistic)*	-26,198	-26.56	1.57	Dominant	Dominant
1 Year					
Not considering the cost of a consultant in the central hospital *(deterministic)*	-131,865	-31.47	310	Dominant	Dominant
Not considering the cost of a consultant in the central hospital *(probabilistic)*	-133,298	-31.50	310	Dominant	Dominant
10 years					
Not considering the cost of a consultant in the central hospital *(deterministic)*	-323,886	-31.57	3,123	Dominant	Dominant

Table Continued

Table 6.6 continued: Results of one-way sensitivity analysis: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
Not considering the cost of a consultant in the central hospital *(probabilistic)*	-324,483	-31.78	3,132	Dominant	Dominant
Costs & QALYs discounted at 1.5% (deterministic)	2,119,335	-31.57	3,365	67,131	630
Costs & QALYs discounted at 1.5% (probabilistic)	1,871,119	-31.54	2,955	59,325	633
Costs & QALYs discounted at 5% (deterministic)	1,897,026	-31.57	2,960	60,090	641
Costs & QALYs discounted at 5% (probabilistic)	1,886,049	-31.70	2,964	59,497	636

Note: Incremental cost, Difference in total death and Incremental QALYs expressed as per 1000 people; QALY: Quality adjusted life year

6.4.3 Modelling heterogeneity

The probabilistic and deterministic incremental cost per death averted and incremental cost per QALY gained for various sub-groups analysed at 30 days, one year and 10 years are presented in Tables 6.7, 6.8 and 6.9 respectively. Only the deterministic cost-effectiveness estimates are presented for the sub-group of age 29 or less because for this group there was hardly any uncertainty in the transition probabilities (standard error was almost equivalent to zero) which did not allow for the computation of distributions needed for probabilistic analysis.

Table 6.7 presents the cost-effectiveness results in the sub-groups at 30 days. In those aged 65 or over, the probabilistic cost-effectiveness analysis showed that the central hospital is dominant (less costly and more effective in terms of deaths averted and QALY gained) over the local hospital. But the deterministic estimates showed that incremental cost per death averted and incremental cost per QALY gained for age group 65 and over was £792 and £14,443 respectively. However, both the deterministic and probabilistic results in the age-group of 30-64 indicate that the central hospital was more costly and had more deaths and therefore was dominated by the local hospital which was cheaper and had fewer deaths. Furthermore, the incremental cost per QALY in the age group 30-64 was well above the £20,000-£30,000 threshold set by NICE.

Among the sub-groups assessed, age group 29 or less had the lowest deterministic estimates of incremental cost per death averted (£559) and incremental cost per QALY gained (£13,468). Both the deterministic and probabilistic estimates in the group with diseases of the circulatory system showed that the central hospital was the dominant alternative. The deterministic and probabilistic estimates of incremental cost per QALY gained for sub-groups IMD 5th quintile, CCI0 and CCI4 were below the £30,000 threshold. Both the deterministic and probabilistic estimates in terms of incremental cost per death averted for all sub-groups analysed were lower than the £30,000. The cost-effectiveness estimates in the males and females were somewhat similar but males had a higher ICER. These results suggest that the cost-effectiveness of central hospital at 30 days could be possibly higher in those aged 65 and over, those who are most deprived, those with diseases of the circulatory diseases and those presenting with a greater number of co-morbidities.

At one year, the cost-effectiveness in the sub-groups improved in general (Table 6.8). The central hospital was no longer a dominant alternative in the age group 65 and over. However, both the deterministic and probabilistic estimates of the incremental cost per death averted and incremental cost per QALY gained were low. With the deterministic estimates of incremental cost of £443 per QALY gained and £4,167 per death averted, the age group 29 or less had the lowest incremental cost-effectiveness ratio (ICER). In the age group 30-34, central hospital was still

dominated by the local hospital (more expensive and less beneficial compared to the local hospital) in terms of incremental cost per death averted. Nevertheless, the incremental cost per QALY gained was £15,963 (deterministic estimate) and £15,589 (probabilistic estimate) were much lower than £226,250 (deterministic estimate) and £155,935 (probabilistic estimate) observed at 30 days. Both the deterministic and probabilistic estimates in the group with diseases of the circulatory system continued to show that the central hospital was the dominant alternative. The incremental costs per QALY gained (both for the deterministic and probabilistic analyses) for sub-groups of IMD 5th quintile, CCI0, CCI4 and age 65 years and over were much lower than the £20,000- £30,000 threshold.

Table 6.7: Results of sub-group analysis at 30 days: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
Male (*deterministic*)	41,987	-15.83	1.23	2,652	34,136
Male (*probabilistic*)	42,330	-15.84	1.23	2,672	34,415
Female (*deterministic*)	54,248	-23.75	1.52	2,284	35,689
Female (*probabilistic*)	54,652	-23.75	1.52	2,301	35,955
Age <=29 (*deterministic*)	25,724	-46.05	1.91	559	13,468
Age 30-64 (*deterministic*)	70,137	0.47	0.31	Dominated	226,250
Age 30-64 (*probabilistic*)	70,171	0.32	0.45	Dominated	155,935
Age 65+ (*deterministic*)	32,496	-41.02	2.25	792	14,443
Age 65+ (*probabilistic*)	-9,923	-41	2.25	Dominant	Dominant
IMD 1 (*deterministic*)	54,024	-14.38	1.19	3,757	45,398
IMD 1 (*probabilistic*)	54,185	-14.48	1.2	3,742	45,154
IMD 5 *(deterministic*)	63,661	-72.68	2.99	876	21,291
IMD 5 (*probabilistic*)	63,742	-72.66	2.99	877	21,318
CCI 0 (*deterministic*)	35,204	-22.17	1.25	1,588	28,164
CCI 0 (*probabilistic*)	35,526	-22.15	1.25	1,604	28,421

Table Continued

Table 6.7 continued: Results of sub-group analysis at 30 days: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
CCI4 (*deterministic*)	61,659	-54.47	3.62	1,132	17,033
CCI4 (*probabilistic*)	61,425	-54.49	3.62	1,127	16,968
Circulatory (*deterministic*)	-17,311	-32.28	2.24	Dominant	Dominant
Circulatory (*probabilistic*)	-17,292	-32.31	2.24	Dominant	Dominant
Respiratory (*deterministic*)	89,681	-51.26	2.70	1,750	33,215
Respiratory (*probabilistic*)	89,718	-51.27	2.71	1,750	33,106
Digestive (*deterministic*)	157,217	-42.41	1.62	3,707	97,047
Digestive (*probabilistic*)	157,244	-42.43	1.62	3,706	97,064
Abnormal (*deterministic*)	33,110	-5.19	0.78	6,380	42,449
Abnormal (*probabilistic*)	32,481	-5.26	0.78	6,175	41,642
Injury (*deterministic*)	104,746	-3.59	0.47	29,177	222,863
Injury (*probabilistic*)	104,976	-3.56	0.47	29,488	223,352

Note: Incremental cost, Difference total death and Incremental QALYs expressed as per 1000 people; QALY: Quality adjusted life year; IMD1: Index of mean deprivation 1st quintile; IMD5: Index of mean deprivation 5th quintile; CCI0: Charlson's co-morbidity index=0; CCI4: Charlson's co-morbidity index>=4; Circulatory: diseases of the circulatory system; Respiratory: diseases of respiratory system; Digestive: diseases of the digestive system; Abnormal: abnormal clinical laboratory findings; Injury: injury poisoning and certain consequences

At one year, the incremental costs per death averted were higher and the incremental QALYs were lower compared to those at 30 days. Age group 29 or less continued to have lowest deterministic ICER (excluding the scenarios where intervention was dominant) among the sub-groups. The ICER for males and females were generally similar but males still had higher incremental cost per death averted. However, the incremental cost per QALY gained were lower in males compared with females. The ICER in the sub-group IMD5 was lower compared to that of sub-group

IMD1 and it was higher in the sub-group CCI4 compared to the CCI0. This suggests that the central hospital is more cost-effective in the more deprived populations compared to the less deprived. Nevertheless, the central hospital appears to be less cost-effective for those with higher number of Charlson's co-morbidities compared to those with zero Charlson's co-morbidities. Among the disease groups, the central hospital was most cost-effective (where central hospital was dominant) in the sub-group of "diseases of circulatory system" and the least cost-effective in the "injury poisoning and certain consequences".

The cost-effectiveness results of sub-group analysis at 10 years are presented in Table 6.9. The analysis showed that central hospital was dominated (more costly and less effective) by the local hospital in the sub-groups of age 30-64 years and for those belonging to the group "injury, poisoning and certain consequences". The central hospital was not dominant in any of the sub-groups. Nevertheless, the incremental costs per QALY gained in all the sub-groups were much lower than the £20,000 per QALY. Similar to the one year results, the ICER of males and females at 10 years were generally similar but males still had higher incremental cost per death averted and a lower incremental cost per QALY gained compared to females. Those aged 29 year or less had the nearly half of the incremental costs per QALY gained (deterministic estimate) of that age group 65 years or over. The ICER in the sub-group IMD5 was lower compared with that of sub-group IMD1 and it was higher in the sub-group CCI4 compared with the CCI0. At 10 years, the central hospital was no longer dominant over the local hospital in the sub-group of "diseases of circulatory system". Among the disease groups, the incremental cost per QALY gained was lowest in the sub-group of "diseases of circulatory system" and was dominated by the local hospital in the "injury poisoning and certain consequences". The incremental costs per death averted were very high at 10 years compared to those at one year, while the incremental costs per QALY gained were lower. It appears that the difference in deaths between the two models remained generally similar over time but the difference in costs and QALYs increased.

Table 6.8: Results of sub-group analysis at one year: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
Male (*deterministic*)	229,932	-17.57	207.06	13,087	1,110
Male (*probabilistic*)	233,319	-17.57	206.94	13,279	1,127
Female (*deterministic*)	348,692	-27.27	278.04	12,787	1,254
Female (*probabilistic*)	349,298	-27.27	277.94	12,809	1,257
Age <=29 (*deterministic*)	289,710	-69.53	654.13	4,167	443
Age 30-64 (*deterministic*)	318,309	2.02	19.94	Dominated	15,963
Age 30-64 (*probabilistic*)	317,089	1.98	20.34	Dominated	15,589
Age 65+ (*deterministic*)	240,364	-44.94	411.79	5,349	584
Age 65+ (*probabilistic*)	196,270	-45	411.85	4,362	477
IMD 1 (*deterministic*)	238,052	-14.60	180.29	16,305	1,320
IMD 1 (*probabilistic*)	242,658	-14.78	181.36	16,418	1,338
IMD 5 *(deterministic*)	511,751	-90.37	743.87	5,663	688
IMD 5 (*probabilistic*)	512,342	-90.42	744.01	5,666	689
CCI 0 (*deterministic*)	141,619	-29.72	306.28	4,765	462
CCI 0 (*probabilistic*)	141,877	-29.68	306	4,780	464
CCI4 (*deterministic*)	442,620	-43.55	423.88	10,163	1,044
CCI4 (*probabilistic*)	442,176	-43.63	424.28	10,135	1,042
Circulatory (*deterministic*)	-66,503	-36.07	405.57	Dominant	Dominant
Circulatory (*probabilistic*)	-67,202	-36.08	405.66	Dominant	Dominant
Respiratory (*deterministic*)	649,545	-52.92	461.32	12,274	1,408
Respiratory (*probabilistic*)	646,389	-52.92	461.59	12,214	1,400
Digestive (*deterministic*)	856,819	-53.11	396.97	16,133	2,158

Table Continued

Table 6.8 continued: Results of sub-group analysis at one year: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
Digestive (*probabilistic*)	856,681	-53.24	397.47	16,091	2,155
Abnormal (*deterministic*)	84,040	-5.46	127.34	15,392	660
Abnormal (*probabilistic*)	79,001	-5.48	128.17	14,416	616
Injury (*deterministic*)	614,474	-1.22	24.05	503,667	25,550
Injury (*probabilistic*)	614,514	-1.18	23.98	520,775	25,626

Note: Incremental cost, Difference total death and Incremental QALYs expressed as per 1000 people; QALY: Quality adjusted life year; IMD1: Index of mean deprivation 1st quintile; IMD5: Index of mean deprivation 5th quintile; CCI0: Charlson's co-morbidity index=0; CCI4: Charlson's co-morbidity index>=4; Circulatory: diseases of the circulatory system; Respiratory: diseases of respiratory system; Digestive: diseases of the digestive system; Abnormal: abnormal clinical laboratory findings; Injury: injury poisoning and certain consequences

Table 6.9: Results of sub-group analysis at 10 years: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
Male (*deterministic*)	1,231,406	-13.25	1,711.42	92,936	720
Male (*probabilistic*)	1,250,691	-13.46	1,718.33	92,919	728
Female (*deterministic*)	2,211,414	-29.39	2,781.31	75,244	795
Female (*probabilistic*)	2,216,837	-29.71	2,791.12	74,616	794
Age <=29 (*deterministic*)	3,758,917	-270.41	14,855.4	13,901	253
Age 30-64 (*deterministic*)	1,977,480	11.37	-287.97	Dominated	Dominated
Age 30-64 (*probabilistic*)	1,971,794	10.83	-268.45	Dominated	Dominated
Age 65+ (*deterministic*)	1,497,510	-20.23	2,992.05	74,024	500
Age 65+ (*probabilistic*)	1,400,130	-20.45	3,004.53	68,466	466
IMD 1 (*deterministic*)	1,243,788	-10.28	1,384.90	120,991	898
IMD 1 (*probabilistic*)	1,283,603	-11.53	1,437.58	111,327	893
IMD 5 *(deterministic*)	4,024,245	-86.83	8,188.11	46,346	491
IMD 5 (*probabilistic*)	4,036,196	-87.61	8,219.30	46,070	491
CCI 0 (*deterministic*)	1,387,852	-73.38	4,765.78	18,913	291
CCI 0 (*probabilistic*)	1,388,099	-73.48	4,764.13	18,891	291
CCI4 (*deterministic*)	1,215,305	-1.07	1,382.26	1,135,799	879
CCI4 (*probabilistic*)	1,220,507	-1.17	1,392.05	1,043,168	877
Circulatory (*deterministic*)	105,515.6	-25.52	3,305.43	4,135	32
Circulatory (*probabilistic*)	114,169.5	-26.58	3,343.64	4,295	34
Respiratory (*deterministic*)	2,891,465	-14.49	2,905.70	199,549	995
Respiratory (*probabilistic*)	2,888,883	-14.89	2,926	194,015	987
Digestive (*deterministic*)	6,225,723	-80.03	5,552.69	77,792	1,121

Table Continued

Table 6.9 continued: Results of sub-group analysis at 10 years: central hospital minus local hospital

Scenarios	Incremental cost (£)	Difference total death	Incremental QALYs	Incremental cost (£) /Death averted	Incremental cost (£) /QALY gained
Digestive (*probabilistic*)	6,249,368	-81.58	5,607.98	76,604	1,114
Abnormal (*deterministic*)	435,681	-6.69	1,124.75	65,124	387
Abnormal (*probabilistic*)	403,306	-7.68	1,153.17	52,514	350
Injury (*deterministic*)	3,670,059	10.09	-345.95	Dominated	Dominated
Injury (*probabilistic*)	3,679,515	8.99	-315.78	Dominated	Dominated

Note: Incremental cost, Difference total death and Incremental QALYs expressed as per 1000 people; QALY: Quality adjusted life year; IMD1: Index of mean deprivation 1st quintile; IMD5: Index of mean deprivation 5th quintile; CCI0: Charlson's co-morbidity index=0; CCI4: Charlson's co-morbidity index>=4; Circulatory: diseases of the circulatory system; Respiratory: diseases of respiratory system; Digestive: diseases of the digestive system; Abnormal: abnormal clinical laboratory findings; Injury: injury poisoning and certain consequences

For each of the sub-groups of patients, the uncertainty in the results at 30 days, one year and 10 years were also represented by a different CEAC. But only selected multiple CEACs are presented here in this Chapter and the rest are shown in Appendix C of this thesis. CEACs in the sub-groups allow the assessment of variation in cost-effectiveness results. The results in the sub-groups show that there is a variation in the probability of cost-effectiveness of central hospital among the sub-groups analysed. The CEACs for males and females were very close to each other in all the time points studied, however the probability that the central hospital would be cost-effective at £20,000 WTP value at 30 days was only 28% for male and 22% for female (Appendix C, Figure C1), which increased to 100% for both male and females at one year and 10 years time (Appendix C, Figure C2 and C3). The CEAC for the age groups at 30 days show that at £20,000 WTP value there is about 94% probability that the central hospital is cost-effective in the age group of 65 or over and nearly 0% probability for the age group 30-64 (Appendix C, Figure C4). Furthermore, the cost-effectiveness probabilities were higher in the age group 65 compared to the age group 30-64 at 1 year and 10 years (Appendix C, Figure C5 & 6.8). The results show a higher probability of cost-effectiveness of central hospital model in CCI4

compared to CCI0 at 30 days (Appendix C, Figure C6). However, at one year and 10 years, the probabilities of cost-effectiveness in CCI0 and CCI4 were very close to each other (Appendix C, Figure C7 and C8). The probabiliy that central hospital is cost-effective is also higher in the most deprived quintile (IMD5) compared to the least deprived qunitile (IMD1) (Figure C9 & C10 and Figure 6.9). However, at one year the probability that the central hospital is cost-effective in the IMD1 and IMD5 were closer to each other (Appendix C, Figure C10). The probability in this two groups again differed at 10 years with IMD5 having higher probability of cost-effectiveness compared to IMD1 (Figure 6.9). At 30 days, among the disease groups, the highest probability of cost-effectiveness for the central hospital was observed in the sub-group of diseases of the circulatory system and the lowest probability was observed in the sub-group of injury (Appendix C, Figure C11). However, at one year, the CEACs in all the disease groups except the injury group were very close to each other (Appendix C, Figure C12). Similarly, at 10 years, the CEACs in all the disease groups were close to each other but this time abnormal and injury group had much lower probabilities of cost-effectiveness of central hospital (Figure 6.10). The CEACs reflect the differences in the uncertainty in cost-effectiveness of the central hospital in the sub-groups of patients. Therefore, considering these differences in the probability of cost-effectiveness of central hospital, different decisions could be made across different categories of patients.

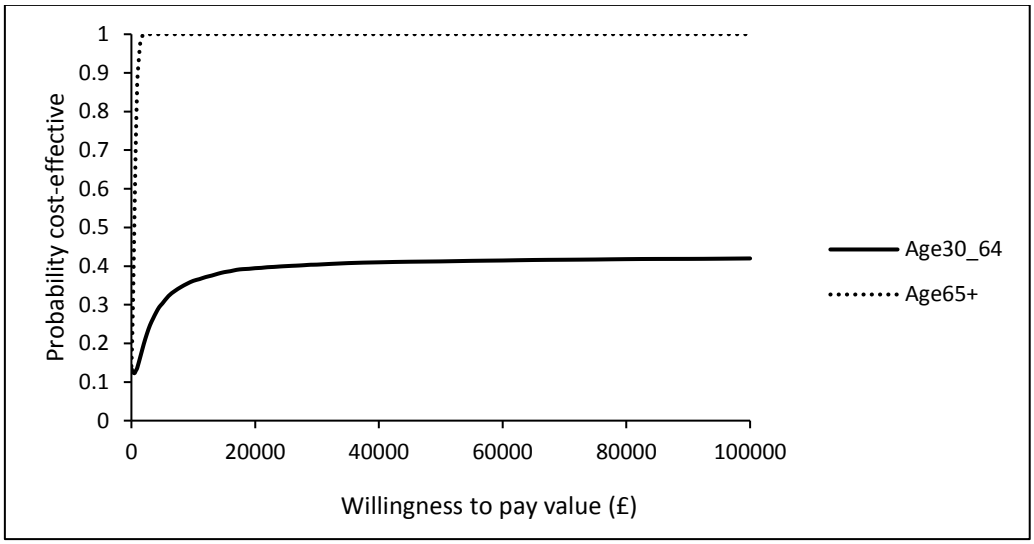

Figure 6.8: Multiple CEAC for sub-groups of age 30-64 and age 65 or over at 10 years

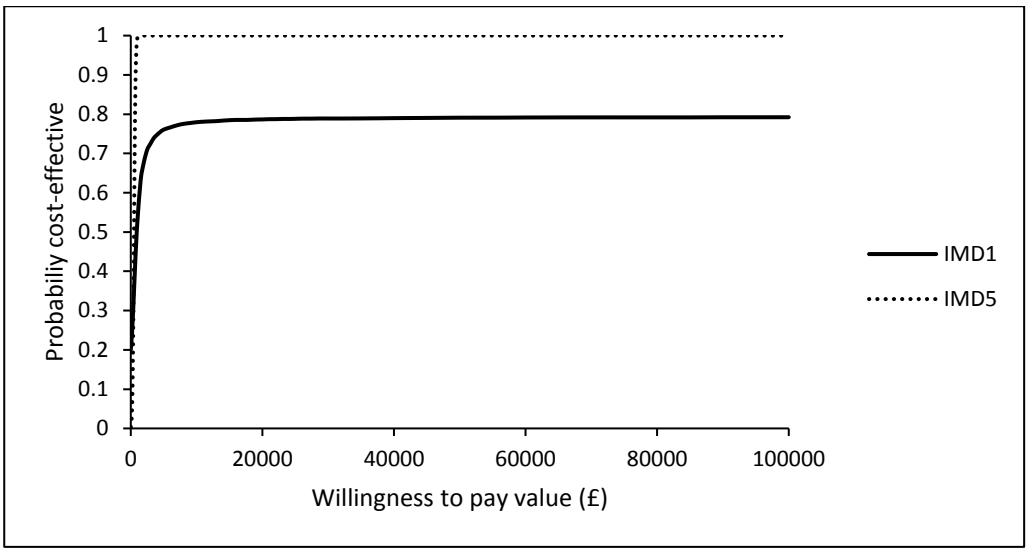

Figure 6.9: Multiple CEAC for sub-groups of IMD1 and IMD5 at 10 years

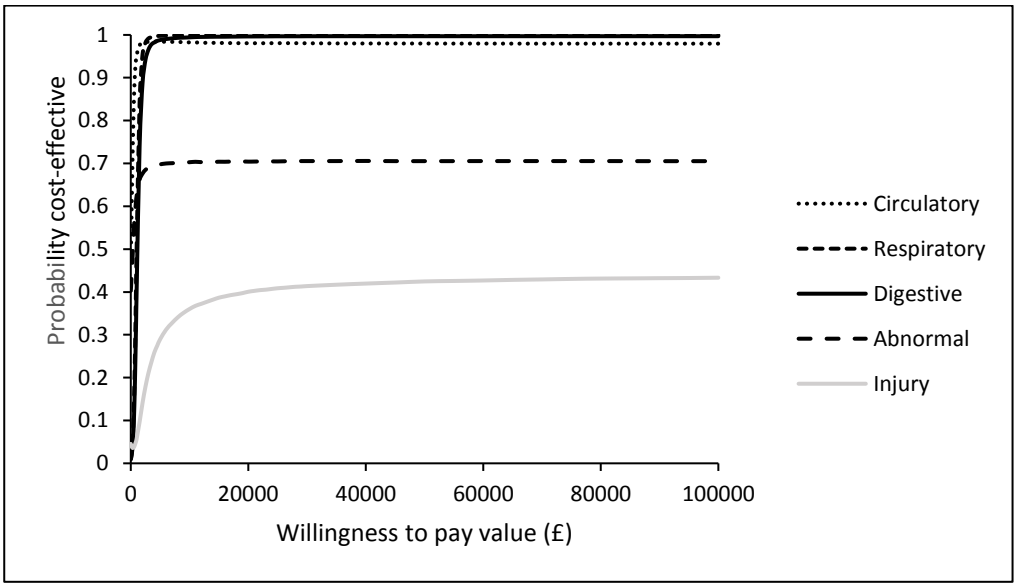

Figure 6.10: Multiple CEAC for sub-groups of disease at 10 years

6.4.4 Value of information

Value of information (VOI) was used to evaluate whether further research was necessary to support the decision-making. A description of VOI analysis can be found in section 5.4.6 in Chapter 5.

The EVPI was calculated using the probabilities of cost-effectiveness for each central hospital over a range of willingness to pay values generated in the CEAC estimation

ranging from 0 to £100,000. The estimates of EVPI were generated from the base-case model. The results showed that at 10 years the EVPI per decision to treat a person in a central hospital at a willingness to pay threshold of £20,000 per QALY gained is £0. However, this result is not surprising as it is in line with the CEAC in Figure 6.7 which demonstrates the decision uncertainty at 10 years. At £20,000 WTP per QALY gained, the probability that a central hospital was cost-effective was 100%. Therefore, it is reasonable to get the EVPI value of 0 when there is 0% probability that the central hospital will not be cost-effective at 10 years at £20,000 per QALY gained. In this case, it suggests that existing information can be regarded as sufficient to support the decision to adopt the central hospital. Given this finding, estimation of population EVPI, EVPPI or EVSI was not relevant.

6.4.5 Cost benefit analysis

The marginal willingness to travel estimates from the DCE in Chapter 4 were used as the proxy for marginal willingness to pay estimates to carry out the cost-benefit analysis. As of figures released on 17 April 2018, the average weekly hours worked in the UK is 37.2 and the average weekly earnings is £513 (Office for National Statistics, 2018a). Therefore, the earnings per working minute is calculated as £0.23 (i.e. £13.79 per hour). In Chapter 4, Table 4.9 shows that the respondents were willing to travel 37.88 minutes (model 1A) for 1 in 100 person reduction in mortality. Thus, this translates to the WTP value of £8.71 (i.e. 37.88*£0.23) for 1 in 100 reduction in mortality and £0.871 for 1 in 1000 reduction in mortality. Therefore, if 26.55 deaths per 1000 persons visiting the emergency hospitals are averted in a month, the WTP value would be £23.13 (i.e. 26.55*£0.871) per month. If 31.47 deaths per 1000 persons visiting the emergency hospitals are averted in 1 year, the WTP value would be £27.41 (i.e.31.47*£0.871). Similarly, the WTP value would be £27.52 (i.e. 31.57*£0.871) at 10 years. The estimates of the WTP values drawn using the probabilistic and deterministic estimates of costs and mortality differences at 30 days, one year and 10 years' time reported in Table 6.5 were used in the cost-benefit analysis of the hospital models assessed. The method of calculation of net monetary benefit has been described in Section 5.5 of Chapter 5. For example, at a WTP value of £0.871 for 1 in 1000 reduction in mortality, the net monetary benefit (NMB) at 30 days (deterministic estimates) would be - £51,362 (i.e. ((£0.871*26.55)-£51,385). Table 6.10 shows the incremental NMB for a cohort of 1000 people.

Table 6.10: Cost-benefit analysis of the base-case scenario

Scenarios	Incremental Cost (£)	Mortality Averted	Incremental Benefit (£)	Net Monetary Benefit (NMB) (£)
30 days				
Deterministic	51385	26.55	23.13	-51,362
Probabilistic	49201	26.55	23.13	-49,178
One Year				
Deterministic	310946	31.47	27.41	-310,919
Probabilistic	312999	31.43	27.36	-312,971
10 Years				
Deterministic	1986329	31.57	27.50	-1,986,301
Probabilistic	2003944	31.60	27.52	-2,003,917

Note: figures expressed are per 1000 people.

The incremental benefits generated for every scenario were far less than the incremental costs of central hospital model vs local hospital model. Hence, the NMB at all the time horizons were negative. This suggests that compared with the local hospital model the central hospital model would not be regarded as being worthwhile. The main driver for these results appeared to be the very low valuation placed on mortality averted in the central hospital model.

6.5 Discussion

6.5.1 Summary of results

The study described in this Chapter demonstrated that emergency medical services in a central hospital can be a cost-effective alternative to those at multiple local hospitals. Although, both the deterministic and probabilistic results of the economic analysis at 30 days showed that the incremental cost per QALY was slightly above the upper bound of £30,000 threshold for willingness to pay value, the cost-effectiveness of the central hospital greatly improved over one year and 10-year time horizon. The incremental cost per QALY gained over one year and 10-year time horizon was much lower than the £20,000 lower bound threshold for willingness to pay. Furthermore, the cost-effectiveness probability of 100% at £20,000 WTP

threshold indicated that there would be a zero chance that choosing the central hospital over the local hospital would be a wrong decision. The EVPI value of zero further suggested that existing information can be regarded as sufficient to support the decision to adopt the central hospital. Therefore, the results indicate that the incremental QALY resulting from the central hospital appear to be worth the incremental costs over one year and 10-year time horizons. In addition, the results also suggested that higher number of deaths were avoided in the central hospital compared to the local hospital.

The sensitivity analysis carried out to assess the robustness of the results indicated that the base case results were largely robust when higher and lower discount rates were applied to costs and QALYs. However, the results were quite sensitive to the assumption of no additional costs of consultant in the central hospital. Under this assumption of no additional cost, the central hospital was observed to be less costly and more effective than the local hospital in the base-case analysis.

The sub-group analysis showed that central hospital is even more cost-effective for a cohort of patients aged 65 or over, for those with CCI4 or more, most deprived, and in those presenting with primary diagnosis of diseases of the circulatory system. In addition, central hospital is also very cost-effective in the cohort of patients with primary diagnosis of diseases of the respiratory system and in those with primary diagnosis of diseases of the digestive system. However, central hospital could be more expensive and less effective for the cohort of patients aged 30-64 years and in those patient cohort with the injury, poisoning and certain consequences. These results suggest that the central hospital can be more cost-effective if delivered to a population more likely to present with more severe health issues.

The results of the cost-benefit analysis suggested a negative monetary benefit which indicates that central hospital would not be worthwhile compared to the local hospital. These negative monetary benefits could be possibly related to the lower willingness to pay values placed by individuals (i.e. potential users) on the central hospital. This lower values for central hospital could possibly be justified by the value and emotional attachment or sense of belonging individuals have for their local hospital in

general. However, the mismatch between the scope of evaluation between the DCE and economic evaluation model could be an important issue in the results of the cost-benefit analysis. In particular, the mismatch can be highlighted in terms of the time horizon used to assess costs and benefits and the elements considered for the assessment of benefits.

The DCE in Chapter 4 did not consider the cost attribute needed to generate the WTP estimate, instead the attribute “travel time to hospital” was monetised though the alternative specific constant (ASC) was not. A time horizon for the travel time would not be appropriate and was not specified. In contrast, the economic evaluation presented in this Chapter was conducted for time horizons of 30 days, one year and 10 years. Therefore, it is possible that the willingness to pay value used in the cost-benefit analysis were influenced by the differences in the way DCE and economic evaluation model were framed.

Another concern is the differences in the DCE attributes/levels and outcomes considered in the economic evaluation; which raises the question whether the same good were valued by both the frameworks. The DCE considered travel time, waiting time, risk of re-admission, risk of mortality, length of stay and follow-up in the local hospital. However, all of the attributes considered in the DCE could not be reflected in the economic evaluation because of the unavailability of data and the complexity in modelling. For example, the economic evaluation did not consider the follow-up at local hospital and waiting times which would have influenced the costs and in the other hand the DCE did not consider cost as one of the attributes which could have influenced the willingness to pay value. Nevertheless, the incorporation of the DCE results into the economic evaluation provided some indication of patients’ willingness to pay and potential cost-benefits of centralisation of emergency medical services.

The review by Sir Bruce Keogh recommends reconfiguration of emergency care and the development of centralised and more specialised emergency units that benefits patients with more serious and life threatening condition by providing best expertise and potentially better quality of care (NHS England, 2013a). In addition, consolidation of specialised medical care is one of the new care models envisaged by the NHS

"Five year forward view" (NHS England, 2014). Therefore, in general, the findings of the economic evaluation described in this study provides some support for the reorganisation of healthcare services taking place in the NHS England.

6.5.2 Comparison with earlier studies

The findings of the economic evaluation described in this Chapter are consistent with the findings of earlier studies assessing the impact of centralisation of emergency medical services. The Health Foundation briefing on the impact of redesigning urgent and emergency care in Northumberland, UK which was based on similar data and context of this Chapter suggested that centralisation of urgent and emergency care resulted in increased service utilisation, shorter A&E visits, and increased discharge or transfer from the A&E within four hours- all of these outcomes could be related to efficient and better quality of care provided at the central hospital (O'Neill *et al.*, 2017). Improved efficiency and better quality of care observed by O'Neill et al (2017) are reflected in the estimates of cost-effectiveness results discussed in this Chapter.

Another study on centralisation of the A&E services in Sheffield, UK showed improvement in both quantity and quality overall, though the waiting time to see a clinician further worsened after centralisation (Simpson *et al.*, 2001). The economic evaluation model in this Chapter did not consider the waiting time to be seen by the consultant, however The Health Foundation briefing (O'Neill *et al.*, 2017) was conducted in the same setting observed shorter A&E visits which indicated shorter waiting times.

The results of the study described in this Chapter also reflect the findings from studies assessing centralisation of specialised health care services. Hunter and colleagues who examined the clinical and cost outcomes of centralised approach to acute stroke care in London suggested that centralised stroke care could be less costly and more effective in terms of QALY gained and mortality averted (Hunter *et al.*, 2013). Another study which used a decision analytic model to assess the difference-in differences in costs and outcomes before and after the implementation of two models of reconfiguration of stroke care in London and Greater Manchester in

England showed that centralised stroke services may result in a net monetary benefit at a threshold of £20,000-£30,000 for a QALY gained (Hunter *et al.*, 2018). Stroke could not be used as one of the sub-groups analysed in this thesis because of limited stroke specific data. However, the central hospital in the sub-group of diseases of circulatory system, a broad category which also includes stroke, was found less costly and more effective compared to the local hospital over 30 days and one year of time and showed very minimum incremental costs at 10 years.

A study which conducted the economic evaluation of trauma care in a tertiary trauma hospital in Canada showed that the specialised trauma centre would be a cost-effective alternative to other treatment programs (Seguin *et al.*, 1999). Another study in the US showed that transferring patients with subarachnoid haemorrhage (an uncommon type of stroke) from a low to high volume hospitals would be cost-effective suggesting the regionalization of care may be justified (Bardach *et al.*, 2004). Furthermore, the results of a study comparing the effectiveness of ST-segment-elevation myocardial infarction regionalization strategies in the United States indicated that transporting every patient to a central hospital with a facility for primary coronary central hospital would be cheaper and more effective compared to all hospital expansion options with the treatment facility (Concannon *et al.*, 2010). This may indicate that having a specialised treatment facility would be better in terms of costs and effects than having less specialised facilities in several locations. Other studies assessing the centralisation of cancer care in the US and the Netherlands also suggested that specialised treatment centres would be cost-effective alternatives to the treatment in general hospitals (Bristow *et al.*, 2007; Greving *et al.*, 2009).

A number of other studies included in the systematic review in Chapter 2, though most of them limited in terms of the methodology, have justified the centralisation of specialised healthcare in terms of costs and effects, but will not be discussed here.

The incorporation of willingness to pay values derived from a DCE into the economic evaluation in the form of CBA is relatively novel. Only a few examples attempting to incorporate a DCE into economic evaluation were identified. Two studies (Petrou and

McIntosh, 2009; van der Pol *et al.*, 2010) conducted a CBA using the DCE data but did not have comparable QALY data. Three studies (Vale, 2005; Burr *et al.*, 2012; Tinelli *et al.*, 2016) compared the net monetary benefits using DCE with the QALY data. Vale (2005) attempted to incorporate the WTP estimates from an existing DCE into an economic evaluation of alternative methods of surgical repair of inguinal hernia, and reported differences in the conclusions drawn from the DCE derived CBA compared with those derived from QALY data (Vale, 2005). It was argued that one reason for these differences was a mismatch between the DCE design and the economic evaluation model. The DCE used was not initially designed to be used in the economic evaluation model. Therefore there were restrictions in incorporating the WTP estimates in the economic model.

Burr and colleagues attempted to use the WTP values from a DCE explicitly designed to facilitate its incorporation into the economic model involving a discrete event simulation evaluating surveillance for ocular hypertension (Burr *et al.*, 2012). This study attempted to learn from the earlier Vale (2005) study and attempted to design the DCE and model iteratively. However, respondents in the Burr *et al.* (2012) study placed very little valuation on prevention of the progression of open angle glaucoma. Consequently this led to negative net benefits of the intervention (surveillance) compared with a hypothetical reference pathway (no surveillance), which was in sharp contrast to the cost-utility results observed for the intervention. Among the five alternatives compared only the “surveillance for ocular hypertension hospital” pathway relative to “no surveillance” had a positive net benefit.

Another study (Tinelli *et al.*, 2016) assessed the value of pharmacy services (intervention) and reported no statistically significant differences in the costs and QALY estimates in both the intervention and control; however the net monetary benefit from the intervention when derived from the DCE data was positive. This indicated the value of the intervention to the respondents (which supports the introduction of intervention). However, this study was underpowered (The Community Pharmacy Medicines Management Project Evaluation, 2007) and the conclusion of no statistically significant differences in the costs and QALY estimates in the intervention and control should be interpreted with caution.

These differences in the results between studies could be because of issues such as mismatch in the respondent characteristics, differences in time horizon, differences in goods being valued that could be faced while trying to incorporate DCE into economic evaluations (McIntosh, 2006). It could be argued that these are general issues faced when trying to combine a DCE into an economic evaluation model and the differences in the results observed in this thesis are not unusual. However, future research should look into better approaches of combining a DCE into an economic model.

6.5.3 Strengths and limitations

Attempting to assess the cost-effectiveness of centralisation of emergency care in a new specialised hospital in Northumberland, England, the first of its kind in the UK, is in itself the key strength of the study presented in this Chapter. No studies hitherto have explored this topic. The analysis in this study provides the policy-makers the real-world implications of the centralisation of emergency care in terms of costs and outcomes and hence can inform the decision-making around centralisation in the future.

Furthermore, the economic evaluation in this Chapter addressed some of the limitations identified in the systematic review of economic evaluation methods in Chapter 2 and presents the results in a way that is helpful to decision-makers. One finding of the systematic review was most of the economic evaluation studies assessing the centralisation of specialised healthcare services did not report results over different time horizons and for other clinical outcomes alongside QALYs. But, decision-makers may find clinical outcomes easier to understand and thus, prefer them over QALYs in economic evaluation (Eddama and Coast, 2009; Sullivan *et al.*, 2015). Therefore, this study reported mortality alongside QALYs over different time horizons which may make it easier for the decision-makers to understand the benefits of centralisation of emergency care.

However, the results of this study needs to be interpreted with caution in light of some limitations.

First, the results are based on estimates of transitional probabilities derived from observational routinely collected hospital data which might be prone to recording errors (Burns *et al.*, 2012). It is likely that any inaccuracies in the data recording could have influenced the transition probabilities used in the economic evaluation model. However, it was assumed that the likelihood of this errors would be random and be equal in both central and local hospital models.

Second, the retrospective nature of the study also meant that the information that was available on the cost and utility of central and local hospital models was limited. The cost and utility data assumed from the secondary sources may not be the true representation of costs and utility in practice. For example, it was assumed that all patients discharged from hospital would go to the community and no additional costs were incurred once discharged into the community. However, in practice patients may be discharged into one of the several destinations in the community, such as nursing homes, residential care homes and some may attend their local hospital for follow-up. There could be additional costs of care involved when patients are discharged into these specific community destinations. If one of the hospitals results in more disability in the long term then the costs for that option over time will be higher. Furthermore, in the absence of data, the cost of 20 minutes of time for an additional emergency consultant was assumed in the central hospital. However, in practice the consultant time could be subject to severity/complexity of the patient condition, which could mean more or less time than the 20 minutes assumed in this study. Hence, consideration of costs in the community and any differences in consultant time input is likely to influence the results observed in this study. However, sensitivity analysis and several sub-group analysis were conducted to assess the results in different scenarios to assess the results arising out of uncertainties in costs and utility parameters.

Third, the before-and-after approach of the study means that there could be potential confounders and biases that could have influenced the study results. For example, some of the effect observed in the central hospital could be because of the effect of other changes that were taking place in Northumberland or England at the same time or could be because of the differences in patient characteristics. There were

differences in the characteristics of patients in the data records for the both groups (Table 6.2) and there could be other unobserved confounders that could have influenced the results. Hence, the results in this study are based on the conservative assumptions that there were no confounders and biases arising solely out of the design used.

Fourth, the cost-benefit estimates could have been influenced by the mismatch between the DCE and the economic evaluation and a perfect compatibility of these two approaches may have generated different estimates of cost benefits. However, a similar problem has been noted in the literature (Burr *et al.*, 2012) and could be a general problem faced while trying to combine a DCE and the economic evaluation.

Fifth, the data used to derive transition probabilities in the central hospital were those recorded in the first 15 months since the opening of the centralised emergency hospital. The first fifteen months could possibly be too short to assess the impact of such a major service reorganisation where both the patient and healthcare professionals may not have been fully prepared to respond to unexpected circumstances caused by the introduction of a central hospital. It could be possible that the true impact of such large scale changes could be only observed after a long period of time. Therefore, it is possible that the central hospital could be more cost-effective than presented in this Chapter.

Finally, it is important to draw attention to the narrow perspective of this study and a number of potential costs might have been left out. A broader perspective, for example inclusion of costs and benefits to the family and friends would have been important in the cost-effectiveness analysis.

6.5.4 Implications for future research

A number of further research priorities can be outlined from the work presented in this Chapter. The model could be extended to include the costs in the community after the discharge from hospital, provided additional data is available. Sub-group analysis based on broader ICD-10 disease classification is presented in this Chapter

because of insufficient data, but more specific disease/condition analysis such as for stroke could prove useful to the decision-makers.

DCE with cost as one of the attributes conducted in patients who have recently attended the emergency medical services could generate more representative willingness to pay and results of cost-benefit. There could be other approaches to incorporate the DCE results into economic evaluation than the one presented in this Chapter. One of the approaches could be to assign the utility weights for each states derived from the DCE into the economic evaluation (Burr *et al.*, 2007). Different methods for converting DCE values into QALYs have been discussed in the literature (Rowen *et al.*, 2015). Exploration of these approaches was beyond the scope of this PhD, nevertheless future studies could look into these approaches of incorporating DCE into economic models.

6.6 Conclusion

The results of the economic evaluation presented in this Chapter demonstrated that the centralised emergency medical care could be more cost-effective alternative (when outcomes are measured in QALYs) to the emergency medical services provided through a number of local hospitals. It appears the cost-effectiveness of centralised services improves in the long-term. In addition, the study findings also suggest that the centralised emergency medical services would be more cost-effective in some specific population groups such as the elderly, the most deprived and those presenting with diseases of circulatory system. However, the findings also indicated that it is also possible for the centralised service to be more expensive and less effective in the 30-64 years of age group of population. In contrast to the cost-effective analysis, the cost-benefit analysis suggested that people may place little value to the centralised services compared to their service provided at their local hospitals. However, these results should be interpreted with caution in the light of limitations in the DCE and its incorporation into an economic evaluation. Nevertheless, this economic evaluation is consistent with findings of many other studies supporting the implementation of major system change similar to centralisation of emergency medical services. Furthermore, the findings also support the recommendations to centralise urgent and emergency care services in the NHS

England and current and future consolidation of specialised care services aimed at providing quality care with increased efficiency. The next Chapter presents the summary of each Chapters of this thesis and discusses the major findings and presents the overall conclusion of this thesis.

Chapter 7. Discussion

7.1 Introduction

Chapter 6 demonstrated that the centralised emergency medical care could be more cost-effective alternative to the emergency medical services provided through a number of local hospitals. This Chapter revisits the aims and objectives of the thesis set out in Chapter 1 and then summarises and discusses the empirical research findings reported in Chapter 2, Chapter 4 and Chapter 6. It then highlights the main contributions of the thesis and policy implications followed by the outline of major limitations and areas for further research. Finally, the overall conclusion of the research is presented.

Within the UK, emergency medical services are typically provided by the local hospitals. There is a perception that emergency medical services are struggling to cope with the increasing demand and extra pressures on NHS resources. Therefore, there is pressure to centralise these services into fewer more specialised units that cater for a larger population. The underlying premise is that this centralisation will benefit patients with more serious and life threatening condition by providing them access to the best expertise and hence potentially better quality of care. Little is known about economic implications of centralisation of emergency medical services or about societal preferences around equality of access. The aim of this thesis was to examine the impact of centralisation of emergency medical services in terms of costs and quality of care and then quantify the strength of individual preferences towards centralised emergency medical services.

7.2 Summary of the Main Findings

Chapter 2 systematically reviewed and critically appraised the methodological quality of published economic evaluations that considered centralisation of specialised healthcare services. The systematic review showed that most of the studies used non-experimental designs, when quasi-experimental designs such as controlled before-after studies, interrupted time series and repeated measures studies (Centre for Review and Dissemination, 2009) could have generated more robust and convincing evidence compared with non-experimental designs. QALYs are widely used in health economics because they provide a summary measure of both quantity and quality of life outcomes but they were used in only a few studies. Most of the

previous economic evaluations were constrained because their results were based on short follow-ups. It is possible that their outcomes would have been different if they had considered a longer time frame.

Cost-effectiveness may vary with the perspective and an intervention which is cost-effective from one view point and may not be from another (Drummond *et al.*, 2005), however a large majority of previous economic evaluation failed to state the perspective of their analysis. It was difficult to infer the perspective of analysis by looking at the cost and effects included. The systematic review demonstrated a considerable variation in conduct and limited methodological quality of the economic evaluations of centralisation of specialised healthcare services in general. In addition, the studies reviewed generally did not adhere to the standards for reporting economic evaluations (Drummond and Jefferson, 1996; Husereau *et al.*, 2013). Evidence coming from methodologically poor studies may force decision-makers to make poorly informed decisions on centralisation of specialised health care services. Therefore, it is important to improve the methodology and reporting of economic evaluations so that decisions on centralisation are informed by more robust evidence. Chapter 2 informed the development of economic model for the economic evaluation of centralisation of emergency medical services, which is presented in Chapter 6.

Chapter 4 presented a DCE which explored and quantified the strength of individuals' preferences towards centralised emergency medical services. It demonstrated how individuals' weigh-up and trade-off between attributes of hospitals in an emergency. Hospital attributes that were considered in the DCE were travel to hospital, waiting time in the emergency department, length of stay in the hospital, risk of death, risk of re-admission, outpatient follow-up care at a local hospital. These attributes were derived from the literature and reflected the key quality measures of emergency medical services. The results suggested that individuals prefer less travel time to hospital, less waiting time, fewer number of days in hospital, low risk of death, low risk of readmission and outpatient follow-up care in their local hospital. The results of the DCE highlighted that follow-up outpatient care at a local hospital is more important to individuals than any other hospital attributes considered in the analysis. Individuals were willing to trade-off increased travel time and waiting time for the lower risk of death, lower risk of readmission, fewer number of days in the hospital and follow-up outpatient care in their local hospital. In general, the results suggested

that people can compromise on other attributes for high quality of healthcare provided by centralised emergency medical services.

Chapter 6 described the economic evaluation of centralised specialised emergency medical service compared to those provided at local hospital in a UK setting. A Markov model using the cohort simulation approach for a 10 year time horizon was constructed. The analysis compared both the deterministic and probabilistic estimates of costs, QALYs and mortality outcomes in centralised hospital model and local hospital models. The results demonstrated that emergency medical services in a centralised hospital can be a cost-effective alternative to those provided at multiple local hospitals, although cost-effectiveness may vary in specific population sub-groups. It was also observed that the centralised emergency medical services can be more cost-effective if delivered to a population more likely to present with more severe health issues. Chapter 6 also attempted to incorporate the results of the DCE in Chapter 4 into the economic evaluation framework. In sharp contrast to the findings on cost-effectiveness, the cost benefit analysis suggested that centralised emergency medical services could have negative societal value when compared to services provided in local hospitals.

7.3 Thesis Contribution and Policy Implications

The empirical contribution of this thesis are the findings from the systematic review of economic evaluation methods used in centralisation of specialised healthcare; the DCE eliciting the preferences for centralised emergency medical services and the findings from the economic evaluation assessing the costs and outcomes of centralisation of emergency medical services. The contributions and policy implications of findings in each of these components are outlined as follows.

7.3.1 Systematic review

The systematic review highlighted the need to improve the methodology and reporting of economic evaluations assessing centralisation of specialised healthcare so that decisions on centralisation are informed by reliable evidence in healthcare quality and efficiency. A number of economic evaluations on centralisation of specialised healthcare services have been conducted, however studies assessing the methodological quality of these economic evaluations are lacking. An earlier

review of economic evaluations considering centralisation was narrower and focussed only on specific health issues like cancer (Ke *et al.*, 2012). To the best of my knowledge, this is the first systematic review to comprehensively attempt to assess the methodological quality of economic evaluations assessing centralisation of specialised healthcare services irrespective of their speciality.

7.3.2 Discrete choice experiment

The DCE suggested that patients are prepared to travel further and wait longer for a better quality of emergency medical services in terms of risk of death, risk of readmissions, length of stay in the hospital and outpatient follow-up care. However, they value the outpatient follow-up care at their local hospital more than anything else considered in this thesis. These findings are consistent with the findings of other relevant DCE studies (Ryan *et al.*, 2000; Gerard *et al.*, 2004; Burge *et al.*, 2005; Gerard and Lattimer, 2005; Schwappach and Strasmann, 2007; Harris *et al.*, 2015; Vallejo-Torres *et al.*, 2018) and other studies assessing choice of healthcare using methods other than DCE (Beckert *et al.*, 2012; Landau *et al.*, 2013; Gutacker *et al.*, 2016; Moscelli *et al.*, 2016). However, these current studies differ with the DCE undertaken in this thesis in terms of healthcare context, design, attributes and attribute levels. Hence, the DCE in this thesis provides valuable insights into patient preferences of emergency medical services and would help decision-makers make informed decisions on future centralisation of emergency medical services or similar specialised healthcare services in a similar healthcare setting. Consideration of individual preferences in future centralisation of emergency medical services may mean increased value and satisfaction across the population and provide efficiency gains.

7.3.3 Economic evaluation

The economic evaluation utilised a real world data and demonstrated that emergency medical services in a centralised hospital can be a cost-effective alternative to those at multiple local hospitals, although cost-effectiveness may vary in specific population sub-groups. No studies have hitherto explored the economic evaluation of centralisation of emergency healthcare in Northumberland, England. Furthermore, the combination of DCE and economic evaluation in the form cost-benefit analysis is a relatively novel approach. The economic evaluation in this thesis provides the

policy-makers the insights into real-world implications of the centralisation of emergency care in terms of costs and outcomes and hence can inform the decision-making around centralisation in the future.

Healthcare resources are limited and therefore decision-makers have to make tough decisions on provision of health care services. There is a pressure to consolidate the emergency medical services provided by the multiple district hospitals into fewer specialised units catering a large population with efficient and high quality care in the NHS England. The concentration of care into specialised centres is one of the new care models suggested by the “Five year forward view” and also recommended by the Keogh report (NHS England, 2013a; NHS England, 2014). The findings of this thesis, adds to the evidence that centralisation offers cost-effective provision of emergency medical services by concentrating and enhancing expertise. Hence, these results back up the NHS effort to centralise emergency medical services into specialised hospitals. However, the thesis also cautions that cost-effectiveness could vary in population sub-groups and any future centralisation efforts should be supported by methodologically strong evidence of cost-effectiveness.

This thesis also addresses the concern that centralisation may have impact on healthcare access. Centralisation of emergency medical services in this thesis has shown to increase the travel times which suggests that centralised healthcare may not be closer to people’s home and the better quality and specialised health care services may come only at the cost of increased travel times to the point of care. However, the DCE results suggested that whilst people may place a high value on their local hospital, they may be willing to trade-off the increased journey time to be treated at a specialised hospital providing better quality service. Hence, the issue of distance decay where the utilisation of healthcare services decreases with the increase in travel distance to the healthcare facility may not apply to emergency medical services, at least in this context. Moreover, there could be other strategies such as investments on better road networks and improved ambulance services which may offset the increased journey times noted here in this thesis. More recently it was observed that patients attending the centralised specialised emergency medical service studied in this thesis, spend less time in the A&E with a higher percentage of patients admitted, transferred or discharged within four hours compared to a synthetic control area (O'Neill *et al.*, 2017). Therefore, it appears that the availability of a specialised team in a centralised emergency services may

improve access and reduce the in house delay in getting appropriate clinical treatment; this may compensate for the increased journey time to arrival. All of these efforts are likely to result in an increase in the cost savings and health care quality beyond those estimated in this thesis.

7.4 Major Strengths and Limitations

The strengths and limitations of the analysis undertaken in this thesis are discussed in detail individual empirical Chapters. Only the most substantive issues will be summarised here. The strengths and limitations can be divided into those relating to the DCE and those relating to the economic evaluation.

Strengths and limitations related to DCEs can be summarised as follows:

1. The sample used in the DCE was considered most appropriate to represent the preferences of potential users of a newly built specialised emergency hospital- the focus of this PhD. A wide cross section of the local general population accessed via Healthwatch and NHCT were surveyed. However, the sample size could possibly have been too small. Therefore the possibility of poor representation of preferences cannot be ruled out. It is likely that some specific population groups from the general population may be under represented, particularly those not registered with the Healthwatch or NHCT. The EQ-5D-5L and EQ-VAS scores of the respondents included in the survey were lower than those of the general population in England (see section 4.4.1, Chapter 4). Therefore, it is likely that the healthiest groups may have been left out. Hence, the study would have benefitted from a larger and more diverse sample of respondents (also representative of very young, very old and those with special needs).

2. Cost was not included as one of the attributes in the DCE. Hence the generation of a marginal willingness to pay from the marginal rates of substitution between cost and the other attributes was not possible. The attribute “travel time to hospital” was used as the basis of a calculation of the marginal willingness to pay incorporated into the cost benefit analysis conducted in Chapter 6. Use of national average wage rate to value patients’

time is considered appropriate in analyses designed to inform policy decisions of public interest (Russell, 2009). This approach of estimating the willingness to pay was useful when framing of a cost attribute was difficult in the context where individuals are not used to out of pocket payments for healthcare at the point of use. One advantage of monetisation of travel time instead of including cost as one of the attributes was that it prevented potential protest responses in the DCE i.e. the risk of respondents trading off only against the cost attribute by always choosing the cheapest alternative or not making a choice at all (Pedersen *et al.*, 2011). However, the monetary valuation of patient time is not straight forward and at times challenging (Russell, 2009).The estimate of monetary value of travel time in this thesis required several assumptions and steps (see section 6.4.5 in Chapter 6). In the case of patients active in the labour market (example, those with paid jobs, self-employed) the wage rate could appropriately shadow the monetary value of travel time spent, but may not be a true representation for patients not in the labour market (such as those retired or unable to work because of health problems) (Borisova and Goodman, 2003). Evidence shows systematic differences between the wage rate and the willingness to pay value of time, which suggests these two are not necessarily equivalent (Borisova and Goodman, 2003).

Another point to note is that the economic evaluation was considered for a 10 years' time horizon, whereas it was inappropriate to include a time-frame for the travel time attribute considered in the DCE. Therefore, it is possible that the mismatch in framing of the DCE and the economic evaluation could have influenced the willingness to pay value and by extension inferences drawn from the cost-benefit analysis. However, the mismatch in the framing of the DCE and the economic evaluation is a general problem faced while trying to combine these two approaches (Burr *et al.*, 2012).

3. There could be other attributes that could be more important to the potential users of emergency medical services but which were not covered in the DCE. Therefore, it is likely that the DCE results could have suffered from the bias resulting from the failure to include any other important attributes. Nevertheless, relevant literature was explored and the attributes chosen

balanced the need to identify important attributes with the need to reflect key hospital quality indicators in the context of this thesis.

Strengths and limitations related to the economic evaluation can be summarised as follows:

1. Utility parameters were taken from the secondary literature (which was not systematically assembled) and were assumed to be similar for the both the models, but in practice these assumptions may not be true which could influence the QALY outcomes in the economic evaluation. For example, specialised hospitals are expected to provide a very high quality service, therefore the utility value of A&E attendance or admissions at a specialised hospital could be higher compared to those at a local hospital. Evidence suggests that centralisation of healthcare in general can offer patients a good care experience (Perry *et al.*, 2018). This means that the QALY gains from centralised specialised hospital could be much higher in practice than the ones observed in this thesis but this would not change the conclusion of this thesis.

2. The perspective of analysis followed in the economic evaluation i.e. the NHS perspective is quite narrow compared to a much broader societal perspective which could have taken other costs borne by the patient, their families or the society into consideration. Therefore, it is possible that the results observed might have suffered from the narrow perspective of analysis taken in this thesis. However, given the better quality of care at the centralised hospital, the consideration of societal costs would still go in favour of the centralised hospital (which is less likely to change the conclusions of this thesis) though at a risk of increase in journey time for patients and their relatives. Furthermore, the economic evaluation did not consider costs of waiting times to be seen and resource utilisation after the discharge into the community such as follow-up care in local hospitals, GP surgery visits; this could have undermined the savings from centralisation. Evidence coming from the setting same as the one considered in this thesis suggested that the centralisation of emergency medical services resulted in increased service utilisation, shorter A&E visits, and increased discharge or transfer from the A&E within four hours. All of

these outcomes could be related to efficient and better quality of care provided at the centralised specialised hospital (O'Neill *et al.*, 2017). Therefore, consideration of additional costs such as waiting times or resource utilisation in the community in the economic evaluation model may result in greater savings than those estimated in this thesis.

3. Utilisation of data from a relatively short-time frame to derive transition probabilities in the centralised model could have under-estimated the true impact of centralisation of emergency medical services. However, the data from a longer time frame was not available during the conduct of economic evaluation in this thesis. Repeating the economic evaluation model with post centralisation data from longer time frame may be useful.

4. The travel time to hospital considered in the Markov model, taken from google maps, are actually average normal car driving time between postcode locations. However, in emergencies, ambulance may travel faster than cars (considering the no restrictions on traffic signals/lanes for ambulances driven in emergency, though ambulances are limited to 60 miles an hour) and it is possible that the costs associated with the travel time to hospital used in the Markov model were over-estimated. But, at the same time, travel time during peak times or essential road works would mean additional travel time to hospital. However, these limitations on travel time affects both the local as well as centralised services and are therefore less likely to change the conclusions of this thesis. Furthermore, other model parameters mainly based on assumptions, may not be transferable to other setting.

5. Apart from the Markov model used in this thesis, a number of other decision models such as patient level simulation, discrete event simulation and dynamic models are commonly used in health economic evaluations. However, in this thesis, as interaction between individuals attending the emergency is ruled out then the use of discrete event simulation (with interactions) and dynamic models is not necessary. However, an economic evaluation using patient level simulation (also known as micro-simulation) which models the progression of individuals one at a time (rather than in cohorts in Markov model) (Briggs *et al.*, 2006; Petrou and Gray, 2011b), could

have generated more accurate estimates of costs and effects than those estimated in this thesis. A recent economic evaluation assessing the centralisation of stroke services has used patient level simulation model the patient level simulations (Lahr *et al.*, 2017). However, the benefits of such models over Markov model can be outweighed by their complexity and high computational burden (Briggs *et al.*, 2006).

7.5 Areas for Further Research

This section outlines a number of outstanding areas for further research which are mainly based on the limitations in the analysis of this thesis highlighted in section 7.4. Although most these areas were noted early on, these could not be adequately addressed for reasons such as unavailability of data (for example: ambulance journey times to hospitals; utility estimates for each state in the model; costs and resource utilisation after the discharge from hospital) or time and resource constraints imposed by the requirements of this thesis (for example: qualitative research on hospital attributes, larger respondent sample in DCE). These areas of further research can be divided into those relating to the DCE and those relating to the economic evaluation model.

Areas of further research related to DCE can be summarised as follows:

1. A respondent sample larger than the one used in the DCE in this thesis may be more representative and may generate more reliable estimates of preferences. A high majority of respondents in this thesis were above 55 years of age- generally high consumers of healthcare. Therefore, the sample in future studies could also include the healthiest group, the most elderly and the ones with special needs possibly left out in this thesis. A respondent sample composed of general public (who have no recent experience of emergency medical services) and patients (with recent experience of emergency medical services) with similar representation from all age-groups of general public could provide further insights on preferences of emergency medical services.

2. As discussed in section 7.4, wage rates are not necessarily equivalent to the value of patient's time. The mismatch in framing of the DCE and economic evaluation is likely to influence the inferences drawn from the cost-benefit

analysis. Inclusion of a cost attribute and construction of DCE scenarios more compatible with the decision problem as expressed by the economic evaluation model may provide a better estimate of willingness to pay value than the one used in the cost-benefit analysis reported in this thesis.

3. Qualitative research exploring the attributes in the DCE scenarios was challenging in terms of time and resource constraints of this PhD thesis. Getting the required sample for the qualitative work within a limited time was difficult. Focus group discussion, brain-storming exercises and interviews with the users of emergency medical services and other stakeholders would generate attributes that were not considered in this thesis but could be more important to the users/potential users.

Areas of further research related to economic evaluation can be summarised as follows:

1. The utility estimates used in the model were taken from secondary literature. However, direct measurement of utilities from patients attending the emergency medical services could be more valuable. Health utilities, also known as health-related quality of life (HRQoL) weights, can be measured using a range of direct (for example VAS, TTO) or indirect (generic preference based measures such as EQ-5D) methods (Whitehead and Ali, 2010). Some of these are also described in Chapter 3 of this thesis. However, considering the seriousness of patients attending the emergency medical services it may not be practical and ethical to administer these utility measurement tools while they are in A&E or admitted in hospital. But, a possibility could be to measure the utility weights from patients with recent experience of utilising the emergency medical services. Health utility parameters assigned to health states in each of the models compared in this thesis were assumed to be the same, but in practice the utilities could be influenced by the differences in hospital care quality. Further research should also explore whether the utilities assigned into local and centralised hospital models are different.

2. The model could be extended to include the costs in the community after the discharge from hospital, provided additional data is available. In practice

patients may be discharged into one of the several destinations in the community, such as nursing homes, residential care homes and some may attend their local hospital or GP surgeries for follow-up. Patients could be discharged after the initial treatment at the centralised specialised hospital to their local hospitals for further care. Therefore, there could be additional costs of care involved when patients are discharged into these specific community destinations. If one of the hospitals results in more disability in the long-term then the costs for that option over time will be higher. Hence the “Community” state in the Markov model described in this thesis could be replaced by several other states such as “Nursing home”, “Rehabilitation”, “Local Hospital” (only for the centralised model) and “Home” to better represent the resource utilisation in the community after the discharge from hospitals. Consideration of resource utilisation in the community could show a different picture of cost-effectiveness.

3. Comparison of average ambulance journey times before and after centralisation may give a more realistic picture of journey times to hospital. The ambulance journey times could be available from records of local ambulance service providers.

4. Consideration of improvement in road networks to centralised hospital, better equipped and skilled ambulance paramedic staff responding to emergency calls and changes in the waiting times to be seen may suggest further cost savings and improvements in effectiveness. Improvement in road networks to centralised hospital would mean less travel time to access the emergency medical service. Better skilled ambulance paramedic staff responding to emergency calls would mean less serious cases are treated at their homes (or point of call or before arrival at the hospital) and may not need to attend the hospital. Decreases in waiting times or time in hospital would mean less utilisation of resources. All of these are likely to generate further savings without compromising the quality of care.

5. Centralisation of emergency medical services in itself is a major service re-organisation where both the patients and professionals may not be fully accustomed to the new re-organisation and may not be prepared to respond

to any unexpected events in the outset of centralised hospital. It could be possible that the true impact of such large scale changes could be only observed after a long period of time. In fact, one of the paradoxes of innovation is that the quality improvement systems in healthcare often fails to keep pace with innovation which disrupts the healthcare service (Dixon-Woods *et al.*, 2011). For example, the consultant presence and different physical configurations of the centralised hospital (compared to those at local hospitals) may give rise to a whole new set of quality challenges. It takes time for people and the quality assurance systems to catch up with the new configurations of care (Dixon-Woods *et al.*, 2011). Therefore, research using post centralisation data collected over a longer term than the one used in this thesis could be valuable.

6. Future studies could look into better approaches of incorporating DCE into economic models than the one used in this thesis. One of the approaches could be to assign the utility weights for each states derived from the DCE into the economic evaluation (Burr *et al.*, 2007). Different methods for converting DCE values into QALYs have been discussed in the literature (Rowen *et al.*, 2015).

7. Economic evaluation models are generally based on assumptions around parameters used to populate the model. It is always beneficial to repeat a similar model in the context other than the one used in this thesis.

8. The perspective of the analysis governs the costs and outcomes considered in an economic evaluation and can ultimately influence the resource allocation decisions. Analysis of centralisation of emergency medical services from a societal perspective considering the costs such as those of social care, informal care and patient out of pocket access costs could help exploration of any differences in results than the ones observed from NHS perspective taken in this thesis.

7.6 Conclusion

This thesis explored the economic evaluation methods used in previous studies assessing centralisation of specialised healthcare services, conducted a DCE to assess people's preferences of centralised healthcare services, and conducted an economic evaluation comparing the emergency medical services provided from the local hospitals with those provided from a centralised specialised hospital. It is important to ensure that decisions to centralise specialised healthcare services are informed by robust evidence of improvements in healthcare quality and efficiency arising out of centralisation. Centralisation of emergency medical services could be cost-effective and patients would be willing to trade-off increased journey times with the better quality of service provided at the centralised specialised facility. Hence, this thesis contributes to the evidence base recommending the centralisation of emergency medical services into fewer more specialised units.

Decision-makers should consider centralisation of similar specialised healthcare services in the NHS. Nonetheless, there are important limitations in the research conducted in this thesis and further investigations are to be undertaken. To conclude, this research is an evidence supporting the centralisation of emergency medical services in terms of costs, quality and preferences.

Appendix A

Table A1: Search strategy used in the review

EMBASE

#1 ((Emergency adj (medici* OR service* OR department)) OR Trauma OR (Speciali* adj (health OR center OR care OR unit OR medical OR service)) OR care OR health OR clinical OR Hospital OR Acute)

#2 (Centrali* OR Regionali* OR Reconfigurat* OR Reorgani* OR Redesign* OR Consolidat* OR Merg*)

#3 1 AND 2

#4 (cost OR cost adj (effective* OR utility* OR saving* OR minimi* OR analysis* OR benefi* OR illness*))

#5 3 AND 4

PubMed

#1 ((Emergency adj (medici* OR service* OR department) OR "ED" OR "A&E" OR Trauma OR (Speciali* adj (health OR center OR care OR unit OR medical OR service)) OR care OR health OR "clinical service*" OR Hospital OR Acute))

#2 (Centrali* OR Regionali* OR Reconfigurat* OR Reorgani* OR Redesign* OR Consolidat* OR Merg* OR Volume)

#3 1 AND 2

#4 (cost OR cost adj (effective* OR utility* OR saving* OR minimi* OR analysis* OR benefi* OR illness*)
#5 3 AND 4

NHS EED

#1 (centralisation OR concentration OR volume OR specialization OR regionalization OR multidisciplinary OR reconfiguration OR Reorganization)

#2 ("Emergency Medical Services" OR "Emergency Department" OR A&E OR Specialized OR Trauma OR "Acute Care" OR Hospital OR "Healthcare" OR "Health Care Service" OR "Clinical Service" OR "Vascular Service" OR Cancer OR Stroke)

#3 Cost OR Economic OR Saving OR Outcome OR Impact OR Implication OR "health economic"

HEED

#1 Hospital OR "health care" OR "health care service" OR Emergency OR Trauma OR "Acute Care" OR "Vascular Service" OR Centre OR Stroke OR Cancer

#2 Centrali* OR Region* OR Reconfigur* OR Consolidat* OR Merg* OR Concentrat* OR Reorgani* OR Redesign* OR "high volume"

#3 1 AND 2

#4 Cost OR Economic OR "health economic" OR Impact OR Implication OR Evaluation OR Outcome OR Effect OR Efficiency OR Sustain

#5 3 AND 4

Table A2: Checklist used to assess the methodological quality in included studies

1. Is a clear description of the study objective and comparators provided?
2. Are the characteristics of target population and subgroups described and analysed?
3. Is the setting and location of the study stated?
4. Is the study perspective clearly stated?
5. Is the time horizon of costs and benefits clear?
6. Is the discount rate stated or an explanation is given if costs or benefits are not discounted (where applicable)?
7. Are the source and methods used to collect effectiveness data described?
8. Are the primary outcome measure(s) for economic evaluation clearly stated?
9. Are the quantities of resources reported separately from their unit costs?
10. Are approaches used to estimate resource use and cost clear?
11. Are the cost components clearly stated?
12. Is the currency/price year explicitly stated?
13. Are the analytic methods supporting the evaluation including methods for dealing with skewed, missing, or censored data, extrapolation methods, methods for pooling data, approaches to validate or make adjustments to a model, methods for handling population heterogeneity and uncertainty described in details?
14. Are the incremental costs and outcomes reported (If applicable incremental cost-effectiveness ratios reported)?
15. Is sensitivity analysis carried out?
16. Are the study limitations discussed?
17. Is the study generalisability discussed?

Table A3: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
1	Nallamothu BK, Saint S, Ramsey SD, et al. The role of hospital volume in coronary artery bypass grafting: is more always better? *J Am Coll Cardiol* 2001;38(7):1923-30.	N=13,644 , >35years age, having undergone isolated, non-emergent CABG, mean age=64.5 years	Non emergent coronary artery bypass grafting	Low Vs High volume hospitals	Direct and indirect hospital costs are said to be included - but cost components not clear	In-hospital mortality rate, length of hospital stay
2	Dimick JB, Cattaneo SM, Lipsett PA, et al. Hospital volume is related to clinical and economic outcomes of esophageal resection in Maryland. *The Annals of Thoracic Surgery* 2001;**72**(2):334-40.	N=1,136, All patients discharged from hospitals with esophageal resection during the study period, mean age=61 years	Esophageal resection	High Vs Medium Vs Low volume hospitals	Hospital charges-but cost components not clear	In-hospital mortality rate, length of hospital stay
3	Lyman S, Jones EC, Bach PB, et al. The association between hospital volume and total shoulder arthroplasty outcomes. *Clin Orthop Relat Res* 2005(432):132-7.	N=1,307, All patients undergoing elective shoulder arthroplasty during the study period, mean age=65.6 years	Shoulder arthroplasty	High Vs Medium Vs Low volume hospitals	Hospital charges reported on the inpatient bill- but cost components not clear	Re-admission rate within 60 days, revision rate within 12 or 24 months, mortality rate within 60 days, length of hospital stay
4	Bardach NS, Olson SJ, Elkins JS, et al. Regionalization of treatment for subarachnoid hemorrhage: a cost-utility analysis. *Circulation* 2004;**109**(18):2207-12.	Base case of 59 year old woman with subarachnoid hemorrhage modelled	Treatment of Subarachnoid Hemorrhage	High Vs Low volume hospitals	Hospital costs, costs of transfer from low volume to high volume hospital, cost of caring disabled,	QALYs
5	Concannon TW, Kent DM, Normand SL, et al. Comparative effectiveness of ST-segment-elevation myocardial infarction regionalization strategies. *Circ Cardiovasc Qual Outcomes* 2010;**3**(5):506-13.	2000 patients simulated, 55.5-66.6 years mean age in different subgroups	Primary percutaneous coronary intervention (PCI)	Standard care Vs Diverting patients to hospitals with PCI facilities Vs scenarios adding PCI facilities to existing hospitals	Not clear what cost components were analysed	QALYs

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
6	Gandjour A, Weyler EJ. Cost-effectiveness of referrals to high-volume hospitals: an analysis based on a probabilistic Markov model for hip fracture surgeries. *Health Care Manag Sci* 2006;**9**(4):359-69.	Hypothetical hip fracture patients hospitalized for surgery, mean age=74 years modelled.	Hip fracture surgery	High Vs Low volume hospitals	Hospital costs including labor and materials costs for clinical care and ancillary services such as radiology, catering and cleaning; costs of hospital infrastructure, travel costs to hospital	Mortality rate, QALYs
7	Geomini PM, Kruitwagen RF, Bremer GL, et al. Should we centralise care for the patient suspected of having ovarian malignancy? *Gynecol Oncol* 2011;**122**(1):95-9.	N=7,598 women who received surgery for an adnexal mass, No mean age reported	Centralised and regular care for ovarian malignancy	General gynaecologists in a general hospital Vs gyanecological oncologist whether or not in a specialised center Vs systematic diagnostic evaluation prior to surgery	Doctors' cost for diagnosis and surgical treatment, salary costs for gyanecological oncologist, costs of chemotherapy	Life years gained
8	Sutton JM, Wilson GC, Paquette IM, et al. Cost effectiveness after a pancreaticoduodenectomy: bolstering the volume argument. *HPB (Oxford)* 2014;**16**(12):1056-61.	N=9883, >18 years age, undergone pancreatico-duodenectomy, modelled	Pancreatic surgery	Lowest Vs Low Vs Middle Vs High Vs Highest volume hospitals	Total direct costs said to be included- but not clear on cost components	Post-operative death prior to discharge
9	Chan T, Kim J, Minich LL, et al. Surgical Volume, Hospital Quality, and Hospitalization Cost in Congenital Heart Surgery in the United States. *Pediatric Cardiology* 2015;**36**(1):205-13.	N=24,992, <18 years age, underwent congenital cardiac surgery	Congenital cardiac surgery	High Vs Medium Vs Low volume hospitals	Hospital costs but cost components not clear	Mortality rate, number of complications

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
10	Hunter RM, Davie C, Rudd A, et al. Impact on Clinical and Cost Outcomes of a Centralized Approach to Acute Stroke Care in London: A Comparative Effectiveness Before and After Model. *PLoS ONE* 2013;**8**(8):e70420.	N=3463, had ischemic or hemorrhagic stroke, mean age=71-72.8 years, modelled	Acute stroke care	Local hospitals Vs Centralised hyper acute stroke units	Costs of transport, acute hospitalisation, imaging and surgical interventions, staff contacts and medications during acute hospitalisation and post-discharge care	QALYs, deaths averted
11	Tanke MAC, Ikkersheim DE. A new approach to the tradeoff between quality and accessibility of health care. *Health Policy* 2012;**105**(2–3):282-87.	Women undergoing breast cancer treatment- modelled	Breast cancer care	Local hospitals Vs Centralised hospital	Travel costs for patients that stem from centralisation	QALYs
12	Losina E, Walensky RP, Kessler CL, et al. Cost-effectiveness of total knee arthroplasty in the United States: patient risk and hospital volume. *Arch Intern Med* 2009;**169**(12):1113-21; discussion 21-2.	N=121,432, >65 years with end stage knee Osteoarthritis, modelled	Total knee arthroplasty(TKA)	Low Vs Medium Vs High volume hospitals	TKA costs-Hospital costs, physician costs, costs of complications, costs of rehabilitation following discharge; Osteoarthritis(OA) cost-Inpatient and ambulatory visits, Knee OA medications, MRIs and radiograms	QALYs
13	Seguin J, Garber BG, Coyle D, et al. An economic evaluation of trauma care in a Canadian lead trauma hospital. *J Trauma* 1999;**47**(3 Suppl):S99-103.	N=484, median age=39 years, trauma admissions with an Injury Severity Score (ISS)>12	Trauma care	Tertiary trauma care center Vs Non trauma center hospital	Direct costs of treatment (e.g. staff, consumables) and indirect costs(e.g. overheads)- cost component not clear	QALYs

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
14	MacKenzie EJ, Weir S, Rivara FP, et al. The value of trauma center care. *J Trauma* 2010;**69**(1):1-10.	N=5043, 18-84 years, treated for a moderately severe to severe injury	Trauma care	Level I trauma center Vs non trauma center hospital	Costs associated with-Index hospitalisation, transport, hospital transfers, re-hospitalisation, inpatient rehabilitation, stays in long-term care, nursing facilities, outpatient care, informal care by friends and family	Incremental lives saved, incremental life years gained, incremental QALY gained
15	Tsao SY, Lee WC, Loong CC, et al. High-surgical-volume hospitals associated with better quality and lower cost of kidney transplantation in Taiwan. *J Chin Med Assoc* 2011;**74**(1):22-7.	N=1060, >18 years of age, patients with kidney transplants	Kidney transplantation	High Vs Low volume hospitals	Total medical cost of the transplant, annual medical cost for 3 years after the transplant	Complications-infection, mortality, readmission in 14 days, patient survival at 1,2, and 3 years of transplantation
16	Yoshioka R, Yasunaga H, Hasegawa K, et al. Impact of hospital volume on hospital mortality, length of stay and total costs after pancreaticoduodenectomy. *British Journal of Surgery* 2014;**101**(5):523-29.	N=10652, mean age=67.3 years, patients undergoing pancreatico-duodenectomy	Pancreatic surgery	Very high Vs High Vs Medium Vs Low Vs Very low volume hospitals	Costs of surgical, pharmaceutical, laboratory and other inpatient services-but cost components not clear	Post-operative mortality, length of hospital stay
17	Joynt KE, Orav EJ, Jha AK. The association between hospital volume and processes, outcomes, and costs of care for congestive heart failure. *Ann Intern Med* 2011;**154**(2):94-102.	N=1,029,497, median age=80 years, patients >65 years of age with discharge diagnosis of congestive heart failure	Congestive heart failure care	High Vs Medium Vs Low volume hospitals	No clear information on cost	Mortality, readmission rates

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
18	Ellison LM, Heaney JA, Birkmeyer JD. The effect of hospital volume on mortality and resource use after radical prostatectomy. *J Urol* 2000;**163**(3):867-9.	N=66,693 men, mean age= 65 years, patients undergoing radical prostatectomy	Radical prostatectomy	High Vs Low volume hospitals	Hospital charges- but no clear information on cost components	In-hospital mortality, length of hospital stay
19	Nathan H, Atoria CL, Bach PB, et al. Hospital Volume, Complications, and Cost of Cancer Surgery in the Elderly. *Journal of Clinical Oncology* 2014	N=60,361, >66 years of age, patients diagnosed with cancer of the bladder, colon, lung, pancreas, prostate, or rectum and undergone surgical resection	Cancer surgery- included colectomy, cystectomy, pancreatectomy, proctectomy, prostatectomy, and pulmonary lobectomy	High Vs Mid Vs Low volume hospitals	Medicare payments for diagnosis related group, index hospitalisation and readmissions within 30 days from discharge; home health agencies, rehabilitation hospital, skilled nursing facilities in the corresponding 30 days after discharge. However unit costs of each not presented.	Post-operative patient outcomes- mortality, complications, readmissions, and emergency room visits within 30 days after surgery
20	Sosa JA, Bowman HM, Gordon TA, et al. Importance of hospital volume in the overall management of pancreatic cancer. *Ann Surg* 1998;**228**(3):429-38.	N=1236, mean age=67 years, patients with pancreatic cancer and undergoing a primary treatment procedure	Palliative procedures and curative surgery for pancreatic cancer	High Vs Medium Vs Low volume hospitals	Hospital charges- but not clear on its components	In-hospital mortality rate, length of hospital stay,
21	Mitsuyasu S, Hagihara A, Horiguchi H, et al. Relationship Between Total Arthroplasty Case Volume and Patient Outcome in an Acute Care Payment System in Japan. *The Journal of Arthroplasty* 2006;**21**(5):656-63.	N=1561, mean age=69.8 years, patients who had undergone joint arthroplasty	Total Arthroplasty	High Vs Low volume hospitals	Hospital costs- but not clear on its components	Length of hospital stay

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
22	Swisher SG, Deford L, Merriman KW, et al. Effect of operative volume on morbidity, mortality, and hospital use after esophagectomy for cancer. *J Thorac Cardiovasc Surg* 2000;**119**(6):1126-32.	N=340, age not specified, patients who underwent esophageal resection for cancer	Esophagectomy	High Vs Low volume; Cancer Specialised Vs Community hospitals	Hospital charge- but not clear on its components	Operative mortality, complications of care
23	Gordon TA, Burleyson GP, Tielsch JM, et al. The effects of regionalization on cost and outcome for one general high-risk surgical procedure. *Ann Surg* 1995;**221**(1):43-9.	N=502, mean age=62 years, patients undergone pancreatico-duodenectomies	Pancreatic surgery	High volume regional hospital Vs numerous lower-volume hospitals	Hospital charges-but not clear on its components	In-hospital mortality, length of ICU and hospital stay
24	Yu HY, Hevelone ND, Patel S, et al. Hospital surgical volume, utilization, costs and outcomes of retroperitoneal lymph node dissection for testis cancer. *Adv Urol* 2012;**2012**:189823.	N=993, >18 years of age, undergone retroperitoneal lymph node dissection for testis cancer, mean age=30.9 years	Retroperitoneal lymph node dissection for testis cancer	High Vs Low volume hospitals	Inpatient charges-but not clear on its components	Mortality, Length of hospital stay,
25	Glasgow RE, Mulvihill SJ. Hospital volume influences outcome in patients undergoing pancreatic resection for cancer. *West J Med* 1996;**165**(5):294-300.	N=1705, median age=65 years (range 2-85 years), patients undergoing pancreatic resection	Pancreatic resection	Comparison of several different volume hospitals	Hospital charges- but not clear on its components	Operative mortality, Length of hospital stay, patient discharged to home
26	Dimick JB, Pronovost PJ, Lipsett PA. The Effect of ICU Physician Staffing and Hospital Volume on Outcomes After Hepatic Resection. *Journal of Intensive Care Medicine* 2002;**17**(1):41-47.	N=569,>18 years of age, having primary procedure code for hepatectomy; mean age=57 years,	Managing Hepatic resection	ICU physician rounds and no ICU physician rounds in High Vs Low volume hospitals, High Vs Low volume surgeons, (only hospital volume was considered in this review)	Hospital charges-but not clear on its components	In-hospital mortality, length of hospital stay

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
27	Slover JD, Tosteson AN, Bozic KJ, et al. Impact of hospital volume on the economic value of computer navigation for total knee replacement. *J Bone Joint Surg Am* 2008;**90**(7):1492-500.	Hypothetical cohort of 65 year old patients with end-stage arthritis of the knee were modelled.	Computer assisted surgery in end-stage arthritis of the knee	Conventional total knee replacement without computer navigation and computer assisted surgery compared in high vs low volume hospitals	Reimbursement costs of primary and revision total knee replacement and computer navigation including cost of computer software and service contract- no information on breakdown of unit costs and resource consumption	QALYs, revision rates
28	Nguyen NT, Paya M, Stevens CM, et al. The relationship between hospital volume and outcome in bariatric surgery at academic medical centers. *Ann Surg* 2004;**240**(4):586-93; discussion 93-4.	N=24,166, patients who underwent Roux-en-Y gastric bypass for the treatment of morbid obesity, No age restrictions,	Bariatric surgery	High Vs Medium Vs Low volume hospitals	Not clear- but appears to be cost of surgery	Perioperative outcomes- length of hospital stay, complications, readmissions; In-hospital mortality
29	Vogel TR, Dombrovskiy VY, Graham AM, et al. The impact of hospital volume on the development of infectious complications after elective abdominal aortic surgery in the Medicare population. *Vasc Endovascular Surg* 2011;**45**(4):317-24.	N=59365 elective aortic surgery procedures, >65 years of age with nonruptured abdominal aortic aneurysms	Elective aortic surgery	High Vs Low volume hospitals	Hospital charges- but not clear on its components	In-hospital mortality, postoperative infectious complications, length of ICU stay, length of hospital stay
30	Ananthakrishnan AN, McGinley EL, Saeian K. Higher hospital volume is associated with lower mortality in acute nonvariceal upper-GI hemorrhage. *Gastrointest Endosc* 2009;**70**(3):422-32.	N=391,119 discharges with a primary diagnosis of nonvariceal upper-GI hemorrhage, >18 years of age	Treatment of acute nonvariceal upper-GI hemorrhage	High Vs Medium Vs Low volume hospitals	Hospital charges- but components not clear	In-hospital mortality, length of hospital stay

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
31	Simpson AN, Wardrope J, Burke D. The Sheffield experiment: the effects of centralising accident and emergency services in a large urban setting. *Emergency Medicine Journal* 2001;**18**(3):193-97.	N=371,293 annual new patient attendances analysed	Centralisation of accident and emergency services	Before centralisation Vs after centralisation	The cost of A&E services as a whole, the cost per case in the A&E; do not include capital expenditure generated by building works/equipment costs as a result of centralisation	Quality of patient care in terms of time to see a doctor or nurse practitioner, time to admission
32	Shen HN, Lu CL, Li CY. The effect of hospital volume on patient outcomes in severe acute pancreatitis. *BMC Gastroenterol* 2012;**12**:112.	N=22,551 patients with severe acute pancreatitis, age range (38-73) years	Treatment of severe acute pancreatitis	Comparison of several different volume quartiles	Hospital charges- but components not clear	Hospital mortality, length of hospital stay
33	Singla A, Simons J, Li Y, et al. Admission Volume Determines Outcome for Patients With Acute Pancreatitis. *Gastroenterology* 2009;**137**(6):1995-2001.	N=416, 489, >18 years of age patients with primary diagnosis of acute pancreatitis, mean age=53 years	Treatment of acute pancreatitis	High Vs Low volume hospitals	Hospital charges- but components not clear	In-hospital mortality, length of hospital stay
34	Koo JJ, Wang J, Thompson CB, et al. Impact of Hospital Volume and Specialization on the Cost of Orbital Trauma Care. *Ophthalmology* 2013;**120**(12):2741-46.	N=499, patients who underwent orbital reconstruction, mean age=34 years (range 3-94)	Orbital trauma care	Specialised eye trauma center Vs Local hospitals	Hospital charges-but components not clear	Readmission, length of hospital stay
35	Gordon TA, Bowman HM, Bass EB, et al. Complex gastrointestinal surgery: impact of provider experience on clinical and economic outcomes. *J Am Coll Surg* 1999;**189**(1):46-56.	N=4,561, patients discharged after complex gastrointestinal surgical procedures, mean age=61.6 years	Complex gastrointestinal surgical procedures	High Vs Medium Vs Low volume hospitals	Hospital charges-but components not clear	In-hospital mortality, length of hospital stay

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
36	Choti MA, Bowman HM, Pitt HA, et al. Should hepatic resections be performed at high-volume referral centers? *J Gastrointest Surg* 1998;**2**(1):11-20.	N=606, patients undergone hepatic resection, mean age=54.8 years	Hepatic resections	High Vs Low volume hospitals	Hospital charges-but components not clear	In-hospital mortality, length of hospital stay
37	Harmon JW, Tang DG, Gordon TA, et al. Hospital volume can serve as a surrogate for surgeon volume for achieving excellent outcomes in colorectal resection. *Ann Surg* 1999;**230**(3):404-11; discussion 11-3.	N=9739, >18 years of age, patients who underwent colorectal section as the primary procedure, mean age=69.2 years	Colorectal resections	High Vs Medium Vs Low volume hospitals and surgeons (but surgeons not included in this review)	Hospital charges-but components not clear	In-hospital mortality, length of hospital stay
38	Díaz-Montes TP, Zahurak ML, Giuntoli Ii RL, et al. Concentration of uterine cancer surgical care among the elderly: A population-based perspective. *Gynecologic Oncology* 2007;**107**(3):436-40.	N=6181, >18 years of age women with primary surgical procedure for a malignant uterine neoplasm,	Uterine cancer surgical care	High Vs Low volume hospitals and surgeons (but surgeons not included in this review)	Hospital costs- but components not clear	Peri-operative mortality rates, length of hospital stay, length of ICU stay
39	Wright JD, Hershman DL, Burke WM, et al. Influence of surgical volume on outcome for laparoscopic hysterectomy for endometrial cancer. *Ann Surg Oncol* 2012;**19**(3):948-58.	N=4,137, women who underwent laparoscopic hysterectomy for endometrial cancer	Laparoscopic hysterectomy	High Vs Intermediate Vs Low volume hospitals and surgeons (but surgeons not included in this review)	Hospital costs-but components not clear	Perioperative morbidity and mortality, length of hospital stay, readmissions within 60 days
40	Diaz-Montes TP, Giuntoli RL. Volume-Based Care among Young Women Diagnosed with Uterine Cancer. *ISRN Surg* 2011;**2011**:541461.	N=6,181, >18 years of age women with primary surgical procedure for a malignant uterine neoplasm	Caring uterine cancer	High Vs Low volume hospitals and surgeons (but surgeons not included in this review)	Hospital costs- but components not clear	Length of hospital stay, length of ICU stay, in-hospital mortality

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
41	Lee JA, Park JH, Lee EJ, et al. High-quality, low-cost gastrectomy care at high-volume hospitals: results from a population-based study in South Korea. *Arch Surg* 2011;**146**(8):930-6.	N=48,938, patient undergoing gastrectomy, mean age=58 years	Gastrectomy care	Very high Vs high Vs Very low Vs Low volume hospitals	Hospital costs-but components not clear	Length of hospital stay, standard mortality ratio
42	Tsugawa Y, Kumamaru H, Yasunaga H, et al. The association of hospital volume with mortality and costs of care for stroke in Japan. *Med Care* 2013;**51**(9):782-8.	N=66,406, primary admission diagnosis of stroke,	Stroke care	High Vs Medium Vs Low volume hospitals	Total costs of hospital care- costs components broken down into: costs of oral medications, injectables, surgical and non-surgical procedures, tests, imaging studies	In-hospital mortality
43	Chiu CC, Wang JJ, Tsai TC, et al. The relationship between volume and outcome after bariatric surgery: a nationwide study in Taiwan. *Obes Surg* 2012;**22**(7):1008-15.	N=2,674, >18 years of age patients who had undergone bariatric surgery, mean age=32.21 years	Bariatric surgery	High Vs Low volume hospitals and surgeons (but surgeons not included in this review)	Hospital treatment cost-but components not clear	Length of hospital stay
44	Safford SD, Pietrobon R, Safford KM, et al. A study of 11,003 patients with hypertrophic pyloric stenosis and the association between surgeon and hospital volume and outcomes. *J Pediatr Surg* 2005;**40**(6):967-72; discussion 72-3.	N=11,003, children with hypertrophic pyloric stenosis, mean age=41.1 days	Hypertrophic pyloric stenosis surgery	High Vs Medium Vs Low volume hospitals and surgeons (but surgeons not included in this review)	Cost components not clear	Length of hospital stay, complications, mortality
45	Long DM, Gordon T, Bowman H, et al. Outcome and cost of craniotomy performed to treat tumors in regional academic referral centers. *Neurosurgery* 2003;**52**(5):1056-63; discussion 63-5.	N= 4,723, patient undergoing a craniotomy for a benign tumor, primary or secondary malignant neoplasm, mean age=54.5 years	Craniotomy	High Vs Low volume hospitals	Hospitals charges-but components not clear	In-hospital mortality, length of hospital stay

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
46	Clement RC, Carr BG, Kallan MJ, et al. Volume-outcome relationship in neurotrauma care. *J Neurosurg* 2013;**118**(3):687-93.	N=61,067, patient with neurological trauma	Neurotrauma care	Several different volume hospitals	Hospital costs-but components not clear	Mortality, length of hospital stay, poor outcomes (not clearly defined)
47	Hamada T, Yasunaga H, Nakai Y, et al. Impact of hospital volume on outcomes in acute pancreatitis: a study using a nationwide administrative database. *J Gastroenterol* 2014;**49**(1):148-55.	N=17,415, >20 years age patients with acute pancreatitis, mean age=61.1 years	Acute pancreatitis care	High Vs Low volume hospitals	Hospital costs- reported the inclusion of item by item price for surgical, pharmaceutical, laboratory and other inpatient services, however cost details not provided	In-hospital mortality, length of hospital stay
48	Gutierrez B, Culler SD, Freund DA. Does hospital procedure-specific volume affect treatment costs? A national study of knee replacement surgery. *Health Serv Res* 1998;**33**(3 Pt 1):489-511.	N=67,041 patient hospitalisation in which knee replacement surgery had been performed, mean age=74 years	Knee replacement surgery	High Vs Medium Vs Low volume hospitals	Hospital costs-but components not clear	Mortality, complications
49	Auerbach AD, Hilton JF, Maselli J, et al. Case volume, quality of care, and care efficiency in coronary artery bypass surgery. *Arch Intern Med* 2010;**170**(14):1202-8.	N=81,289 patients who underwent coronary artery bypass surgery, mean age=65 years	Coronary artery bypass surgery	Several volume quartiles hospitals and surgeons (but surgeons not included in this review)	Hospital costs-but components not clear	Length of hospital stay, care quality
50	Gourin CG, Forastiere AA, Sanguineti G, et al. Impact of surgeon and hospital volume on short-term outcomes and cost of oropharyngeal cancer surgical care. *Laryngoscope* 2011;**121**(4):746-52.	N=1,534, >18 years of age patients with a diagnosis of oropharyngeal cancer, mean age=58.3 years	Oropharyngeal cancer surgical care	High Vs low volume hospitals and surgeons (but surgeons not included in this review)	Hospital costs-but components not clear	In-hospital mortality, length of hospital stay, readmissions

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
51	Lu CC, Chiu CC, Wang JJ, et al. Volume-outcome associations after major hepatectomy for hepatocellular carcinoma: a nationwide Taiwan study. *J Gastrointest Surg* 2014;**18**(6):1138-45.	N=23,107, patients undergone major hepatectomy for hepatocellular carcinoma, mean age=58.1 years	Major Hepatectomy	High Vs Low volume hospitals and surgeons (but surgeons not included in this review)	Hospital costs- reported inclusion of cost of operating room, radiology, physical therapy, hospital room, anesthetist, pharmacy, laboratory, special materials, surgeon and others, however cost details not provided	Length of hospital stay, survival
52	Macomber CW, Shaw JJ, Santry H, et al. Centre volume and resource consumption in liver transplantation. *HPB (Oxford)* 2012;**14**(8):554-9.	N=5310, patients who underwent liver transplants, age range:18-81 years	Liver transplantation	High Vs Medium Vs Low volume hospitals	Reported as directed costs of transplant-but cost components not clear	Mortality, Transplant to length of hospital stay, ICU length of stay
53	Kuo EY, Chang Y, Wright CD. Impact of hospital volume on clinical and economic outcomes for esophagectomy. *Ann Thorac Surg* 2001;**72**(4):1118-24.	N=1,193, patients who underwent esophagectomy, mean age=64.3 years	Esophagectomy	High Vs Low volume hospitals	Hospital costs-but components not clear	Length of hospital stay, length of ICU stay, In-hospital mortality, discharge destination
54	Bristow RE, Santillan A, Diaz-Montes TP, et al. Centralisation of care for patients with advanced-stage ovarian cancer: a cost-effectiveness analysis. *Cancer* 2007;**109**(8):1513-22.	Hypothetical cohort of women with advanced-stage ovarian cancer-modelled	Advanced-stage ovarian cancer care	Expert center Vs Less experienced center	Direct costs-costs of primary surgery, chemotherapy regimens, hospitalisation costs for treatment related toxicity Indirect costs- cost of lost productivity, care giver support. Cost components clearly stated.	QALYs

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
55	Greving JP, Vernooij F, Heintz AP, et al. Is centralisation of ovarian cancer care warranted? A cost-effectiveness analysis. *Gynecol Oncol* 2009;**113**(1):68-74.	N=879 ,Hypothetical cohort of women with ovarian cancer and a mean age of 63 years	Ovarian cancer care	General Vs Semi-specialised Vs Tertiary hospitals	Direct costs and included- personnel costs, operating room costs, costs of follow-up monitoring and treatment. Indirect costs were not included.	QALYs, overall survival
56	Fader DJ, Wise CG, Normolle DP, et al. The multidisciplinary melanoma clinic: a cost outcomes analysis of specialty care. *J Am Acad Dermatol* 1998;**38**(5 Pt 1):742-51.	N=208 for cost analysis, N=954 for long-term survival, patients with melanoma (study suffers from a fragmented effectiveness analyses)	Melanoma care	All treatment at Multi-disciplinary Melanoma Clinic Vs Traditional strategy of treating patients referred by physicians for second opinion	Direct costs- costs of office visits/consultations, surgeries, radiology, medical tests, laboratories, pathology, facility and anesthesia included. Indirect costs were not considered.	Short-term outcomes- surgical morbidity, length of hospital stay Long-term outcomes – 5 year survival
57	Regenbogen SE, Gust C, Birkmeyer JD. Hospital Surgical Volume and Cost of Inpatient Surgery in the Elderly. *Journal of the American College of Surgeons* 2012;**215**(6):758-65.	N=101,349,Patients undergoing coronary artery bypass grafting, elective abdominal aortic aneurysm, or colectomy; older than 65 years and younger than 99 years of age; mean age=78.4 years	Inpatient operations for colectomy, coronary artery bypass grafting and elective abdominal aortic aneurysm	Several volume quintiles hospitals	Hospital costs- included costs of index hospitalization, readmissions, physician services, post-discharge ancillary care	Complication, mortality
58	Avritscher EB, Cooksley CD, Rolston KV, et al. Serious postoperative infections following resection of common solid tumors: outcomes, costs, and impact of hospital surgical volume. *Support Care Cancer* 2014;**22**(2):527-35.	N=37,582, >75 years of age patients who underwent resection of cancer of the lung, esophagus, stomach, pancreas, colon, or rectum;	Resection of common surgical tumors	High Vs Intermediate Vs Low volume hospitals	Hospital costs-but cost components not clear	Serious postoperative infection, length of hospital stay, In-hospital mortality

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
59	Kilic A, Shah AS, Conte JV, et al. Operative outcomes in mitral valve surgery: Combined effect of surgeon and hospital volume in a population-based analysis. *The Journal of Thoracic and Cardiovascular Surgery* 2013;**146**(3):638-46.	N=50,152, patients undergoing isolated mitral valve surgery for mitral regurgitation, mean age=61.9 years	Mitral valve surgery	High Vs Intermediate Vs Low volume hospitals and surgeons (surgeons not included in this review)	Hospital costs- but cost components not clear	Operative mortality, mitral valve repair rate
60	Sutton JM, Hoehn RS, Ertel AE, et al. Cost-Effectiveness in Hepatic Lobectomy: the Effect of Case Volume on Mortality, Readmission, and Cost of Care. *Journal of Gastrointestinal Surgery* 2015;**20**(2):253-61.	N= 4163, >18 years of age patients who underwent hepatic lobectomy, mean age= 58 years,	Hepatic lobectomy	High Vs Medium Vs Low volume hospitals	Hospital costs- but components not clear	Peri-operative mortality, Readmissions
61	Kim A, Yoon SJ, Kim YA, et al. The burden of acute myocardial infarction after a regional cardiovascular center project in Korea. *Int J Qual Health Care* 2015;**27**(5):349-55.	N=1469 in each of the two regions, >18 years age patients with acute myocardial infarction	Acute myocardial infarction care	Before regionalisation Vs After regionalisation	Hospital costs-but components not clear	Length of stay
62	Arora S, Panaich SS, Patel N, et al. Impact of Hospital Volume on Outcomes of Lower Extremity Endovascular Interventions (Insights from the Nationwide Inpatient Sample [2006 to 2011]). *The American Journal of Cardiology* 2015;**116**(5):791-800.	N=92,714, >18 years of age patients undergoing peripheral endovascular interventions	Peripheral endovascular interventions	Several volume quartiles hospitals	Hospital costs-but components not clear	In-hospital mortality and peri-procedural complications
63	Wakeam E, Hyder JA, Lipsitz SR, et al. Outcomes and Costs for Major Lung Resection in the United States: Which Patients Benefit Most From High-Volume Referral? *The Annals of Thoracic Surgery* 2015;**100**(3):939-46.	N= 37,746, >18 years of age patients who underwent a major lung resection	Major lung resection	Very high Vs High Vs Moderate Vs Low volume hospitals according to risk groups	Inpatient costs- but components not clear	In-hospital mortality

Table Continued

Table A3 continued: Basic information on included studies

Study Reference	Study	Population sample assessed	Healthcare assessed	Alternatives compared	Costs analysed	Outcomes assessed
64	Bhatt P, Patel NJ, Patel A, et al. Impact of Hospital Volume on Outcomes of Endovascular Stenting for Adult Aortic Coarctation. *The American Journal of Cardiology* 2015;**116**(9):1418-24.	N=105, >18 years of age patients with coarctation of aorta, mean age= 36.9 years,	Treatment of coarctation of aorta	High Vs Low volume hospitals	Hospital costs- but components not clear	Length of stay, complications

QALYs= Quality Adjusted Life Years; ICU= Intensive Care Unit

Appendix B

B1. Ethical approval document from the Ethics Committee

Nawaraj Bhattarai
Health Foundation Doctoral Fellow
Health Economics Group
Institute of Health and Society

Faculty of Medical Sciences
Newcastle University
The Medical School
Framlington Place
Newcastle upon Tyne
NE2 4HH United Kingdom

FACULTY OF MEDICAL SCIENCES: ETHICS COMMITTEE

Dear Nawaraj,

Title: Eliciting public preferences for the provision of emergency medical care
Application No: 00893
Start date to end date: 03-08-2015 to 18-12-2015

On behalf of the Faculty of Medical Sciences Ethics Committee, I am writing to confirm that the ethical aspects of your proposal have been considered and your study has been given ethical approval.

The approval is limited to this project: **00893/2015**. If you wish for a further approval to extend this project, please submit a re-application to the FMS Ethics Committee and this will be considered.

During the course of your research project you may find it necessary to revise your protocol. Substantial changes in methodology, or changes that impact on the interface between the researcher and the participants must be considered by the FMS Ethics Committee, prior to implementation.*

At the close of your research project, please report any adverse events that have occurred and the actions that were taken to the FMS Ethics Committee.*

Best wishes,
Yours sincerely

K. Sutherland

Kimberley Sutherland
On behalf of Faculty Ethics Committee

cc.
Professor Daniel Nettle, Chair of FMS Ethics Committee
Ms Lois Neal, Assistant Registrar (Research Strategy)

*Please refer to the latest guidance available on the internal Newcastle web-site.

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B2. One of the two blocks of questionnaire used in the DCE survey

Survey on Hospital Preferences

(Block-1)

This survey is being carried out by a researcher in health economics at the Institute of Health & Society, Newcastle University. We would like to know what is important to you when thinking about hospitals which provide accident and emergency care. To do this we will ask you to **make a series of choices between two hospitals** which do not exist, but this will allow us to understand what people think is important when designing emergency services. We would like to know which hospital you personally would prefer to go to if you were suddenly unwell and had called 999, and whether your view would change if the hospitals performed differently e.g. reduced or increased waiting times or survival rates. We have not suggested a reason why you would be unwell, but it is not a painful condition. You would require treatment on the same day to feel better and this can only be given in hospital.

The answers you provide here will only be used for research purposes and will not directly affect the healthcare that you need. There are no right or wrong choices, we are just interested in knowing your views. **You cannot be identified from your answers**. Please do not write anything which might give away your identity.

The hospitals **differ** in terms of the following ways:

1) **Travel time to the hospital**: This is the time it takes you to reach the hospital by ambulance.
2) **Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment**: This is the time you need to wait at the A&E to be given specific treatment for your problem by a doctor or nurse.
3) **Length of stay at the hospital before going home:** This is the number of days you need to stay in this hospital.
4) **Risk of dying from the illness:** This is a comparison of the average number of persons dying because of this illness after attending hospital.
5) **Risk of being re-admitted to the hospital after going home:** This is the likelihood of being re-admitted to the hospital after you are discharged.

6) **Outpatient care after emergency treatment:** This is the hospital you need to go for outpatient care after discharge following your emergency treatment.

All other aspects of the two hospitals are the same.

Example of the task (*Please do not fill this one*)

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, Hospital A and Hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	Hospital B
Travel time to hospital	1 and half hours	1 hour
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	4 hours or more	Less than 30 minutes
Length of stay at the hospital before going home	3 days	5 days
Risk of dying from the illness	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box)	☐	☐

In this example,

- It takes 1 and half hours to reach hospital A and takes 1 hour to reach hospital B.
- You need to wait 4 hours or more in the A&E to be treated in hospital A, but less than 30 minutes hospital B.
- The length of stay in Hospital A is 3 days whereas it is 5 days in Hospital B.
- Patient has moderate risks of death in Hospital A but has mild risks in Hospital B.

- The risk of being re-admitted is mild for Hospital A and is moderate for Hospital B.
- Outpatient care, after emergency treatment, at hospital B is provided at local hospital and at hospital A is provided at a hospital which is about 1 hour travel time away from the local hospital.

  Here if hospital B is chosen, the box in the Hospital B column is marked with a √ in the box. Or if hospital A is chosen, the box in the Hospital A column is marked with √**.**

In addition, we will ask you few other questions about you, but remain assured that no questions will identify who you are.

It takes about 15 minutes to complete the survey. Your participation in this survey is voluntary and you can stop at any time without providing any reason. If you do complete the survey it is not possible to remove your answers later. We cannot identify them, but nobody else will know your answers either. Should you have any queries regarding the survey you can contact the researcher on this telephone 01912087821, or email: nawaraj.bhattarai@ncl.ac.uk .

If you agree to take part in this survey, then please choose which emergency hospital you would like to go to in the following situations. **Please note that in each of the situations the characteristics of hospitals change**.

For each situation please indicate which hospital you prefer by putting a tick (√) in the appropriate box.

Scenario 1

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	1 hour	1 and half hours
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	2 and half hours	1 hour
Length of stay at the hospital before going home	3 days	5 days
Risk of dying from the illness	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Risk of being re-admitted to the hospital after going home	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Outpatient care after emergency treatment	At your local hospital	At a hospital which is about an extra 1 hour travel time from your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 2

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	1 hour	1 and half hours
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	1 hour	2 and half hours
Length of stay at the hospital before going home	5 days	3 days
Risk of dying from the illness	High (7 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 3

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	2 hours or more	Less than 30 minutes
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	4 hours or more	1 hour
Length of stay at the hospital before going home	1 day or less	6 days or more
Risk of dying from the illness	Low (1 in 100 patients)	High (7 in 100 patients)
Risk of being re-admitted to the hospital after going home	High (7 in 100 patients)	Low (1 in 100 patients)
Outpatient care after emergency treatment	At your local hospital	At a hospital which about an extra 1 hour travel time from your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 4

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	1 hour	1 and half hours
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	4 hours or more	Less than 30 minutes
Length of stay at the hospital before going home	5 days	3 days
Risk of dying from the illness	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Outpatient care after emergency treatment	At your local hospital	At a hospital which is about an extra 1 hour travel time from your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 5

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	1 and half hours	1 hour
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	2 and half hours	1 hour
Length of stay at the hospital before going home	3 days	5 days
Risk of dying from the illness	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 6

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	Less than 30 minutes	1 and half hours
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	1 hour	2 and half hours
Length of stay at the hospital before going home	6 days or more	3 days
Risk of dying from the illness	High (7 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	Low (1 in 100 patients)	Mild (3 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 7

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	2 hours or more	Less than 30 minutes
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	Less than 30 minutes	4 hours or more
Length of stay at the hospital before going home	6 days or more	1 day or less
Risk of dying from the illness	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	Low (1 in 100 patients)	High (7 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 8

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	1 and half hours	1 hour
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	1 hour	2 and half hours
Length of stay at the hospital before going home	3 days	5 days
Risk of dying from the illness	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Risk of being re-admitted to the hospital after going home	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Outpatient care after emergency treatment	At your local hospital	At a hospital which is about an extra 1 hour travel time from your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 9

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	2 hours or more	1 and half hours
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	4 hours or more	2 and half hours
Length of stay at the hospital before going home	1 day or less	3 days
Risk of dying from the illness	Low (1 in 100 patients)	Mild (3 in 100 patients)
Risk of being re-admitted to the hospital after going home	High (7 in 100 patients)	Mild (3 in 100 patients)
Outpatient care after emergency treatment	At your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 10

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	Less than 30 minutes	2 hours or more
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	1 hour	2 and half hours
Length of stay at the hospital before going home	1 day or less	6 days or more
Risk of dying from the illness	High (7 in 100 patients)	Low (1 in 100 patients)
Risk of being re-admitted to the hospital after going home	Low (1 in 100 patients)	High (7 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 11

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	Less than 30 minutes	2 hours or more
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	2 and half hours	1 hour
Length of stay at the hospital before going home	6 days or more	1 day or less
Risk of dying from the illness	Low (1 in 100 patients)	High (7 in 100 patients)
Risk of being re-admitted to the hospital after going home	Moderate (5 in 100 patients)	Mild (3 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 12

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	2 hours or more	Less than 30 minutes
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	4 hours or more	Less than 30 minutes
Length of stay at the hospital before going home	6 days or more	1 day or less
Risk of dying from the illness	High (7 in 100 patients)	Low (1 in 100 patients)
Risk of being re-admitted to the hospital after going home	High (7 in 100 patients)	Low (1 in 100 patients)
Outpatient care after emergency treatment	At a hospital which is about an extra 1 hour travel time from your local hospital	At your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Scenario 13

Imagine you have an emergency healthcare need which requires calling an ambulance. Below are two hospitals, hospital A and hospital B, each with different characteristics. If you have a choice, which hospital would you choose from below?

	Hospital A	**Hospital B**
Travel time to hospital	1 and half hours	1 hour
Waiting time in the A&E department to be seen by a doctor or nurse who can provide treatment	Less than 30 minutes	4 hours or more
Length of stay at the hospital before going home	5 days	3 days
Risk of dying from the illness	Mild (3 in 100 patients)	Moderate (5 in 100 patients)
Risk of being re-admitted to the hospital after going home	High (7 in 100 patients)	Low (1 in 100 patients)
Outpatient care after emergency treatment	At your local hospital	At a hospital which is about an extra 1 hour travel time from your local hospital
Which hospital would you choose to go in an emergency? (Please tick one box**)**	☐	☐

Could you please indicate how easy or difficult it has been to complete the above choice sets (Please tick only one of the boxes)

Very difficult ☐

Difficult ☐

Somewhat Difficult ☐

Neutral ☐

Somewhat Easy ☐

Easy ☐

Very Easy ☐

Finally, we would be grateful if you could provide the following information about you. (Remain assured that no questions will identify who you are)

Are you a male or female? (Please tick one of the boxes below)

Male ☐

Female ☐

Prefer not to say ☐

Which of the following age group do you belong to? (Please tick one of the boxes below)

16-29 ☐ 30-34 ☐ 35-39 ☐

40-44 ☐ 45-49 ☐ 50-54 ☐

55-59 ☐ 60-64 ☐ 65-69 ☐

70-75 ☐ 75-79 ☐ 80-84 ☐

85+ ☐

What is your post code? (Please fill in below; we only need your partial post code, not the house/flat or street name, example NE30)

What is the name of the GP surgery you are registered with? (Please write in the space below. Please note we will not contact them. This is simply to help understand the results of the survey better).

……

In the last 12 months how many times have you visited the hospital with emergency healthcare need?

0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 or more ☐

Under each heading, please tick the ONE box that best describes your current state of health.

MOBILITY

I have no problems in walking about ☐

I have slight problems in walking about ☐

I have moderate problems in walking about ☐

I have severe problems in walking about ☐

I am unable to walk about ☐

SELF-CARE

I have no problems washing or dressing myself ☐

I have slight problems washing or dressing myself ☐

I have moderate problems washing or dressing myself ☐

I have severe problems washing or dressing myself ☐

I am unable to wash or dress myself ☐

USUAL ACTIVITIES (e.g. work, study, housework, family or leisure activities)

I have no problems doing my usual activities ☐

I have slight problems doing my usual activities ☐

I have moderate problems doing my usual activities ☐

I have severe problems doing my usual activities ☐

I am unable to do my usual activities ☐

PAIN / DISCOMFORT

I have no pain or discomfort ☐

I have slight pain or discomfort ☐

I have moderate pain or discomfort ☐

I have severe pain or discomfort ☐

I have extreme pain or discomfort ☐

ANXIETY / DEPRESSION

I am not anxious or depressed ☐

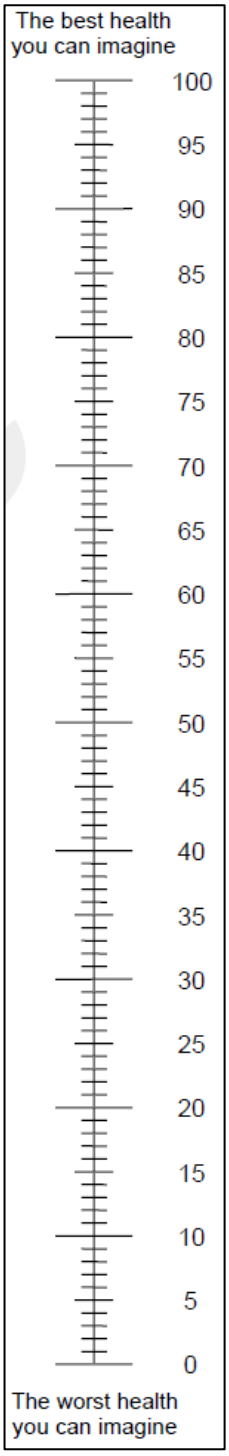
I am slightly anxious or depressed ☐

I am moderately anxious or depressed ☐

I am severely anxious or depressed ☐

I am extremely anxious or depressed ☐

How would you rate the current state of your health? (Please indicate by marking whichever point on the scale below indicates how good or bad your health state is today, imagining best state is marked 100 and the worst state is marked 0**)**



Now please write the number you marked on the scale in the box below

Your health today = ☐

Thank you for taking part in this survey.

B3. Email confirming the approval of Caldicott proposal form regarding the use of HES data

From: Christopher Price
Sent: 20 November 2018 13:59
To: Nawaraj Bhattarai; Peter McMeekin
Subject: FW: Caldicott Request Re-organisation of Emergency Medical Services
Attachments: CaldicottApprovalFormv912112012 Chris Price.pdf

Hi – here's the Caldicott form and the email confirming approval.
Chris

From: Hetherington Ellis (RTF) NHCT
Sent: Tuesday, July 23, 2013 11:00 AM
To: Price Christopher (RTF) NHCT
Subject: Caldicott Request Re-organisation of Emergency Medical Services

Your Caldicott proposal form entitled Re-organisation of Emergency Medical Services which has been given reference C2678 has been approved, but with the following security /confidentiality instruction:

1. No patient identifiable data is to be stored on a laptop.

2. No patient identifiable data to be stored on any removable media for example CD, floppy disc or USB.

3. Patient identifiable data must be stored on the secure systems and networks only.

4. No identifiable patient information can be used in any reports, publications or presentations.

If you disregard any of the above you are in breach of Caldicott approval and may result in disciplinary action.

The signed form is being returned to you today.

Ellis Hetherington
Business Admin Apprentice
Computer Services
Cobalt Business Park

Tel: 0191 2031278

B4. Caldicott proposal form regarding the use of HES data

For office use only			
Ref. no:		**Date Received**	

Northumbria Healthcare NHS
NHS Foundation Trust

Use & Release of Personal Identifiable Data (Caldicott Approval Form)

-**(Please print clearly)**

Introduction

The purpose of the Request for Use or Release of Person-identifiable Data Form is to record the details of identifiable information sent from the Trust to other partners/agencies/organisations. This will ensure that all data flows of personal and/or sensitive information, including healthcare, medical and non-medical, are conducted in a secure and confidential manner and approved by the Trust Caldicott Guardian where necessary.

Division/Directorate: **Medicine**

Data Flow Title: Re-organisation of Emergency Medical Services

Description of proposal:
This is a health services research collaboration between Northumbria Healthcare (Chris Price; Kate Martin; Birju Rana) and Newcastle University (Peter Mc Meekin) funded by Northumbria R&D with Trust CPG approval. The purpose is to understand the impact on mortality and readmissions of centralising emergency admissions to the Northumbria Specialist Emergency Care Hospital. Using complex modelling methods we aim to establish how health outcomes for patients with a representative range of conditions are affected by the relocation of emergency medical services from three sites into a single large central site. We will do this using routinely collected data to observe the effects of the change in configuration of emergency medical services on outcomes, and identify the effects that the change might have on certain groups of patients i.e. stratified by age and geography. This application is to seek approval for the transfer of a spreadsheet containing 2 years worth of Northumbria hospitals emergency admissions data to the Institute of Health and Society at Newcastle University which will include for each admission the ICD10 code for healthcare episodes, outcome (alive/dead), hospital site, GP practice code, age, gender and first three characters of the patient residential postcode.

Identify purpose:

Healthcare Medical Purpose (Primary) ☐ **Non-Healthcare Medical Purpose (Secondary)** X **Non-Medical Purpose** ☐

Indicate which data items have been requested:

Forename: ☐ **Surname:** ☐ **DoB:** ☐ **Age:** X **Sex:** X **Address:** ☐

Postcode: X **(first 3 characters)** **NHS No.** ☐ **Ethnic Origin** ☐

Other (please specify) ICD 10 codes at discharge from hospital, GP practice code

Time period for data required: **Start date: 01/09/13** **End date: 01/09/15**

Please state regularity e.g. monthly. Two occasions (before and after NSECH opening)

Trust appointed person/Safe Haven responsible for release of data :

Name: Christopher Price **Title: Consultant**

Division: **Department: Medicine**

Address: Wansbeck General Hospital

Telephone: ext 3302 **Email: christopher.price@nhct.nhs.uk**

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Ref. no:		**Date Received**	

Receiving Organisation/individual

Organisation Name: Institute for Health and Society, Newcastle University
Adddress: The Baddiley-Clark Building, Richardson Road, Newcastle upon Tyne NE2 4AX

Appointed person responsible for data: Dr Peter McMeekin (research principal, health economics)

Contact details: as above **Email address: peter.mcmeekin@ncl.ac.uk**

Recipients location for receiving and processing Trust data:

NHS Organisation ☐ **Government Dept.** ☐ **UK X**

EEA Country ☐ **Non EEA Country** ☐

Who else will have access to the data?
(If data recipients are not employed by the NHS please state whether NHS honorary contracts are in place. If not – detail confidentiality agreements.)
Peter McMeekin (research principal) Health Economics department, IHS, Newcastle University. An honorary contract has previously been held for a different project but expired. A new one is being processed.

Method of secure information / data transfer (please tick):

NHSmail.net ☐ **Secure fax** ☐ **Removable media encryption AES 256 X**

Email (secured) ☐ **Special Delivery / courier** ☐ **Electronic File Transfer** ☐

Trust Safe Haven ...Data will pass from Kate Martin (clinical coding) via NHCT email to Chris Price for transfer to encrypted USB memory stick. Safe haven is Chris Price Northumbria Healthcare H: drive.

Please describe the applicable security arrangements for the transfer: (ie xx@nhs.net to xx@nhs.net)
Data will be on a single Excel spreadsheet with password protection. This will be transferred onto a trust-approved encrypted USB memory stick owned by Chris Price, and taken by Chris Price to Peter McMeekin at Newcastle University in person.

How will the service users be contacted? N/A

What information will be given to the service user about the purpose?

How will the service users consent be obtained?

If no consent being obtained, please detail the reason why not e.g. exemption under Section 251 of the NHS Act 2006. This is health services research using only routinely collected data which will not identify individuals. It will be used to model different future service scenarios not to impact upon current clinical care. This has been approved by Northumbria Trust Governors.

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Ref. no:		**Date Received**	

How long will the data be stored? 12 months

Where will the data be physically stored: Password protected server at Newcastle University, accessible only to Peter MckMeekin

If the data is on a computer is there access via a local network or the internet? Not via internet but it will be accessible by only Peter McMeekin through the university network within the IHS research institute. Research institute network access is only granted to employees of Newcastle University and as the NIHR host for regional academic public health research, is already considered a secure location for data storage.

How will data be protected? (Please detail security measures to be taken).
The spreadsheet will have its own password protection, and will be held only within a server account under Peter McMeekin's university login and password.

At the end of this period how will the data be disposed? Irretrievable deletion confirmed by Newcastle University computer services to Chris Price.

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Ref. no:		**Date Received**	

You must address the 6 Caldicott Principles – please give a brief description under each of the following headings

Principle 1 - **Justify the purpose(s)**
Every proposed use or transfer of service user-identifiable information within or from an organisation should be clearly defined and scrutinised, with continuing uses regularly reviewed, by an appropriate guardian.
It is important that any new health service development considers the impact upon patient care. By using existing coding data we can model the possible effects of a large scale changed in emergency care provision for patients living within the trust boundary. This modelling is a specialised process which cannot be done within the trust and requires expertise based at the partner university. This project has backing from R&D, trust CPG and the NSECH steering group. Regular updates will be provided to these groups.

Principle 2 - **Don't use service user-identifiable information unless it is absolutely necessary**
Service user-identifiable information items should not be included unless it is essential for the specified purpose(s) of that flow. The need for service users to be identified should be considered at each stage of satisfying the purpose(s).
The impact of this analysis will have the greatest patient benefit if it can consider age, gender and patient location. Other identifiable information (e.g. name) is not being requested. In case Peter McMeekin has a query about a record, clinical coding will assign each record with a unique numerical code unrelated to any other data so that a trust employee can then assist.

Principle 3 - Use the minimum necessary service user-identifiable information
Where use of service user-identifiable information is considered to be essential, the inclusion of each individual item of information should be considered and justified so that the minimum amount of identifiable information is transferred or accessible as is necessary for a given function to be carried out.
It is essential that the data includes ICD10 code and outcome (alive/dead). We do not require DOB as age can be provided, and only first 3 characters of postcode will suffice for geographical modelling.

Principle 4 - Access to service user-identifiable information should be on a strictly need-to-know basis
Only those individuals who need access to service user-identifiable information should have access to it, and they should only have access to the information items that they need to see. This may mean introducing access controls or splitting information flows where one information flow is used for several purposes.
Only Dr Peter McMeekin will have access to age, gender and postcode data.

Principle 5 - Everyone with access to service user-identifiable information should be aware of their responsibilities
Action should be taken to ensure that those handling service user-identifiable information - both clinical and non-clinical staff - are made fully aware of their responsibilities and obligations to respect service user confidentiality.
IHS is host to the regional academic public health network ("FUSE") and already supports a large number of projects involving primary and secondary healthcare data, including previous collaborations with NHCT. Dr Peter McMeekin is an experienced health economist who has a long term contract with Newcastle University, and has undertaken previous projects with NHCT and other NHS trusts in the region (e.g. stroke, falls).

Principle 6 - Understand and comply with the law
Every use of service user-identifiable information must be lawful. Someone in each organisation handling service user information should be responsible for ensuring that the organisation complies with legal requirements.
Dr Christopher Price will carry this responsibility, and has done for previous health services research projects as well as clinical trials.

Other supporting information e.g. Ethics approval, correspondence etc

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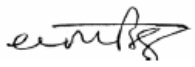
Ref. no:		**Date Received**	

I confirm that the data will be held and used according to the conditions and information given as described within this approval from.

Name:…Christopher Price…….. Title: Consultant……..……

Signature: ….  …… Date:…19/07/2013……..……

If the form has been completed by a Medical Student or other similar training posts a supervisory signature or equivalent is required below:

Name:…….. Title:……..……

Signature: …… Date:……..

Please return the form to :

Deputy Caldicott Guardian **Northumbria Healthcare NHS Foundation Trust:**	**Caldicott Guardian** **Northumbria Healthcare NHS Foundation Trust:**
Tracey Best Information Governance Manager Computer Services Northumbria House 7/8 Silver Fox Way Cobalt Business Park North Shields NE27 0QJ	Mr Dave Evans Medical Director / Consultant Obstetrics and Gynaecology Department North Tyneside General Hospital Rake Lane North Shields NE29 8NH

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Approving Officer please identify the type of data to be provided:

Identifiable Data ☐ Anomymised ☐ Pseudonymised ☐

Approving Officer please identify whether an Information Sharing Protocol or Third Party Data Transfer Agreement is required.

- Information Sharing Protocol Required ☐
- Third Party Data Transfer Agreement Required ☐

The release and use of data as described above: **approved / not approved**

Justification :……

Caldicott Guardian/Delegated Authority signature…… Date:……..

Recipient copy sent/informed by (name): …… Date:……..

All staff given access to the data will be made aware of these conditions (principle 5)

1. The data will be treated as confidential.
2. The data will be used only for the purposes described.
3. In the case of anonymised or confidential aggregated data, no attempt will be made to identify or contact individuals or organisations identified through these data.
4. The data may be disclosed to staff of the above organisation but only for the purposes described.
5. The data may not be disclosed to any third party.
6. The data will be stored in secure condition at all times whether held on computer medium or as a printed copy.
7. The organisation to which the data are released will maintain and comply with a Data Protection Registration which encompasses the data and data usage described.
8. When the purpose has been completed the data will be securely destroyed in line with NHS approved information destruction/deletion standards (printed copies securely shredded, files securely deleted from computer systems (including any copies held on backup or archive media) and appropriately certificated)
9. Assurance/certificates of secure disposal must be sent to the department above

Appendix C

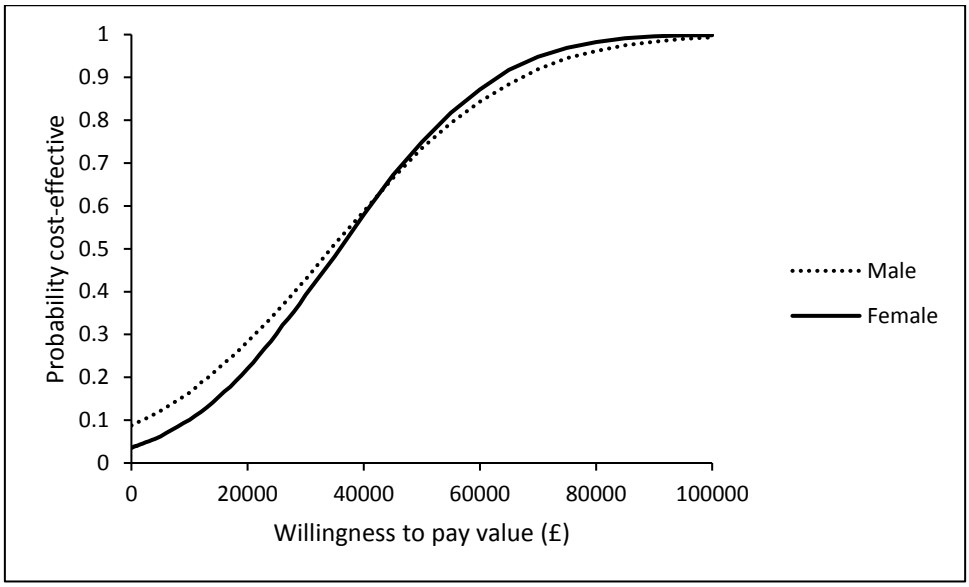

Figure C1: Multiple CEAC for sub-groups of Males and Females at 30 days

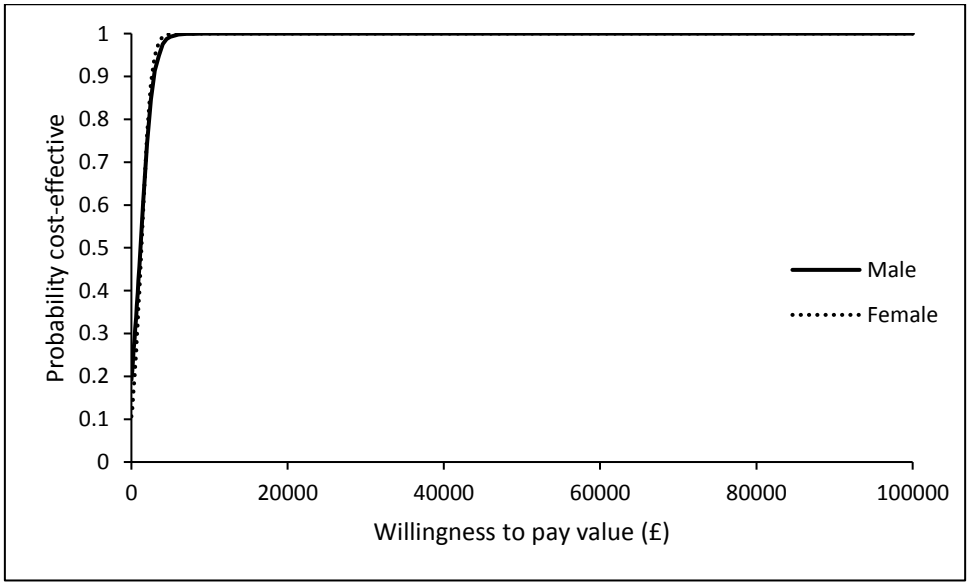

Figure C2: Multiple CEAC for sub-groups of Males and Females at one year

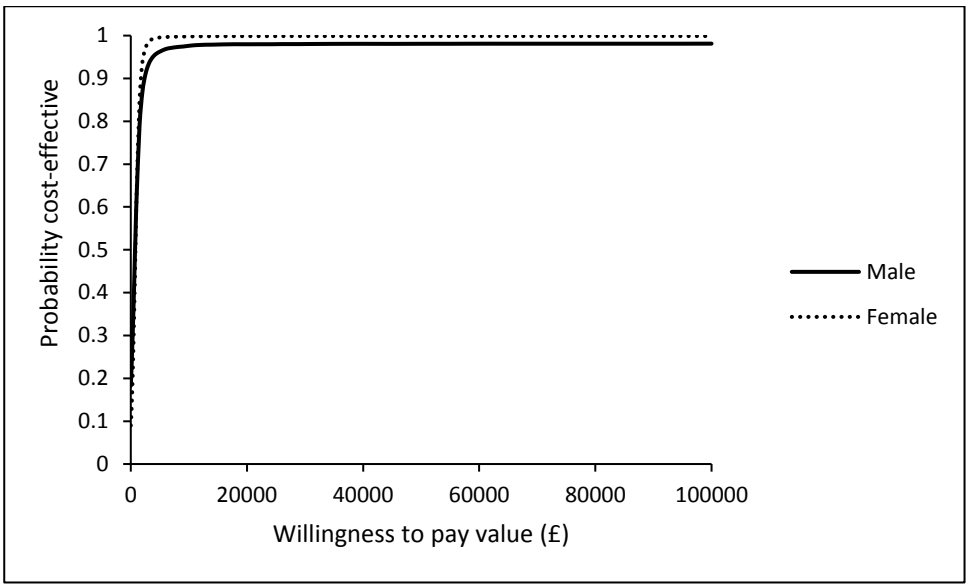

Figure C3: Multiple CEAC for sub-groups of Males and Females at 10 years

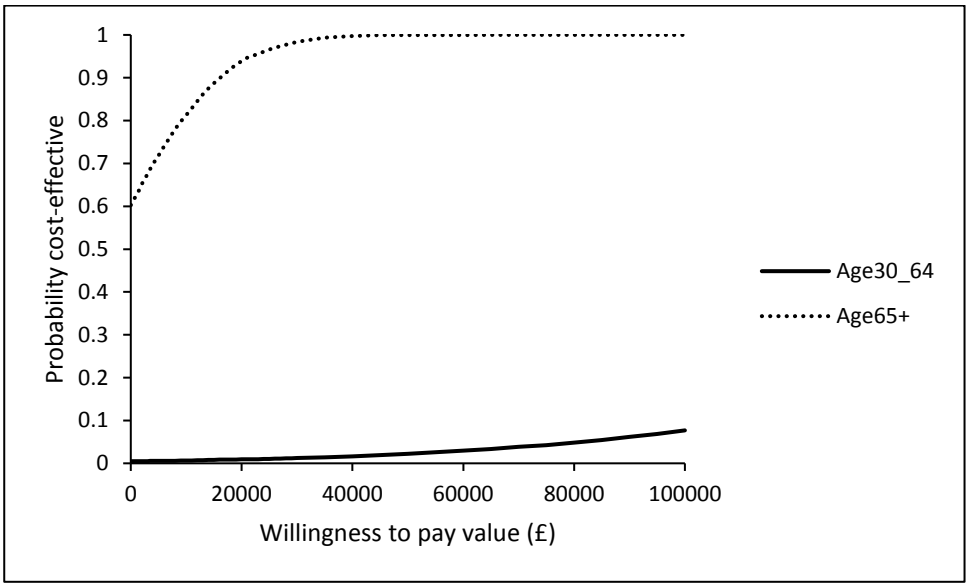

Figure C4: Multiple CEAC for sub-groups of Age 30-64 and Age 65 or over at 30 days

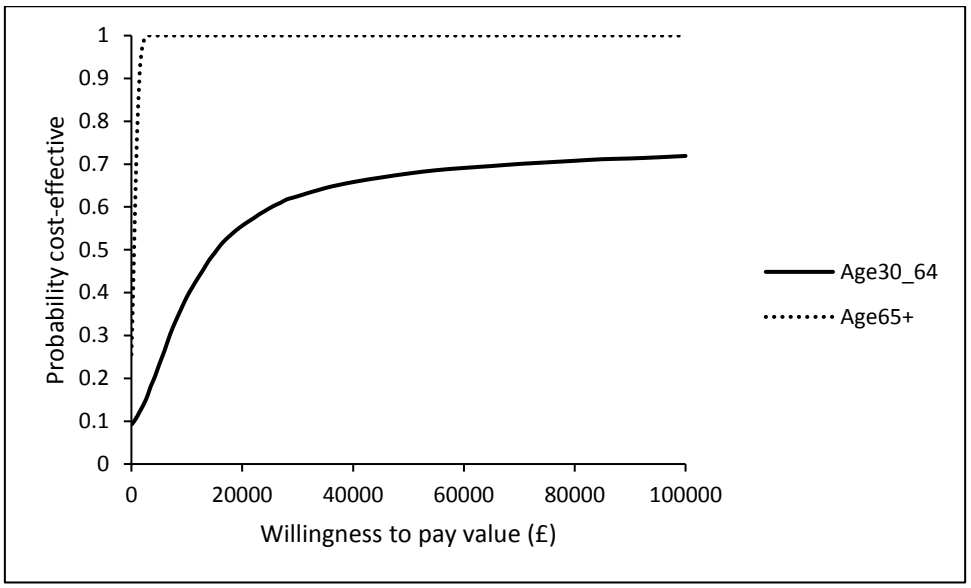

Figure C5: Multiple CEAC for sub-groups of Age 30-64 and Age 65 or over at one year

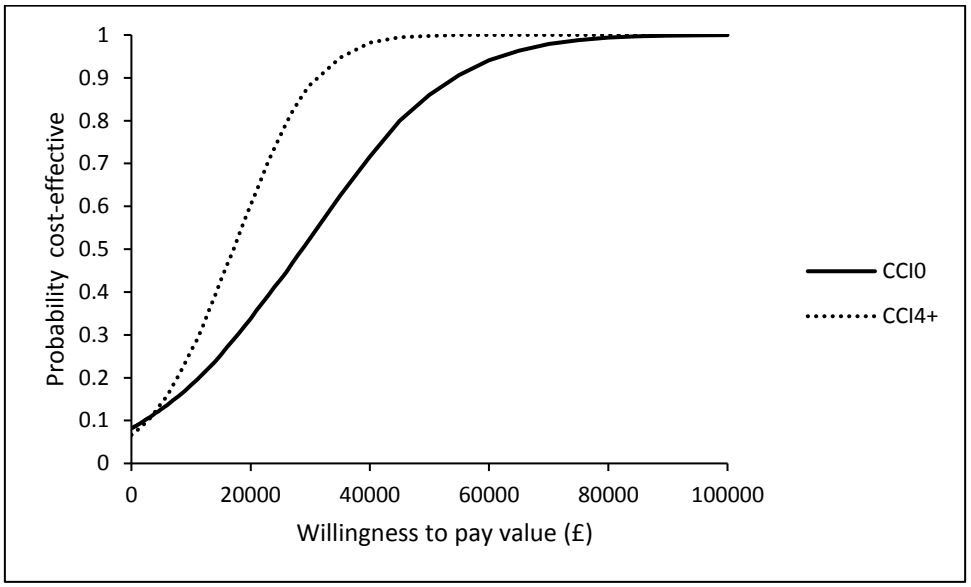

Figure C6: Multiple CEAC for sub-groups of CCI0 and CCI4 at 30 days

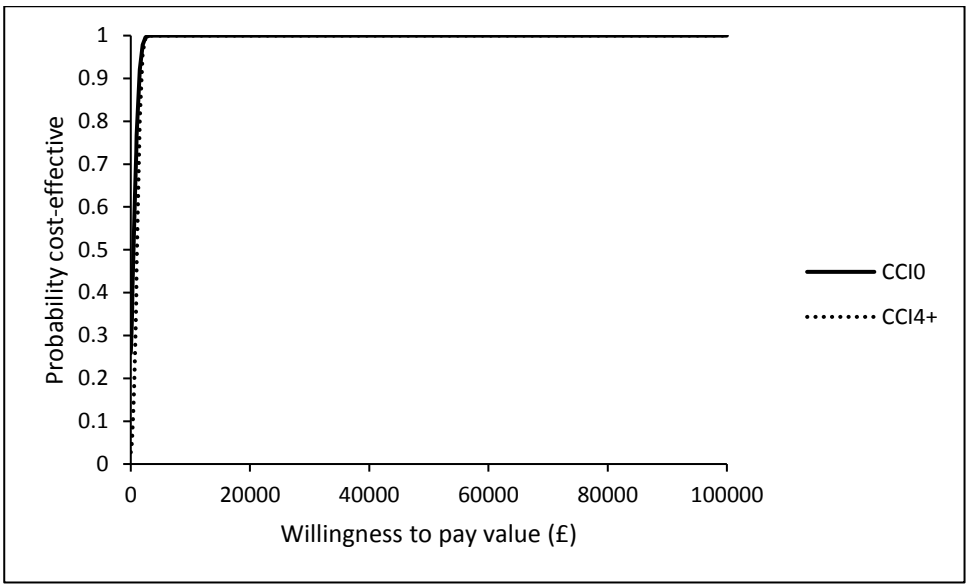

Figure C7: Multiple CEAC for sub-groups of CCI0 and CCI4 at one year

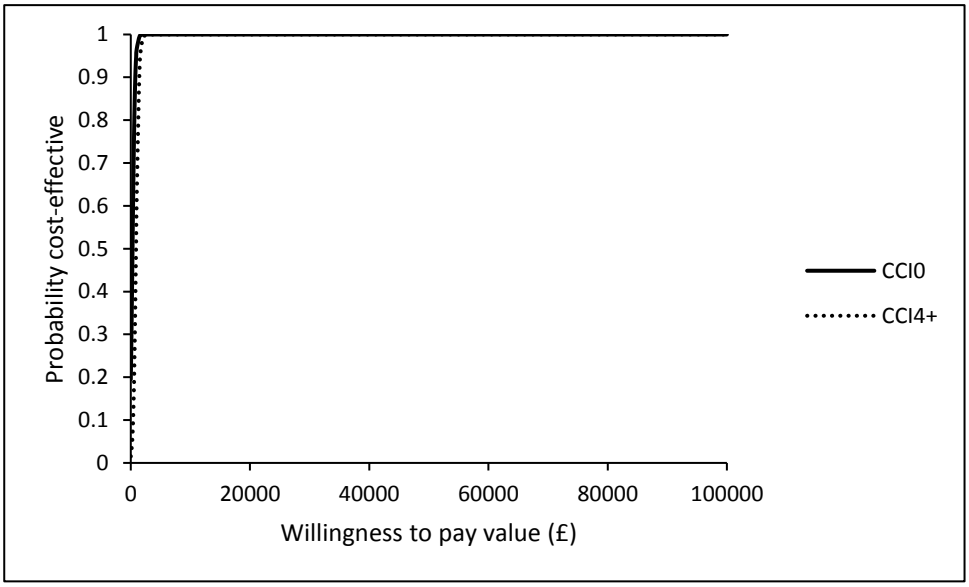

Figure C8: Multiple CEAC for sub-groups of CCI0 and CCI4 at 10 years

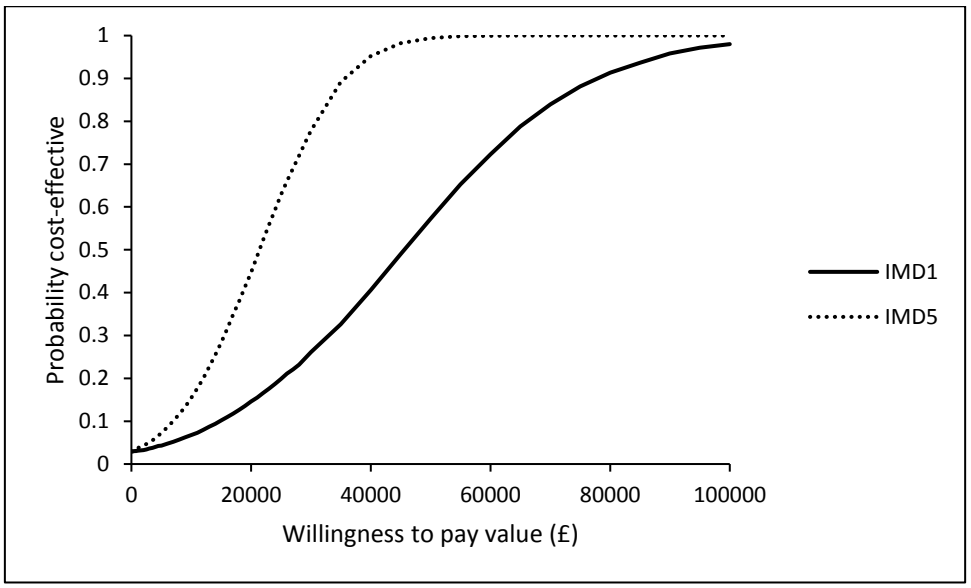

Figure C9: Multiple CEAC for sub-groups of IMD1 and IMD5 at 30 days

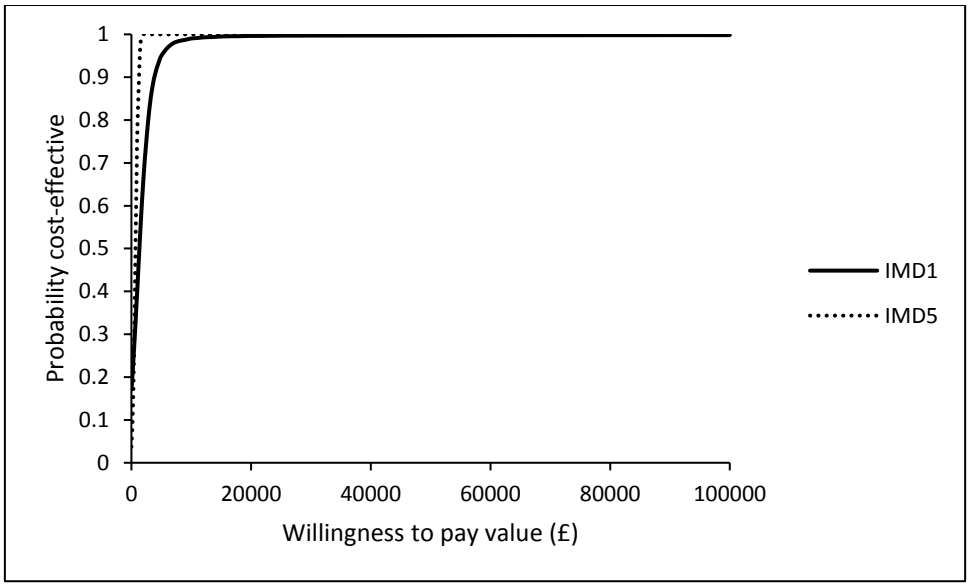

Figure C10: Multiple CEAC for sub-groups of IMD1 and IMD5 at one year

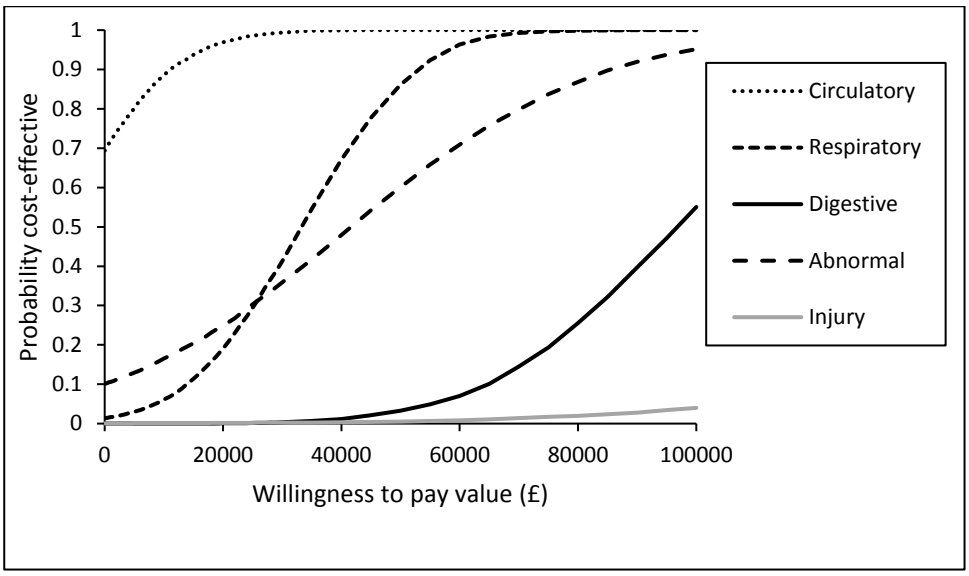

Figure C11: Multiple CEAC for sub-groups of disease at 30 days

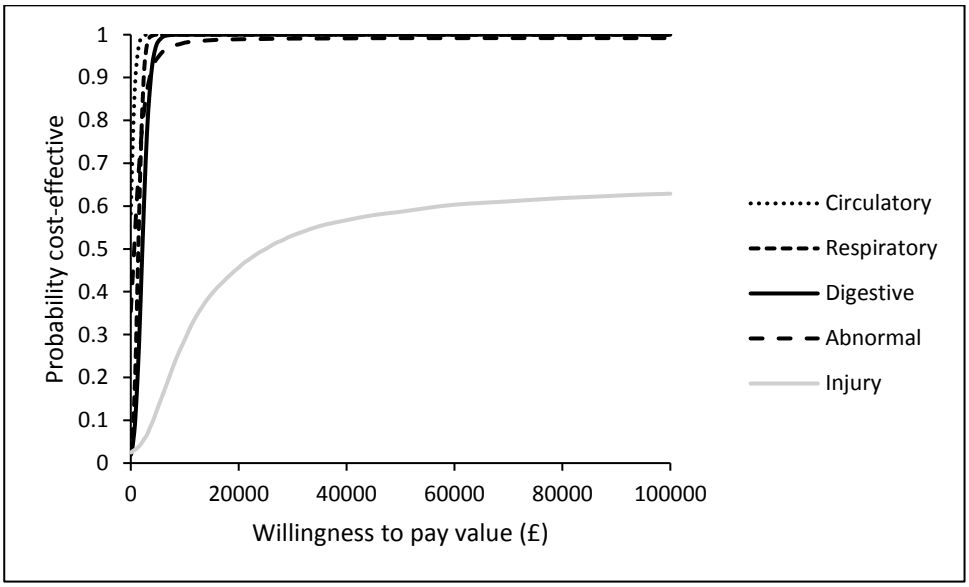

Figure C12: Multiple CEAC for sub-groups of disease at one year

Table C1: Transition probabilities for the first 30 days used in the local hospital – Base case

Day	Transition probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9744	0.0215 (0.0002)	0.0041 (0.0001)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.7669	0.22 (0.0008)	0.0131 (0.0002)
2	0.9669	0.0283 (0.0003)	0.0048 (0.0001)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.6547	0.3238 (0.0009)	0.0215 (0.0003)
3	0.9614	0.0333 (0.0003)	0.0053 (0.0001)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.5726	0.3992 (0.001)	0.0282 (0.0003)
4	0.9570	0.0373 (0.0003)	0.0057 (0.0001)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.5076	0.4585 (0.001)	0.0339 (0.0004)
5	0.9533	0.0407 (0.0003)	0.006 (0.0001)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.4541	0.5071 (0.001)	0.0388 (0.0004)
6	0.9499	0.0438 (0.0004)	0.0063 (0.0001)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.4089	0.548 (0.001)	0.0431 (0.0004)
7	0.9470	0.0465 (0.0004)	0.0065 (0.0001)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.3702	0.583 (0.001)	0.0468 (0.0004)
8	0.9442	0.0491 (0.0004)	0.0067 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.3365	0.6133 (0.0009)	0.0502 (0.0004)
9	0.9417	0.0514 (0.0004)	0.0069 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.3070	0.6398 (0.0009)	0.0532 (0.0004)
10	0.9393	0.0536 (0.0004)	0.0071 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.2810	0.6631 (0.0009)	0.0559 (0.0004)
11	0.9372	0.0556 (0.0004)	0.0072 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.2578	0.6839 (0.0009)	0.0583 (0.0005)
12	0.9351	0.0575 (0.0004)	0.0074 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.2372	0.7023 (0.0009)	0.0605 (0.0005)
13	0.9331	0.0594 (0.0004)	0.0075 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.2186	0.7189 (0.0009)	0.0625 (0.0005)
14	0.9313	0.0611 (0.0004)	0.0076 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.2018	0.7338 (0.0009)	0.0644 (0.0005)
15	0.9294	0.0628 (0.0004)	0.0078 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1866	0.7473 (0.0009)	0.0661 (0.0005)
16	0.9277	0.0644 (0.0004)	0.0079 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1729	0.7595 (0.0008)	0.0676 (0.0005)
17	0.9261	0.0659 (0.0004)	0.008 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1604	0.7706 (0.0008)	0.069 (0.0005)
18	0.9245	0.0674 (0.0004)	0.0081 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1490	0.7807 (0.0008)	0.0703 (0.0005)
19	0.9229	0.0689 (0.0004)	0.0082 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1386	0.7899 (0.0008)	0.0715 (0.0005)
20	0.9214	0.0703 (0.0005)	0.0083 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1289	0.7984 (0.0008)	0.0727 (0.0005)
21	0.9200	0.0716 (0.0005)	0.0084 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1202	0.8061 (0.0008)	0.0737 (0.0005)
22	0.9186	0.0729 (0.0005)	0.0085 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1121	0.8132 (0.0008)	0.0747 (0.0005)
23	0.9173	0.0742 (0.0005)	0.0085 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.1047	0.8198 (0.0008)	0.0755 (0.0005)
24	0.9160	0.0754 (0.0005)	0.0086 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.0978	0.8258 (0.0007)	0.0764 (0.0005)
25	0.9147	0.0766 (0.0005)	0.0087 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.0916	0.8313 (0.0007)	0.0771 (0.0005)
26	0.9134	0.0778 (0.0005)	0.0088 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.0857	0.8365 (0.0007)	0.0778 (0.0005)
27	0.9121	0.079 (0.0005)	0.0089 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.0803	0.8412 (0.0007)	0.0785 (0.0005)
28	0.9110	0.0801 (0.0005)	0.0089 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.0753	0.8456 (0.0007)	0.0791 (0.0005)
29	0.9098	0.0812 (0.0005)	0.009 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.0706	0.8497 (0.0007)	0.0797 (0.0005)
30	0.9086	0.0823 (0.0005)	0.0091 (0.0002)	0.3754	0.6215 (0.0010)	0.0031 (0.0001)	0.0662	0.8535 (0.0007)	0.0803 (0.0005)

Table C2: Transition probabilities for the first 30 days used in the central hospital- Base case

Day	Transition probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9830	0.0137 (0.0004)	0.0033 (0.0002)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.7828	0.2112 (0.0016)	0.006 (0.0002)
2	0.9765	0.0194 (0.0005)	0.0041 (0.0002)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.6615	0.3272 (0.002)	0.0113 (0.0004)
3	0.9718	0.0236 (0.0005)	0.0046 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.5702	0.4139 (0.0021)	0.0159 (0.0004)
4	0.9676	0.0273 (0.0006)	0.0051 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.4971	0.4829 (0.0021)	0.02 (0.0005)
5	0.9642	0.0304 (0.0006)	0.0054 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.4366	0.5397 (0.0021)	0.0237 (0.0006)
6	0.9609	0.0333 (0.0006)	0.0058 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.3858	0.5872 (0.0021)	0.027 (0.0006)
7	0.9580	0.0359 (0.0007)	0.0061 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.3425	0.6276 (0.0021)	0.0299 (0.0006)
8	0.9554	0.0383 (0.0007)	0.0063 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.3051	0.6623 (0.002)	0.0326 (0.0007)
9	0.9528	0.0406 (0.0007)	0.0066 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.2728	0.6923 (0.002)	0.0349 (0.0007)
10	0.9505	0.0427 (0.0007)	0.0068 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.2444	0.7185 (0.0019)	0.0371 (0.0007)
11	0.9482	0.0448 (0.0008)	0.007 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.2196	0.7414 (0.0019)	0.039 (0.0007)
12	0.9461	0.0467 (0.0008)	0.0072 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.1977	0.7615 (0.0018)	0.0408 (0.0007)
13	0.9440	0.0486 (0.0008)	0.0074 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.1784	0.7793 (0.0017)	0.0423 (0.0007)
14	0.9421	0.0504 (0.0008)	0.0075 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.1612	0.795 (0.0017)	0.0438 (0.0007)
15	0.9402	0.0521 (0.0008)	0.0077 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.1459	0.809 (0.0016)	0.0451 (0.0008)
16	0.9383	0.0538 (0.0008)	0.0079 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.1322	0.8215 (0.0016)	0.0463 (0.0008)
17	0.9366	0.0554 (0.0008)	0.008 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.1199	0.8327 (0.0015)	0.0474 (0.0008)
18	0.9350	0.0569 (0.0009)	0.0081 (0.0003)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.1090	0.8426 (0.0015)	0.0484 (0.0008)
19	0.9333	0.0584 (0.0009)	0.0083 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0991	0.8516 (0.0014)	0.0493 (0.0008)
20	0.9317	0.0599 (0.0009)	0.0084 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0903	0.8596 (0.0014)	0.0501 (0.0008)
21	0.9302	0.0613 (0.0009)	0.0085 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0823	0.8669 (0.0014)	0.0508 (0.0008)
22	0.9286	0.0627 (0.0009)	0.0087 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0751	0.8734 (0.0013)	0.0515 (0.0008)
23	0.9271	0.0641 (0.0009)	0.0088 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0685	0.8793 (0.0013)	0.0522 (0.0008)
24	0.9257	0.0654 (0.0009)	0.0089 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0626	0.8846 (0.0013)	0.0528 (0.0008)
25	0.9243	0.0667 (0.0009)	0.009 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0573	0.8894 (0.0012)	0.0533 (0.0008)
26	0.9229	0.068 (0.0009)	0.0091 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0524	0.8938 (0.0012)	0.0538 (0.0008)
27	0.9215	0.0693 (0.0009)	0.0092 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0481	0.8977 (0.0012)	0.0542 (0.0008)
28	0.9202	0.0705 (0.0009)	0.0093 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0441	0.9013 (0.0011)	0.0546 (0.0008)
29	0.9189	0.0717 (0.001)	0.0094 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0404	0.9046 (0.0011)	0.055 (0.0008)
30	0.9176	0.0729 (0.001)	0.0095 (0.0004)	0.3670	0.6298 (0.0021)	0.0032 (0.0002)	0.0370	0.9076 (0.0011)	0.0554 (0.0008)

Table C3: Transition probabilities for the first 30 days used in the local hospital- Age group <=29

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9784	0.0215(0.0007)	0.0001 (0.0001)	0.646	0.353 (0.003)	0.000 (0.0001)	0.7618	0.2261 (0.0012)	0.0121 (0.0003)
2	0.9726	0.0273(0.0008)	0.0001 (0.0001)	0.646	0.353 (0.003)	0.000 (0.0001)	0.6479	0.3313 (0.0013)	0.0208 (0.0004)
3	0.9686	0.0313 (0.0009)	0.0001 (0.0001)	0.646	0.353 (0.003)	0.000 (0.0001)	0.5646	0.4073 (0.0014)	0.0281 (0.0005)
4	0.9653	0.0346 (0.001)	0.0001 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.4989	0.4668 (0.0014)	0.0343 (0.0005)
5	0.9626	0.0373 (0.001)	0.0001 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.4449	0.5154 (0.0014)	0.0397 (0.0006)
6	0.9602	0.0397(0.001)	0.0001 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.3994	0.5561 (0.0014)	0.0445 (0.0006)
7	0.9579	0.0419 (0.0011)	0.0002 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.3604	0.5908 (0.0014)	0.0488 (0.0006)
8	0.956	0.0438 (0.0011)	0.0002 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.3266	0.6207 (0.0014)	0.0527 (0.0006)
9	0.9542	0.0456 (0.0011)	0.0002 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.2971	0.6468 (0.0014)	0.0561 (0.0006)
10	0.9525	0.0473 (0.0011)	0.0002 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.2710	0.6697 (0.0014)	0.0593 (0.0007)
11	0.951	0.0488 (0.0012)	0.0002 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.2480	0.6899 (0.0013)	0.0621 (0.0007)
12	0.9495	0.0503 (0.0012)	0.0002 (0.0002)	0.646	0.353 (0.003)	0.000 (0.0001)	0.2274	0.7079 (0.0013)	0.0647 (0.0007)
13	0.9481	0.0517 (0.0012)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.2089	0.724 (0.0013)	0.0671 (0.0007)
14	0.9468	0.053 (0.0012)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1922	0.7385 (0.0013)	0.0693 (0.0007)
15	0.9455	0.0543 (0.0012)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1772	0.7515 (0.0013)	0.0713 (0.0007)
16	0.9443	0.0555 (0.0012)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1637	0.7632 (0.0013)	0.0731 (0.0007)
17	0.9432	0.0566 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1514	0.7738 (0.0012)	0.0748 (0.0007)
18	0.9421	0.0577 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1401	0.7835 (0.0012)	0.0764 (0.0007)
19	0.941	0.0588 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1300	0.7922 (0.0012)	0.0778 (0.0007)
20	0.94	0.0598 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1207	0.8002 (0.0012)	0.0791 (0.0007)
21	0.939	0.0608 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1120	0.8076 (0.0012)	0.0804 (0.0008)
22	0.938	0.0618 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.1042	0.8143 (0.0012)	0.0815 (0.0008)
23	0.9371	0.0627 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0970	0.8204 (0.0011)	0.0826 (0.0008)
24	0.9362	0.0636 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0904	0.826 (0.0011)	0.0836 (0.0008)
25	0.9353	0.0645 (0.0013)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0843	0.8312 (0.0011)	0.0845 (0.0008)
26	0.9345	0.0653 (0.0014)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0787	0.836 (0.0011)	0.0853 (0.0008)
27	0.9336	0.0662 (0.0014)	0.0002 (0.0003)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0735	0.8404 (0.0011)	0.0861 (0.0008)
28	0.9328	0.067 (0.0014)	0.0002 (0.0004)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0686	0.8445 (0.0011)	0.0869 (0.0008)
29	0.932	0.0678 (0.0014)	0.0002 (0.0004)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0642	0.8482 (0.001)	0.0876 (0.0008)
30	0.9312	0.0686 (0.0014)	0.0002 (0.0004)	0.646	0.353 (0.003)	0.000 (0.0001)	0.0601	0.8517 (0.0011)	0.0882 (0.0008)

Table C4: Transition probabilities for the first 30 days used in the central hospital-Age group <=29

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9848	0.0152 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.6326	0.3674 (0)	0 (0)
2	0.9801	0.0199 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.3105	0.6895 (0)	0 (0)
3	0.9767	0.0233 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.1300	0.87 (0)	0 (0)
4	0.9739	0.0261 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0476	0.9524 (0)	0 (0)
5	0.9716	0.0284 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0154	0.9846 (0)	0 (0)
6	0.9695	0.0305 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0045	0.9955 (0)	0 (0)
7	0.9676	0.0324 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0012	0.9988 (0)	0 (0)
8	0.9659	0.0341 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0003	0.9997 (0)	0 (0)
9	0.9643	0.0357 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0001	0.9999 (0)	0 (0)
10	0.9628	0.0372 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
11	0.9614	0.0386 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
12	0.9601	0.0399 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
13	0.9588	0.0412 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
14	0.9577	0.0423 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
15	0.9565	0.0435 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
16	0.9554	0.0446 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
17	0.9544	0.0456 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
18	0.9533	0.0467 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
19	0.9524	0.0476 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
20	0.9514	0.0486 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
21	0.9505	0.0495 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
22	0.9496	0.0504 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
23	0.9487	0.0513 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
24	0.9479	0.0521 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
25	0.9471	0.0529 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
26	0.9463	0.0537 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
27	0.9455	0.0545 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
28	0.9447	0.0553 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
29	0.944	0.056 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)
30	0.9432	0.0568 (0)	0 (0)	0.5838	0.4160 (0.0078)	0.0002 (0.0002)	0.0000	1 (0)	0 (0)

Table C5: Transition probabilities for the first 30 days used in the local hospital- Age group 30-64

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9789	0.0196 (0.0004)	0.0015 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.6964	0.3001 (0.0015)	0.0035 (0.0001)
2	0.9728	0.0254 (0.0004)	0.0018 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.5467	0.4466 (0.0017)	0.0067 (0.0002)
3	0.9686	0.0295 (0.0005)	0.0019 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.4424	0.5483 (0.0017)	0.0093 (0.0003)
4	0.9651	0.0328 (0.0005)	0.0021 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.3640	0.6243 (0.0017)	0.0117 (0.0003)
5	0.9621	0.0357 (0.0005)	0.0022 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.3031	0.6833 (0.0016)	0.0136 (0.0003)
6	0.9595	0.0382 (0.0005)	0.0023 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.2545	0.7301 (0.0015)	0.0154 (0.0004)
7	0.9573	0.0404 (0.0006)	0.0023 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.2153	0.7679 (0.0015)	0.0168 (0.0004)
8	0.9552	0.0424 (0.0006)	0.0024 (0.0001)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.1830	0.7989 (0.0014)	0.0181 (0.0004)
9	0.9532	0.0443 (0.0006)	0.0025 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.1563	0.8244 (0.0013)	0.0193 (0.0004)
10	0.9514	0.0461 (0.0006)	0.0025 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.1341	0.8457 (0.0013)	0.0202 (0.0004)
11	0.9497	0.0477 (0.0006)	0.0026 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.1154	0.8635 (0.0012)	0.0211 (0.0004)
12	0.9481	0.0493 (0.0006)	0.0026 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0997	0.8785 (0.0011)	0.0218 (0.0004)
13	0.9465	0.0508 (0.0006)	0.0027 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0863	0.8912 (0.0011)	0.0225 (0.0004)
14	0.9451	0.0522 (0.0006)	0.0027 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0749	0.902 (0.001)	0.0231 (0.0005)
15	0.9437	0.0535 (0.0006)	0.0028 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0652	0.9112 (0.0011)	0.0236 (0.0005)
16	0.9424	0.0548 (0.0007)	0.0028 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0569	0.9191 (0.0009)	0.024 (0.0005)
17	0.9412	0.056 (0.0007)	0.0028 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0497	0.9259 (0.0009)	0.0244 (0.0005)
18	0.9399	0.0572 (0.0007)	0.0029 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0435	0.9318 (0.0008)	0.0247 (0.0005)
19	0.9387	0.0584 (0.0007)	0.0029 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0382	0.9368 (0.0008)	0.025 (0.0005)
20	0.9376	0.0595 (0.0007)	0.0029 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0335	0.9412 (0.0008)	0.0253 (0.0005)
21	0.9365	0.0605 (0.0007)	0.003 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0294	0.945 (0.0007)	0.0256 (0.0005)
22	0.9354	0.0616 (0.0007)	0.003 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0259	0.9483 (0.0007)	0.0258 (0.0005)
23	0.9344	0.0626 (0.0007)	0.003 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0228	0.9512 (0.0007)	0.026 (0.0005)
24	0.9333	0.0636 (0.0007)	0.0031 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0202	0.9537 (0.0006)	0.0261 (0.0005)
25	0.9324	0.0645 (0.0007)	0.0031 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0178	0.9559 (0.0006)	0.0263 (0.0005)
26	0.9314	0.0655 (0.0007)	0.0031 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0158	0.9578 (0.0006)	0.0264 (0.0005)
27	0.9305	0.0664 (0.0007)	0.0031 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0140	0.9595 (0.0006)	0.0265 (0.0005)
28	0.9295	0.0673 (0.0007)	0.0032 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0124	0.961 (0.0006)	0.0266 (0.0005)
29	0.9287	0.0681 (0.0007)	0.0032 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0110	0.9623 (0.0006)	0.0267 (0.0005)
30	0.9278	0.069 (0.0007)	0.0032 (0.0002)	0.479	0.520 (0.0017)	0.001 (0.0001)	0.0098	0.9634 (0.0006)	0.0268 (0.0005)

Table C6: Transition probabilities for the first 30 days used in the central hospital-Age group 30-64

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9842	0.0144 (0.0007)	0.0014 (0.0002)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.7110	0.2866 (0.0032)	0.0024 (0.0002)
2	0.9786	0.0197 (0.0008)	0.0017 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.5396	0.4555 (0.0036)	0.0049 (0.0004)
3	0.9745	0.0236 (0.0009)	0.0019 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.4176	0.5753 (0.0035)	0.0071 (0.0005)
4	0.9712	0.0268 (0.001)	0.002 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.3269	0.664 (0.0033)	0.0091 (0.0006)
5	0.9682	0.0296 (0.001)	0.0022 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.2581	0.7312 (0.0031)	0.0107 (0.0006)
6	0.9656	0.0321 (0.0011)	0.0023 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.2050	0.7829 (0.0028)	0.0121 (0.0007)
7	0.9632	0.0344 (0.0011)	0.0024 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.1637	0.8231 (0.0026)	0.0132 (0.0007)
8	0.9610	0.0365 (0.0012)	0.0025 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.1312	0.8546 (0.0024)	0.0142 (0.0007)
9	0.9590	0.0384 (0.0012)	0.0026 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.1056	0.8794 (0.0021)	0.015 (0.0007)
10	0.9570	0.0403 (0.0012)	0.0027 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0852	0.8991 (0.0019)	0.0157 (0.0007)
11	0.9553	0.042 (0.0013)	0.0027 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0690	0.9148 (0.0018)	0.0162 (0.0008)
12	0.9536	0.0436 (0.0013)	0.0028 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0559	0.9274 (0.0016)	0.0167 (0.0008)
13	0.9519	0.0452 (0.0013)	0.0029 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0454	0.9375 (0.0015)	0.0171 (0.0008)
14	0.9504	0.0467 (0.0013)	0.0029 (0.0003)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0370	0.9456 (0.0013)	0.0174 (0.0008)
15	0.9488	0.0482 (0.0013)	0.003 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0303	0.9521 (0.0012)	0.0176 (0.0008)
16	0.9473	0.0496 (0.0014)	0.0031 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0247	0.9574 (0.0012)	0.0179 (0.0008)
17	0.9460	0.0509 (0.0014)	0.0031 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0202	0.9617 (0.0011)	0.0181 (0.0008)
18	0.9446	0.0522 (0.0014)	0.0032 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0166	0.9652 (0.001)	0.0182 (0.0008)
19	0.9433	0.0535 (0.0014)	0.0032 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0137	0.968 (0.001)	0.0183 (0.0008)
20	0.9420	0.0547 (0.0014)	0.0033 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0112	0.9704 (0.0009)	0.0184 (0.0008)
21	0.9408	0.0559 (0.0014)	0.0033 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0093	0.9722 (0.0009)	0.0185 (0.0008)
22	0.9396	0.057 (0.0014)	0.0034 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0076	0.9738 (0.0009)	0.0186 (0.0008)
23	0.9385	0.0581 (0.0015)	0.0034 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0062	0.9751 (0.0009)	0.0187 (0.0008)
24	0.9374	0.0592 (0.0015)	0.0034 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0052	0.9761 (0.0008)	0.0187 (0.0008)
25	0.9362	0.0603 (0.0015)	0.0035 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0042	0.977 (0.0008)	0.0188 (0.0008)
26	0.9352	0.0613 (0.0015)	0.0035 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0035	0.9777 (0.0008)	0.0188 (0.0008)
27	0.9340	0.0624 (0.0015)	0.0036 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0030	0.9782 (0.0008)	0.0188 (0.0008)
28	0.9330	0.0634 (0.0015)	0.0036 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0024	0.9787 (0.0008)	0.0189 (0.0008)
29	0.9320	0.0644 (0.0015)	0.0036 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0020	0.9791 (0.0008)	0.0189 (0.0008)
30	0.9310	0.0653 (0.0015)	0.0037 (0.0004)	0.484	0.515 (0.0036)	0.001 (0.0002)	0.0017	0.9794 (0.0008)	0.0189 (0.0008)

Table C7: Transition probabilities for the first 30 days used in the local hospital- Age group 65+

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9722	0.0211 (0.0003)	0.0067 (0.0002)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.8374	0.1533 (0.0009)	0.0093 (0.0002)
2	0.9631	0.0288 (0.0004)	0.0081 (0.0002)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.7439	0.2394 (0.0011)	0.0167 (0.0003)
3	0.9566	0.0345 (0.0004)	0.0089 (0.0002)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.6708	0.3061 (0.0012)	0.0231 (0.0003)
4	0.9512	0.0392 (0.0005)	0.0096 (0.0002)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.6100	0.3612 (0.0012)	0.0288 (0.0004)
5	0.9466	0.0432 (0.0005)	0.0102 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.5579	0.4081 (0.0013)	0.034 (0.0004)
6	0.9424	0.0469 (0.0005)	0.0107 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.5125	0.4488 (0.0013)	0.0387 (0.0004)
7	0.9387	0.0502 (0.0005)	0.0111 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.4725	0.4846 (0.0013)	0.0429 (0.0005)
8	0.9353	0.0532 (0.0006)	0.0115 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.4368	0.5164 (0.0013)	0.0468 (0.0005)
9	0.9321	0.0561 (0.0006)	0.0118 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.4047	0.5449 (0.0013)	0.0504 (0.0005)
10	0.9292	0.0587 (0.0006)	0.0121 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.3757	0.5705 (0.0013)	0.0538 (0.0005)
11	0.9263	0.0613 (0.0006)	0.0124 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.3495	0.5937 (0.0013)	0.0568 (0.0005)
12	0.9237	0.0636 (0.0006)	0.0127 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.3256	0.6147 (0.0012)	0.0597 (0.0006)
13	0.9212	0.0659 (0.0006)	0.0129 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.3038	0.6339 (0.0012)	0.0623 (0.0006)
14	0.9187	0.0681 (0.0006)	0.0132 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.2837	0.6515 (0.0012)	0.0648 (0.0006)
15	0.9164	0.0702 (0.0007)	0.0134 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.2653	0.6676 (0.0012)	0.0671 (0.0006)
16	0.9142	0.0722 (0.0007)	0.0136 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.2485	0.6823 (0.0012)	0.0692 (0.0006)
17	0.9121	0.0741 (0.0007)	0.0138 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.2328	0.696 (0.0012)	0.0712 (0.0006)
18	0.9100	0.076 (0.0007)	0.014 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.2184	0.7085 (0.0012)	0.0731 (0.0006)
19	0.9080	0.0778 (0.0007)	0.0142 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.2050	0.7202 (0.0012)	0.0748 (0.0006)
20	0.9060	0.0796 (0.0007)	0.0144 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1926	0.7309 (0.0011)	0.0765 (0.0006)
21	0.9041	0.0813 (0.0007)	0.0146 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1811	0.7409 (0.0011)	0.078 (0.0006)
22	0.9024	0.0829 (0.0007)	0.0147 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1704	0.7502 (0.0011)	0.0794 (0.0006)
23	0.9005	0.0846 (0.0007)	0.0149 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1604	0.7588 (0.0011)	0.0808 (0.0006)
24	0.8988	0.0861 (0.0007)	0.0151 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1511	0.7668 (0.0011)	0.0821 (0.0006)
25	0.8971	0.0877 (0.0007)	0.0152 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1424	0.7743 (0.0011)	0.0833 (0.0007)
26	0.8954	0.0892 (0.0007)	0.0154 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1343	0.7813 (0.0011)	0.0844 (0.0007)
27	0.8939	0.0906 (0.0007)	0.0155 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1267	0.7878 (0.001)	0.0855 (0.0007)
28	0.8923	0.0921 (0.0008)	0.0156 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1197	0.7939 (0.001)	0.0864 (0.0007)
29	0.8907	0.0935 (0.0008)	0.0158 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1130	0.7996 (0.001)	0.0874 (0.0007)
30	0.8892	0.0949 (0.0008)	0.0159 (0.0003)	0.248	0.747 (0.0012)	0.005 (0.0002)	0.1068	0.8049 (0.001)	0.0883 (0.0007)

Table C8: Transition probabilities for the first 30 days used in the central hospital-Age group 65+

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9822	0.0128 (0.0005)	0.005 (0.0003)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.8315	0.1607 (0.0018)	0.0078 (0.0003)
2	0.9750	0.0187 (0.0006)	0.0063 (0.0004)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.7285	0.2571 (0.0022)	0.0144 (0.0005)
3	0.9695	0.0233 (0.0007)	0.0072 (0.0004)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.6472	0.3325 (0.0025)	0.0203 (0.0006)
4	0.9648	0.0273 (0.0008)	0.0079 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.5797	0.3947 (0.0026)	0.0256 (0.0007)
5	0.9607	0.0308 (0.0009)	0.0085 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.5223	0.4474 (0.0026)	0.0303 (0.0008)
6	0.9569	0.034 (0.0009)	0.0091 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.4725	0.4929 (0.0026)	0.0346 (0.0009)
7	0.9536	0.0369 (0.0009)	0.0095 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.4289	0.5326 (0.0026)	0.0385 (0.0009)
8	0.9503	0.0397 (0.001)	0.01 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.3904	0.5675 (0.0026)	0.0421 (0.001)
9	0.9473	0.0423 (0.001)	0.0104 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.3563	0.5984 (0.0025)	0.0453 (0.001)
10	0.9445	0.0448 (0.0011)	0.0107 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.3257	0.626 (0.0025)	0.0483 (0.001)
11	0.9418	0.0471 (0.0011)	0.0111 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.2983	0.6507 (0.0025)	0.051 (0.0011)
12	0.9392	0.0494 (0.0011)	0.0114 (0.0005)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.2737	0.6728 (0.0024)	0.0535 (0.0011)
13	0.9368	0.0515 (0.0011)	0.0117 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.2514	0.6928 (0.0024)	0.0558 (0.0011)
14	0.9344	0.0536 (0.0012)	0.012 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.2313	0.7108 (0.0023)	0.0579 (0.0011)
15	0.9321	0.0556 (0.0012)	0.0123 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.2131	0.7271 (0.0023)	0.0598 (0.0012)
16	0.9299	0.0576 (0.0012)	0.0125 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1965	0.7419 (0.0023)	0.0616 (0.0012)
17	0.9277	0.0595 (0.0012)	0.0128 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1813	0.7554 (0.0022)	0.0633 (0.0012)
18	0.9257	0.0613 (0.0013)	0.013 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1675	0.7677 (0.0022)	0.0648 (0.0012)
19	0.9237	0.0631 (0.0013)	0.0132 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1549	0.7789 (0.0021)	0.0662 (0.0012)
20	0.9217	0.0649 (0.0013)	0.0134 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1433	0.7892 (0.0021)	0.0675 (0.0012)
21	0.9197	0.0666 (0.0013)	0.0137 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1327	0.7986 (0.0021)	0.0687 (0.0012)
22	0.9178	0.0683 (0.0013)	0.0139 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1229	0.8072 (0.002)	0.0699 (0.0012)
23	0.9160	0.0699 (0.0013)	0.0141 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1140	0.8151 (0.002)	0.0709 (0.0012)
24	0.9142	0.0715 (0.0014)	0.0143 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.1058	0.8223 (0.0019)	0.0719 (0.0013)
25	0.9125	0.073 (0.0014)	0.0145 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.0982	0.829 (0.0019)	0.0728 (0.0013)
26	0.9108	0.0746 (0.0014)	0.0146 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.0913	0.8351 (0.0019)	0.0736 (0.0013)
27	0.9091	0.0761 (0.0014)	0.0148 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.0848	0.8408 (0.0018)	0.0744 (0.0013)
28	0.9074	0.0776 (0.0014)	0.015 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.0789	0.846 (0.0018)	0.0751 (0.0013)
29	0.9058	0.079 (0.0014)	0.0152 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.0734	0.8508 (0.0018)	0.0758 (0.0013)
30	0.9043	0.0804 (0.0014)	0.0153 (0.0006)	0.261	0.735 (0.0026)	0.005 (0.0004)	0.0684	0.8552 (0.0018)	0.0764 (0.0013)

Table C9: Transition probabilities for the first 30 days used in the local hospital- Male

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9738	0.0216 (0.0003)	0.0046 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.7618	0.2261 (0.0012)	0.0121 (0.0003)
2	0.9662	0.0284 (0.0004)	0.0054 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.6479	0.3313 (0.0014)	0.0208 (0.0004)
3	0.9607	0.0334 (0.0005)	0.0059 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.5646	0.4073 (0.0015)	0.0281 (0.0005)
4	0.9562	0.0374 (0.0005)	0.0064 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.4989	0.4668 (0.0015)	0.0343 (0.0005)
5	0.9525	0.0408 (0.0005)	0.0067 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.4449	0.5154 (0.0015)	0.0397 (0.0006)
6	0.9491	0.0439 (0.0005)	0.007 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.3994	0.5561 (0.0015)	0.0445 (0.0006)
7	0.9462	0.0466 (0.0006)	0.0072 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.3604	0.5908 (0.0015)	0.0488 (0.0006)
8	0.9434	0.0491 (0.0006)	0.0075 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.3266	0.6207 (0.0015)	0.0527 (0.0006)
9	0.9408	0.0515 (0.0006)	0.0077 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.2971	0.6468 (0.0014)	0.0561 (0.0007)
10	0.9385	0.0536 (0.0006)	0.0079 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.2710	0.6697 (0.0014)	0.0593 (0.0007)
11	0.9362	0.0557 (0.0006)	0.0081 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.2480	0.6899 (0.0014)	0.0621 (0.0007)
12	0.9342	0.0576 (0.0006)	0.0082 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.2274	0.7079 (0.0014)	0.0647 (0.0007)
13	0.9322	0.0594 (0.0006)	0.0084 (0.0002)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.2089	0.724 (0.0013)	0.0671 (0.0007)
14	0.9303	0.0612 (0.0007)	0.0085 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1922	0.7385 (0.0013)	0.0693 (0.0007)
15	0.9284	0.0629 (0.0007)	0.0087 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1772	0.7515 (0.0013)	0.0713 (0.0007)
16	0.9267	0.0645 (0.0007)	0.0088 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1637	0.7632 (0.0013)	0.0731 (0.0007)
17	0.9251	0.066 (0.0007)	0.0089 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1514	0.7738 (0.0013)	0.0748 (0.0008)
18	0.9235	0.0675 (0.0007)	0.009 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1401	0.7835 (0.0012)	0.0764 (0.0008)
19	0.922	0.0689 (0.0007)	0.0091 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1300	0.7922 (0.0012)	0.0778 (0.0008)
20	0.9205	0.0703 (0.0007)	0.0092 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1207	0.8002 (0.0012)	0.0791 (0.0008)
21	0.9189	0.0717 (0.0007)	0.0094 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1120	0.8076 (0.0012)	0.0804 (0.0008)
22	0.9175	0.073 (0.0007)	0.0095 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.1042	0.8143 (0.0012)	0.0815 (0.0008)
23	0.9163	0.0742 (0.0007)	0.0095 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0970	0.8204 (0.0012)	0.0826 (0.0008)
24	0.9149	0.0755 (0.0007)	0.0096 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0904	0.826 (0.0011)	0.0836 (0.0008)
25	0.9136	0.0767 (0.0007)	0.0097 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0843	0.8312 (0.0011)	0.0845 (0.0008)
26	0.9124	0.0778 (0.0007)	0.0098 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0787	0.836 (0.0011)	0.0853 (0.0008)
27	0.9111	0.079 (0.0007)	0.0099 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0735	0.8404 (0.0011)	0.0861 (0.0008)
28	0.9099	0.0801 (0.0008)	0.01 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0686	0.8445 (0.0011)	0.0869 (0.0008)
29	0.9087	0.0812 (0.0008)	0.0101 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0642	0.8482 (0.0011)	0.0876 (0.0008)
30	0.9076	0.0823 (0.0008)	0.0101 (0.0003)	0.357	0.640 (0.0015)	0.003 (0.0002)	0.0601	0.8517 (0.0011)	0.0882 (0.0008)

Table C10: Transition probabilities for the first 30 days used in the central hospital-Male

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9823	0.0137 (0.0006)	0.004 (0.0003)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.7766	0.2169 (0.0024)	0.0065 (0.0004)
2	0.9758	0.0193 (0.0007)	0.0049 (0.0004)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.6514	0.3363 (0.0028)	0.0123 (0.0006)
3	0.9708	0.0236 (0.0008)	0.0056 (0.0004)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.5574	0.4253 (0.003)	0.0173 (0.0007)
4	0.9666	0.0273 (0.0009)	0.0061 (0.0004)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.4825	0.4957 (0.0031)	0.0218 (0.0008)
5	0.9629	0.0305 (0.0009)	0.0066 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.4209	0.5533 (0.0031)	0.0258 (0.0009)
6	0.9597	0.0333 (0.001)	0.007 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.3694	0.6013 (0.003)	0.0293 (0.0009)
7	0.9567	0.036 (0.001)	0.0073 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.3257	0.6419 (0.003)	0.0324 (0.001)
8	0.954	0.0384 (0.0011)	0.0076 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.2883	0.6765 (0.0029)	0.0352 (0.001)
9	0.9514	0.0407 (0.0011)	0.0079 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.2560	0.7063 (0.0028)	0.0377 (0.001)
10	0.9489	0.0429 (0.0011)	0.0082 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.2279	0.7321 (0.0028)	0.04 (0.0011)
11	0.9467	0.0449 (0.0012)	0.0084 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.2035	0.7545 (0.0027)	0.042 (0.0011)
12	0.9444	0.0469 (0.0012)	0.0087 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.1820	0.7742 (0.0026)	0.0438 (0.0011)
13	0.9423	0.0488 (0.0012)	0.0089 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.1631	0.7914 (0.0025)	0.0455 (0.0011)
14	0.9403	0.0506 (0.0012)	0.0091 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.1465	0.8066 (0.0025)	0.0469 (0.0012)
15	0.9384	0.0523 (0.0013)	0.0093 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.1317	0.82 (0.0024)	0.0483 (0.0012)
16	0.9365	0.054 (0.0013)	0.0095 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.1187	0.8318 (0.0023)	0.0495 (0.0012)
17	0.9347	0.0556 (0.0013)	0.0097 (0.0005)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.1070	0.8424 (0.0022)	0.0506 (0.0012)
18	0.933	0.0572 (0.0013)	0.0098 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0966	0.8518 (0.0022)	0.0516 (0.0012)
19	0.9313	0.0587 (0.0013)	0.01 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0873	0.8602 (0.0021)	0.0525 (0.0012)
20	0.9297	0.0602 (0.0014)	0.0101 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0791	0.8676 (0.0021)	0.0533 (0.0012)
21	0.9281	0.0616 (0.0014)	0.0103 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0716	0.8743 (0.002)	0.0541 (0.0012)
22	0.9266	0.063 (0.0014)	0.0104 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0650	0.8803 (0.0019)	0.0547 (0.0012)
23	0.925	0.0644 (0.0014)	0.0106 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0589	0.8857 (0.0019)	0.0554 (0.0012)
24	0.9236	0.0657 (0.0014)	0.0107 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0536	0.8905 (0.0018)	0.0559 (0.0012)
25	0.922	0.0671 (0.0014)	0.0109 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0487	0.8949 (0.0018)	0.0564 (0.0012)
26	0.9207	0.0683 (0.0015)	0.011 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0443	0.8988 (0.0018)	0.0569 (0.0012)
27	0.9193	0.0696 (0.0015)	0.0111 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0404	0.9023 (0.0017)	0.0573 (0.0013)
28	0.918	0.0708 (0.0015)	0.0112 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0368	0.9055 (0.0017)	0.0577 (0.0013)
29	0.9165	0.0721 (0.0015)	0.0114 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0335	0.9084 (0.0016)	0.0581 (0.0013)
30	0.9152	0.0733 (0.0015)	0.0115 (0.0006)	0.365	0.632 (0.0031)	0.003 (0.0004)	0.0306	0.911 (0.0016)	0.0584 (0.0013)

Table C11: Transition probabilities for the first 30 days used in the local hospital- Female

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9748	0.0214 (0.0003)	0.0038 (0.0001)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.8065	0.1869 (0.001)	0.0066 (0.0002)
2	0.9674	0.0282 (0.0004)	0.0044 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.6988	0.2893 (0.0012)	0.0119 (0.0002)
3	0.9619	0.0332 (0.0004)	0.0049 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.6165	0.367 (0.0013)	0.0165 (0.0003)
4	0.9576	0.0372 (0.0004)	0.0052 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.5496	0.4299 (0.0013)	0.0205 (0.0003)
5	0.9538	0.0407 (0.0004)	0.0055 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.4934	0.4825 (0.0013)	0.0241 (0.0004)
6	0.9506	0.0437 (0.0005)	0.0057 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.4453	0.5274 (0.0013)	0.0273 (0.0004)
7	0.9476	0.0465 (0.0005)	0.0059 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.4036	0.5662 (0.0013)	0.0302 (0.0004)
8	0.9449	0.049 (0.0005)	0.0061 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.3670	0.6002 (0.0013)	0.0328 (0.0004)
9	0.9424	0.0513 (0.0005)	0.0063 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.3347	0.6301 (0.0013)	0.0352 (0.0005)
10	0.9401	0.0535 (0.0005)	0.0064 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.3060	0.6566 (0.0013)	0.0374 (0.0005)
11	0.9379	0.0555 (0.0005)	0.0066 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.2804	0.6802 (0.0012)	0.0394 (0.0005)
12	0.9358	0.0575 (0.0005)	0.0067 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.2574	0.7014 (0.0012)	0.0412 (0.0005)
13	0.9338	0.0593 (0.0006)	0.0069 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.2367	0.7204 (0.0012)	0.0429 (0.0005)
14	0.9319	0.0611 (0.0006)	0.007 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.2180	0.7376 (0.0012)	0.0444 (0.0005)
15	0.9301	0.0628 (0.0006)	0.0071 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.2011	0.7531 (0.0011)	0.0458 (0.0005)
16	0.9284	0.0644 (0.0006)	0.0072 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1857	0.7672 (0.0011)	0.0471 (0.0005)
17	0.9268	0.0659 (0.0006)	0.0073 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1717	0.78 (0.0011)	0.0483 (0.0005)
18	0.9252	0.0674 (0.0006)	0.0074 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1588	0.7917 (0.0011)	0.0495 (0.0005)
19	0.9237	0.0688 (0.0006)	0.0075 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1472	0.8023 (0.0011)	0.0505 (0.0005)
20	0.9222	0.0702 (0.0006)	0.0076 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1366	0.812 (0.001)	0.0514 (0.0005)
21	0.9208	0.0716 (0.0006)	0.0076 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1268	0.8209 (0.001)	0.0523 (0.0006)
22	0.9194	0.0729 (0.0006)	0.0077 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1177	0.8291 (0.001)	0.0532 (0.0006)
23	0.9180	0.0742 (0.0006)	0.0078 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1095	0.8366 (0.001)	0.0539 (0.0006)
24	0.9167	0.0754 (0.0006)	0.0079 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.1019	0.8435 (0.001)	0.0546 (0.0006)
25	0.9154	0.0766 (0.0006)	0.008 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.0948	0.8499 (0.0009)	0.0553 (0.0006)
26	0.9142	0.0778 (0.0006)	0.008 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.0884	0.8557 (0.0009)	0.0559 (0.0006)
27	0.9129	0.079 (0.0006)	0.0081 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.0824	0.8611 (0.0009)	0.0565 (0.0006)
28	0.9117	0.0801 (0.0006)	0.0082 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.0769	0.8661 (0.0009)	0.057 (0.0006)
29	0.9106	0.0812 (0.0006)	0.0082 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.0718	0.8707 (0.0009)	0.0575 (0.0006)
30	0.9094	0.0823 (0.0007)	0.0083 (0.0002)	0.389	0.608 (0.0013)	0.003 (0.0001)	0.0670	0.875 (0.0009)	0.058 (0.0006)

Table C12: Transition probabilities for the first 30 days used in the central hospital-Female

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9835	0.0138 (0.0005)	0.0027 (0.0003)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.7881	0.2063 (0.0022)	0.0056 (0.0003)
2	0.9772	0.0194 (0.0007)	0.0034 (0.0003)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.6699	0.3196 (0.0026)	0.0105 (0.0005)
3	0.9725	0.0237 (0.0008)	0.0038 (0.0003)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.5807	0.4045 (0.0028)	0.0148 (0.0006)
4	0.9685	0.0273 (0.0008)	0.0042 (0.0003)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.5089	0.4725 (0.0029)	0.0186 (0.0007)
5	0.9651	0.0304 (0.0009)	0.0045 (0.0003)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.4495	0.5285 (0.0029)	0.022 (0.0008)
6	0.9619	0.0333 (0.0009)	0.0048 (0.0003)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.3992	0.5757 (0.0029)	0.0251 (0.0008)
7	0.9591	0.0359 (0.001)	0.005 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.3561	0.616 (0.0029)	0.0279 (0.0009)
8	0.9565	0.0383 (0.001)	0.0052 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.3188	0.6508 (0.0028)	0.0304 (0.0009)
9	0.9540	0.0406 (0.001)	0.0054 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.2863	0.681 (0.0027)	0.0327 (0.0009)
10	0.9517	0.0427 (0.0011)	0.0056 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.2579	0.7074 (0.0027)	0.0347 (0.001)
11	0.9495	0.0447 (0.0011)	0.0058 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.2328	0.7306 (0.0026)	0.0366 (0.001)
12	0.9474	0.0467 (0.0011)	0.0059 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.2107	0.7511 (0.0025)	0.0382 (0.001)
13	0.9454	0.0485 (0.0011)	0.0061 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.1909	0.7693 (0.0025)	0.0398 (0.001))
14	0.9435	0.0503 (0.0012)	0.0062 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.1733	0.7855 (0.0024)	0.0412 (0.001)
15	0.9416	0.052 (0.0012)	0.0064 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.1575	0.8 (0.0023)	0.0425 (0.001)
16	0.9399	0.0536 (0.0012)	0.0065 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.1435	0.8129 (0.0023)	0.0436 (0.0011)
17	0.9382	0.0552 (0.0012)	0.0066 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.1308	0.8245 (0.0022)	0.0447 (0.0011)
18	0.9364	0.0568 (0.0012)	0.0068 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.1194	0.8349 (0.0021)	0.0457 (0.0011)
19	0.9348	0.0583 (0.0012)	0.0069 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.1091	0.8443 (0.0021)	0.0466 (0.0011)
20	0.9333	0.0597 (0.0013)	0.007 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0998	0.8528 (0.002)	0.0474 (0.0011)
21	0.9317	0.0612 (0.0013)	0.0071 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0913	0.8605 (0.002)	0.0482 (0.0011)
22	0.9303	0.0625 (0.0013)	0.0072 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0837	0.8674 (0.0019)	0.0489 (0.0011)
23	0.9288	0.0639 (0.0013)	0.0073 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0768	0.8737 (0.0019)	0.0495 (0.0011)
24	0.9274	0.0652 (0.0013)	0.0074 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0705	0.8794 (0.0018)	0.0501 (0.0011)
25	0.9260	0.0665 (0.0013)	0.0075 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0648	0.8846 (0.0018)	0.0506 (0.0011)
26	0.9246	0.0678 (0.0013)	0.0076 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0596	0.8893 (0.0017)	0.0511 (0.0011)
27	0.9233	0.069 (0.0014)	0.0077 (0.0004)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0548	0.8936 (0.0017)	0.0516 (0.0011)
28	0.9220	0.0702 (0.0014)	0.0078 (0.0005)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0504	0.8976 (0.0016)	0.052 (0.0012)
29	0.9208	0.0714 (0.0014)	0.0078 (0.0005)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0465	0.9011 (0.0016)	0.0524 (0.0012)
30	0.9195	0.0726 (0.0014)	0.0079 (0.0005)	0.369	0.628 (0.0029)	0.003 (0.0003)	0.0428	0.9044 (0.0016)	0.0528 (0.0012)

Table C13: Transition probabilities for the first 30 days used in the local hospital- CCI0

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9801	0.0184 (0.0003)	0.0015 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.7097	0.281 (0.0013)	0.0093 (0.0003)
2	0.9742	0.024 (0.0004)	0.0018 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.5891	0.3964 (0.0014)	0.0145 (0.0003)
3	0.9699	0.0281 (0.0004)	0.002 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.5051	0.4764 (0.0015)	0.0185 (0.0004)
4	0.9665	0.0314 (0.0004)	0.0021 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.4408	0.5375 (0.0015)	0.0217 (0.0004)
5	0.9637	0.0341 (0.0004)	0.0022 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.3892	0.5864 (0.0015)	0.0244 (0.0005)
6	0.9611	0.0366 (0.0005)	0.0023 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.3466	0.6267 (0.0015)	0.0267 (0.0005)
7	0.9588	0.0388 (0.0005)	0.0024 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.3107	0.6606 (0.0014)	0.0287 (0.0005)
8	0.9568	0.0408 (0.0005)	0.0024 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.2800	0.6896 (0.0014)	0.0304 (0.0005)
9	0.9548	0.0427 (0.0005)	0.0025 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.2536	0.7145 (0.0014)	0.0319 (0.0005)
10	0.9529	0.0445 (0.0005)	0.0026 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.2304	0.7363 (0.0014)	0.0333 (0.0005)
11	0.9513	0.0461 (0.0005)	0.0026 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.2100	0.7555 (0.0013)	0.0345 (0.0006)
12	0.9496	0.0477 (0.0005)	0.0027 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1920	0.7724 (0.0013)	0.0356 (0.0006)
13	0.9482	0.0491 (0.0006)	0.0027 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1760	0.7874 (0.0013)	0.0366 (0.0006)
14	0.9468	0.0505 (0.0006)	0.0027 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1617	0.8008 (0.0013)	0.0375 (0.0006)
15	0.9453	0.0519 (0.0006)	0.0028 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1489	0.8128 (0.0012)	0.0383 (0.0006)
16	0.9441	0.0531 (0.0006)	0.0028 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1373	0.8236 (0.0012)	0.0391 (0.0006)
17	0.9427	0.0544 (0.0006)	0.0029 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1269	0.8334 (0.0012)	0.0397 (0.0006)
18	0.9415	0.0556 (0.0006)	0.0029 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1174	0.8422 (0.0012)	0.0404 (0.0006)
19	0.9404	0.0567 (0.0006)	0.0029 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1088	0.8503 (0.0011)	0.0409 (0.0006)
20	0.9392	0.0578 (0.0006)	0.003 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.1009	0.8576 (0.0011)	0.0415 (0.0006)
21	0.9381	0.0589 (0.0006)	0.003 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0938	0.8643 (0.0011)	0.0419 (0.0006)
22	0.9371	0.0599 (0.0006)	0.003 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0872	0.8704 (0.0011)	0.0424 (0.0006)
23	0.9359	0.061 (0.0006)	0.0031 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0813	0.8759 (0.001)	0.0428 (0.0006)
24	0.935	0.0619 (0.0006)	0.0031 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0757	0.8811 (0.001)	0.0432 (0.0006)
25	0.934	0.0629 (0.0006)	0.0031 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0707	0.8858 (0.001)	0.0435 (0.0006)
26	0.9331	0.0638 (0.0006)	0.0031 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0661	0.8901 (0.001)	0.0438 (0.0006)
27	0.9321	0.0647 (0.0006)	0.0032 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0618	0.8941 (0.001)	0.0441 (0.0006)
28	0.9312	0.0656 (0.0006)	0.0032 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0578	0.8978 (0.001)	0.0444 (0.0006)
29	0.9303	0.0665 (0.0006)	0.0032 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0541	0.9012 (0.0009)	0.0447 (0.0006)
30	0.9294	0.0674 (0.0007)	0.0032 (0.0001)	0.502	0.496 (0.0015)	0.002 (0.0001)	0.0507	0.9044 (0.0009)	0.0449 (0.0006)

CCI0: Charlson's co-morbidity index=0

Table C14: Transition probabilities for the first 30 days used in the central hospital-CCI0

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.986	0.0129 (0.0006)	0.0011 (0.0002)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.7031	0.2934 (0.003)	0.0035 (0.0003)
2	0.9811	0.0175 (0.0007)	0.0014 (0.0002)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.5551	0.4386 (0.0033)	0.0063 (0.0004)
3	0.9774	0.021 (0.0008)	0.0016 (0.0002)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.4512	0.5401 (0.0034)	0.0087 (0.0005)
4	0.9744	0.0239 (0.0009)	0.0017 (0.0002)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.3729	0.6164 (0.0033)	0.0107 (0.0006)
5	0.9718	0.0264 (0.0009)	0.0018 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.3118	0.6758 (0.0031)	0.0124 (0.0007)
6	0.9695	0.0286 (0.0009)	0.0019 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.2629	0.7233 (0.003)	0.0138 (0.0007)
7	0.9674	0.0306 (0.001)	0.002 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.2232	0.7617 (0.0029)	0.0151 (0.0007)
8	0.9654	0.0325 (0.001)	0.0021 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.1905	0.7934 (0.0027)	0.0161 (0.0007)
9	0.9636	0.0342 (0.001)	0.0022 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.1634	0.8196 (0.0026)	0.017 (0.0008)
10	0.962	0.0358 (0.0011)	0.0022 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.1407	0.8415 (0.0024)	0.0178 (0.0008)
11	0.9603	0.0374 (0.0011)	0.0023 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.1216	0.8599 (0.0023)	0.0185 (0.0008)
12	0.9587	0.0389 (0.0011)	0.0024 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.1054	0.8755 (0.0022)	0.0191 (0.0008)
13	0.9573	0.0403 (0.0011)	0.0024 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0915	0.8888 (0.002)	0.0197 (0.0008)
14	0.9559	0.0416 (0.0011)	0.0025 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0798	0.9001 (0.0019)	0.0201 (0.0008)
15	0.9546	0.0429 (0.0012)	0.0025 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0697	0.9098 (0.0018)	0.0205 (0.0008)
16	0.9533	0.0441 (0.0012)	0.0026 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0610	0.9181 (0.0017)	0.0209 (0.0008)
17	0.9521	0.0453 (0.0012)	0.0026 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0535	0.9253 (0.0016)	0.0212 (0.0008)
18	0.9508	0.0465 (0.0012)	0.0027 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0470	0.9315 (0.0015)	0.0215 (0.0008)
19	0.9497	0.0476 (0.0012)	0.0027 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0414	0.9369 (0.0015)	0.0217 (0.0008)
20	0.9486	0.0487 (0.0012)	0.0027 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0365	0.9416 (0.0014)	0.0219 (0.0008)
21	0.9475	0.0497 (0.0013)	0.0028 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0322	0.9457 (0.0013)	0.0221 (0.0008)
22	0.9465	0.0507 (0.0013)	0.0028 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0284	0.9493 (0.0013)	0.0223 (0.0008)
23	0.9454	0.0517 (0.0013)	0.0029 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0251	0.9524 (0.0012)	0.0225 (0.0008)
24	0.9444	0.0527 (0.0013)	0.0029 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0223	0.9551 (0.0012)	0.0226 (0.0008)
25	0.9434	0.0537 (0.0013)	0.0029 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0198	0.9575 (0.0011)	0.0227 (0.0008)
26	0.9424	0.0546 (0.0013)	0.003 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0176	0.9596 (0.0011)	0.0228 (0.0008)
27	0.9415	0.0555 (0.0013)	0.003 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0156	0.9615 (0.0011)	0.0229 (0.0008)
28	0.9406	0.0564 (0.0013)	0.003 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0139	0.9631 (0.001)	0.023 (0.0009)
29	0.9397	0.0573 (0.0013)	0.003 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0123	0.9646 (0.001)	0.0231 (0.0009)
30	0.9388	0.0581 (0.0013)	0.0031 (0.0003)	0.505	0.494 (0.0033)	0.002 (0.0003)	0.0110	0.9659 (0.001)	0.0231 (0.0009)

CCI0: Charlson's co-morbidity index=0

Table C15: Transition probabilities for the first 30 days used in the local hospital- CCI4

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9574	0.0268 (0.0008)	0.0158 (0.0007)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.8935	0.0951 (0.0015)	0.0114 (0.0005)
2	0.9443	0.0364 (0.001)	0.0193 (0.0008)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.8170	0.1614 (0.0021)	0.0216 (0.0007)
3	0.935	0.0434 (0.0011)	0.0216 (0.0009)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.7522	0.2169 (0.0024)	0.0309 (0.0009)
4	0.9274	0.0492 (0.0012)	0.0234 (0.0009)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.6954	0.2651 (0.0026)	0.0395 (0.001)
5	0.9209	0.0542 (0.0013)	0.0249 (0.0009)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.6447	0.3079 (0.0027)	0.0474 (0.0011)
6	0.9152	0.0586 (0.0014)	0.0262 (0.0009)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.5990	0.3462 (0.0028)	0.0548 (0.0012)
7	0.91	0.0627 (0.0014)	0.0273 (0.001)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.5575	0.3808 (0.0028)	0.0617 (0.0013)
8	0.9052	0.0664 (0.0015)	0.0284 (0.001)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.5197	0.4122 (0.0029)	0.0681 (0.0014)
9	0.9009	0.0698 (0.0015)	0.0293 (0.001)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.4851	0.4409 (0.0029)	0.074 (0.0014)
10	0.8968	0.073 (0.0015)	0.0302 (0.001)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.4532	0.4672 (0.0029)	0.0796 (0.0015)
11	0.8929	0.0761 (0.0016)	0.031 (0.001)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.4238	0.4914 (0.0029)	0.0848 (0.0015)
12	0.8893	0.079 (0.0016)	0.0317 (0.001)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.3968	0.5136 (0.0029)	0.0896 (0.0015)
13	0.8859	0.0817 (0.0016)	0.0324 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.3717	0.5341 (0.0029)	0.0942 (0.0016)
14	0.8826	0.0843 (0.0017)	0.0331 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.3485	0.5531 (0.0029)	0.0984 (0.0016)
15	0.8795	0.0868 (0.0017)	0.0337 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.3269	0.5707 (0.0028)	0.1024 (0.0016)
16	0.8765	0.0892 (0.0017)	0.0343 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.3068	0.587 (0.0028)	0.1062 (0.0017)
17	0.8736	0.0916 (0.0017)	0.0348 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.2881	0.6022 (0.0028)	0.1097 (0.0017)
18	0.8708	0.0938 (0.0018)	0.0354 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.2707	0.6163 (0.0028)	0.113 (0.0017)
19	0.8681	0.096 (0.0018)	0.0359 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.2545	0.6294 (0.0028)	0.1161 (0.0017)
20	0.8655	0.0981 (0.0018)	0.0364 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.2394	0.6416 (0.0027)	0.119 (0.0017)
21	0.863	0.1001 (0.0018)	0.0369 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.2252	0.653 (0.0027)	0.1218 (0.0017)
22	0.8606	0.1021 (0.0018)	0.0373 (0.0011)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.2120	0.6636 (0.0027)	0.1244 (0.0018)
23	0.8582	0.104 (0.0019)	0.0378 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1996	0.6736 (0.0027)	0.1268 (0.0018)
24	0.8559	0.1059 (0.0019)	0.0382 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1880	0.6829 (0.0026)	0.1291 (0.0018)
25	0.8537	0.1077 (0.0019)	0.0386 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1772	0.6916 (0.0026)	0.1312 (0.0018)
26	0.8515	0.1095 (0.0019)	0.039 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1670	0.6997 (0.0026)	0.1333 (0.0018)
27	0.8494	0.1112 (0.0019)	0.0394 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1575	0.7073 (0.0026)	0.1352 (0.0018)
28	0.8473	0.1129 (0.0019)	0.0398 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1486	0.7144 (0.0026)	0.137 (0.0018)
29	0.8452	0.1146 (0.002)	0.0402 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1402	0.7211 (0.0025)	0.1387 (0.0018)
30	0.8433	0.1162 (0.002)	0.0405 (0.0012)	0.146	0.847 (0.0024)	0.007 (0.0006)	0.1323	0.7274 (0.0025)	0.1403 (0.0019)

CCI4: Charlson's co-morbidity index>=4

Table C16: Transition probabilities for the first 30 days used in the central hospital-CCI4

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9733	0.0154 (0.0011)	0.0113 (0.0011)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.8815	0.1099 (0.003)	0.0086 (0.0007)
2	0.9626	0.0228 (0.0014)	0.0146 (0.0013)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.7959	0.1869 (0.004)	0.0172 (0.0012)
3	0.9543	0.0287 (0.0016)	0.017 (0.0014)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.7237	0.2509 (0.0046)	0.0254 (0.0015)
4	0.9475	0.0337 (0.0018)	0.0188 (0.0015)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.6609	0.3061 (0.0049)	0.033 (0.0018)
5	0.9414	0.0382 (0.002)	0.0204 (0.0016)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.6052	0.3546 (0.005)	0.0402 (0.002)
6	0.9359	0.0423 (0.0021)	0.0218 (0.0016)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.5555	0.3976 (0.0051)	0.0469 (0.0021)
7	0.9308	0.0461 (0.0022)	0.0231 (0.0017)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.5109	0.436 (0.0052)	0.0531 (0.0023)
8	0.9262	0.0496 (0.0023)	0.0242 (0.0017)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.4705	0.4706 (0.0052)	0.0589 (0.0024)
9	0.9218	0.053 (0.0024)	0.0252 (0.0018)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.4338	0.5019 (0.0052)	0.0643 (0.0025)
10	0.9176	0.0562 (0.0024)	0.0262 (0.0018)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.4005	0.5302 (0.0051)	0.0693 (0.0026)
11	0.9137	0.0592 (0.0025)	0.0271 (0.0018)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.3701	0.5559 (0.0051)	0.074 (0.0026)
12	0.9099	0.0621 (0.0026)	0.028 (0.0019)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.3424	0.5793 (0.0051)	0.0783 (0.0027)
13	0.9063	0.0649 (0.0026)	0.0288 (0.0019)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.3169	0.6007 (0.005)	0.0824 (0.0028)
14	0.9029	0.0676 (0.0027)	0.0295 (0.0019)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.2935	0.6203 (0.0049)	0.0862 (0.0028)
15	0.8995	0.0702 (0.0028)	0.0303 (0.002)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.2721	0.6382 (0.0049)	0.0897 (0.0029)
16	0.8963	0.0727 (0.0028)	0.031 (0.002)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.2523	0.6547 (0.0048)	0.093 (0.0029)
17	0.8932	0.0752 (0.0029)	0.0316 (0.002)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.2341	0.6698 (0.0048)	0.0961 (0.0029)
18	0.8901	0.0776 (0.0029)	0.0323 (0.002)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.2173	0.6837 (0.0048)	0.099 (0.003)
19	0.8872	0.0799 (0.003)	0.0329 (0.002)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.2019	0.6964 (0.0047)	0.1017 (0.003)
20	0.8844	0.0821 (0.003)	0.0335 (0.0021)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1876	0.7082 (0.0046)	0.1042 (0.003)
21	0.8815	0.0844 (0.003)	0.0341 (0.0021)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1744	0.7191 (0.0046)	0.1065 (0.0031)
22	0.8789	0.0865 (0.0031)	0.0346 (0.0021)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1622	0.7291 (0.0045)	0.1087 (0.0031)
23	0.8763	0.0886 (0.0031)	0.0351 (0.0021)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1510	0.7383 (0.0045)	0.1107 (0.0031)
24	0.8736	0.0907 (0.0032)	0.0357 (0.0021)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1405	0.7469 (0.0044)	0.1126 (0.0031)
25	0.8711	0.0927 (0.0032)	0.0362 (0.0021)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1308	0.7548 (0.0044)	0.1144 (0.0031)
26	0.8686	0.0947 (0.0032)	0.0367 (0.0022)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1218	0.7621 (0.0043)	0.1161 (0.0032)
27	0.8662	0.0966 (0.0033)	0.0372 (0.0022)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1135	0.7689 (0.0043)	0.1176 (0.0032)
28	0.8639	0.0985 (0.0033)	0.0376 (0.0022)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.1057	0.7752 (0.0042)	0.1191 (0.0032)
29	0.8615	0.1004 (0.0033)	0.0381 (0.0022)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.0986	0.781 (0.0042)	0.1204 (0.0032)
30	0.8592	0.1023 (0.0034)	0.0385 (0.0022)	0.141	0.854 (0.0043)	0.005 (0.0009)	0.0919	0.7864 (0.0041)	0.1217 (0.0032)

CCI4: Charlson's co-morbidity index>=4

Table C17: Transition probabilities for the first 30 days used in the local hospital- IMD1

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9768	0.0191 (0.0006)	0.0041 (0.0003)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.7964	0.1968 (0.002)	0.0068 (0.0003)
2	0.9701	0.0251 (0.0007)	0.0048 (0.0003)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.6859	0.3019 (0.0024)	0.0122 (0.0005)
3	0.9653	0.0294 (0.0008)	0.0053 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.6024	0.3808 (0.0026)	0.0168 (0.0006)
4	0.9614	0.0329 (0.0008)	0.0057 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.5348	0.4443 (0.0026)	0.0209 (0.0007)
5	0.9581	0.0359 (0.0009)	0.006 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.4785	0.497 (0.0026)	0.0245 (0.0007)
6	0.9553	0.0385 (0.0009)	0.0062 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.4305	0.5418 (0.0026)	0.0277 (0.0008)
7	0.9527	0.0409 (0.0009)	0.0064 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.3890	0.5804 (0.0026)	0.0306 (0.0008)
8	0.9503	0.0431 (0.0009)	0.0066 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.3528	0.614 (0.0025)	0.0332 (0.0009)
9	0.9481	0.0451 (0.001)	0.0068 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.3209	0.6435 (0.0025)	0.0356 (0.0009)
10	0.946	0.047 (0.001)	0.007 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.2926	0.6696 (0.0024)	0.0378 (0.0009)
11	0.9441	0.0488 (0.001)	0.0071 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.2676	0.6927 (0.0024)	0.0397 (0.0009)
12	0.9423	0.0504 (0.001)	0.0073 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.2451	0.7134 (0.0023)	0.0415 (0.0009)
13	0.9406	0.052 (0.0011)	0.0074 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.2249	0.7319 (0.0023)	0.0432 (0.001)
14	0.939	0.0535 (0.0011)	0.0075 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.2067	0.7486 (0.0023)	0.0447 (0.001)
15	0.9373	0.055 (0.0011)	0.0077 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1903	0.7636 (0.0022)	0.0461 (0.001)
16	0.9358	0.0564 (0.0011)	0.0078 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1755	0.7772 (0.0022)	0.0473 (0.001)
17	0.9344	0.0577 (0.0011)	0.0079 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1619	0.7896 (0.0021)	0.0485 (0.001)
18	0.933	0.059 (0.0011)	0.008 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1496	0.8008 (0.0021)	0.0496 (0.001)
19	0.9317	0.0602 (0.0011)	0.0081 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1384	0.811 (0.002)	0.0506 (0.001)
20	0.9304	0.0614 (0.0011)	0.0082 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1282	0.8203 (0.002)	0.0515 (0.001)
21	0.9291	0.0626 (0.0012)	0.0083 (0.0004)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1187	0.8289 (0.002)	0.0524 (0.0011)
22	0.9279	0.0637 (0.0012)	0.0084 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1101	0.8367 (0.0019)	0.0532 (0.0011)
23	0.9268	0.0648 (0.0012)	0.0084 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.1023	0.8438 (0.0019)	0.0539 (0.0011)
24	0.9256	0.0659 (0.0012)	0.0085 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.0950	0.8504 (0.0018)	0.0546 (0.0011)
25	0.9245	0.0669 (0.0012)	0.0086 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.0883	0.8564 (0.0018)	0.0553 (0.0011)
26	0.9234	0.0679 (0.0012)	0.0087 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.0821	0.862 (0.0018)	0.0559 (0.0011)
27	0.9223	0.0689 (0.0012)	0.0088 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.0765	0.8671 (0.0017)	0.0564 (0.0011)
28	0.9213	0.0699 (0.0012)	0.0088 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.0713	0.8718 (0.0017)	0.0569 (0.0011)
29	0.9203	0.0708 (0.0012)	0.0089 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.0665	0.8761 (0.0017)	0.0574 (0.0011)
30	0.9192	0.0718 (0.0012)	0.009 (0.0005)	0.375	0.623 (0.0027)	0.003 (0.0003)	0.0620	0.8802 (0.0016)	0.0578 (0.0011)

IMD1: Index of mean deprivation 1st quintile

Table C18: Transition probabilities for the first 30 days used in the central hospital-IMD1

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9846	0.0123 (0.001)	0.0031 (0.0006)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.7771	0.217 (0.0043)	0.0059 (0.0006)
2	0.9788	0.0173 (0.0012)	0.0039 (0.0006)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.6540	0.335 (0.0051)	0.011 (0.001)
3	0.9745	0.0211 (0.0014)	0.0044 (0.0007)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.5619	0.4227 (0.0054)	0.0154 (0.0012)
4	0.9709	0.0242 (0.0015)	0.0049 (0.0007)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.4885	0.4922 (0.0055)	0.0193 (0.0014)
5	0.9678	0.027 (0.0016)	0.0052 (0.0007)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.4280	0.5492 (0.0055)	0.0228 (0.0015)
6	0.965	0.0295 (0.0017)	0.0055 (0.0008)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.3773	0.5968 (0.0054)	0.0259 (0.0016)
7	0.9624	0.0318 (0.0018)	0.0058 (0.0008)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.3342	0.6371 (0.0053)	0.0287 (0.0017)
8	0.96	0.0339 (0.0018)	0.0061 (0.0008)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.2972	0.6716 (0.0052)	0.0312 (0.0018)
9	0.9578	0.0359 (0.0019)	0.0063 (0.0008)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.2651	0.7015 (0.005)	0.0334 (0.0018)
10	0.9557	0.0378 (0.0019)	0.0065 (0.0008)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.2372	0.7274 (0.0049)	0.0354 (0.0019)
11	0.9537	0.0396 (0.002)	0.0067 (0.0008)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.2128	0.75 (0.0047)	0.0372 (0.0019)
12	0.9518	0.0413 (0.002)	0.0069 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.1913	0.7699 (0.0046)	0.0388 (0.0019)
13	0.95	0.0429 (0.0021)	0.0071 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.1723	0.7874 (0.0045)	0.0403 (0.002)
14	0.9483	0.0445 (0.0021)	0.0072 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.1554	0.8029 (0.0043)	0.0417 (0.002)
15	0.9466	0.046 (0.0022)	0.0074 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.1404	0.8167 (0.0042)	0.0429 (0.002)
16	0.9451	0.0474 (0.0022)	0.0075 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.1271	0.8289 (0.0041)	0.044 (0.0021)
17	0.9435	0.0488 (0.0022)	0.0077 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.1152	0.8398 (0.004)	0.045 (0.0021)
18	0.942	0.0502 (0.0023)	0.0078 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.1045	0.8496 (0.0038)	0.0459 (0.0021)
19	0.9406	0.0515 (0.0023)	0.0079 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0950	0.8583 (0.0037)	0.0467 (0.0021)
20	0.9391	0.0528 (0.0023)	0.0081 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0863	0.8662 (0.0036)	0.0475 (0.0021)
21	0.9378	0.054 (0.0023)	0.0082 (0.0009)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0786	0.8732 (0.0035)	0.0482 (0.0021)
22	0.9365	0.0552 (0.0024)	0.0083 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0716	0.8796 (0.0034)	0.0488 (0.0021)
23	0.9352	0.0564 (0.0024)	0.0084 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0653	0.8853 (0.0033)	0.0494 (0.0022)
24	0.9339	0.0576 (0.0024)	0.0085 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0597	0.8904 (0.0032)	0.0499 (0.0022)
25	0.9326	0.0587 (0.0024)	0.0087 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0545	0.8951 (0.0032)	0.0504 (0.0022)
26	0.9314	0.0598 (0.0025)	0.0088 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0498	0.8993 (0.0031)	0.0509 (0.0022)
27	0.9302	0.0609 (0.0025)	0.0089 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0456	0.9031 (0.003)	0.0513 (0.0022)
28	0.929	0.062 (0.0025)	0.009 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0418	0.9066 (0.003)	0.0516 (0.0022)
29	0.9279	0.063 (0.0025)	0.0091 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0382	0.9098 (0.0029)	0.052 (0.0022)
30	0.9267	0.0641 (0.0025)	0.0092 (0.001)	0.378	0.619 (0.0057)	0.003 (0.0006)	0.0351	0.9126 (0.0028)	0.0523 (0.0022)

IMD1: Index of mean deprivation 1st quintile

Table C19: Transition probabilities for the first 30 days used in the local hospital- IMD5

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9729	0.0232 (0.0005)	0.0039 (0.0002)	0.394	0.603 (0.002)	0.003 (0.0002)	0.7868	0.1759 (0.0013)	0.0373 (0.0009)
2	0.9647	0.0307 (0.0005)	0.0046 (0.0002)	0.394	0.603 (0.002)	0.003 (0.0002)	0.6800	0.2658 (0.0016)	0.0542 (0.0011)
3	0.9587	0.0362 (0.0006)	0.0051 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.6007	0.3329 (0.0017)	0.0664 (0.0012)
4	0.954	0.0406 (0.0007)	0.0054 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.5372	0.3868 (0.0018)	0.076 (0.0013)
5	0.9498	0.0445 (0.0007)	0.0057 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.4844	0.4317 (0.0018)	0.0839 (0.0013)
6	0.9463	0.0478 (0.0007)	0.0059 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.4395	0.47 (0.0019)	0.0905 (0.0013)
7	0.9429	0.0509 (0.0007)	0.0062 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.4006	0.5032 (0.0019)	0.0962 (0.0014)
8	0.9399	0.0537 (0.0008)	0.0064 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.3666	0.5323 (0.0019)	0.1011 (0.0014)
9	0.9372	0.0563 (0.0008)	0.0065 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.3366	0.558 (0.0019)	0.1054 (0.0014)
10	0.9346	0.0587 (0.0008)	0.0067 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.3100	0.5808 (0.0019)	0.1092 (0.0014)
11	0.9322	0.061 (0.0008)	0.0068 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.2861	0.6013 (0.002)	0.1126 (0.0014)
12	0.9299	0.0631 (0.0008)	0.007 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.2646	0.6197 (0.002)	0.1157 (0.0015)
13	0.9277	0.0652 (0.0009)	0.0071 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.2452	0.6364 (0.002)	0.1184 (0.0015)
14	0.9257	0.0671 (0.0009)	0.0072 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.2276	0.6515 (0.002)	0.1209 (0.0015)
15	0.9237	0.069 (0.0009)	0.0073 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.2117	0.6652 (0.002)	0.1231 (0.0015)
16	0.9217	0.0708 (0.0009)	0.0075 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1971	0.6778 (0.002)	0.1251 (0.0015)
17	0.9199	0.0725 (0.0009)	0.0076 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1838	0.6892 (0.002)	0.127 (0.0015)
18	0.9181	0.0742 (0.0009)	0.0077 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1716	0.6998 (0.0019)	0.1286 (0.0015)
19	0.9165	0.0758 (0.0009)	0.0077 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1603	0.7095 (0.0019)	0.1302 (0.0015)
20	0.9149	0.0773 (0.0009)	0.0078 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1500	0.7184 (0.0019)	0.1316 (0.0015)
21	0.9133	0.0788 (0.0009)	0.0079 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1405	0.7266 (0.0019)	0.1329 (0.0015)
22	0.9117	0.0803 (0.001)	0.008 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1317	0.7342 (0.0019)	0.1341 (0.0015)
23	0.9102	0.0817 (0.001)	0.0081 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1236	0.7412 (0.0019)	0.1352 (0.0015)
24	0.9087	0.0831 (0.001)	0.0082 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1159	0.7478 (0.0019)	0.1363 (0.0015)
25	0.9074	0.0844 (0.001)	0.0082 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1090	0.7538 (0.0019)	0.1372 (0.0015)
26	0.9059	0.0858 (0.001)	0.0083 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.1025	0.7594 (0.0019)	0.1381 (0.0015)
27	0.9046	0.087 (0.001)	0.0084 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.0964	0.7647 (0.0019)	0.1389 (0.0015)
28	0.9032	0.0883 (0.001)	0.0085 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.0908	0.7695 (0.0018)	0.1397 (0.0015)
29	0.902	0.0895 (0.001)	0.0085 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.0855	0.7741 (0.0018)	0.1404 (0.0015)
30	0.9007	0.0907 (0.001)	0.0086 (0.0003)	0.394	0.603 (0.002)	0.003 (0.0002)	0.0807	0.7783 (0.0018)	0.141 (0.0015)

IMD5: Index of mean deprivation 5th quintile

Table C20: Transition probabilities for the first 30 days used in the central hospital-IMD5

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9818	0.0149 (0.0008)	0.0033 (0.0004)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.7789	0.2144 (0.0031)	0.0067 (0.0005)
2	0.9747	0.0212 (0.001)	0.0041 (0.0005)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.6542	0.3333 (0.0038)	0.0125 (0.0008)
3	0.9694	0.026 (0.0011)	0.0046 (0.0005)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.5605	0.422 (0.004)	0.0175 (0.0009)
4	0.9649	0.03 (0.0012)	0.0051 (0.0006)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.4858	0.4924 (0.0041)	0.0218 (0.0011)
5	0.9609	0.0336 (0.0013)	0.0055 (0.0006)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.4243	0.55 (0.004)	0.0257 (0.0012)
6	0.9574	0.0368 (0.0014)	0.0058 (0.0006)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.3727	0.5982 (0.004)	0.0291 (0.0012)
7	0.9542	0.0397 (0.0014)	0.0061 (0.0006)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.3289	0.6389 (0.0039)	0.0322 (0.0013)
8	0.9512	0.0425 (0.0015)	0.0063 (0.0006)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.2914	0.6737 (0.0038)	0.0349 (0.0013)
9	0.9484	0.045 (0.0015)	0.0066 (0.0006)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.2590	0.7037 (0.0037)	0.0373 (0.0014)
10	0.9457	0.0475 (0.0016)	0.0068 (0.0006)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.2310	0.7296 (0.0036)	0.0394 (0.0014)
11	0.9432	0.0498 (0.0016)	0.007 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.2063	0.7523 (0.0035)	0.0414 (0.0014)
12	0.9408	0.052 (0.0017)	0.0072 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.1848	0.7721 (0.0034)	0.0431 (0.0015)
13	0.9386	0.0541 (0.0017)	0.0073 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.1658	0.7895 (0.0033)	0.0447 (0.0015)
14	0.9364	0.0561 (0.0017)	0.0075 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.1490	0.8049 (0.0031)	0.0461 (0.0015)
15	0.9343	0.058 (0.0018)	0.0077 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.1341	0.8185 (0.003)	0.0474 (0.0015)
16	0.9323	0.0599 (0.0018)	0.0078 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.1209	0.8305 (0.003)	0.0486 (0.0015)
17	0.9303	0.0617 (0.0018)	0.008 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.1091	0.8413 (0.0029)	0.0496 (0.0015)
18	0.9284	0.0635 (0.0019)	0.0081 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0986	0.8508 (0.0028)	0.0506 (0.0016)
19	0.9265	0.0652 (0.0019)	0.0083 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0893	0.8593 (0.0027)	0.0514 (0.0016)
20	0.9247	0.0669 (0.0019)	0.0084 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0809	0.8669 (0.0026)	0.0522 (0.0016)
21	0.923	0.0685 (0.0019)	0.0085 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0733	0.8738 (0.0025)	0.0529 (0.0016)
22	0.9213	0.0701 (0.0019)	0.0086 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0665	0.8799 (0.0025)	0.0536 (0.0016)
23	0.9195	0.0717 (0.002)	0.0088 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0605	0.8854 (0.0024)	0.0541 (0.0016)
24	0.9179	0.0732 (0.002)	0.0089 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0550	0.8903 (0.0023)	0.0547 (0.0016)
25	0.9163	0.0747 (0.002)	0.009 (0.0007)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0500	0.8948 (0.0023)	0.0552 (0.0016)
26	0.9148	0.0761 (0.002)	0.0091 (0.0008)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0456	0.8988 (0.0022)	0.0556 (0.0016)
27	0.9133	0.0775 (0.0021)	0.0092 (0.0008)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0416	0.9024 (0.0022)	0.056 (0.0016)
28	0.9118	0.0789 (0.0021)	0.0093 (0.0008)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0379	0.9057 (0.0021)	0.0564 (0.0016)
29	0.9103	0.0803 (0.0021)	0.0094 (0.0008)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0346	0.9087 (0.0021)	0.0567 (0.0016)
30	0.9089	0.0816 (0.0021)	0.0095 (0.0008)	0.374	0.623 (0.0042)	0.003 (0.0005)	0.0315	0.9114 (0.002)	0.0571 (0.0016)

IMD5: Index of mean deprivation 5th quintile

Table C21: Transition probabilities for the first 30 days used in the local hospital- Circulatory

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9754	0.0196 (0.0007)	0.005 (0.0004)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.8077	0.1824 (0.002)	0.0099 (0.0004)
2	0.9676	0.0265 (0.0008)	0.0059 (0.0004)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.6970	0.2856 (0.0024)	0.0174 (0.0006)
3	0.962	0.0315 (0.0009)	0.0065 (0.0004)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.6120	0.3644 (0.0026)	0.0236 (0.0008)
4	0.9573	0.0357 (0.001)	0.007 (0.0004)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.5427	0.4283 (0.0027)	0.029 (0.0009)
5	0.9534	0.0393 (0.001)	0.0073 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.4847	0.4816 (0.0027)	0.0337 (0.0009)
6	0.9498	0.0425 (0.0011)	0.0077 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.4350	0.5271 (0.0027)	0.0379 (0.001)
7	0.9466	0.0454 (0.0011)	0.008 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.3921	0.5663 (0.0027)	0.0416 (0.001)
8	0.9437	0.0481 (0.0012)	0.0082 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.3546	0.6005 (0.0026)	0.0449 (0.0011)
9	0.941	0.0506 (0.0012)	0.0084 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.3215	0.6306 (0.0026)	0.0479 (0.0011)
10	0.9385	0.0529 (0.0012)	0.0086 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.2923	0.6571 (0.0025)	0.0506 (0.0011)
11	0.9361	0.0551 (0.0012)	0.0088 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.2663	0.6807 (0.0025)	0.053 (0.0012)
12	0.9338	0.0572 (0.0013)	0.009 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.2431	0.7017 (0.0025)	0.0552 (0.0012)
13	0.9316	0.0592 (0.0013)	0.0092 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.2223	0.7205 (0.0024)	0.0572 (0.0012)
14	0.9296	0.0611 (0.0013)	0.0093 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.2035	0.7374 (0.0024)	0.0591 (0.0012)
15	0.9276	0.0629 (0.0013)	0.0095 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1867	0.7526 (0.0023)	0.0607 (0.0012)
16	0.9258	0.0646 (0.0014)	0.0096 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1714	0.7663 (0.0023)	0.0623 (0.0012)
17	0.9239	0.0663 (0.0014)	0.0098 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1576	0.7788 (0.0022)	0.0636 (0.0012)
18	0.9221	0.068 (0.0014)	0.0099 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1450	0.7901 (0.0022)	0.0649 (0.0013)
19	0.9205	0.0695 (0.0014)	0.01 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1336	0.8003 (0.0021)	0.0661 (0.0013)
20	0.9188	0.0711 (0.0014)	0.0101 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1232	0.8096 (0.0021)	0.0672 (0.0013)
21	0.9172	0.0725 (0.0014)	0.0103 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1137	0.8181 (0.0021)	0.0682 (0.0013)
22	0.9156	0.074 (0.0015)	0.0104 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.1050	0.8259 (0.002)	0.0691 (0.0013)
23	0.9141	0.0754 (0.0015)	0.0105 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0972	0.8329 (0.002)	0.0699 (0.0013)
24	0.9127	0.0767 (0.0015)	0.0106 (0.0005)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0899	0.8394 (0.002)	0.0707 (0.0013)
25	0.9112	0.0781 (0.0015)	0.0107 (0.0006)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0832	0.8454 (0.0019)	0.0714 (0.0013)
26	0.9098	0.0794 (0.0015)	0.0108 (0.0006)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0771	0.8508 (0.0019)	0.0721 (0.0013)
27	0.9084	0.0807 (0.0015)	0.0109 (0.0006)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0715	0.8558 (0.0019)	0.0727 (0.0013)
28	0.9072	0.0819 (0.0015)	0.0109 (0.0006)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0664	0.8604 (0.0018)	0.0732 (0.0013)
29	0.9059	0.0831 (0.0015)	0.011 (0.0006)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0615	0.8647 (0.0018)	0.0738 (0.0013)
30	0.9046	0.0843 (0.0016)	0.0111 (0.0006)	0.187	0.806 (0.0025)	0.007 (0.0005)	0.0571	0.8686 (0.0018)	0.0743 (0.0013)

Circulatory: diseases of the circulatory system

Table C22: Transition probabilities for the first 30 days used in the central hospital-Circulatory

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9851	0.0112 (0.001)	0.0037 (0.0007)	0.268	0.726 (0.0058)	0.006 (0.001)	0.7740	0.2153 (0.0046)	0.0107 (0.0009)
2	0.9791	0.0162 (0.0013)	0.0047 (0.0008)	0.268	0.726 (0.0058)	0.006 (0.001)	0.6538	0.3276 (0.0054)	0.0186 (0.0013)
3	0.9746	0.0201 (0.0015)	0.0053 (0.0009)	0.268	0.726 (0.0058)	0.006 (0.001)	0.5643	0.4105 (0.0057)	0.0252 (0.0016)
4	0.9708	0.0234 (0.0016)	0.0058 (0.0009)	0.268	0.726 (0.0058)	0.006 (0.001)	0.4932	0.4761 (0.0058)	0.0307 (0.0018)
5	0.9674	0.0264 (0.0017)	0.0062 (0.0009)	0.268	0.726 (0.0058)	0.006 (0.001)	0.4346	0.5298 (0.0058)	0.0356 (0.0019)
6	0.9643	0.0291 (0.0019)	0.0066 (0.001)	0.268	0.726 (0.0058)	0.006 (0.001)	0.3855	0.5747 (0.0057)	0.0398 (0.002)
7	0.9615	0.0316 (0.0019)	0.0069 (0.001)	0.268	0.726 (0.0058)	0.006 (0.001)	0.3435	0.6129 (0.0056)	0.0436 (0.0021)
8	0.9589	0.0339 (0.002)	0.0072 (0.001)	0.268	0.726 (0.0058)	0.006 (0.001)	0.3074	0.6457 (0.0055)	0.0469 (0.0022)
9	0.9564	0.0361 (0.0021)	0.0075 (0.001)	0.268	0.726 (0.0058)	0.006 (0.001)	0.2761	0.6741 (0.0053)	0.0498 (0.0022)
10	0.954	0.0382 (0.0022)	0.0078 (0.001)	0.268	0.726 (0.0058)	0.006 (0.001)	0.2486	0.6989 (0.0052)	0.0525 (0.0023)
11	0.9519	0.0401 (0.0022)	0.008 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.2244	0.7207 (0.0051)	0.0549 (0.0023)
12	0.9498	0.042 (0.0023)	0.0082 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.2031	0.7399 (0.005)	0.057 (0.0024)
13	0.9478	0.0438 (0.0023)	0.0084 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.1842	0.7569 (0.0049)	0.0589 (0.0024)
14	0.9458	0.0456 (0.0024)	0.0086 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.1673	0.772 (0.0047)	0.0607 (0.0024)
15	0.9439	0.0473 (0.0024)	0.0088 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.1523	0.7855 (0.0046)	0.0622 (0.0025)
16	0.9421	0.0489 (0.0025)	0.009 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.1387	0.7976 (0.0045)	0.0637 (0.0025)
17	0.9403	0.0505 (0.0025)	0.0092 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.1266	0.8084 (0.0044)	0.065 (0.0025)
18	0.9387	0.052 (0.0026)	0.0093 (0.0011)	0.268	0.726 (0.0058)	0.006 (0.001)	0.1157	0.8181 (0.0043)	0.0662 (0.0025)
19	0.937	0.0535 (0.0026)	0.0095 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.1058	0.8269 (0.0042)	0.0673 (0.0026)
20	0.9354	0.055 (0.0027)	0.0096 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0970	0.8348 (0.0041)	0.0682 (0.0026)
21	0.9338	0.0564 (0.0027)	0.0098 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0889	0.8419 (0.004)	0.0692 (0.0026)
22	0.9323	0.0578 (0.0027)	0.0099 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0816	0.8484 (0.0039)	0.07 (0.0026)
23	0.9307	0.0592 (0.0028)	0.0101 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0750	0.8543 (0.0039)	0.0707 (0.0026)
24	0.9293	0.0605 (0.0028)	0.0102 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0690	0.8596 (0.0038)	0.0714 (0.0026)
25	0.9279	0.0618 (0.0028)	0.0103 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0634	0.8645 (0.0037)	0.0721 (0.0026)
26	0.9264	0.0631 (0.0028)	0.0105 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0584	0.8689 (0.0036)	0.0727 (0.0027)
27	0.925	0.0644 (0.0029)	0.0106 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0539	0.8729 (0.0036)	0.0732 (0.0027)
28	0.9237	0.0656 (0.0029)	0.0107 (0.0012)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0497	0.8766 (0.0035)	0.0737 (0.0027)
29	0.9224	0.0668 (0.0029)	0.0108 (0.0013)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0458	0.88 (0.0035)	0.0742 (0.0027)
30	0.9211	0.068 (0.003)	0.0109 (0.0013)	0.268	0.726 (0.0058)	0.006 (0.001)	0.0423	0.8831(0.0034)	0.0746 (0.0027)

Circulatory: diseases of the circulatory system

Table C23: Transition probabilities for the first 30 days used in the local hospital- Respiratory

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9682	0.0243 (0.0007)	0.0075 (0.0004)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.8786	0.1102 (0.0015)	0.0112 (0.0004)
2	0.9583	0.0327 (0.0009)	0.009 (0.0005)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.7821	0.196 (0.002)	0.0219 (0.0007)
3	0.9512	0.0389 (0.001)	0.0099 (0.0005)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.6993	0.269 (0.0023)	0.0317 (0.0008)
4	0.9454	0.0439 (0.001)	0.0107 (0.0005)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.6269	0.3324 (0.0025)	0.0407 (0.0009)
5	0.9404	0.0483 (0.0011)	0.0113 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.5631	0.388 (0.0026)	0.0489 (0.001)
6	0.936	0.0522 (0.0012)	0.0118 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.5064	0.4372 (0.0027)	0.0564 (0.0011)
7	0.932	0.0557 (0.0012)	0.0123 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.4561	0.4807 (0.0027)	0.0632 (0.0012)
8	0.9284	0.0589 (0.0012)	0.0127 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.4111	0.5195 (0.0027)	0.0694 (0.0012)
9	0.9251	0.0619 (0.0013)	0.013 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.3710	0.554 (0.0026)	0.075 (0.0013)
10	0.9219	0.0647 (0.0013)	0.0134 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.3350	0.5849 (0.0026)	0.0801 (0.0013)
11	0.9189	0.0674 (0.0013)	0.0137 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.3027	0.6126 (0.0026)	0.0847 (0.0014)
12	0.9161	0.0699 (0.0014)	0.014 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.2737	0.6374 (0.0025)	0.0889 (0.0014)
13	0.9135	0.0722 (0.0014)	0.0143 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.2476	0.6597 (0.0025)	0.0927 (0.0014)
14	0.911	0.0745 (0.0014)	0.0145 (0.0006)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.2241	0.6797 (0.0024)	0.0962 (0.0014)
15	0.9085	0.0767 (0.0014)	0.0148 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.2029	0.6977 (0.0024)	0.0994 (0.0015)
16	0.9062	0.0788 (0.0015)	0.015 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.1839	0.7139 (0.0023)	0.1022 (0.0015)
17	0.904	0.0808 (0.0015)	0.0152 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.1667	0.7285 (0.0023)	0.1048 (0.0015)
18	0.9018	0.0828 (0.0015)	0.0154 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.1511	0.7417 (0.0022)	0.1072 (0.0015)
19	0.8998	0.0846 (0.0015)	0.0156 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.1370	0.7536 (0.0022)	0.1094 (0.0015)
20	0.8977	0.0865 (0.0015)	0.0158 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.1243	0.7643 (0.0022)	0.1114 (0.0015)
21	0.8958	0.0882 (0.0016)	0.016 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.1129	0.774 (0.0021)	0.1131 (0.0015)
22	0.8939	0.0899 (0.0016)	0.0162 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.1024	0.7828 (0.0021)	0.1148 (0.0015)
23	0.892	0.0916 (0.0016)	0.0164 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0930	0.7907 (0.002)	0.1163 (0.0015)
24	0.8903	0.0932 (0.0016)	0.0165 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0845	0.7979 (0.002)	0.1176 (0.0016)
25	0.8885	0.0948 (0.0016)	0.0167 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0768	0.8044 (0.002)	0.1188 (0.0016)
26	0.8867	0.0964 (0.0016)	0.0169 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0697	0.8103 (0.0019)	0.12 (0.0016)
27	0.8851	0.0979 (0.0016)	0.017 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0634	0.8156 (0.0019)	0.121 (0.0016)
28	0.8834	0.0994 (0.0016)	0.0172 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0577	0.8204 (0.0019)	0.1219 (0.0016)
29	0.8819	0.1008 (0.0017)	0.0173 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0524	0.8248 (0.0019)	0.1228 (0.0016)
30	0.8804	0.1022 (0.0017)	0.0174 (0.0007)	0.173	0.819 (0.0023)	0.008 (0.0005)	0.0477	0.8288 (0.0018)	0.1235 (0.0016)

Respiratory: diseases of respiratory system

Table C24: Transition probabilities for the first 30 days used in the central hospital-Respiratory

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.979	0.0155 (0.0012)	0.0055 (0.0009)	0.154	0.840 (0.0046)	0.006 (0.001)	0.8622	0.1281 (0.0032)	0.0097 (0.0008)
2	0.9706	0.0225 (0.0015)	0.0069 (0.001)	0.154	0.840 (0.0046)	0.006 (0.001)	0.7550	0.2257 (0.0044)	0.0193 (0.0013)
3	0.9642	0.0279 (0.0017)	0.0079 (0.0011)	0.154	0.840 (0.0046)	0.006 (0.001)	0.6645	0.3074 (0.0049)	0.0281 (0.0016)
4	0.9587	0.0326 (0.0019)	0.0087 (0.0011)	0.154	0.840 (0.0046)	0.006 (0.001)	0.5866	0.3772 (0.0052)	0.0362 (0.0018)
5	0.9539	0.0367 (0.002)	0.0094 (0.0012)	0.154	0.840 (0.0046)	0.006 (0.001)	0.5190	0.4375 (0.0053)	0.0435 (0.002)
6	0.9497	0.0404 (0.0021)	0.0099 (0.0012)	0.154	0.840 (0.0046)	0.006 (0.001)	0.4600	0.4899 (0.0054)	0.0501 (0.0021)
7	0.9457	0.0439 (0.0022)	0.0104 (0.0012)	0.154	0.840 (0.0046)	0.006 (0.001)	0.4083	0.5357 (0.0053)	0.056 (0.0022)
8	0.942	0.0471 (0.0023)	0.0109 (0.0012)	0.154	0.840 (0.0046)	0.006 (0.001)	0.3628	0.5758 (0.0052)	0.0614 (0.0023)
9	0.9386	0.0501 (0.0024)	0.0113 (0.0013)	0.154	0.840 (0.0046)	0.006 (0.001)	0.3227	0.6111 (0.0052)	0.0662 (0.0024)
10	0.9353	0.053 (0.0025)	0.0117 (0.0013)	0.154	0.840 (0.0046)	0.006 (0.001)	0.2872	0.6422 (0.005)	0.0706 (0.0025)
11	0.9322	0.0557 (0.0025)	0.0121 (0.0013)	0.154	0.840 (0.0046)	0.006 (0.001)	0.2559	0.6696 (0.0049)	0.0745 (0.0025)
12	0.9292	0.0584 (0.0026)	0.0124 (0.0013)	0.154	0.840 (0.0046)	0.006 (0.001)	0.2281	0.6939 (0.0048)	0.078 (0.0026)
13	0.9264	0.0609 (0.0027)	0.0127 (0.0013)	0.154	0.840 (0.0046)	0.006 (0.001)	0.2036	0.7153 (0.0047)	0.0811 (0.0026)
14	0.9237	0.0633 (0.0027)	0.013 (0.0014)	0.154	0.840 (0.0046)	0.006 (0.001)	0.1817	0.7343 (0.0046)	0.084 (0.0027)
15	0.9211	0.0656 (0.0028)	0.0133 (0.0014)	0.154	0.840 (0.0046)	0.006 (0.001)	0.1623	0.7512 (0.0044)	0.0865 (0.0027)
16	0.9185	0.0679 (0.0028)	0.0136 (0.0014)	0.154	0.840 (0.0046)	0.006 (0.001)	0.1450	0.7662 (0.0043)	0.0888 (0.0027)
17	0.916	0.0701 (0.0029)	0.0139 (0.0014)	0.154	0.840 (0.0046)	0.006 (0.001)	0.1296	0.7795 (0.0042)	0.0909 (0.0027)
18	0.9137	0.0722 (0.0029)	0.0141 (0.0014)	0.154	0.840 (0.0046)	0.006 (0.001)	0.1160	0.7913 (0.0041)	0.0927 (0.0028)
19	0.9113	0.0743 (0.0029)	0.0144 (0.0014)	0.154	0.840 (0.0046)	0.006 (0.001)	0.1037	0.8019 (0.004)	0.0944 (0.0028)
20	0.9091	0.0763 (0.003)	0.0146 (0.0014)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0928	0.8113 (0.0039)	0.0959 (0.0028)
21	0.9069	0.0783 (0.003)	0.0148 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0831	0.8196 (0.0038)	0.0973 (0.0028)
22	0.9048	0.0802 (0.0031)	0.015 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0744	0.8271 (0.0037)	0.0985 (0.0028)
23	0.9027	0.082 (0.0031)	0.0153 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0667	0.8337 (0.0037)	0.0996 (0.0028)
24	0.9006	0.0839 (0.0031)	0.0155 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0597	0.8397 (0.0036)	0.1006 (0.0029)
25	0.8986	0.0857 (0.0032)	0.0157 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0536	0.845 (0.0035)	0.1014 (0.0029)
26	0.8967	0.0874 (0.0032)	0.0159 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0481	0.8497 (0.0034)	0.1022 (0.0029)
27	0.8948	0.0892 (0.0032)	0.016 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0431	0.8539 (0.0034)	0.103 (0.0029)
28	0.8929	0.0909 (0.0032)	0.0162 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0387	0.8577 (0.0033)	0.1036 (0.0029)
29	0.8911	0.0925 (0.0033)	0.0164 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0347	0.8611 (0.0033)	0.1042 (0.0029)
30	0.8893	0.0941(0.0033)	0.0166 (0.0015)	0.154	0.840 (0.0046)	0.006 (0.001)	0.0312	0.8641 (0.0032)	0.1047 (0.0029)

Respiratory: diseases of respiratory system

Table C25: Transition probabilities for the first 30 days used in the local hospital- Digestive

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9729	0.024 (0.0007)	0.0031 (0.0003)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.8149	0.1799 (0.002)	0.0052 (0.0003)
2	0.965	0.0313 (0.0009)	0.0037 (0.0003)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.6913	0.2986 (0.0025)	0.0101 (0.0005)
3	0.9593	0.0367 (0.001)	0.004 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.5936	0.3919 (0.0026)	0.0145 (0.0006)
4	0.9547	0.041 (0.001)	0.0043 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.5136	0.4681 (0.0027)	0.0183 (0.0007)
5	0.9508	0.0447 (0.0011)	0.0045 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.4465	0.5317 (0.0027)	0.0218 (0.0007)
6	0.9474	0.0479 (0.0011)	0.0047 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.3897	0.5855 (0.0026)	0.0248 (0.0008)
7	0.9443	0.0508 (0.0012)	0.0049 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.3412	0.6312 (0.0026)	0.0276 (0.0008)
8	0.9414	0.0535 (0.0012)	0.0051 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.2995	0.6705 (0.0025)	0.03 (0.0009)
9	0.9388	0.056 (0.0012)	0.0052 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.2636	0.7043 (0.0024)	0.0321 (0.0009)
10	0.9364	0.0583 (0.0012)	0.0053 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.2324	0.7336 (0.0023)	0.034 (0.0009)
11	0.9342	0.0604 (0.0013)	0.0054 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.2053	0.759 (0.0023)	0.0357 (0.0009)
12	0.9319	0.0625 (0.0013)	0.0056 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.1816	0.7812 (0.0022)	0.0372 (0.001)
13	0.9299	0.0644 (0.0013)	0.0057 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.1608	0.8006 (0.0021)	0.0386 (0.001)
14	0.928	0.0662 (0.0013)	0.0058 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.1426	0.8176 (0.002)	0.0398 (0.001)
15	0.9262	0.068 (0.0014)	0.0058 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.1266	0.8325 (0.002)	0.0409 (0.001)
16	0.9244	0.0697 (0.0014)	0.0059 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.1126	0.8456 (0.0019)	0.0418 (0.001)
17	0.9227	0.0713 (0.0014)	0.006 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.1001	0.8572 (0.0018)	0.0427 (0.001)
18	0.921	0.0729 (0.0014)	0.0061 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0891	0.8674 (0.0018)	0.0435 (0.001)
19	0.9194	0.0744 (0.0014)	0.0062 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0794	0.8764 (0.0017)	0.0442 (0.001)
20	0.918	0.0758 (0.0014)	0.0062 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0709	0.8843 (0.0016)	0.0448 (0.001)
21	0.9164	0.0773 (0.0014)	0.0063 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0633	0.8914 (0.0016)	0.0453 (0.001)
22	0.915	0.0786 (0.0015)	0.0064 (0.0004)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0566	0.8976 (0.0015)	0.0458 (0.001)
23	0.9136	0.08 (0.0015)	0.0064 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0505	0.9032 (0.0015)	0.0463 (0.001)
24	0.9122	0.0813 (0.0015)	0.0065 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0452	0.9081 (0.0014)	0.0467 (0.001)
25	0.9109	0.0825 (0.0015)	0.0066 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0405	0.9125 (0.0014)	0.047 (0.001)
26	0.9096	0.0838 (0.0015)	0.0066 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0362	0.9164 (0.0014)	0.0474 (0.0011)
27	0.9083	0.085 (0.0015)	0.0067 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0325	0.9199 (0.0013)	0.0476 (0.0011)
28	0.9072	0.0861 (0.0015)	0.0067 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0291	0.923 (0.0013)	0.0479 (0.0011)
29	0.9059	0.0873 (0.0015)	0.0068 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0262	0.9257 (0.0013)	0.0481 (0.0011)
30	0.9048	0.0884 (0.0015)	0.0068 (0.0005)	0.233	0.764 (0.0028)	0.004 (0.0004)	0.0234	0.9282 (0.0013)	0.0484 (0.0011)

Digestive: diseases of the digestive system

Table C26: Transition probabilities for the first 30 days used in the central hospital-Digestive

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9776	0.0206 (0.0015)	0.0018 (0.0005)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.7761	0.219 (0.0044)	0.0049 (0.0006)
2	0.9698	0.0279 (0.0018)	0.0023 (0.0006)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.6309	0.3594 (0.0053)	0.0097 (0.0009)
3	0.9641	0.0333 (0.002)	0.0026 (0.0006)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.5201	0.466 (0.0056)	0.0139 (0.0011)
4	0.9595	0.0377 (0.0022)	0.0028 (0.0006)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.4323	0.55 (0.0056)	0.0177 (0.0013)
5	0.9555	0.0415 (0.0023)	0.003 (0.0007)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.3615	0.6176 (0.0054)	0.0209 (0.0014)
6	0.9519	0.0449 (0.0024)	0.0032 (0.0007)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.3036	0.6726 (0.0052)	0.0238 (0.0015)
7	0.9486	0.048 (0.0025)	0.0034 (0.0007)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.2560	0.7178 (0.005)	0.0262 (0.0016)
8	0.9457	0.0508 (0.0025)	0.0035 (0.0007)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.2165	0.7552 (0.0048)	0.0283 (0.0016)
9	0.9429	0.0535 (0.0026)	0.0036 (0.0007)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.1836	0.7863 (0.0045)	0.0301 (0.0017)
10	0.9402	0.056 (0.0027)	0.0038 (0.0007)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.1560	0.8123 (0.0043)	0.0317 (0.0017)
11	0.9378	0.0583 (0.0027)	0.0039 (0.0007)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.1328	0.8341 (0.0041)	0.0331 (0.0017)
12	0.9355	0.0605 (0.0028)	0.004 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.1132	0.8525 (0.0039)	0.0343 (0.0018)
13	0.9333	0.0626 (0.0028)	0.0041 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0968	0.8679 (0.0036)	0.0353 (0.0018)
14	0.9312	0.0646 (0.0029)	0.0042 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0828	0.881 (0.0034)	0.0362 (0.0018)
15	0.9292	0.0665 (0.0029)	0.0043 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0710	0.8921 (0.0033)	0.0369 (0.0018)
16	0.9272	0.0684 (0.0029)	0.0044 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0608	0.9016 (0.0031)	0.0376 (0.0018)
17	0.9254	0.0702 (0.003)	0.0044 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0522	0.9096 (0.0029)	0.0382 (0.0018)
18	0.9236	0.0719 (0.003)	0.0045 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0449	0.9164 (0.0028)	0.0387 (0.0018)
19	0.9218	0.0736 (0.003)	0.0046 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0387	0.9222 (0.0027)	0.0391 (0.0018)
20	0.9201	0.0752 (0.0031)	0.0047 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0333	0.9272 (0.0026)	0.0395 (0.0018)
21	0.9185	0.0768 (0.0031)	0.0047 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0287	0.9315 (0.0025)	0.0398 (0.0019)
22	0.9169	0.0783 (0.0031)	0.0048 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0248	0.9351 (0.0024)	0.0401 (0.0019)
23	0.9153	0.0798 (0.0032)	0.0049 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0213	0.9383 (0.0023)	0.0404 (0.0019)
24	0.9139	0.0812 (0.0032)	0.0049 (0.0008)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0185	0.9409 (0.0022)	0.0406 (0.0019)
25	0.9123	0.0827 (0.0032)	0.005 (0.0009)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0159	0.9433 (0.0022)	0.0408 (0.0019)
26	0.9109	0.084 (0.0032)	0.0051 (0.0009)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0139	0.9452 (0.0021)	0.0409 (0.0019)
27	0.9095	0.0854 (0.0032)	0.0051 (0.0009)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0119	0.947 (0.0021)	0.0411 (0.0019)
28	0.9081	0.0867 (0.0033)	0.0052 (0.0009)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0104	0.9484 (0.0021)	0.0412 (0.0019)
29	0.9068	0.088 (0.0033)	0.0052 (0.0009)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0090	0.9497 (0.002)	0.0413 (0.0019)
30	0.9054	0.0893 (0.0033)	0.0053 (0.0009)	0.241	0.755 (0.0057)	0.004 (0.0008)	0.0078	0.9508 (0.002)	0.0414 (0.0019)

Digestive: diseases of the digestive system

Table C27: Transition probabilities for the first 30 days used in the local hospital- Abnormal

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9793	0.019 (0.0005)	0.0017 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.6926	0.306 (0.0024)	0.0014 (0.0001)
2	0.9729	0.0251 (0.0006)	0.002 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.5488	0.4484 (0.0027)	0.0028 (0.0002)
3	0.9682	0.0296 (0.0007)	0.0022 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.4490	0.5469 (0.0027)	0.0041 (0.0003)
4	0.9644	0.0332 (0.0007)	0.0024 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.3740	0.6207 (0.0026)	0.0053 (0.0003)
5	0.9612	0.0363 (0.0008)	0.0025 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.3155	0.6782 (0.0025)	0.0063 (0.0004)
6	0.9583	0.039 (0.0008)	0.0027 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.2684	0.7243 (0.0024)	0.0073 (0.0004)
7	0.9557	0.0415 (0.0008)	0.0028 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.2300	0.7619 (0.0023)	0.0081 (0.0004)
8	0.9534	0.0438 (0.0009)	0.0028 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.1982	0.7929 (0.0022)	0.0089 (0.0004)
9	0.9512	0.0459 (0.0009)	0.0029 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.1718	0.8187 (0.0021)	0.0095 (0.0004)
10	0.9491	0.0479 (0.0009)	0.003 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.1494	0.8405 (0.0019)	0.0101 (0.0005)
11	0.9472	0.0497 (0.0009)	0.0031 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.1303	0.859 (0.0018)	0.0107 (0.0005)
12	0.9454	0.0515 (0.0009)	0.0031 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.1142	0.8747 (0.0017)	0.0111 (0.0005)
13	0.9437	0.0531 (0.001)	0.0032 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.1002	0.8882 (0.0016)	0.0116 (0.0005)
14	0.942	0.0547 (0.001)	0.0033 (0.0002)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0882	0.8998 (0.0015)	0.012 (0.0005)
15	0.9405	0.0562 (0.001)	0.0033 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0779	0.9098 (0.0015)	0.0123 (0.0005)
16	0.9389	0.0577 (0.001)	0.0034 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0689	0.9185 (0.0014)	0.0126 (0.0005)
17	0.9375	0.0591 (0.001)	0.0034 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0610	0.9261 (0.0013)	0.0129 (0.0005)
18	0.9361	0.0604 (0.001)	0.0035 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0542	0.9327 (0.0012)	0.0131 (0.0005)
19	0.9347	0.0618 (0.001)	0.0035 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0481	0.9385 (0.0012)	0.0134 (0.0005)
20	0.9335	0.063 (0.001)	0.0035 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0429	0.9435 (0.0011)	0.0136 (0.0005)
21	0.9321	0.0643 (0.0011)	0.0036 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0382	0.948 (0.0011)	0.0138 (0.0005)
22	0.931	0.0654 (0.0011)	0.0036 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0342	0.9519 (0.001)	0.0139 (0.0005)
23	0.9297	0.0666 (0.0011)	0.0037 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0305	0.9554 (0.001)	0.0141 (0.0005)
24	0.9286	0.0677 (0.0011)	0.0037 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0274	0.9584 (0.0009)	0.0142 (0.0005)
25	0.9275	0.0688 (0.0011)	0.0037 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0245	0.9612 (0.0009)	0.0143 (0.0005)
26	0.9263	0.0699 (0.0011)	0.0038 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0219	0.9636 (0.0008)	0.0145 (0.0005)
27	0.9253	0.0709 (0.0011)	0.0038 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0197	0.9657 (0.0008)	0.0146 (0.0005)
28	0.9242	0.072 (0.0011)	0.0038 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0177	0.9676 (0.0008)	0.0147 (0.0005)
29	0.9231	0.073 (0.0011)	0.0039 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0160	0.9693 (0.0007)	0.0147 (0.0005)
30	0.9221	0.074 (0.0011)	0.0039 (0.0003)	0.5435	0.4560 (0.0025)	0.0005 (0.0001)	0.0144	0.9708 (0.0007)	0.0148 (0.0005)

Abnormal: abnormal clinical laboratory findings

Table C28: Transition probabilities for the first 30 days used in the central hospital-Abnormal

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9867	0.0119 (0.0009)	0.0014 (0.0004)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.6568	0.3422 (0.0056)	0.001 (0.0002)
2	0.9815	0.0168 (0.0011)	0.0017 (0.0004)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.5055	0.4924 (0.006)	0.0021 (0.0004)
3	0.9775	0.0206 (0.0012)	0.0019 (0.0005)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.4039	0.5931 (0.0059)	0.003 (0.0005)
4	0.9741	0.0238 (0.0013)	0.0021 (0.0005)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.3294	0.6667 (0.0057)	0.0039 (0.0006)
5	0.9711	0.0266 (0.0014)	0.0023 (0.0005)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.2724	0.7229 (0.0053)	0.0047 (0.0007)
6	0.9685	0.0291 (0.0015)	0.0024 (0.0005)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.2276	0.7669 (0.005)	0.0055 (0.0007)
7	0.9661	0.0314 (0.0016)	0.0025 (0.0005)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.1917	0.8022 (0.0047)	0.0061 (0.0008)
8	0.9639	0.0335 (0.0016)	0.0026 (0.0005)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.1625	0.8308 (0.0044)	0.0067 (0.0008)
9	0.9617	0.0356 (0.0017)	0.0027 (0.0005)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.1386	0.8542 (0.0041)	0.0072 (0.0008)
10	0.9597	0.0375 (0.0017)	0.0028 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.1187	0.8737 (0.0038)	0.0076 (0.0008)
11	0.9578	0.0393 (0.0018)	0.0029 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.1021	0.8899 (0.0035)	0.008 (0.0009)
12	0.956	0.041 (0.0018)	0.003 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0881	0.9035 (0.0033)	0.0084 (0.0009)
13	0.9542	0.0427 (0.0019)	0.0031 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0763	0.915 (0.0031)	0.0087 (0.0009)
14	0.9527	0.0442 (0.0019)	0.0031 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0662	0.9248 (0.0029)	0.009 (0.0009)
15	0.951	0.0458 (0.0019)	0.0032 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0577	0.9331 (0.0027)	0.0092 (0.0009)
16	0.9495	0.0472 (0.002)	0.0033 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0504	0.9402 (0.0025)	0.0094 (0.0009)
17	0.948	0.0487 (0.002)	0.0033 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0441	0.9463 (0.0023)	0.0096 (0.0009)
18	0.9465	0.0501 (0.002)	0.0034 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0386	0.9516 (0.0022)	0.0098 (0.0009)
19	0.9451	0.0514 (0.002)	0.0035 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0339	0.9561 (0.0021)	0.01 (0.0009)
20	0.9438	0.0527 (0.0021)	0.0035 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0298	0.9601 (0.0019)	0.0101 (0.001)
21	0.9424	0.054 (0.0021)	0.0036 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0263	0.9635 (0.0018)	0.0102 (0.001)
22	0.9411	0.0553 (0.0021)	0.0036 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0232	0.9664 (0.0017)	0.0104 (0.001)
23	0.9398	0.0565 (0.0021)	0.0037 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0205	0.969 (0.0016)	0.0105 (0.001)
24	0.9386	0.0577 (0.0022)	0.0037 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0182	0.9713 (0.0016)	0.0105 (0.001)
25	0.9374	0.0588 (0.0022)	0.0038 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0161	0.9733 (0.0015)	0.0106 (0.001)
26	0.9362	0.06 (0.0022)	0.0038 (0.0006)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0143	0.975 (0.0014)	0.0107 (0.001)
27	0.935	0.0611 (0.0022)	0.0039 (0.0007)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0126	0.9766 (0.0014)	0.0108 (0.001)
28	0.9339	0.0622 (0.0022)	0.0039 (0.0007)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0113	0.9779 (0.0013)	0.0108 (0.001)
29	0.9329	0.0632 (0.0022)	0.0039 (0.0007)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0100	0.9791 (0.0013)	0.0109 (0.001)
30	0.9317	0.0643 (0.0023)	0.004 (0.0007)	0.5739	0.4258 (0.0053)	0.0003 (0.0002)	0.0090	0.9801 (0.0012)	0.0109 (0.001)

Abnormal: abnormal clinical laboratory findings

Table C29: Transition probabilities for the first 30 days used in the local hospital- Injury

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission (SE)*	*Dead (SE)*	*Admission*	*Community(SE)*	*Dead(SE)*
1	0.9791	0.0184 (0.0005)	0.0025 (0.0002)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.7921	0.205 (0.0022)	0.0029 (0.0002)
2	0.9729	0.0242 (0.0006)	0.0029 (0.0002)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.6926	0.3023 (0.0026)	0.0051 (0.0003)
3	0.9684	0.0284 (0.0007)	0.0032 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.6189	0.374 (0.0027)	0.0071 (0.0004)
4	0.9648	0.0318 (0.0008)	0.0034 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.5597	0.4315 (0.0028)	0.0088 (0.0005)
5	0.9616	0.0348 (0.0008)	0.0036 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.5103	0.4793 (0.0028)	0.0104 (0.0005)
6	0.959	0.0373 (0.0008)	0.0037 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.4679	0.5202 (0.0028)	0.0119 (0.0006)
7	0.9564	0.0397 (0.0009)	0.0039 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.4310	0.5558 (0.0028)	0.0132 (0.0006)
8	0.9542	0.0418 (0.0009)	0.004 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.3986	0.587 (0.0028)	0.0144 (0.0006)
9	0.9521	0.0438 (0.0009)	0.0041 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.3696	0.6148 (0.0027)	0.0156 (0.0006)
10	0.9502	0.0456 (0.0009)	0.0042 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.3438	0.6396 (0.0027)	0.0166 (0.0007)
11	0.9483	0.0474 (0.001)	0.0043 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.3205	0.6619 (0.0026)	0.0176 (0.0007)
12	0.9466	0.049 (0.001)	0.0044 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.2993	0.6822 (0.0026)	0.0185 (0.0007)
13	0.9449	0.0506 (0.001)	0.0045 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.2801	0.7006 (0.0026)	0.0193 (0.0007)
14	0.9435	0.052 (0.001)	0.0045 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.2625	0.7174 (0.0025)	0.0201 (0.0007)
15	0.9419	0.0535 (0.001)	0.0046 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.2463	0.7328 (0.0025)	0.0209 (0.0007)
16	0.9405	0.0548 (0.001)	0.0047 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.2315	0.7469 (0.0024)	0.0216 (0.0008)
17	0.9392	0.0561 (0.0011)	0.0047 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.2179	0.7599 (0.0024)	0.0222 (0.0008)
18	0.9378	0.0574 (0.0011)	0.0048 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.2052	0.7719 (0.0024)	0.0229 (0.0008)
19	0.9365	0.0586 (0.0011)	0.0049 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1936	0.783 (0.0023)	0.0234 (0.0008)
20	0.9353	0.0598 (0.0011)	0.0049 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1827	0.7933 (0.0023)	0.024 (0.0008)
21	0.9341	0.0609 (0.0011)	0.005 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1726	0.8029 (0.0022)	0.0245 (0.0008)
22	0.933	0.062 (0.0011)	0.005 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1632	0.8118 (0.0022)	0.025 (0.0008)
23	0.9318	0.0631 (0.0011)	0.0051 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1544	0.8201 (0.0022)	0.0255 (0.0008)
24	0.9307	0.0642 (0.0011)	0.0051 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1463	0.8278 (0.0021)	0.0259 (0.0008)
25	0.9296	0.0652 (0.0011)	0.0052 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1386	0.8351 (0.0021)	0.0263 (0.0008)
26	0.9286	0.0662 (0.0012)	0.0052 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1314	0.8419 (0.0021)	0.0267 (0.0008)
27	0.9275	0.0672 (0.0012)	0.0053 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1247	0.8482 (0.002)	0.0271 (0.0008)
28	0.9266	0.0681 (0.0012)	0.0053 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1185	0.8541 (0.002)	0.0274 (0.0009)
29	0.9256	0.069 (0.0012)	0.0054 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1125	0.8597 (0.0019)	0.0278 (0.0009)
30	0.9246	0.07 (0.0012)	0.0054 (0.0003)	0.4192	0.5801 (0.0027)	0.0007 (0.0001)	0.1069	0.865 (0.0019)	0.0281 (0.0009)

Injury: injury poisoning and certain consequences

Table C30: Transition probabilities for the first 30 days used in the central hospital-Injury

Day	Transition Probability (Standard Error)								
	Community to			*A&E to*			*Admission to*		
	Community	*A&E (SE)*	*Dead (SE)*	*Community*	*Admission(SE)*	*Dead(SE)*	*Admission*	*Community(SE)*	*Dead (SE)*
1	0.9846	0.0136 (0.0011)	0.0018 (0.0005)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.7839	0.2139 (0.0045)	0.0022 (0.0004)
2	0.9787	0.019 (0.0013)	0.0023 (0.0005)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.6791	0.3167 (0.0053)	0.0042 (0.0006)
3	0.9743	0.0231 (0.0015)	0.0026 (0.0006)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.6017	0.3923 (0.0056)	0.006 (0.0008)
4	0.9706	0.0265 (0.0016)	0.0029 (0.0006)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.5397	0.4526 (0.0057)	0.0077 (0.0009)
5	0.9675	0.0294 (0.0018)	0.0031 (0.0006)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.4881	0.5026 (0.0057)	0.0093 (0.001)
6	0.9646	0.0321 (0.0018)	0.0033 (0.0006)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.4441	0.5451 (0.0057)	0.0108 (0.0011)
7	0.962	0.0345 (0.0019)	0.0035 (0.0006)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.4061	0.5818 (0.0056)	0.0121 (0.0012)
8	0.9596	0.0368 (0.002)	0.0036 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.3728	0.6138 (0.0055)	0.0134 (0.0012)
9	0.9573	0.0389 (0.002)	0.0038 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.3432	0.6422 (0.0055)	0.0146 (0.0013)
10	0.9552	0.0409 (0.0021)	0.0039 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.3169	0.6674 (0.0054)	0.0157 (0.0013)
11	0.9531	0.0428 (0.0021)	0.0041 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.2934	0.6899 (0.0053)	0.0167 (0.0014)
12	0.9513	0.0445 (0.0022)	0.0042 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.2721	0.7102 (0.0052)	0.0177 (0.0014)
13	0.9494	0.0463 (0.0022)	0.0043 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.2528	0.7286 (0.0051)	0.0186 (0.0015)
14	0.9477	0.0479 (0.0023)	0.0044 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.2353	0.7452 (0.005)	0.0195 (0.0015)
15	0.946	0.0495 (0.0023)	0.0045 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.2193	0.7604 (0.0049)	0.0203 (0.0015)
16	0.9444	0.051 (0.0023)	0.0046 (0.0007)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.2048	0.7742 (0.0048)	0.021 (0.0015)
17	0.9428	0.0525 (0.0024)	0.0047 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1914	0.7869 (0.0047)	0.0217 (0.0016)
18	0.9413	0.0539 (0.0024)	0.0048 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1791	0.7985 (0.0046)	0.0224 (0.0016)
19	0.9398	0.0553 (0.0024)	0.0049 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1678	0.8092 (0.0045)	0.023 (0.0016)
20	0.9384	0.0567 (0.0025)	0.0049 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1573	0.8191 (0.0044)	0.0236 (0.0016)
21	0.937	0.058 (0.0025)	0.005 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1477	0.8281 (0.0044)	0.0242 (0.0016)
22	0.9357	0.0592 (0.0025)	0.0051 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1387	0.8366 (0.0043)	0.0247 (0.0017)
23	0.9343	0.0605 (0.0025)	0.0052 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1304	0.8444 (0.0042)	0.0252 (0.0017)
24	0.9331	0.0617 (0.0026)	0.0052 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1227	0.8516 (0.0041)	0.0257 (0.0017)
25	0.9318	0.0629 (0.0026)	0.0053 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1155	0.8583 (0.004)	0.0262 (0.0017)
26	0.9305	0.0641 (0.0026)	0.0054 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1089	0.8645 (0.0039)	0.0266 (0.0017)
27	0.9294	0.0652 (0.0026)	0.0054 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.1026	0.8704 (0.0039)	0.027 (0.0017)
28	0.9282	0.0663 (0.0027)	0.0055 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.0968	0.8758 (0.0038)	0.0274 (0.0017)
29	0.927	0.0674 (0.0027)	0.0056 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.0915	0.8808 (0.0037)	0.0277 (0.0017)
30	0.9259	0.0685 (0.0027)	0.0056 (0.0008)	0.371	0.628 (0.0059)	0.001 (0.0004)	0.0863	0.8856 (0.0036)	0.0281 (0.0018)

Injury: injury poisoning and certain consequences

Table C31: Cost and utility parameters used in models of sub-group- Male

Resource	Unit (Standard Error)		Reference
	Local Model	Central Model	
Cost			
Mean travel time to the A&E	14.69 min (0.038)	19.7 min (0.088)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£120.16 (£0.31)	£161.15 (£0.72)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.48	0.0097	*Goodacre et al 2012*
Admission	0.48	0.0097	*Goodacre et al 2012*
Community	0.85	0.0017	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Table C32: Cost and utility parameters used in models of sub-group- Female

Resource	Unit (Standard Error)		Reference
	Local Model	Central Model	
Cost			
Mean travel time to the A&E	14.2 min (0.031)	19.42 min (0.08)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£116.16 (£0.25)	£158.86 (£0.66)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.43	0.0091	*Goodacre et al 2012*
Admission	0.43	0.0091	*Goodacre et al 2012*
Community	0.815	0.002	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Table C33: Cost and utility parameters used in models of sub-group- Age <=29

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	13.61 min (0.065)	17.64 min (0.19)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£111.33 (£0.53)	£144.30 (£1.54)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.65	0.0362	*Goodacre et al 2012*
Admission	0.65	0.0362	*Goodacre et al 2012*
Community	0.905	0.0021	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Table C34: Cost and utility parameters used in models of sub-group- Age-30-64

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	14.21 min (0.04)	18.77 min (0.09)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£116.24 (£0.32)	£153.54 (£0.76)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.51	0.0488	*Goodacre et al 2012*
Admission	0.51	0.0488	*Goodacre et al 2012*
Community	0.828	0.0049	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Table C35: Cost and utility parameters used in models of sub-group- Age 65+

Resource	Unit (Standard Error)		Reference
	Local Model	Central Model	
Cost			
Mean travel time to the A&E	14.71 min (0.03)	20.32 min (0.08)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£120.33 (£0.28)	£166.22 (£0.68)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.45	0.0164	*Goodacre et al 2012*
Admission	0.45	0.0164	*Goodacre et al 2012*
Community	0.774	0.0039	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Table C36: Cost and utility parameters used in models of sub-group- CCI0

Resource	Unit (Standard Error)		Reference
	Local Model	Central Model	
Cost			
Mean travel time to the A&E	14.47 min (0.03)	19.46 min (0.09)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£118.36 (£0.27)	£159.18 (£0.71)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.45	0.006	*Goodacre et al 2012*
Admission	0.45	0.006	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

CCI0: Charlson's co-morbidity index=0

Table C37: Cost and utility parameters used in models of sub-group- CCI4

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	14.52 min (0.08)	20.49 min (0.18)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£118.77 (£0.64)	£167.61 (£1.48)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.45	0.006	*Goodacre et al 2012*
Admission	0.45	0.006	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

CCI4: Charlson's co-morbidity index>=4

Table C38: Cost and utility parameters used in models of sub-group- IMD1

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	12.57 min (0.05)	18.81 min (0.11)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£102.82 (£0.39)	£153.87 (£0.88)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.45	0.006	*Goodacre et al 2012*
Admission	0.45	0.006	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

IMD1: Index of mean deprivation 1st quintile

Table C39: Cost and utility parameters used in models of sub-group- IMD5

Resource	Unit (Standard Error)		Reference
	Local Model	Central Model	
Cost			
Mean travel time to the A&E	10.48 min (0.02)	14.11 min (0.03)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£85.73 (£0.14)	£115.42 (£0.28)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.45	0.006	*Goodacre et al 2012*
Admission	0.45	0.006	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

IMD5: Index of mean deprivation 5th quintile

Table C40: Cost and utility parameters used in models of sub-group- Circulatory

Resource	Unit (Standard Error)		Reference
	Local Model	Central Model	
Cost			
Mean travel time to the A&E	15.17 min (0.08)	20.22 min (0.18)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£124.09 (£0.64)	£165.40 (£1.51)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.46	0.0141	*Goodacre et al 2012*
Admission	0.46	0.0141	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Circulatory: diseases of the circulatory system

Table C41: Cost and utility parameters used in models of sub-group- Respiratory

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	13.88 min (0.06)	18.99 min (0.17)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£113.54 (£0.54)	£155.34 (£1.38)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.39	0.0148	*Goodacre et al 2012*
Admission	0.39	0.0148	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Respiratory: diseases of respiratory system

Table C42: Cost and utility parameters used in models of sub-group- Digestive

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	14.63 min (0.08)	19.5 min (0.18)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£119.67 (£0.64)	£159.51 (£1.46)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.53	0.0225	*Goodacre et al 2012*
Admission	0.53	0.0225	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Digestive: diseases of the digestive system

Table C43: Cost and utility parameters used in models of sub-group- Abnormal

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	13.9 min (0.05)	19.34 min (0.14)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£113.70 (£0.44)	£158.20 (£1.18)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.5	0.0152	*Goodacre et al 2012*
Admission	0.5	0.0152	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Abnormal: abnormal clinical laboratory findings

Table C44: Cost and utility parameters used in models of sub-group- Injury

Resource	Unit (Standard Error)		Reference
	Local Model	**Central Model**	
Cost			
Mean travel time to the A&E	14.99 min (0.07)	20.06 min (0.17)	Estimated from HES data
Cost per minute of ambulance journey	£8.18	£8.18	PSSRU 2008
Cost of mean travel time to the A&E	£122.62 (£0.57)	£164.09 (£1.39)	Product of mean travel time and cost per minute ambulance journey
Cost per attendance of A&E	£115.01 (£10.39)	£115.01 (£10.39)	PSSRU 2010
Cost per day admitted in the hospital	£155.32 (£16.64)	£115.01 (£10.39)	PSSRU 2010
Cost per day in the community	0	0	Assumed
Cost per 20 minutes time of emergency medicine consultant	0	£35.67	PSSRU 2016/17- assumed same as consultant-surgical and computed from £107 per hour cost
Utility	*Mean*	*Standard Error*	
A&E	0.43	0.0173	*Goodacre et al 2012*
Admission	0.43	0.0173	*Goodacre et al 2012*
Community	0.828	0.0015	*Sullivan et al 2011*
Dead	0	0	*Assumed*

Injury: injury poisoning and certain consequences

References

Acute surveys co-ordination centre for the NHS patient survey programme (2009) *The key findings report for the 2008 emergency department survey*. Picker Institute Europe.

Ades, A.E., Lu, G. and Claxton, K. (2004) 'Expected value of sample information calculations in medical decision modeling', *Med Decis Making*, 24(2), pp. 207-27.

Adrian, C., Wright, S. and Kilgore, A. (2016) 'Adaptive Conjoint Analysis: A New Approach to Defining Corporate Governance', *Corporate Governance: An International Review*.

Afzali, H.H. and Karnon, J. (2015) 'Exploring structural uncertainty in model-based economic evaluations', *Pharmacoeconomics*, 33(5), pp. 435-43.

Ali, S. and Ronaldson, S. (2012) 'Ordinal preference elicitation methods in health economics and health services research: using discrete choice experiments and ranking methods', *British Medical Bulletin*, 103(1), pp. 21-44.

Amaya-Amaya, M., Gerard, K. and Ryan, M. (2008) 'Discrete choice experiments in a nutshell', in Ryan, M., Gerard, K. and Amaya-Amaya, M. (eds.) *Using Discrete Choice Experiments to Value Health and Health Care*. Springer.

Appleby, J. (2013) *Spending on health and social care over the next 50 years: Why think long term?* London: The King's Fund The King's Fund.

Appleby, J. (2016) 'Crossing the line: NICE’s value for money threshold', *BMJ*, 352:i1336.

Arnesen, T.M. and Norheim, O.F. (2003) 'Quantifying quality of life for economic analysis: time out for time trade off', *Medical Humanities*, 29(2), pp. 81-86.

Austin, P.C., Lee, D.S. and Fine, J.P. (2016) 'Introduction to the Analysis of Survival Data in the Presence of Competing Risks', *Circulation*, 133(6), pp. 601-609.

Baird, A.G. and Wright, N. (2006) *Poor access to care: rural health deprivation?*

Bansback, N., Brazier, J., Tsuchiya, A. and Anis, A. (2012) 'Using a discrete choice experiment to estimate health state utility values', *J Health Econ*, 31(1), pp. 306-18.

Bardach, N.S., Olson, S.J., Elkins, J.S., Smith, W.S., Lawton, M.T. and Johnston, S.C. (2004) 'Regionalization of treatment for subarachnoid hemorrhage: a cost-utility analysis', *Circulation*, 109(18), pp. 2207-12.

Barnett, K., Mercer, S.W., Norbury, M., Watt, G., Wyke, S. and Guthrie, B. (2012) 'Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study', *The Lancet*, 380(9836), pp. 37-43.

Barratt, H. and Raine, R. (2012) 'Hospital service reconfiguration: the battle for hearts and minds', *BMJ*, 344:e953.

Barton, P., Bryan, S. and Robinson, S. (2004) 'Modelling in the economic evaluation of health care: selecting the appropriate approach', *J Health Serv Res Policy*, 9(2), pp. 110-8.

Basu, A. and Sullivan, S.D. (2017) 'Toward a Hedonic Value Framework in Health Care', *Value in Health*, 20(2), pp. 261-265.

Bech, M., Kjaer, T. and Lauridsen, J. (2011) 'Does the number of choice sets matter? Results from a web survey applying a discrete choice experiment', *Health Econ*, 20(3), pp. 273-86.

Beckert, W., Christensen, M. and Collyer, K. (2012) 'Choice of NHS-funded Hospital Services in England', *The Economic Journal*, 122(560), pp. 400-417.

Bhattarai, N., McMeekin, P., Price, C. and Vale, L. (2016) 'Economic evaluations on centralisation of specialised healthcare services: a systematic review of methods', *BMJ Open*, 6:e011214. doi: 10.1136/bmjopen-2016-011214.

Bilcke, J., Beutels, P., Brisson, M. and Jit, M. (2011) 'Accounting for Methodological, Structural, and Parameter Uncertainty in Decision-Analytic Models:A Practical Guide', *Medical Decision Making*, 31(4), pp. 675-692.

Birol, E., Karousakis, K. and Koundouri, P. (2006) 'Using economic valuation techniques to inform water resources management: A survey and critical appraisal of available techniques and an application', *Science of The Total Environment*, 365(1), pp. 105-122.

Bleichrodt, H. (2002) 'A new explanation for the difference between time trade-off utilities and standard gamble utilities', *Health Economics*, 11(5), pp. 447-456.

Bleichrodt, H. and Johannesson, M. (1997) 'Standard gamble, time trade-off and rating scale: Experimental results on the ranking properties of QALYs', *Journal of Health Economics*, 16(2), pp. 155-175.

Bojke, L., Claxton, K., Sculpher, M. and Palmer, S. (2009) 'Characterizing structural uncertainty in decision analytic models: a review and application of methods', *Value Health*, 12(5), pp. 739-49.

Borisova, N.N. and Goodman, A.C. (2003) 'Measuring the value of time for methadone maintenance clients: willingness to pay, willingness to accept, and the wage rate', *Health Econ*, 12(4), pp. 323-34.

Boyle, A., Fuld, J., Ahmed, V., Bennett, T. and Robinson, S. (2012) 'Does integrated emergency care reduce mortality and non-elective admissions? A retrospective analysis', *Emergency Medicine Journal*, 29(3), pp. 208-212.

Boyle, K.J., Holmes, T.P., Teisl, M.F. and Roe, B. (2001) 'A Comparison of Conjoint Analysis Response Formats', *American Journal of Agricultural Economics*, 83(2), pp. 441-454.

Brasel, K.J., Lim, H.J., Nirula, R. and Weigelt, J.A. (2007) 'Length of stay: An appropriate quality measure?', *Archives of Surgery*, 142(5), pp. 461-466.

Brazell, J.D., Diener, C.G., Karniouchina, E., Moore, W.L., Séverin, V. and Uldry, P.-F. (2006) 'The no-choice option and dual response choice designs', *Marketing Letters*, 17(4), pp. 255-268.

Brazier, J., Akehurst, R., Brennan, A., Dolan, P., Claxton, K., McCabe, C., Sculpher, M. and Tsuchyia, A. (2005) 'Should patients have a greater role in valuing health states?', *Appl Health Econ Health Policy*, 4(4), pp. 201-8.

Brazier, J., Deverill, M., Green, C., Harper, R. and Booth, A. (1999) 'A review of the use of health status measures in economic evaluation', *Health Technol Assess*, 3(9), pp. i-iv, 1-164.

Brazier, J., Rowen, D., Yang, Y. and Tsuchiya, A. (2012) 'Comparison of health state utility values derived using time trade-off, rank and discrete choice data anchored on the full health-dead scale', *The European Journal of Health Economics*, 13(5), pp. 575-587.

Brennan, A. and Akehurst, R. (2000) 'Modelling in Health Economic Evaluation', *PharmacoEconomics*, 17(5), pp. 445-459.

Brennan, A., Chick, S.E. and Davies, R. (2006) 'A taxonomy of model structures for economic evaluation of health technologies', *Health Econ*, 15(12), pp. 1295-310.

Brennan, M.J., Schwartz, E.S. and Lagnado, R. (1997) 'Strategic asset allocation', *Journal of Economic Dynamics and Control*, 21(8), pp. 1377-1403.

Briggs A, Claxton K and Sculpher M (2006) *Decision modelling for health economic evaluation. Handbooks in health economic evaluation*. Oxford University Press.

Briggs, A., Sculpher, M. and Claxton, K. (2006) *Decision Modelling for Health Economic Evaluation*. Oxford University Press.

Briggs, A.H. (1999) 'A Bayesian approach to stochastic cost-effectiveness analysis', *Health Econ*, 8(3), pp. 257-61.

Briggs, A.H. (2000) 'Handling Uncertainty in Cost-Effectiveness Models', *PharmacoEconomics*, 17(5), pp. 479-500.

Briggs, A.H., Ades, A.E. and Price, M.J. (2003) 'Probabilistic sensitivity analysis for decision trees with multiple branches: use of the Dirichlet distribution in a Bayesian framework', *Med Decis Making*, 23(4), pp. 341-50.

Briggs, A.H., Weinstein, M.C., Fenwick, E.A., Karnon, J., Sculpher, M.J. and Paltiel, A.D. (2012) 'Model parameter estimation and uncertainty analysis: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force Working Group-6', *Med Decis Making*, 32(5), pp. 722-32.

Brisson, M. and Edmunds, W.J. (2006) 'Impact of model, methodological, and parameter uncertainty in the economic analysis of vaccination programs', *Med Decis Making*, 26(5), pp. 434-46.

Bristow, R.E., Santillan, A., Diaz-Montes, T.P., Gardner, G.J., Giuntoli, R.L., 2nd, Meisner, B.C., Frick, K.D. and Armstrong, D.K. (2007) 'Centralization of care for patients with advanced-stage ovarian cancer: a cost-effectiveness analysis', *Cancer*, 109(8), pp. 1513-22.

Brock, G.N., Barnes, C., Ramirez, J.A. and Myers, J. (2011) 'How to handle mortality when investigating length of hospital stay and time to clinical stability', *BMC Medical Research Methodology*, 11(1), p. 144.

Brusselaers, N., Mattsson, F. and Lagergren, J. (2014) 'Hospital and surgeon volume in relation to long-term survival after oesophagectomy: systematic review and meta-analysis', *Gut*, 63(9), pp. 1393-400.

Burge, P., Devlin, N., Appleby, J., Rohr, C. and Grant, J. (2005) *London Patient Choice Project Evaluation: A model of patients' choices of hospital from stated and revealed preference choice data*. RAND Europe & The King's Fund &The City University.

Burns, E.M., Rigby, E., Mamidanna, R., Bottle, A., Aylin, P., Ziprin, P. and Faiz, O.D. (2012) 'Systematic review of discharge coding accuracy', *Journal of Public Health*, 34(1), pp. 138-148.

Burr, J.M., Botello-Pinzon, P., Takwoingi, Y., Hernandez, R., Vazquez-Montes, M., Elders, A., Asaoka, R., Banister, K., van der Schoot, J., Fraser, C., King, A., Lemij, H., Sanders, R., Vernon, S., Tuulonen, A., Kotecha, A., Glasziou, P., Garway-Heath, D., Crabb, D., Vale, L., Azuara-Blanco, A., Perera, R., Ryan, M., Deeks, J. and Cook, J. (2012) 'Surveillance for ocular hypertension: an evidence synthesis and economic evaluation', *Health Technol Assess*, 16(29), pp. 1-271, iii-iv.

Burr, J.M., Kilonzo, M., Vale, L. and Ryan, M. (2007) 'Developing a preference-based Glaucoma Utility Index using a discrete choice experiment', *Optom Vis Sci*, 84(8), pp. 797-808.

Buxton, M.J., Drummond, M.F., Van Hout, B.A., Prince, R.L., Sheldon, T.A., Szucs, T. and Vray, M. (1997) 'Modelling in economic evaluation: an unavoidable fact of life', *Health Econ*, 6(3), pp. 217-27.

Cameron, P.A., Schull, M.J. and Cooke, M.W. (2011) 'A framework for measuring quality in the emergency department', *Emergency Medicine Journal*, 28(9), pp. 735-740.

Campbell, D., Hensher, D.A. and Scarpa, R. (2011) 'Non-attendance to attributes in environmental choice analysis: a latent class specification', *Journal of Environmental Planning and Management*, 54(8), pp. 1061-1076.

Campbell, D., Hutchinson, W.G. and Scarpa, R. (2008) 'Incorporating Discontinuous Preferences into the Analysis of Discrete Choice Experiments', *Environmental and Resource Economics*, 41(3), pp. 401-417.

Canadian Agency for Drugs and Technologies in Health (CADTH) (2017) *Guidelines for the Economic Evaluation of Health Technologies*. Ottawa, Canada: CADTH.

Carlsson, F., Kataria, M. and Lampi, E. (2010) 'Dealing with Ignored Attributes in Choice Experiments on Valuation of Sweden's Environmental Quality Objectives', *Environmental and Resource Economics*, 47(1), pp. 65-89.

Caro, J.J., Briggs, A.H., Siebert, U. and Kuntz, K.M. (2012) 'Modeling good research practices--overview: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-1', *Med Decis Making*, 32(5), pp. 667-77.

Carson, R.T., Flores, N.E. and Meade, N.F. (2001) 'Contingent Valuation: Controversies and Evidence', *Environmental and Resource Economics*, 19(2), pp. 173-210.

Centre for Review and Dissemination (2009) *Systematic Reviews. CRD's guidance for undertaking reviews in health care* Centre for Reviews and Dissemination, University of York.

Cerri, K.H., Knapp, M. and Fernandez, J.L. (2014) 'Decision making by NICE: examining the influences of evidence, process and context', *Health Econ Policy Law*, 9(2), pp. 119-41.

Chapko, M.K., Liu, C.F., Perkins, M., Li, Y.F., Fortney, J.C. and Maciejewski, M.L. (2009) 'Equivalence of two healthcare costing methods: bottom-up and top-down', *Health Econ*, 18(10), pp. 1188-201.

Cheung, K.L., Wijnen, B.F.M., Hollin, I.L., Janssen, E.M., Bridges, J.F., Evers, S.M.A.A. and Hiligsmann, M. (2016) 'Using Best–Worst Scaling to Investigate Preferences in Health Care', *Pharmacoeconomics*, 34(12), pp. 1195-1209.

ChoiceMetrics (2012) *Ngene 1.1.1 User Manual & Reference Guide,* [Computer program]. Available at: http://www.choice-metrics.com.

Church, A.H. (1993) 'ESTIMATING THE EFFECT OF INCENTIVES ON MAIL SURVEY RESPONSE RATES: A META-ANALYSIS', *Public Opinion Quarterly*, 57(1), pp. 62-79.

Clark, M.D., Determann, D., Petrou, S., Moro, D. and de Bekker-Grob, E.W. (2014) 'Discrete choice experiments in health economics: a review of the literature', *Pharmacoeconomics*, 32(9), pp. 883-902.

Clarke, P.M. (2002) 'Testing the convergent validity of the contingent valuation and travel cost methods in valuing the benefits of health care', *Health Economics*, 11(2), pp. 117-127.

Claxton, K. (1999) 'The irrelevance of inference: a decision-making approach to the stochastic evaluation of health care technologies', *Journal of Health Economics*, 18(3), pp. 341-364.

Claxton, K. and Posnett, J. (1996) 'An economic approach to clinical trial design and research priority-setting', *Health Economics*, 5(6), pp. 513-524.

Claxton, K., Sculpher, M. and Drummond, M. (2002) 'A rational framework for decision making by the National Institute For Clinical Excellence (NICE)', *The Lancet*, 360(9334), pp. 711-715.

Claxton, K., Sculpher, M., McCabe, C., Briggs, A., Akehurst, R., Buxton, M., Brazier, J. and O'Hagan, T. (2005) 'Probabilistic sensitivity analysis for NICE technology assessment: not an optional extra', *Health Econ*, 14(4), pp. 339-47.

Clement, R.C., Carr, B.G., Kallan, M.J., Wolff, C., Reilly, P.M. and Malhotra, N.R. (2013) 'Volume-outcome relationship in neurotrauma care', *J Neurosurg*, 118(3), pp. 687-93.

Coast, J., Al-Janabi, H., Sutton, E.J., Horrocks, S.A., Vosper, A.J., Swancutt, D.R. and Flynn, T.N. (2012) 'Using qualitative methods for attribute development for discrete choice experiments: issues and recommendations', *Health Econ*, 21(6), pp. 730-41.

College of Emergency Medicine (2010) *Emergency medicine consultants workforce recommendations*. London: College of Emergency Medicine College of Emergency Medicine.

Colombo, S., Christie, M. and Hanley, N. (2013) 'What are the consequences of ignoring attributes in choice experiments? Implications for ecosystem service valuation', *Ecological Economics*, 96, pp. 25-35.

Concannon, T.W., Kent, D.M., Normand, S.L., Newhouse, J.P., Griffith, J.L., Cohen, J., Beshansky, J.R., Wong, J.B., Aversano, T. and Selker, H.P. (2010) 'Comparative effectiveness of ST-segment-elevation myocardial infarction regionalization strategies', *Circ Cardiovasc Qual Outcomes*, 3(5), pp. 506-13.

Cook, J.A., Hislop, J., Adewuyi, T.E., Harrild, K., Altman, D.G., Ramsay, C.R., Fraser, C., Buckley, B., Fayers, P., Harvey, I., Briggs, A.H., Norrie, J.D., Fergusson, D., Ford, I. and Vale, L.D. (2014) 'Assessing methods to specify the target difference for a randomised controlled trial: DELTA (Difference ELicitation in TriAls) review', *Health Technol Assess*, 18(28), pp. v-vi, 1-175.

Cooper, K., Brailsford, S.C. and Davies, R. (2007a) 'Choice of modelling technique for evaluating health care interventions', *Journal of the Operational Research Society*, 58(2), pp. 168-176.

Cooper, N.J., Sutton, A.J., Ades, A.E., Paisley, S. and Jones, D.R. (2007b) 'Use of evidence in economic decision models: practical issues and methodological challenges', *Health Econ*, 16(12), pp. 1277-86.

Cornwell, J., Levenson, R., Sonola, L. and Poteliakhoff, E. (2012) *Continuity of care for older hospital patients: A call for action*. London: The King's Fund The King's Fund.

Coulter, A. and Collins, A. (2011) *Making shared decision-making a reality.No decision about me, without me*. London: The King's Fund.

Cunningham, C.E., Deal, K. and Chen, Y. (2010) 'Adaptive Choice-Based Conjoint Analysis: A New Patient-Centered Approach to the Assessment of Health Service Preferences', *The Patient*, 3(4), pp. 257-273.

Curtis, L. (2008) *Unit Costs of Health and Social Care 2008*.Personal Social Services Research Unit, University of Kent, Canterbury.

Curtis, L. (2010) *Unit Costs of Health and Social Care 2010*.Personal Social Services Research Unit, University of Kent, Canterbury.

Curtis, L. and Burns, A. (2017) *Unit Costs of Health and Social Care 2017*.Personal Social Services Research Unit, University of Kent, Canterbury. [Online]. Available at: https://doi.org/10.22024/UniKent/01.02/65559.

Dakin, H., Devlin, N., Feng, Y., Rice, N., O'Neill, P. and Parkin, D. (2015) 'The Influence of Cost-Effectiveness and Other Factors on Nice Decisions', *Health Economics*, 24(10), pp. 1256-1271.

Darzi, A. (2007) *Healthcare for London: A framework for action*. London: NHS London NHS London.

de Bekker-Grob, E.W., Donkers, B., Jonker, M.F. and Stolk, E.A. (2015) 'Sample Size Requirements for Discrete-Choice Experiments in Healthcare: a Practical Guide', *Patient*.

de Bekker-Grob, E.W., Ryan, M. and Gerard, K. (2012) 'Discrete choice experiments in health economics: a review of the literature', *Health Economics*, 21(2), pp. 145-172.

De Brún, A., Flynn, D., Ternent, L., Price, C.I., Rodgers, H., Ford, G.A., Rudd, M., Lancsar, E., Simpson, S., Teah, J. and Thomson, R.G. (2018) 'A novel design process for selection of attributes for inclusion in discrete choice experiments: case study exploring variation in clinical decision-making about thrombolysis in the treatment of acute ischaemic stroke', *BMC Health Services Research*, 18(1), p. 483.

Department of Health (2007) *National Stroke Strategy*. London: Department of Health Department of Health.

Department of Health (2012) *Long Term Conditions Compendium of Information*. London: Department of Health.

Department of Health (2010) *Equity and excellence: Liberating the NHS*. London: The Stationery Office.

Devlin, N.J. and Brooks, R. (2017) 'EQ-5D and the EuroQol Group: Past, Present and Future', *Applied Health Economics and Health Policy*, 15(2), pp. 127-137.

Devlin, N.J. and Shah, K.K. (2018) 'Valuing health-related quality of life: An EQ-5D-5L value set for England', 27(1), pp. 7-22.

Devlin, N.J., Tsuchiya, A., Buckingham, K. and Tilling, C. (2011) 'A uniform time trade off method for states better and worse than dead: feasibility study of the 'lead time' approach', *Health Econ*, 20(3), pp. 348-61.

Dhar, R. and Simonson, I. (2003) 'The Effect of Forced Choice on Choice', *Journal of Marketing Research*, 40(2), pp. 146-160.

Dickie, M. (2017) 'Averting Behavior Methods', in Champ, P.A., Boyle, K.J. and Brown, T.C. (eds.) *A Primer on Nonmarket Valuation*. Dordrecht: Springer Netherlands, pp. 293-346.

Diener, A., O'Brien, B. and Gafni, A. (1998) 'Health care contingent valuation studies: a review and classification of the literature', *Health Economics*, 7(4), pp. 313-326.

Dirksen, C.D., Utens, C.M.A., Joore, M.A., van Barneveld, T.A., Boer, B., Dreesens, D.H.H., van Laarhoven, H., Smit, C., Stiggelbout, A.M. and van der Weijden, T. (2013) 'Integrating evidence on patient preferences in healthcare policy decisions: protocol of the patient-VIP study', *Implementation Science : IS*, 8, pp. 64-64.

Dixon-Woods, M., Amalberti, R., Goodman, S., Bergman, B. and Glasziou, P. (2011) 'Problems and promises of innovation: why healthcare needs to rethink its love/hate relationship with the new', *BMJ Quality & Safety*, 20(Suppl 1), pp. i47-i51.

Dixon, A., Robertson, R., Appleby, J., Burge, P., Devlin, N. and Magee, H. (2010a) *Patient Choice: How patients choose and how providers respond*. London: The King's Fund.

Dixon, A., Robertson, R. and Bal, R. (2010b) 'The experience of implementing choice at point of referral: a comparison of the Netherlands and England', *Health Econ Policy Law*, 5(3), pp. 295-317.

Dolan, J.G. and Iadarola, S. (2008) 'Risk communication formats for low probability events: an exploratory study of patient preferences', *BMC Medical Informatics and Decision Making*, 8(1), p. 14.

Dolan, P. (1999) 'Whose preferences count?', *Med Decis Making*, 19(4), pp. 482-6.

Donegan, S., Williamson, P., Gamble, C. and Tudur-Smith, C. (2010) 'Indirect comparisons: a review of reporting and methodological quality', *PLoS One*, 5(11), p. e11054.

Doshi, J.A., Glick, H.A. and Polsky, D. (2006) 'Analyses of Cost Data in Economic Evaluations Conducted Alongside Randomized Controlled Trials', *Value in Health*, 9(5), pp. 334-340.

Drummond, M., O'Brien, B., Stoddart, G. and Torrance, G. (2005) *Methods for the economic evaluation of Health Care Programmes*. Oxford: Oxford University Press.

Drummond, M. and Sculpher, M. (2005) 'Common methodological flaws in economic evaluations', *Med Care*, 43(7 Suppl), pp. 5-14.

Drummond, M.F. and Jefferson, T.O. (1996) 'Guidelines for authors and peer reviewers of economic submissions to the BMJ. The BMJ Economic Evaluation Working Party', *BMJ : British Medical Journal*, 313(7052), pp. 275-283.

Eckermann, S. and Willan, A.R. (2007) 'Expected value of information and decision making in HTA', *Health Economics*, 16(2), pp. 195-209.

Eddama, O. and Coast, J. (2008) 'A systematic review of the use of economic evaluation in local decision-making', *Health Policy*, 86(2–3), pp. 129-141.

Eddama, O. and Coast, J. (2009) 'Use of economic evaluation in local health care decision-making in England: a qualitative investigation', *Health Policy*, 89(3), pp. 261-70.

Effective Practice and Organisation of Care (EPOC) (2015. Available at: http://epoc.cochrane.org/epoc-specific-resources-review-authors) 'EPOC Resources for review authors'. 05 Jan 2016. Oslo: Norwegian Knowledge Centre for the Health Services. Available at: http://epoc.cochrane.org/epoc-specific-resources-review-authors.

Eichler, K., Hess, S., Chmiel, C., Bögli, K., Sidler, P., Senn, O., Rosemann, T. and Brügger, U. (2014) 'Sustained health-economic effects after reorganisation of a Swiss hospital emergency centre: a cost comparison study', *Emergency Medicine Journal*, 31(10), pp. 818-823.

Elliott, R. and Payne, K. (2004) 'Chapter 10. Statistical handling of data in economic analysis', in *Essentials of Economic Evaluation in Healthcare*. First edn., pp. 185-202.

Estellat, C. and Ravaud, P. (2012) 'Lack of head-to-head trials and fair control arms: randomized controlled trials of biologic treatment for rheumatoid arthritis', *Arch Intern Med*, 172(3), pp. 237-44.

Felli, J.C. and Hazen, G.B. (1999) 'A Bayesian approach to sensitivity analysis', *Health Economics*, 8(3), pp. 263-268.

Fenwick, E., Claxton, K. and Sculpher, M. (2001) 'Representing uncertainty: the role of cost-effectiveness acceptability curves', *Health Econ*, 10(8), pp. 779-87.

Fenwick, E., Marshall, D.A., Levy, A.R. and Nichol, G. (2006) 'Using and interpreting cost-effectiveness acceptability curves: an example using data from a trial of management strategies for atrial fibrillation', *BMC Health Services Research*, 6, pp. 52 DOI 10.1186/1472-6963-6-52.

Fenwick, E., O'Brien, B.J. and Briggs, A. (2004) 'Cost-effectiveness acceptability curves – facts, fallacies and frequently asked questions', *Health Economics*, 13(5), pp. 405-415.

Fernandes, A. (2011) *Guidance for commissioning integrated urgent and emergency care: A 'whole system' approach*. London: The Royal College of General Practitioners, Centre for Commissioning.

Fiebig, D.G., Keane, M.P., Louviere, J. and Wasi, N. (2010) 'The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity', *Marketing Science*, 29(3), pp. 393-421.

Fielding, R., Kause, J., Arnell-Cullen, V. and Sandeman, D. (2013) 'The impact of consultant-delivered multidisciplinary inpatient medical care on patient outcomes', *Clinical Medicine*, 13(4), pp. 344-348.

Finkler, S.A. (1982) 'The distinction between cost and charges', *Ann Intern Med*, 96(1), pp. 102-9.

Finlayson, S.R., Birkmeyer, J.D., Tosteson, A.N. and Nease, R.F., Jr. (1999) 'Patient preferences for location of care: implications for regionalization', *Med Care*, 37(2), pp. 204-9.

Fitzsimons, K., Mukarram, S., Copley, L., Deacon, S. and van der Meulen, J. (2012) 'Centralisation of services for children with cleft lip or palate in England: a study of hospital episode statistics', *BMC Health Services Research*, 12(1), p. 148.

Fleurence, R.L. and Hollenbeak, C.S. (2007) 'Rates and Probabilities in Economic Modelling', *PharmacoEconomics*, 25(1), pp. 3-6.

Florin, D. and Dixon, J. (2004) 'Public involvement in health care', *BMJ*, 328(7432), pp. 159-161.

Flynn, T.N. (2010) 'Valuing citizen and patient preferences in health: recent developments in three types of best–worst scaling', *Expert Review of Pharmacoeconomics & Outcomes Research*, 10(3), pp. 259-267.

Flynn, T.N., Louviere, J.J., Peters, T.J. and Coast, J. (2007) 'Best--worst scaling: What it can do for health care research and how to do it', *J Health Econ*, 26(1), pp. 171-89.

Fosbol, E.L., Granger, C.B., Jollis, J.G., Monk, L., Lin, L., Lytle, B.L., Xian, Y., Garvey, J.L., Mears, G., Corbett, C.C., Peterson, E.D. and Glickman, S.W. (2013) 'The impact of a statewide pre-hospital STEMI strategy to bypass hospitals without percutaneous coronary intervention capability on treatment times', *Circulation*, 127(5), pp. 604-12.

Fraenkel, L. (2010) 'Feasibility of Using Modified Adaptive Conjoint Analysis Importance Questions', *Patient*, 3(4), pp. 209-215.

Full Fact (2018) *Spending on the NHS in England*. Available at: https://fullfact.org/health/spending-english-nhs/ (Accessed: 10 July 2018).

Gabbe, B.J., Simpson, P.M., Sutherland, A.M., Wolfe, R., Fitzgerald, M.C., Judson, R. and Cameron, P.A. (2012) 'Improved functional outcomes for major trauma patients in a regionalized, inclusive trauma system', *Ann Surg*, 255(6), pp. 1009-15.

Gandjour, A. (2010) 'Theoretical foundation of patient v. population preferences in calculating QALYs', *Med Decis Making*, 30(4), pp. E57-63.

Geelhoed, G.C. and Geelhoed, E.A. (2008) 'Positive impact of increased number of emergency consultants', *Arch Dis Child*, 93(1), pp. 62-4.

Gerard, K. and Lattimer, V. (2005) 'Preferences of patients for emergency services available during usual GP surgery hours: a discrete choice experiment', *Family Practice*, 22(1), pp. 28-36.

Gerard, K., Lattimer, V., Turnbull, J., Smith, H., George, S., Brailsford, S. and Maslin-Prothero, S. (2004) 'Reviewing emergency care systems 2: measuring patient preferences using a discrete choice experiment', *Emergency Medicine Journal*, 21(6), pp. 692-697.

Goodacre, S. (2015) 'Uncontrolled before-after studies: discouraged by Cochrane and the EMJ', *Emergency Medicine Journal*.

Goodacre, S.W., Wilson, R.W., Bradburn, M., Santarelli, M. and Nicholl, J.P. (2012) 'Health utility after emergency medical admission: a cross-sectional survey', *Health and Quality of Life Outcomes*, 10, pp. 20-20.

Gooley, T.A., Leisenring, W., Crowley, J. and Storer, B.E. (1999) 'Estimation of failure probabilities in the presence of competing risks: new representations of old estimators', *Statistics in Medicine*, 18(6), pp. 695-706.

Grammatikopoulou, I. and Olsen, S.B. (2013) 'Accounting protesting and warm glow bidding in Contingent Valuation surveys considering the management of environmental goods – An empirical case study assessing the value of protecting a

Natura 2000 wetland area in Greece', *Journal of Environmental Management*, 130(Supplement C), pp. 232-241.

Gray, A.M. and Wilkinson, T. (2016) 'Economic evaluation of healthcare interventions: old and new directions', *Oxford Review of Economic Policy*, 32(1), pp. 102-121.

Greving, J.P., Vernooij, F., Heintz, A.P., van der Graaf, Y. and Buskens, E. (2009) 'Is centralization of ovarian cancer care warranted? A cost-effectiveness analysis', *Gynecol Oncol*, 113(1), pp. 68-74.

Griffin, S., Claxton, K., Hawkins, N. and Sculpher, M. (2007) 'Decision Models Need to be “Fit for Purpose” for Decision-Making: Response to Caro et al', *Value in Health*, 10(4), pp. 319-319.

Grutters, J.P., Sculpher, M., Briggs, A.H., Severens, J.L., Candel, M.J., Stahl, J.E., De Ruysscher, D., Boer, A., Ramaekers, B.L. and Joore, M.A. (2013) 'Acknowledging patient heterogeneity in economic evaluation : a systematic literature review', *Pharmacoeconomics*, 31(2), pp. 111-23.

Gutacker, N., Siciliani, L., Moscelli, G. and Gravelle, H. (2016) 'Choice of hospital: Which type of quality matters?', *Journal of Health Economics*, 50, pp. 230-246.

Halm, E.A., Lee, C. and Chassin, M.R. (2002) 'Is volume related to outcome in health care? A systematic review and methodologic critique of the literature', *Ann Intern Med*, 137(6), pp. 511-20.

Ham, C., Dixon, A. and Brooke, B. (2012) *Transforming the delivery of health and social care: The case for fundamental change*. London: The King's Fund The King's Fund.

Hanley, N. and Barbier, E.B. (2009) *Pricing Nature. Cost-Benefit Analysis and Environmental Policy*. Cheltenham, UK: Edward Elgar Publishing Limited.

Hanley, N., Mourato, S. and Wright, R.E. (2001) 'Choice Modelling Approaches: A Superior Alternative for Environmental Valuatioin?', *Journal of Economic Surveys*, 15(3), pp. 435-462.

Hanley, N., Ryan, M. and Wright, R. (2003) 'Estimating the monetary value of health care: lessons from environmental economics', *Health Economics*, 12(1), pp. 3-16.

Harris, P., Whitty, J.A., Kendall, E., Ratcliffe, J., Wilson, A., Littlejohns, P. and Scuffham, P.A. (2015) 'The Australian public's preferences for emergency care alternatives and the influence of the presenting context: a discrete choice experiment', *BMJ Open*, 5(4).

Hassan, T., MCMillan, P., Walsh, C. and Higginson, I. (2013) *The drive for quality: How to achieve safe, sustainable care in our emergency departments? System benchmarks & recommendations*. London: The College of Emergency Medicine The College of Emergency Medicine.

Hauber, A.B., González, J.M., Groothuis-Oudshoorn, C.G.M., Prior, T., Marshall, D.A., Cunningham, C., Ijzerman, M.J. and Bridges, J.F.P. (2016) 'Statistical Methods for the Analysis of Discrete Choice Experiments: A Report of the ISPOR Conjoint Analysis Good Research Practices Task Force', *Value in Health*, 19(4), pp. 300-315.

HCL Workforce Solutions (2013) *The Real Emergency in Emergency Departments: Is the chronic shortage of England's A&E doctors reaching crisis point?* London: HCL Workforce Solutions HCL plc.

Health and Social Care Information Centre (2015). Available at: http://www.hscic.gov.uk/hes (Accessed: 5th May).

Healthcare for London (2008) *Stroke strategy for London*. London: Healthcare for London Healthcare for London.

Healthwatch. Available at: http://www.healthwatch.co.uk/.

Helter, T.M. and Boehler, C.E.H. (2016) 'Developing attributes for discrete choice experiments in health: a systematic literature review and case study of alcohol misuse interventions', *Journal of Substance Use*, pp. 1-7.

Hensher, D.A. and Greene, W.H. (2003) 'The Mixed Logit model: The state of practice', *Transportation*, 30(2), pp. 133-176.

Hensher, D.A. and Greene, W.H. (2010) 'Non-attendance and dual processing of common-metric attributes in choice analysis: a latent class specification', *Empirical Economics*, 39(2), pp. 413-426.

Hensher, D.A., Rose, J. and Greene, W.H. (2005) 'The implications on willingness to pay of respondents ignoring specific attributes', *Transportation*, 32(3), pp. 203-222.

Herdman, M., Gudex, C., Lloyd, A., Janssen, M., Kind, P., Parkin, D., Bonsel, G. and Badia, X. (2011) 'Development and preliminary testing of the new five-level version of EQ-5D (EQ-5D-5L)', *Qual Life Res*, 20(10), pp. 1727-36.

Hess, S. and Train, K. (2017) 'Correlation and scale in mixed logit models', *Journal of Choice Modelling*, 23, pp. 1-8.

Hifinger, M., Hiligsmann, M., Ramiro, S., Severens, J.L., Fautrel, B., Watson, V. and Boonen, A. (2017) 'Patients' preferences and economic considerations play an important role in treatment decisions: a discrete choice experiment among rheumatologists', *Rheumatology*, 56(1), pp. 68-76.

Higgins JPT and Green S (eds.) (2011) *Cochrane Handbook for Systematic Reviews of Interventions* Version 5.1.0 [updated March 2011] edn. The Cochrane Collaboration.

Higginson, I., Hughes, T. and Hassan, T. (2013) *Funding Emergency Departments: why the current system is failing our patients and what needs to be done about it*. London: The College of Emergency Medicine The College of Emergency Medicine.

Hole, A.R., Kolstad, J.R. and Gyrd-Hansen, D. (2013) 'Inferred vs. stated attribute non-attendance in choice experiments: A study of doctors' prescription behaviour', *Journal of Economic Behavior & Organization*, 96, pp. 21-31.

Holt, P.J., Gogalniceanu, P., Murray, S., Poloniecki, J.D., Loftus, I.M. and Thompson, M.M. (2010) 'Screened individuals' preferences in the delivery of abdominal aortic aneurysm repair', *Br J Surg*, 97(4), pp. 504-10.

Holt, P.J., Poloniecki, J.D., Gerrard, D., Loftus, I.M. and Thompson, M.M. (2007) 'Meta-analysis and systematic review of the relationship between volume and outcome in abdominal aortic aneurysm surgery', *Br J Surg*, 94(4), pp. 395-403.

Howard, K. and Salkeld, G. (2009) 'Does Attribute Framing in Discrete Choice Experiments Influence Willingness to Pay? Results from a Discrete Choice Experiment in Screening for Colorectal Cancer', *Value in Health*, 12(2), pp. 354-363.

Hsia, R.Y., Kanzaria, H.K., Srebotnjak, T., Maselli, J., McCulloch, C. and Auerbach, A.D. (2012) 'Is emergency department closure resulting in increased distance to the nearest emergency department associated with increased inpatient mortality?', *Ann Emerg Med*, 60(6), pp. 707-715.e4.

Hunter, R.M., Davie, C., Rudd, A., Thompson, A., Walker, H., Thomson, N., Mountford, J., Schwamm, L., Deanfield, J., Thompson, K., Dewan, B., Mistry, M., Quoraishi, S. and Morris, S. (2013) 'Impact on Clinical and Cost Outcomes of a Centralized Approach to Acute Stroke Care in London: A Comparative Effectiveness Before and After Model', *PLoS ONE*, 8(8), p. e70420.

Hunter, R.M., Fulop, N.J., Boaden, R.J., McKevitt, C., Perry, C., Ramsay, A.I.G., Rudd, A.G., Turner, S.J., Tyrrell, P.J., Wolfe, C.D.A. and Morris, S. (2018) 'The potential role of cost-utility analysis in the decision to implement major system change in acute stroke services in metropolitan areas in England', *Health Research Policy and Systems*, 16(1), p. 23.

Husereau, D., Drummond, M., Petrou, S., Carswell, C., Moher, D., Greenberg, D., Augustovski, F., Briggs, A.H., Mauskopf, J. and Loder, E. (2013) 'Consolidated Health Economic Evaluation Reporting Standards (CHEERS)—Explanation and Elaboration: A Report of the ISPOR Health Economic Evaluation Publication Guidelines Good Reporting Practices Task Force', *Value in Health*, 16(2), pp. 231-250.

Hutton, J., McGrath, C., Frybourg, J.-M., Tremblay, M., Bramley-Harker, E. and Henshall, C. (2006) 'Framework for describing and classifying decision-making systems using technology assessment to determine the reimbursement of health technologies (fourth hurdle systems)', *International Journal of Technology Assessment in Health Care*, 22(1), pp. 10-18.

Hutubessy, R., Chisholm, D., Edejer, T.T.-T. and WHO-CHOICE (2003) 'Generalized cost-effectiveness analysis for national-level priority-setting in the health sector', *Cost Effectiveness and Resource Allocation*, 1(1), pp. 1-13.

Imison, C., Poteliakhoff, E. and Thompson, J. (2012) *Older people and emergency bed use: Exploring variation*. London: The King's Fund.

Imison, C., Sonola, L., Honeyman, M. and Ross, S. (2014) *The reconfiguration of clinical services. What is the evidence?* London: The King's Fund Fund, T.K.s.

Independent working time regulations taskforce (2014) *The implementation of the working time directive, and its impact on the NHS and health professionals: Report of the independent working time regulations taskforce to the Department of Health*. London: The Royal College of Surgeons of England The Royal College of Surgeons of England.

Institute for Public Policy Research (2006) *Hospital reconfiguration: ippr briefing*. London: Institute for Public Policy Research Institute for Public Policy Research.

Jackson, C. (2016) 'flexsurv: A Platform for Parametric Survival Modeling in R.', *Journal of Statistical Software*, 70 (8), pp. 1-33.

Jackson, C.H., Bojke, L., Thompson, S.G., Claxton, K. and Sharples, L.D. (2011) 'A framework for addressing structural uncertainty in decision models', *Med Decis Making*, 31(4), pp. 662-74.

Jackson, C.H., Thompson, S.G. and Sharples, L.D. (2009) 'Accounting for uncertainty in health economic decision models by using model averaging', *J R Stat Soc Ser A Stat Soc*, 172(2), pp. 383-404.

Jagpreet, C., Suren, J. and Elamin, H.E. (2016) 'Changing Cycle Lengths in State-Transition Models:Challenges and Solutions', *Medical Decision Making*, 36(8), pp. 952-964.

Jansen, J.P., Fleurence, R., Devine, B., Itzler, R., Barrett, A., Hawkins, N., Lee, K., Boersma, C., Annemans, L. and Cappelleri, J.C. (2011) 'Interpreting indirect treatment comparisons and network meta-analysis for health-care decision making: report of the ISPOR Task Force on Indirect Treatment Comparisons Good Research Practices: part 1', *Value Health*, 14(4), pp. 417-28.

Janssen, B. and Szende, A. (2014) 'Population Norms for the EQ-5D', in Szende, A., Janssen, B. and Cabases, J. (eds.) *Self-Reported Population Health: An International Perspective based on EQ-5D*. Dordrecht: Springer Netherlands, pp. 19-30.

Jensen, G.A. and Morrisey, M.A. (1990) 'Group Health Insurance: A Hedonic Price Approach', *The Review of Economics and Statistics*, 72(1), pp. 38-44.

Johnson, F.R., Mohamed, A.F., Zdemir, S.Ö., Marshall, D.A. and Phillips, K.A. (2011) 'HOW DOES COST MATTER IN HEALTH-CARE DISCRETE-CHOICE EXPERIMENTS?', *Health economics*, 20(3), pp. 323-330.

Karimi, M., Brazier, J. and Paisley, S. (2017) 'Are preferences over health states informed?', *Health and Quality of Life Outcomes*, 15, p. 105.

Karnon, J. (2003) 'Alternative decision modelling techniques for the evaluation of health care technologies: Markov processes versus discrete event simulation', *Health Econ*, 12(10), pp. 837-48.

Karnon, J. and Brown, J. (1998) 'Selecting a decision model for economic evaluation: a case study and review', *Health Care Management Science*, 1(2), pp. 133-140.

Ke, K.M., Hollingworth, W. and Ness, A.R. (2012) 'The costs of centralisation: a systematic review of the economic impact of the centralisation of cancer services', *European Journal of Cancer Care*, 21(2), pp. 158-168.

Kelly, C., Hulme, C., Farragher, T. and Clarke, G. (2016) 'Are differences in travel time or distance to healthcare for adults in global north countries associated with an impact on health outcomes? A systematic review', *BMJ Open*, 6(11).

Khuri, S.F. and Henderson, W.G. (2005) 'The case against volume as a measure of quality of surgical care', *World J Surg*, 29(10), pp. 1222-9.

Kind, P., Lafata, J.E., Matuszewski, K. and Raisch, D. (2009) 'The Use of QALYs in Clinical and Patient Decision-Making: Issues and Prospects', *Value in Health*, 12, Supplement 1, pp. S27-S30.

Klose, K., Kreimeier, S., Tangermann, U., Aumann, I., Damm, K. and on behalf of the, R.H.O.G. (2016) 'Patient- and person-reports on healthcare: preferences, outcomes, experiences, and satisfaction – an essay', *Health Economics Review*, 6, p. 18.

Klose, T. (1999) 'The contingent valuation method in health care', *Health Policy*, 47(2), pp. 97-123.

Kragt, M. and Bennett, J. (2012) 'Attribute Framing in Choice Experiments: How Do Attribute Level Descriptions Affect Value Estimates?', *Environmental and Resource Economics*, 51(1), pp. 43-59.

Krucien, N., Watson, V. and Ryan, M. (2016) 'Is Best–Worst Scaling Suitable for Health State Valuation? A Comparison with Discrete Choice Experiments', *Health Economics*, pp. n/a-n/a.

Lahr, M.M., van der Zee, D.J., Luijckx, G.J., Vroomen, P.C. and Buskens, E. (2017) 'Centralising and optimising decentralised stroke care systems: a simulation study on short-term costs and effects', *BMC Med Res Methodol*, 17(1), p. 5.

Lancaster, K.J. (1966) 'A New Approach to Consumer Theory', *Journal of Political Economy*, 74(2), pp. 132-157.

Lancsar, E. and Louviere, J. (2006) 'Deleting 'irrational' responses from discrete choice experiments: a case of investigating or imposing preferences?', *Health Econ*, 15(8), pp. 797-811.

Lancsar, E. and Louviere, J. (2008) 'Conducting discrete choice experiments to inform healthcare decision making: a user's guide', *Pharmacoeconomics*, 26(8), pp. 661-77.

Lancsar, E., Louviere, J., Donaldson, C., Currie, G. and Burgess, L. (2013) 'Best worst discrete choice experiments in health: Methods and an application', *Social Science & Medicine*, 76(Supplement C), pp. 74-82.

Landau, J.H., Novick, T.V., Dubois, L., Power, A.H., Harris, J.R., DeRose, G. and Forbes, T.L. (2013) 'Determination of Patient Preference for Location of Elective Abdominal Aortic Aneurysm Surgery', *Vascular and Endovascular Surgery*, 47(4), pp. 288-293.

Lathyris, D.N., Patsopoulos, N.A., Salanti, G. and Ioannidis, J.P. (2010) 'Industry sponsorship and selection of comparators in randomized clinical trials', *Eur J Clin Invest*, 40(2), pp. 172-82.

Latimer, N. (2011) *NICE DSU Technical Support Document 14: Undertaking survival analysis for economic evaluations alongside clinical trials - extrapolation with patient-level data*. [Online]. Available at: http://www.nicedsu.org.uk.

Lawrie, M. and Battye, F. (2012) *Older people's experience of emergency hospital readmission*. London: Age UK Age UK.

Lazo, J.K., McClelland, G.H. and Schulze, W.D. (1997) 'Economic Theory and Psychology of Non-Use Values', *Land Economics*, 73(3), pp. 358-371.

Lee, J.E., Sung, J.H., Ward, W.B., Fos, P.J., Lee, W.J. and Kim, J.C. (2007) 'Utilization of the emergency room: impact of geographic distance', *Geospat Health*, 1(2), pp. 243-53.

Limpert, E. and Stahel, W.A. (2011) 'Problems with Using the Normal Distribution – and Ways to Improve Quality and Efficiency of Data Analysis', *PLoS ONE*, 6(7), p. e21403.

Limpert, E. and Stahel, W.A. (2017) 'The log-normal distribution', *Significance*, 14(1), pp. 8-9.

Louviere, J.J., Flynn, T.N. and Carson, R.T. (2010) 'Discrete Choice Experiments Are Not Conjoint Analysis', *Journal of Choice Modelling*, 3(3), pp. 57-72.

Lu, G. and Ades, A.E. (2004) 'Combination of direct and indirect evidence in mixed treatment comparisons', *Stat Med*, 23(20), pp. 3105-24.

Lumley, T. (2002) 'Network meta-analysis for indirect treatment comparisons', *Stat Med*, 21(16), pp. 2313-24.

Lusk, J.L. and Norwood, F.B. (2009) 'An Inferred Valuation Method', *Land Economics*, 85(3), pp. 500-514.

Mark, T.L. and Swait, J. (2004) 'Using stated preference and revealed preference modeling to evaluate prescribing decisions', *Health Econ*, 13(6), pp. 563-73.

Marshall, D., Bridges, J.F., Hauber, B., Cameron, R., Donnalley, L., Fyie, K. and Johnson, F.R. (2010) 'Conjoint Analysis Applications in Health - How are Studies being Designed and Reported?: An Update on Current Practice in the Published Literature between 2005 and 2008', *Patient*, 3(4), pp. 249-56.

McCabe, C., Claxton, K. and Culyer, A.J. (2008) 'The NICE cost-effectiveness threshold: what it is and what that means', *Pharmacoeconomics*, 26(9), pp. 733-44.

McCaffery, K.J., Dixon, A., Hayen, A., Jansen, J., Smith, S. and Simpson, J.M. (2012) 'The influence of graphic display format on the interpretations of quantitative risk information among adults with lower education and literacy: a randomized experimental study', *Med Decis Making*, 32(4), pp. 532-44.

McCrone, P., Dhanasiri, S., Patel, A., Knapp, M. and Lawton-Smith, S. (2008) *Paying the price: The cost of mental health care in England to 2026*. London: The King's Fund The King's Fund.

McFadden, D. (1974) 'Conditional logit analysis of qualitative choice behaviour', in Zarembka, P. (ed.) *Frontiers in Econometrics*. New York: Academic Press INC, pp. 105-142.

McIntosh, E. (2006) 'Using discrete choice experiments within a cost-benefit analysis framework: some considerations', *Pharmacoeconomics*, 24(9), pp. 855-68.

McMeekin, P., Gray, J., Ford, G.A., Rodgers, H. and Price, C.I. (2013) 'Modelling the Efficiency of Local Versus Central Provision of Intravenous Thrombolysis After Acute Ischemic Stroke', *Stroke*, 44(11), pp. 3114-3119.

Meadows, C., Rattenberry, W. and Waldmann, C. (2011) 'Centralisation of specialist critical care services', *Journal of the Intensive Care Society*, 12(2), pp. 87-89.

Melzer, D., Tavakoly, B., Winder, R., Richards, S., Mounce, L., Gericke, C. and Lang, I. (May 2012, selected graphs updated August 2013) *Health Care Quality for an Active Later Life: Improving quality of prevention and treatment through information - England 2005 to 2012. A report from the Peninsula College of Medicine and Dentistry Ageing Research Group for Age UK.* Exeter UK: PCMD / University of Exeter,.

Mesman, R., Westert, G.P., Berden, B.J. and Faber, M.J. (2015) 'Why do high-volume hospitals achieve better outcomes? A systematic review about intermediate factors in volume-outcome relationships', *Health Policy*, 119(8), pp. 1055-67.

Metcalfe, D., Bouamra, O., Parsons, N.R., Aletrari, M.O., Lecky, F.E. and Costa, M.L. (2014) 'Effect of regional trauma centralization on volume, injury severity and outcomes of injured patients admitted to trauma centres', *British Journal of Surgery*, 101(8), pp. 959-964.

Mihaylova, B., Briggs, A., O'Hagan, A. and Thompson, S.G. (2011) 'Review of Statistical Methods for Analysing Healthcare Resources and Costs', *Health Economics*, 20(8), pp. 897-916.

Mockford, C., Staniszewska, S., Griffiths, F. and Herron-Marx, S. (2012) 'The impact of patient and public involvement on UK NHS health care: a systematic review', *International Journal for Quality in Health Care*, 24(1), pp. 28-38.

Moher, D., Liberati, A., Tetzlaff, J. and Altman, D.G. (2009) 'Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement', *BMJ*, 339:b2535.

Morimoto, T. and Fukui, T. (2002) 'Utilities measured by rating scale, time trade-off, and standard gamble: review and reference for health care professionals', *J Epidemiol*, 12(2), pp. 160-78.

Morris, S., Hunter, R.M., Ramsay, A.I.G., Boaden, R., McKevitt, C., Perry, C., Pursani, N., Rudd, A.G., Schwamm, L.H., Turner, S.J., Tyrrell, P.J., Wolfe, C.D.A. and Fulop, N.J. (2014) 'Impact of centralising acute stroke services in English metropolitan areas on mortality and length of hospital stay: difference-in-differences analysis', *BMJ*, 349:g4757.

Moscelli, G., Siciliani, L., Gutacker, N. and Gravelle, H. (2016) 'Location, quality and choice of hospital: Evidence from England 2002–2013', *Regional Science and Urban Economics*, 60, pp. 112-124.

Mott, D.J. and Najafzadeh, M. (2016) 'Whose preferences should be elicited for use in health-care decision-making? A case study using anticoagulant therapy', *Expert Rev Pharmacoecon Outcomes Res*, 16(1), pp. 33-9.

Mulley, A., Trimble, C. and Elwyn, G. (2012) *PATIENTS' PREFERENCES MATTER Stop the silent misdiagnosis*. London: The King's Fund.

Mungall, I.J. (2005) 'Trend towards centralisation of hospital services, and its effect on access to care for rural and remote communities in the UK', *Rural Remote Health*, 5(2), p. 390.

Murphy, J.J., Allen, P.G., Stevens, T.H. and Weatherhead, D. (2005) 'A Meta-analysis of Hypothetical Bias in Stated Preference Valuation', *Environmental and Resource Economics*, 30(3), pp. 313-325.

Naimark, D.M.J., Bott, M. and Krahn, M. (2008) 'The Half-Cycle Correction Explained: Two Alternative Pedagogical Approaches', *Medical Decision Making*, 28(5), pp. 706-712.

National Health Services (2016). Available at: http://www.nhs.uk/NHSEngland/thenhs/about/Pages/overview.aspx (Accessed: 10 July, 2018).

National Institute for Health and Care Excellence (2013) *Guide to the methods of technology appraisal*. London: National Institute for Health and Care Excellence.

National Institute for Health and Care Excellence (2014) *Developing NICE guidelines: the manual*.NICE. [Online]. Available at: nice.org.uk/process/pmg20.

Nexo, M.A., Cleal, B., Hagelund, L., Willaing, I. and Olesen, K. (2017) 'Willingness to pay for flexible working conditions of people with type 2 diabetes: discrete choice experiments', *BMC Public Health*, 17(1), p. 938.

NHS Confederation (2013a) *Emergency care: an accident waiting to happen?* London: NHS Confederation NHS Confederation.

NHS Confederation (2013b) *Tough times tough choices. How does the NHS financial situation compare*. London: NHS Confederation NHS Confederation.

NHS England (2013a) *High quality care for all, now and for future generations: Transforming urgent and emergency care services in England- Urgent and Emergency Care Review End of Phase 1 Report*. London: NHS England NHS England.

NHS England (2013b) *High quality care for all, now and for future generations: Transforming urgent and emergency care services in England-Urgent and Emergency Care Review. End of Phase 1 Report, Appendix 1- Revised Evidence Base from the Urgent and Emergency Care Review*. London: NHS England NHS England.

NHS England (2013c) *The NHS belongs to the people: A call to action*. London: NHS England.

NHS England (2014) *Five year forward view*. London: NHS England.

Nicholl, J., West, J., Goodacre, S. and Turner, J. (2007) 'The relationship between distance to hospital and patient mortality in emergencies: an observational study', *Emergency Medicine Journal*, 24(9), pp. 665-668.

Nicky, J.W. and Ades, A.E. (2005) 'Estimation of Markov Chain Transition Probabilities and Rates from Fully and Partially Observed Data: Uncertainty Propagation, Evidence Synthesis, and Model Calibration', *Medical Decision Making*, 25(6), pp. 633-645.

Noordzij, M., Leffondré, K., van Stralen, K.J., Zoccali, C., Dekker, F.W. and Jager, K.J. (2013) 'When do we need competing risks methods for survival analysis in nephrology?', *Nephrology Dialysis Transplantation*, 28(11), pp. 2670-2677.

O'Brien, B. and Gafni, A. (1996) 'When Do the "Dollars" Make Sense? Toward a Conceptual Framework for Contingent Valuation

Studies in Health Care', *Medical Decision Making*, 16(3), pp. 288-299.

O'Neill, S., Wolters, A. and Stevenson, A. (2017) *Briefing: The impact of redesigning urgent and emergency care in Northumberland*. London: The Health Foundation.

O'Sullivan, A.K., Thompson, D. and Drummond, M.F. (2005) 'Collection of Health-Economic Data Alongside Clinical Trials: Is There a Future for Piggyback Evaluations?', *Value in Health*, 8(1), pp. 67-79.

Ocloo, J. and Matthews, R. (2016) 'From tokenism to empowerment: progressing patient and public involvement in healthcare improvement', *BMJ Quality & Safety*.

Office for National Statistics (2012) *Population Ageing in the United Kingdom,its Constituent Countries and the European Union*. London: Office for National Statistics.

Office for National Statistics (2014a) *National Population Projections, 2012-based Reference Volume: Series PP2*. Available at: http://www.ons.gov.uk/ons/rel/npp/national-population-projections/2012-based-reference-volume--series-pp2/results.html#tab-Age-Structure (Accessed: 03 September, 2014).

Office for National Statistics (2014b) *UK Population Estimates 1851-2012 (Excel sheet 199 kb)*. Available at: http://www.ons.gov.uk/ons/search/index.html?newquery=UK+population+1948 (Accessed: 02 September, 2014).

Office for National Statistics (2018a). London: Office for National Statistics. Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours#timeseries , Date Accessed 17 April 2018.

Office for National Statistics (2018b) *Statistical bulletin: Population estimates for UK, England and Wales, Scotland and Northern Ireland: mid-2017*. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2017 (Accessed: 10 July, 2018).

Oliver, D., Foot, C. and Humphries, R. (2014) *Making our health and care systems fit for an ageing population*. London: The King's Fund The King's Fund.

Olsen, J.A. and Smith, R.D. (2001) 'Theory versus practice: a review of 'willingness-to-pay' in health and health care', *Health Economics*, 10(1), pp. 39-52.

Oostenbrink, J.B., Al, M.J., Oppe, M. and Rutten-van Mölken, M.P.M.H. (2008) 'Expected Value of Perfect Information: An Empirical Example of Reducing Decision Uncertainty by Conducting Additional Research', *Value in Health*, 11(7), pp. 1070-1080.

Orme, B. (1998) *Sample size issues for conjoint analysis studies*.

Orme, B. (2010) 'Sample Size Issues for Conjoint Analysis Studies', in *Sawtooth Software Technical Paper*. Sequim.

Ozdemir, S., Mohamed, A.F., Johnson, F.R. and Hauber, A.B. (2010) 'Who pays attention in stated-choice surveys?', *Health Econ*, 19(1), pp. 111-8.

Parker, J.R. and Schrift, R.Y. (2011) 'Rejectable Choice Sets: How Seemingly Irrelevant No-Choice Options Affect Consumer Decision Processes', *Journal of Marketing Research*, 48(5), pp. 840-854.

Parsons, G.R. (2017) 'Travel Cost Models', in Champ, P.A., Boyle, K.J. and Brown, T.C. (eds.) *A Primer on Nonmarket Valuation*. Dordrecht: Springer Netherlands, pp. 187-233.

Pedersen, L.B., Kjær, T., Kragstrup, J. and Gyrd-Hansen, D. (2011) 'Does the Inclusion of a Cost Attribute in Forced and Unforced Choices Matter?: Results from a Web Survey Applying the Discrete Choice Experiment', *Journal of Choice Modelling*, 4(3), pp. 88-109.

Peñaloza Ramos, M.C., Barton, P., Jowett, S. and Sutton, A.J. (2015) 'A Systematic Review of Research Guidelines in Decision-Analytic Modeling', *Value in Health*, 18(4), pp. 512-529.

Perry, C., Papachristou, I., Ramsay, A.I.G., Boaden, R.J. and McKevitt, C. (2018) 'Patient experience of centralized acute stroke care pathways'.

Petrou, S. and Gray, A. (2011a) 'Economic evaluation alongside randomised controlled trials: design, conduct, analysis, and reporting', *Bmj*, 342, p. d1548.

Petrou, S. and Gray, A. (2011b) 'Economic evaluation using decision analytical modelling: design, conduct, analysis, and reporting', *Bmj*, 342, p. d1766.

Petrou, S. and McIntosh, E. (2009) 'Women's preferences for attributes of first-trimester miscarriage management: a stated preference discrete-choice experiment', *Value Health*, 12(4), pp. 551-9.

Pharmaceutical Benefits Advisory Committee (PBAC) (2016) *Guidelines for preparing submissions to the Pharmaceutical Benefits Advisory Committee.* . Canberra, Australia. : Department of Health.

Philips, Z., Bojke, L., Sculpher, M., Claxton, K. and Golder, S. (2006) 'Good Practice Guidelines for Decision-Analytic Modelling in Health Technology Assessment', *PharmacoEconomics*, 24(4), pp. 355-371.

Pieterse, A.H., Stiggelbout, A.M. and Marijnen, C.A.M. (2010) 'Methodologic evaluation of adaptive conjoint analysis to assess patient preferences: an application in oncology', *Health Expectations*, 13(4), pp. 392-405.

Pitman, R., Fisman, D., Zaric, G.S., Postma, M., Kretzschmar, M., Edmunds, J. and Brisson, M. (2012) 'Dynamic transmission modeling: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force Working Group-5', *Med Decis Making*, 32(5), pp. 712-21.

Portela, M.C., Pronovost, P.J., Woodcock, T., Carter, P. and Dixon-Woods, M. (2015) 'How to study improvement interventions: a brief overview of possible study types', *BMJ Quality & Safety*.

Posnett, J. (1999) 'Is bigger better? Concentration in the provision of secondary care', *BMJ : British Medical Journal*, 319(7216), pp. 1063-1065.

Potoglou, D., Burge, P., Flynn, T., Netten, A., Malley, J., Forder, J. and Brazier, J.E. (2011) 'Best–worst scaling vs. discrete choice experiments: An empirical comparison using social care data', *Social Science & Medicine*, 72(10), pp. 1717-1727.

Prince, M., Knapp, M., Guerchet, M., McCrone, P., Prina, M., Comas-Herrera, A., Wittenberg, R., Adelaja, B., Hu, B., King, D., Rehill, A. and Salimkumar, D. (2014) *Dementia UK: Second edition – Overview*. London: Alzheimer's Society.

Quaife, M., Terris-Prestholt, F., Di Tanna, G.L. and Vickerman, P. (2018) 'How well do discrete choice experiments predict health choices? A systematic review and meta-analysis of external validity', *The European Journal of Health Economics*.

Qualtrics (2015). Available at: http://www.qualtrics.com.

R Core Team (2016) 'R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.'. Available at: https://www.R-project.org/.

Raknes, G., Hansen, E. and Hunskaar, S. (2013) 'Distance and utilisation of out-of-hours services in a Norwegian urban/rural district: an ecological study', *BMC Health Services Research*, 13(1), p. 222.

Ramsey, S.D., Willke, R.J., Glick, H., Reed, S.D., Augustovski, F., Jonsson, B., Briggs, A. and Sullivan, S.D. (2015) 'Cost-effectiveness analysis alongside clinical trials II-An ISPOR Good Research Practices Task Force report', *Value Health*, 18(2), pp. 161-72.

Randall, A. (1994) 'Difficulty with the Travel Cost Method', *Land Economics*, 70(1), pp. 88-96.

Ratcliffe, J. (2000) 'The use of conjoint analysis to elicit willingness-to-pay values. Proceed with caution?', *Int J Technol Assess Health Care*, 16(1), pp. 270-5.

Ratcliffe, J., Brazier, J., Tsuchiya, A., Symonds, T. and Brown, M. (2009) 'Using DCE and ranking data to estimate cardinal values for health states for deriving a preference-based single index from the sexual quality of life questionnaire', *Health Econ*, 18(11), pp. 1261-76.

Ravi, P., Bianchi, M., Hansen, J., Trinh, Q.-D., Tian, Z., Meskawi, M., Abdollah, F., Briganti, A., Shariat, S.F., Perrotte, P., Montorsi, F., Karakiewicz, P.I. and Sun, M. (2014) 'Benefit in regionalisation of care for patients treated with radical cystectomy: a nationwide inpatient sample analysis', *BJU International*, 113(5), pp. 733-740.

Reed Johnson, F., Lancsar, E., Marshall, D., Kilambi, V., Muhlbacher, A., Regier, D.A., Bresnahan, B.W., Kanninen, B. and Bridges, J.F. (2013) 'Constructing experimental designs for discrete-choice experiments: report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force', *Value Health*, 16(1), pp. 3-13.

Roberts, A., Blunt, I. and Bardsley, M. (2014) *Focus On: Distance from home to emergency care*. London: The Health Foundation and the Nuffield Trust The Health Foundation and the Nuffield Trust.

Roberts, M., Russell, L.B., Paltiel, A.D., Chambers, M., McEwan, P. and Krahn, M. (2012) 'Conceptualizing a Model: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force-2', *Value in Health*, 15(6), pp. 804-811.

Robinson, A. and Spencer, A. (2006) 'Exploring challenges to TTO utilities: valuing states worse than dead', *Health Econ*, 15(4), pp. 393-402.

Robinson, R. (1993) 'Cost-utility analysis', *Bmj*, 307(6908), pp. 859-62.

Robst, J. (2006) 'Estimation of a Hedonic Pricing Model for Medigap Insurance', *Health Services Research*, 41(6), pp. 2097-2113.

Rose, J. and Bliemer, M.J. (2013) 'Sample size requirements for stated choice experiments', *Transportation*, 40(5), pp. 1021-1041.

Rose, J.M. and Bliemer, M.C.J. (2009) 'Constructing Efficient Stated Choice Experimental Designs', *Transport Reviews*, 29(5), pp. 587-617.

Rose, J.M., Bliemer, M.C.J., Hensher, D.A. and Collins, A.T. (2008) 'Designing efficient stated choice experiments in the presence of reference alternatives', *Transportation Research Part B: Methodological*, 42(4), pp. 395-406.

Rose, J.M. and Hess, S. (2009) 'Dual-Response Choices in Pivoted Stated Choice Experiments', *Transportation Research Record: Journal of the Transportation Research Board*, 2135, pp. 25-33.

Rowen, D., Brazier, J. and Van Hout, B. (2015) 'A Comparison of Methods for Converting DCE Values onto the Full Health-Dead QALY Scale', *Medical Decision Making*, 35(3), pp. 328-340.

Russell, L.B. (2009) 'Completing Costs: Patients' Time', *Medical Care*, 47(7), pp. S89-S93.

Russell, L.B., Gold, M.R., Siegel, J.E., Daniels, N. and Weinstein, M.C. (1996) 'The role of cost-effectiveness analysis in health and medicine. Panel on Cost-Effectiveness in Health and Medicine', *Jama*, 276(14), pp. 1172-7.

Ryan, M. (1999) 'A role for conjoint analysis in technology assessment in health care?', *Int J Technol Assess Health Care*, 15(3), pp. 443-57.

Ryan, M. and Bate, A. (2001) 'Testing the assumptions of rationality, continuity and symmetry when applying discrete choice experiments in health care', *Applied Economic Letters*, 8(1), pp. 59-63.

Ryan, M. and Gerard, K. (2003) 'Using discrete choice experiments to value health care programmes: current practice and future research reflections', *Appl Health Econ Health Policy*, 2(1), pp. 55-64.

Ryan, M., Gerard, K. and Amaya-Amaya, M. (2008) *Using Discrete Choice Experiments to Value Health and Health Care*. Springer.

Ryan, M., McIntosh, E., Dean, T. and Old, P. (2000) 'Trade-offs between location and waiting times in the provision of health care: the case of elective surgery on the Isle of Wight', *J Public Health Med*, 22(2), pp. 202-10.

Ryan, M. and San Miguel, F. (2003) 'Revisiting the axiom of completeness in health care', *Health Econ*, 12(4), pp. 295-307.

Ryan, M., Scott, D., Reeves, C., Bate, A. and van Teijlingen, E. (2001) 'Eliciting public preferences for healthcare: a systematic review of techniques', *Health Technology Assessment*, 5(5), p. 186.

Ryan, M., Watson, V. and Entwistle, V. (2009) 'Rationalising the 'irrational': a think aloud study of discrete choice experiment responses', *Health Economics*, 18(3), pp. 321-336.

Salampessy, B.H., Veldwijk, J., Jantine Schuit, A., van den Brekel-Dijkstra, K., Neslo, R.E., Ardine de Wit, G. and Lambooij, M.S. (2015) 'The Predictive Value of Discrete Choice Experiments in Public Health: An Exploratory Application', *Patient*.

San Miguel, F., Ryan, M. and Amaya-Amaya, M. (2005) ''Irrational' stated preferences: a quantitative and qualitative investigation', *Health Economics*, 14(3), pp. 307-322.

Schwappach, D.L. and Strasmann, T.J. (2007) 'Does location matter? A study of the public's preferences for surgical care provision', *J Eval Clin Pract*, 13(2), pp. 259-64.

Scottish Medicines Consortium (SMC) (2017) *Guidance to Manufacturers for Completion of New Product Assessment Form (NPAF)*. Glasgow, UK: Scottish Medicines Consortium (SMC).

Sculpher, M., Drummond, M. and Buxton, M. (1997) 'The iterative use of economic evaluation as part of the process of health technology assessment', *J Health Serv Res Policy*, 2(1), pp. 26-30.

Sculpher, M., Fenwick, E. and Claxton, K. (2000) 'Assessing quality in decision analytic cost-effectiveness models. A suggested framework and example of application', *Pharmacoeconomics*, 17(5), pp. 461-77.

Sculpher, M.J., Claxton, K., Drummond, M. and McCabe, C. (2006) 'Whither trial-based economic evaluation for health care decision making?', *Health Economics*, 15(7), pp. 677-687.

Seguin, J., Garber, B.G., Coyle, D. and Hebert, P.C. (1999) 'An economic evaluation of trauma care in a Canadian lead trauma hospital', *J Trauma*, 47(3 Suppl), pp. S99-103.

Shackley, P. and Ryan, M. (1995) 'Involving consumers in health care decision making', *Health Care Analysis*, 3(3), pp. 196-204.

Shackley, P., Slack, R. and Michaels, J. (2001) 'Vascular patients' preferences for local treatment: an application of conjoint analysis', *J Health Serv Res Policy*, 6(3), pp. 151-7.

Shalowitz, D.I., Nivasch, E., Burger, R.A. and Schapira, M.M. (2018) 'Are patients willing to travel for better ovarian cancer care?', *Gynecol Oncol*, 148(1), pp. 42-48.

Shaw, M.J., Beebe, T.J., Jensen, H.L. and Adlis, S.A. (2001) 'The use of monetary incentives in a community survey: impact on response rates, data quality, and cost', *Health Services Research*, 35(6), pp. 1339-1346.

Sheldon, T.A. (1996) 'Problems of using modelling in the economic evaluation of health care', *Health Economics*, 5(1), pp. 1-11.

Siebert, U., Alagoz, O., Bayoumi, A.M., Jahn, B., Owens, D.K., Cohen, D.J. and Kuntz, K.M. (2012) 'State-Transition Modeling: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force–3', *Medical Decision Making*, 32(5), pp. 690-700.

Simoens, S. (2010) 'Use of economic evaluation in decision making: evidence and recommendations for improvement', *Drugs*, 70(15), pp. 1917-26.

Simpson, A.N., Wardrope, J. and Burke, D. (2001) 'The Sheffield experiment: the effects of centralising accident and emergency services in a large urban setting', *Emergency Medicine Journal*, 18(3), pp. 193-197.

Singer, E. and Ye, C. (2013) 'The Use and Effects of Incentives in Surveys', *The ANNALS of the American Academy of Political and Social Science*, 645(1), pp. 112-141.

Sonnenberg, F.A. and Beck, J.R. (1993) 'Markov models in medical decision making: a practical guide', *Med Decis Making*, 13(4), pp. 322-38.

Sonnenberg, F.A., Roberts, M.S., Tsevat, J., Wong, J.B., Barry, M. and Kent, D.L. (1994) 'Toward a peer review process for medical decision analysis models', *Med Care*, 32(7 Suppl), pp. Js52-64.

Sorup, C., Jacobsen, P. and Forberg, J. (2013) 'Evaluation of emergency department performance - a systematic review on recommended performance and quality-in-care measures', *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, 21(1), p. 62.

Spinks, J. and Mortimer, D. (2016) 'Lost in the crowd? Using eye-tracking to investigate the effect of complexity on attribute non-attendance in discrete choice experiments', *BMC Medical Informatics and Decision Making*, 16, p. 14.

Spurgeon, P., Cooke, M., Fulop, N., Walters, R., West, P., 6, P., Barwell, F. and Mazelan, P. (2010) *Evaluating models of service delivery: reconfiguration principles*. National Institute for Health Research Service Delivery and Organisation Programme Queen’s Printer and Controller of HMSO.

Stamuli, E. (2011) 'Health outcomes in economic evaluation: who should value health?', *British Medical Bulletin*, 97(1), pp. 197-210.

StataCorp (2013) *Stata Statistical Software: Release 13.* [Computer program]. StataCorp LP.

Steuten, L., van de Wetering, G., Groothuis-Oudshoorn, K. and Retel, V. (2013) 'A systematic and critical review of the evolving methods and applications of value of information in academia and practice', *Pharmacoeconomics*, 31(1), pp. 25-48.

Stinnett, A.A. and Mullahy, J. (1998) 'Net Health Benefits', *Medical Decision Making*, 18(2_suppl), pp. S68-S80.

Stinnett, A.A. and Paltiel, A.D. (1997) 'Estimating CE ratios under second-order uncertainty: the mean ratio versus the ratio of means', *Med Decis Making*, 17(4), pp. 483-9.

Stitzenberg, K.B., Sigurdson, E.R., Egleston, B.L., Starkey, R.B. and Meropol, N.J. (2009) 'Centralization of Cancer Surgery: Implications for Patient Access to Optimal Care', *Journal of Clinical Oncology*, 27(28), pp. 4671-4678.

Stolk, E.A., Oppe, M., Scalone, L. and Krabbe, P.F.M. (2010) 'Discrete Choice Modeling for the Quantification of Health States: The Case of the EQ-5D', *Value in Health*, 13(8), pp. 1005-1013.

Sullivan, P.W., Slejko, J.F., Sculpher, M.J. and Ghushchyan, V. (2011) 'Catalogue of EQ-5D scores for the United Kingdom', *Med Decis Making*, 31(6), pp. 800-4.

Sullivan, S.M., Wells, G. and Coyle, D. (2015) 'What Guidance are Economists Given on How to Present Economic Evaluations for Policymakers? A Systematic Review', *Value in Health*, 18(6), pp. 915-924.

Sun, X. and Faunce, T. (2008) 'Decision-analytical modelling in health-care economic evaluations', *Eur J Health Econ*, 9(4), pp. 313-23.

Tait, A.R., Voepel-Lewis, T., Zikmund-Fisher, B.J. and Fagerlin, A. (2010a) 'The effect of format on parents' understanding of the risks and benefits of clinical research: a comparison between text, tables, and graphics', *J Health Commun*, 15(5), pp. 487-501.

Tait, A.R., Voepel-Lewis, T., Zikmund-Fisher, B.J. and Fagerlin, A. (2010b) 'Presenting research risks and benefits to parents: does format matter?', *Anesth Analg*, 111(3), pp. 718-23.

Taylor, L.O. (2017) 'Hedonics', in Champ, P.A., Boyle, K.J. and Brown, T.C. (eds.) *A Primer on Nonmarket Valuation*. Second edn. Dordrecht: Springer Netherlands, pp. 235-292.

Terris-Prestholt, F., Quaife, M. and Vickerman, P. (2016) 'Parameterising User Uptake in Economic Evaluations: The role of discrete choice experiments', *Health Econ*, 25 Suppl 1, pp. 116-23.

The College of Emergency Medicine (2011) *Emergency Department Clinical Quality Indicators: -A CEM guide to implementation*. London: The College of Emergency Medicine The College of Emergency Medicine.

The Community Pharmacy Medicines Management Project Evaluation, T. (2007) 'The MEDMAN study: a randomized controlled trial of community pharmacy-led medicines management for patients with coronary heart disease', *Family Practice*, 24(2), pp. 189-200.

Thomson, M., MacInnis, D.J. and Whan Park, C. (2005) 'The Ties That Bind: Measuring the Strength of Consumers' Emotional Attachments to Brands', *Journal of Consumer Psychology*, 15(1), pp. 77-91.

Thurstone, L.L. (1927) 'A Law of Comparative Judgment', *Psychology Review*, 34, pp. 273-286.

Tinelli, M., Ryan, M. and Bond, C. (2016) 'What, who and when? Incorporating a discrete choice experiment into an economic evaluation', *Health Economics Review*, 6, p. 31.

Torrance, G.W. (1986) 'Measurement of health state utilities for economic appraisal', *J Health Econ*, 5(1), pp. 1-30.

Torrance, G.W. and Feeny, D. (1989) 'Utilities and quality-adjusted life years', *Int J Technol Assess Health Care*, 5(4), pp. 559-75.

Torrance, G.W., Feeny, D. and Furlong, W. (2001) 'Visual Analog Scales', *Medical Decision Making*, 21(4), pp. 329-334.

Tuffaha, H.W., Gordon, L.G. and Scuffham, P.A. (2014) 'Value of information analysis in healthcare: a review of principles and applications', *J Med Econ*, 17(6), pp. 377-83.

Turnbull, J., Martin, D., Lattimer, V., Pope, C. and Culliford, D. (2008) 'Does distance matter? Geographical variation in GP out-of-hours service use: an observational study', *Br J Gen Pract*, 58(552), pp. 471-7.

Vale, L. (2005) *The progressive economic evaluation of a surgical technology: a case study of surgical repair of inguinal hernia*. University of Aberdeen.

Vallejo-Torres, L., Melnychuk, M., Vindrola-Padros, C., Aitchison, M., Clarke, C.S., Fulop, N.J., Hines, J., Levermore, C., Maddineni, S.B., Perry, C., Pritchard-Jones, K., Ramsay, A.I.G., Shackley, D.C. and Morris, S. (2018) 'Discrete-choice experiment to analyse preferences for centralizing specialist cancer surgery services', *Br J Surg*, 105(5), pp. 587-596.

van der Pol, M., Shiell, A., Au, F., Jonhston, D. and Tough, S. (2010) 'Eliciting individual preferences for health care: a case study of perinatal care', *Health Expect*, 13(1), pp. 4-12.

van Exel, N.J.A., Brouwer, W.B.F., van den Berg, B. and Koopmanschap, M.A. (2006) 'With a little help from an anchor: Discussion and evidence of anchoring effects in contingent valuation', *The Journal of Socio-Economics*, 35(5), pp. 836-853.

van Gijn, W., Gooiker, G.A., Wouters, M.W., Post, P.N., Tollenaar, R.A. and van de Velde, C.J. (2010) 'Volume and outcome in colorectal cancer surgery', *Eur J Surg Oncol*, 36 Suppl 1, pp. S55-63.

van Helvoort-Postulart, D., van der Weijden, T., Dellaert, B., de Kok, M., von Meyenfeldt, M. and Dirksen, C. (2009) 'Investigating the complementary value of discrete choice experiments for the evaluation of barriers and facilitators in implementation research: a questionnaire survey', *Implementation Science*, 4(1), p. 10.

van Osch, S.M.C., Wakker, P.P., van den Hout, W.B. and Stiggelbout, A.M. (2004) 'Correcting Biases in Standard Gamble and Time Tradeoff Utilities', *Medical Decision Making*, 24(5), pp. 511-517.

Vass, C., Rigby, D. and Payne, K. (2017) 'The Role of Qualitative Research Methods in Discrete Choice Experiments', *Med Decis Making*, 37(3), pp. 298-313.

Vass, C.M., Wright, S., Burton, M. and Payne, K. (2018) 'Scale Heterogeneity in Healthcare Discrete Choice Experiments: A Primer', *Patient*, 11(2), pp. 167-173.

Veldwijk, J., Essers, B.A.B., Lambooij, M.S., Dirksen, C.D., Smit, H.A. and de Wit, G.A. (2016) 'Survival or Mortality: Does Risk Attribute Framing Influence Decision-Making Behavior in a Discrete Choice Experiment?', *Value in Health*, 19(2), pp. 202-209.

Veldwijk, J., Lambooij, M.S., de Bekker-Grob, E.W., Smit, H.A. and de Wit, G.A. (2014) 'The Effect of Including an Opt-Out Option in Discrete Choice Experiments', *PLoS ONE*, 9(11), p. e111805.

Veldwijk, J., Lambooij, M.S., van Til, J.A., Groothuis-Oudshoorn, C.G., Smit, H.A. and de Wit, G.A. (2015) 'Words or graphics to present a Discrete Choice Experiment: Does it matter?', *Patient Educ Couns*, 98(11), pp. 1376-84.

Weernink, M.G.M., Janus, S.I.M., van Til, J.A., Raisch, D.W., van Manen, J.G. and Ijzerman, M.J. (2014) 'A Systematic Review to Identify the Use of Preference Elicitation Methods in Healthcare Decision Making', *Pharmaceutical Medicine*, 28(4), pp. 175-185.

Wei, L., Lang, C.C., Sullivan, F.M., Boyle, P., Wang, J., Pringle, S.D. and MacDonald, T.M. (2008) 'Impact on mortality following first acute myocardial infarction of distance between home and hospital: cohort study', *Heart*, 94(9), pp. 1141-6.

Weinstein, M.C. (2006) 'Recent Developments in Decision-Analytic Modelling for Economic Evaluation', *PharmacoEconomics*, 24(11), pp. 1043-1053.

Weinstein, M.C., O'Brien, B., Hornberger, J., Jackson, J., Johannesson, M., McCabe, C. and Luce, B.R. (2003) 'Principles of good practice for decision analytic modeling in health-care evaluation: report of the ISPOR Task Force on Good Research Practices--Modeling Studies', *Value Health*, 6(1), pp. 9-17.

Weinstein, M.C., Torrance, G. and McGuire, A. (2009) 'QALYs: the basics', *Value Health*, 12 Suppl 1, pp. S5-9.

Wessels, H., de Graeff, A., Wynia, K., de Heus, M., Kruitwagen, C.L.J.J., Woltjer, G.T.G.J., Teunissen, S.C.C.M. and Voest, E.E. (2010) 'Gender-Related Needs and Preferences in Cancer Care Indicate the Need for an Individualized Approach to Cancer Patients', *The Oncologist*, 15(6), pp. 648-655.

White, A.L., Armstrong, P.A.R. and Thakore, S. (2010) 'Impact of senior clinical review on patient disposition from the emergency department', *Emergency Medicine Journal*, 27(4), pp. 262-265.

Whitehead, S.J. and Ali, S. (2010) 'Health outcomes in economic evaluation: the QALY and utilities', *British Medical Bulletin*, 96(1), pp. 5-21.

Whitty, J.A., Walker, R., Golenko, X. and Ratcliffe, J. (2014) 'A Think Aloud Study Comparing the Validity and Acceptability of Discrete Choice and Best Worst Scaling Methods', *PLOS ONE*, 9(4), p. e90635.

Williams I, McIver S, Moore D and S., B. (2008) 'The use of economic evaluations in NHS decision-making: a review and empirical investigation. ', *Health Technol Assess* 12(7).

Woo, Y.L., Kyrgiou, M., Bryant, A., Everett, T. and Dickinson, H.O. (2012) 'Centralisation of services for gynaecological cancer', *Cochrane Database Syst Rev*, 3, p. Cd007945.

Xie, F., Pullenayegum, E., Gaebel, K., Oppe, M. and Krabbe, P.F.M. (2014) 'Eliciting preferences to the EQ-5D-5L health states: discrete choice experiment or multiprofile case of best–worst scaling?', *The European Journal of Health Economics*, 15(3), pp. 281-288.

Young, E.L., Holt, P.J.E., Poloniecki, J.D., Loftus, I.M. and Thompson, M.M. (2007) 'Meta-analysis and systematic review of the relationship between surgeon annual caseload and mortality for elective open abdominal aortic aneurysm repairs', *Journal of Vascular Surgery*, 46(6), pp. 1287-1294.