DEVELOPMENT OF A HOSPITAL ELECTRONIC RECORD FRAILTY INDEX (HerFI): AN ENHANCED CARE ALERT SCORE TO IDENTIFY OLDER PATIENTS LIKELY TO REQUIRE ENHANCED CARE ON DISCHARGE FROM HOSPITAL

by

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Abstract

This thesis explores the different methods that are currently used to define frailty and the development of a new frailty index using routinely collected hospital data. The increasing ageing population means that older people account for the majority of the UK healthcare usage and spend therefore if the need for intervention can be quantified, adverse outcomes could be prevented. Data were extracted from the local systems at the Queen Elizabeth Hospital Birmingham for patients over 65 who were admitted as an emergency. A combination of 31 routinely collected test results were extracted and used to calculate a frailty score called FI-QEHB, by taking the sum of deficits divided by the total number of measurements for each patient.

Machine Learning techniques were then used to firstly perform multiple imputation on missing data and then Classification and Regression Tree Analysis to determine the most important variables that predict mortality. This technique reduced the number of variables required to calculate a frailty score down to 6 from 31, and the area under the receiving operating characteristic (ROC) curve was used to assess the performance when the frailty score was added into a multivariable logistic regression model to predict emergency readmissions, mortality and whether a patient was discharged to a care home.

Dedication

To my Dad, who passed away suddenly at the beginning of my research. To my baby boy who I am due to meet in a few weeks' time, for giving me the motivation to never give up.

Acknowledgements

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Abbreviations

ALT – Alanine Aminotransferase

AUROC – Area under Receiver Operation Characteristic

BP – Blood Pressure

CART – Classification and Regression Tree

CFS – Clinical Frailty Scale

CGA – Comprehensive Geriatric Assessment

CI – Confidence Interval

CRP – C-reactive protein

DTOC – Delayed Transfer of Care

eGFR – estimated Glomerular Filtration Rate

EHR – Electronic Health Records

EPR – Electronic Patient Records

FI-Baseline – Frailty Index Baseline

FI-LAB – Frailty Index developed by Rockwood et al.

FI-QEHB – Frailty Index Queen Elizabeth Hospitals Birmingham

HerFI - Hospital Electronic Record Frailty Index

HES – Hospital Episode Statistics

ICD-10 – International Classification of Diseases, Tenth revision

INR – International Normalised Ratio

LOS – Length of Stay

MCV – Mean Corpuscular Volume

MUST – Malnutrition Universal Screening Tool

NHS – National Health Service

NICE – The National Institute for Health and Care Excellence

ONS – Office of National Statistics

OR – Odds Ratio

PAS – Patient Administration Solution

PICS – Prescribing Information and Communications System

QEHB – Queen Elizabeth Hospital Birmingham

SD – Standard Deviation

SEWS – Standardised Early Warning Score

SQL – Structured Query Language

SSMS – SQL Server Management Server

UHBFT – University Hospitals Birmingham Foundation Trust

WCC – White Cell Count

1 Introduction

The world's population is getting older and this is a major healthcare challenge globally. From an estimated 461 million people aged 65 and over in 2004, it is predicted that there will be over 2 billion by 2050 [1, 2]. This has potentially very serious consequences for healthcare systems and society at large. Older people account for the majority of UK healthcare use and spend. In 2016–17, people aged over 65 accounted for over half of the 16 million admissions to acute hospitals and the annual spend by local authorities on social care in this group was £8.9 billion [3]. Age is a fundamental driver of adverse outcomes after admission to hospital, including admission to a new care home, greater functional dependence, or death, but there is heterogeneity in how we age.

Frailty is a means to describe this unmeasured heterogeneity in older people [2] and the degree of frailty predicts the risk of adverse events independent of age [4]. Frailty and frailty syndromes (falls, delirium, polypharmacy effects) are common in unplanned hospital admissions [5]. Frailty develops as a result of age-related decline in several physiological systems. As a direct consequence of this, individuals are left vulnerable to minor stressor events that can result in serious health problems. Somewhere between 25-50% of the population aged over 85 are thought to be frail with a consequent high risk of falling, disability, requirement for long-term care and death [2, 6]. Older people with frailty are less likely to recover from the acute illness that has caused the admission, leading to worsened function (physical and cognitive) [7]. In hospital this may cause increased length of stay or mortality; and at discharge, an escalation of social care package or a care home admission [8].

In UK hospitals, an escalation of care package, or new care home admission, often leads to a delayed transfer of care (DTOC). The process of assessment and securing of services contributes to DTOC. In 2017–2018, 66% of all DTOC occurred in acute National Health Service (NHS) Trusts, accounting for 102,574 delayed days in March 2018, and costing £41,029,600 [9]. DTOCs are associated with adverse outcomes [10] including increased mortality, nosocomial infection, reduced mobility and function [11-15], higher healthcare costs [16], and adverse patient and staff experience [17-20].

As somewhere between 25-50% of the population aged over 85 are thought to be frail, this does mean that somewhere between 50-75% of this group might not be frail. This makes it important to be able to reliably detect frailty so that resources can be appropriately directed to an at-risk population.

1.1 Definitions and Presentations

The term frailty is a well-established expression that suggests concern about a person's vulnerability and prognosis. It is something clinicians readily recognise but it has proved difficult to generate a clinically meaningful and useful definition [21]. In broad terms, frailty could probably be best defined as "a state of increased vulnerability to poor resolution of homeostasis after a stressor event, which increases the risk of adverse outcomes, including falls, delirium and disability" [6, 22, 23]. This can be represented diagrammatically (Figure 1). A minor illness, adverse event or change such as an infection, surgery or new medication results in a significant and exaggerated change in health status with increasing dependence [24]. These swings in dependency seen in the frail elderly have been referred to as "unstable disability" given the often profound changes in functional ability [24]. Some of the more

common clinical manifestations of frailty include extreme fatigue, unexplained weight loss,

frequent infections, falls, delirium and fluctuating disability [2].

Figure 1: Vulnerability of frail elderly people to a sudden change in health status after a minor illness (Adapted from Clegg et al). [1]
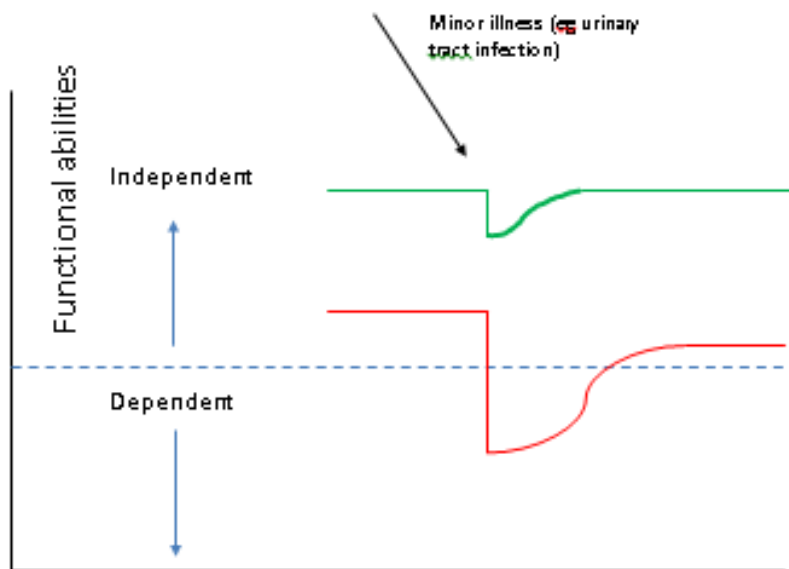
The green line represents a fit elderly individual who, after a minor stressor event such as an infection, has a small deterioration in function and then returns to homoeostasis. The red line represents a frail elderly individual who, after a similar stressor event, undergoes a larger deterioration, which may manifest as functional dependency, and who does not return to baseline homoeostasis. The horizontal dashed line represents the cut-off between dependent and independent.

1.2 Pathophysiology

Frailty arises as a consequence of disorders in several physiological systems [2] (Figure 2). A

decrease in physiological reserve happens naturally with aging. However, in frail individuals

this decline is accelerated and homeostatic systems fail [25]. This loss of compensatory

reserve, results in a vulnerability to large changes in health status in response to minor

stressor events. These complex aging mechanisms happen as a result of environmental

factors, underlying genetic make-up and epigenetic mechanisms that control gene expression

in cells [26, 27].

Figure 2: Schematic Representation of the pathophysiology of frailty (Adapted from Clegg et al). [1]
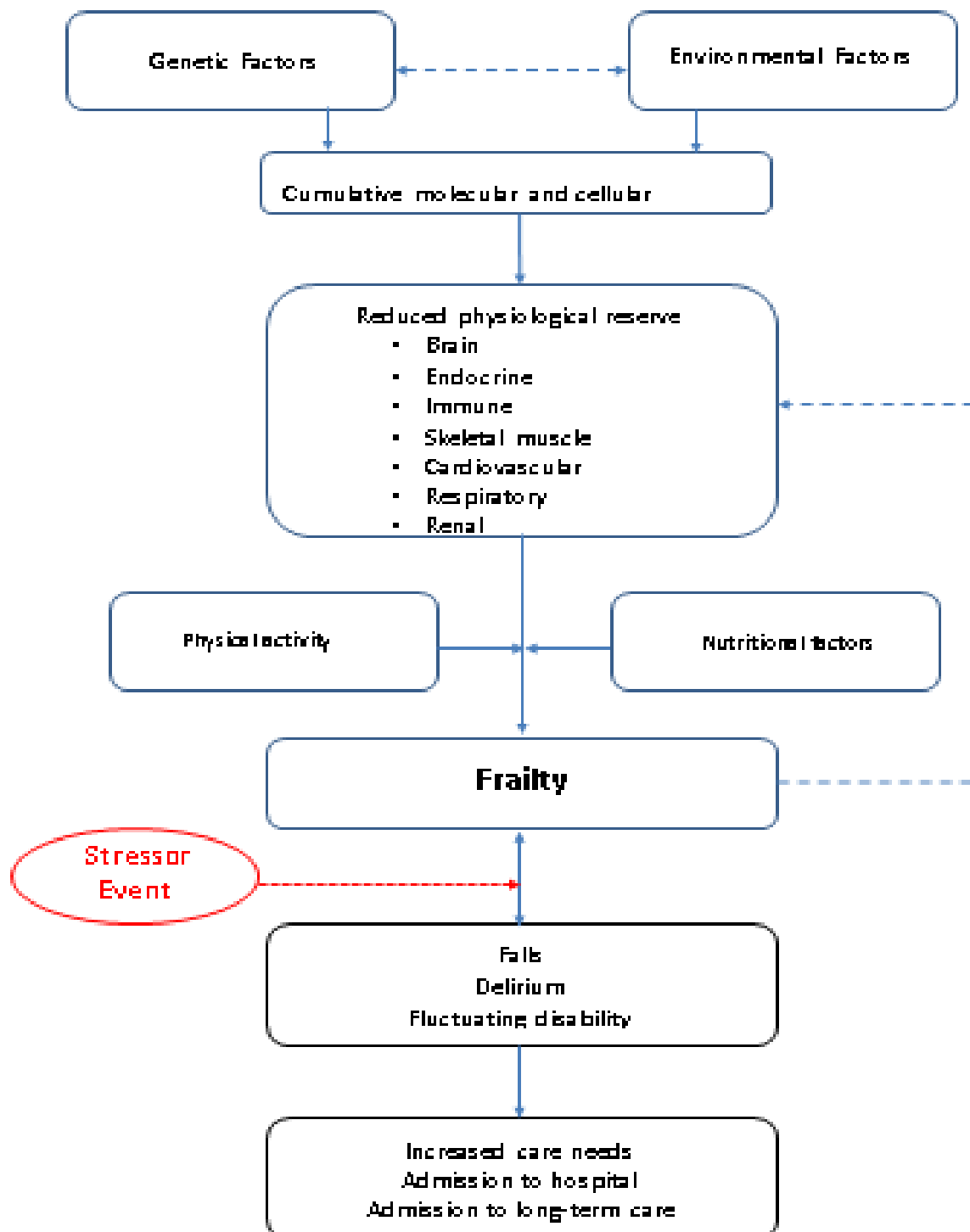
Many organs and systems have significant redundancy allowing them to compensate for aging and disease-related processes [28]. For example, the brain and muscle system have more neurons and myocytes than are generally required [28]. A key study in 2009 of 1002 women demonstrated a non-linear relationship between the number of abnormal systems (adiposity, haematological, hormonal, inflammatory, micronutrient and neuromuscular) and frailty, independent of age and co-morbidities [29]. An abnormality in three or more systems was strongly associated with frailty. Perhaps most importantly, the number of abnormal systems was much more strongly associated with frailty than abnormalities in any individual system [29].

The brain [23, 30-39] as well as the endocrine [40-58], immune [59-76] and musculo-skeletal systems [77-81] have been extensively studied in the development of frailty [22]. Frailty is also linked to loss of function in the cardiovascular [82, 83], haematopoietic and clotting systems [62, 84], renal [85], and respiratory systems [86]. Nutritional status is also thought to be an important factor in the development of frailty [6, 87-89].

1.3 Frailty Models

Robust frailty models should be underpinned by plausible biological causality and judged by their ability to predict both the natural history and response to treatments [2, 90]. The two main emerging models of frailty are the phenotype and cumulative deficit models [2, 6, 91].

1.3.1 Phenotype Model

A frailty phenotype has been designed consisting of five variables: unintentional self-report weight loss, self-reported exhaustion, low energy outlay, slow gait speed and weak grip

strength [6]. The lowest quintile values used to define the presence of these variables. The presence of three or more variables was defined as frailty (7%), presence of one to two factors as pre-frailty (47%) and absence of all variables as no frailty (46%). There was a graded relationship with these definitions with worse outcomes including falls, loss of mobility, hospitalisation and death at 3, 5 and 7 years [6]. Although an important study, suggesting that a frailty phenotype can be defined and therefore detected in routine care, it should be noted that this was an opportunistic secondary analysis of the Cardiovascular Health Study (n=5210, men and women aged over 65) [92]. This study was not designed to prospectively assess frailty and the five factors studied were available purely by chance rather than intention. Other potentially important parameters, cognitive impairment for example, were not studied. Nevertheless, the principle that clusters of variables can be used to define frailty has been prospectively and independently validated [93, 94].

1.3.2 Cumulative Deficit Model

The Canadian Study of Health and Aging (CSHA) was a 5-year prospective observational study (n=10,263, mean age 82) examining the burden of dementia [91]. Ninety-two baseline variables of symptoms, signs, laboratory parameters, disease states and disabilities were collected. These were collectively referred to as deficits. For a deficit to be included it must have a prevalence that increases with age, does not become too prevalent at a younger age, and is associated with worse outcomes [95]. The frailty index is a straightforward computation of the presence or absence of each deficit (e.g 22 deficits present out of a total of 92 equates to a frailty index of 22/92=0.24). Frailty can therefore be defined, quantified and graded by an accumulation of these deficits [96, 97]. Importantly, a score of more than 0.67 appeared to identify an accumulation beyond which any further deficit accumulation is not sustainable and death likely [98]. Further work has shown that the 92 variables can be

reduced to 30 without loss of predictive ability [99]. The frailty index has been shown to be strongly associated with death and institutionalization [96, 99, 100].

A further analysis of participants of the CHSA study, who volunteered for a blood test (n=1,013), generated a frailty index from 23 routinely collected clinical and laboratory variables [101]. A frailty index constructed from these deficits identified participants with a higher mortality. The authors of this study concluded that "the feasibility and utility of adding a large number of items to a frailty index using commonly evaluated laboratory tests might importantly advance routine frailty assessment, especially when these tests are used in conjunction with other relevant items from electronic medical records" [101].

1.3.3 Phenotype model versus cumulative deficit model

Both models overlap and demonstrate significant statistical convergence [102, 103]. However, the continuous frailty index has greater discriminatory ability for moderate to severe frailty than the categorical phenotype model [104]. Use of continuous models may identify frail individuals more accurately with a view to interventions [2, 105].

1.4 Current clinical guidelines and practice

The National Institute for Health and Care Excellence (NICE) Guidance in hospitals (NG 94) and at transition from hospital (NG 27) recommends comprehensive early multidisciplinary assessment for older people with complex needs, delivered in a specialist, geriatrician led unit [106]. This facilitates interventions such as comprehensive geriatric assessment (CGA) [7], and early discharge planning. Early discharge planning is associated with a reduced length of stay of 0.91 days [95% Confidence Interval (CI) -1.55 to -0.27], reduced readmissions and

increased patient and carer satisfaction [107]. But given finite levels of expertise against rising demand, the systematic delivery of specialist multi-disciplinary geriatrician-led care to all older patients is not feasible.

A validated tool to identify those who will need enhanced care on discharge which can be applied at the point of admission would allow clinicians, social care services, patients, carers and policy makers to facilitate timely interventions to improve patient care and patient flow to appropriate community environments. Half of admissions to care homes come from the acute hospital setting [108], yet it is unclear what proportion of acute admissions result in an admission to a new care home, or increase in a home care package. A systematic review of 26 studies of elderly patients discharged from emergency services reported readmission rates of 40% within 6 months [109]. The reasons for readmission probably reflect a combination of ongoing or unresolved medical problems as well as insufficient support in the community. It is not known whether interventions targeted at frail patients would prevent readmissions. However, there is clearly great potential to improve outcomes after an emergency admission.

The longstanding approach to discharge planning and social care is to start when patients are "medically fit" for discharge towards the end of their hospital stay. This potentially increases the risk of delayed and/or poorly coordinated hospital discharges. A different approach in acute healthcare could transform this process [110, 111]. Currently it is not known if the routine identification of frailty on admission to hospital can identify those at risk of poor recovery; and hence of adverse outcomes which could be improved by early targeted clinical review [7]. This would be hugely beneficial to patients, carers, and the health and social care services. Therefore, a validated tool to systematically predict patient's care needs at discharge, when they are first admitted to hospital, is required. In future, patients who

registered a particular score on a frailty index generated at, or soon after accessing health care services could trigger access to a specialist in hospital, but also early access to community and social care partners to begin planning for discharge on admission.

Chronological age is a poor predictor of adverse outcomes among frail older inpatients. Frailty is a health state with a spectrum of impact explaining heterogeneity in clinical outcomes among older people [9] and allows us to predict the risk of adverse events independent of age [4]. Frailty assessed at the point of admission could be used to identify those who will recover well, or decline, after an acute admission to hospital. Elderly people living with frailty frequently present to acute care settings including emergency departments, medical assessment units and out of hours general practice [21]. However, a recent systematic review highlighted that although frailty/risk stratification tools do exist, these take between *only* 1-10 minutes to complete and less than 50% of patients presenting to an emergency department and participating in these studies were actually screened using any of these tools [112]. These tools are, in any case, of limited utility in emergency situations, with most of them performing better than chance in predicting poor outcomes but none performing adequately for individual clinical decision making [113, 114].

Emergency care settings are intensely stressful, not only for the patients, but also for carers and staff. The prompt identification of a frail patient prompts further assessment and appropriate management [21]. Identifying these people on admission would allow early targeted interventions such as physiotherapy [115], CGA [7], or social services review. A CGA is "a specialist, multidimensional and interdisciplinary process focused on determining a person's medical, psychosocial, and functional capabilities in order to develop a coordinated and integrated plan for treatment and follow-up" [7, 21, 116]. These

interventions would aim to improve recovery, or allow early input from services to reduce hospital length of stay. A stratified approach to focus resource is necessary but this involves accurate identification of those who are predicted to require enhanced care on discharge, at the time of arrival in hospital.

1.5 Frailty measures in acute hospital

Frailty measures were first developed in community populations, and there are limitations in their evidence base in acute hospitals. Many frailty tools have been used in acute hospital settings [8], but a brief subjective scale, the Clinical Frailty Scale (CFS), is the most used. On admission the CFS predicts in-hospital mortality [8, 117], failure to recover mobility [118], and institutionalisation [119] – but not in UK hospital settings. The CFS relies on a subjective clinical assessment, requires rating of frailty before the person became ill, and is not specific to assessment on admission. An objective frailty measure has been developed using Hospital Episode Statistics (HES) data which record discharge diagnoses (The Hospital Frailty Risk Score) [120]. Although this model predicts mortality, it is limited in its application as it relies on information derived at the time of discharge, not admission. This introduces an immortal time bias (where only patients who survive to discharge are included) and cannot be used to target interventions at an early stage in the acute care journey. There is a critical need for an objective frailty score which can be used at an early time point in the acute care pathway in hospital to direct care provision.

1.6 Using Electronic Health Records to measure frailty

Electronic health records (EHR) are evolving, replacing paper records and are increasingly used in routine clinical practice. Use of EHR can facilitate the conduct of observational

studies as patients can be pre-identified and followed up using routinely collected clinical data [121-127]. The frailty index approach is particularly allied to using clinical data in EHRs, as it defines frailty as a measure of age-related deficit accumulation, rather than a subjective syndrome. Age related deficits recorded in an EHR can be standardised and used to quantify a frailty index, which is a ratio of the deficits present over those deficits evaluated for a given individual. This has been operationalized in Primary Care. For example, the Electronic Frailty Index, using coded diagnoses to predict risk of frailty and adverse outcomes including mortality and institutionalization [128]. However, the primary care-based score cannot be carried through to this project for two reasons. First, there is no consistent access to primary care records in UK acute care settings, and where it exists it is often limited to medications or current coded 'active' diagnoses. Although several health economies have good access in hospitals to primary care records, a strategy based on a fully shared record between primary and secondary care will not be generalisable to much of the UK. Secondly, the primary care based frailty index is based on chronic disease states, which is a static measure implying that it will not take into account the contribution of acute illness, or of early change. For these reasons, a new frailty measure is needed that balances background conditions and acute changes measured during the very early period of hospital assessment and treatment – a Hospital Electronic Record Frailty Index (HerFI).

1.7 Aims

The aims of this work are:

1. Set up a dataset of all patients aged over 65 admitted over a 6 month period (1st July 2014 to 31st December 2014) to the Queen Elizabeth Hospital Birmingham. Patient demographics to be linked to all routinely recorded data within the patients EHR on or as soon after hospital admission. Data to include clinical observations, blood tests and health assessments. Link this dataset to Hospital Episode Statistics (HES) and Office of National Statistics (ONS) for outcome data.

2. Use routinely collected hospital data to calculate a frailty score following the methods of the FI-LAB by Rockwood et al.

3. Calculate a new frailty score with additional routinely collected data that is available at the Queen Elizabeth Hospital Birmingham (QEHB).

4. Analyse both scores using multivariable logistic regression and assess their performance.

5. Use machine learning techniques to develop a HerFI.

6. Assess the HerFI performance against outcomes, to include in-hospital, 30 day, 12 month and 3 year mortality, readmission rates and discharge to care home.

7. Validate findings in a separate dataset collected over a different time-period in the same hospital.

2 Methods

2.1 Setting

This study was conducted at the new Queen Elizabeth Hospital Birmingham (QEHB), part of the University Hospitals Birmingham NHS Foundation Trust (UHBFT). QEHB is the leading university teaching hospital in the West Midlands. On the 16th June 2010, the new QEHB opened as a new £545 million acute hospital with 1,200 beds making it the largest single-site hospital in the country. It provides traditional secondary care services to the South Birmingham catchment area and tertiary services to the West Midlands and nationally. The new hospital replaced Selly Oak and the old Queen Elizabeth Hospitals. It provides adult services to more than 700,000 patients every year and admits approximately 42,000 emergency admissions per year. It does not have paediatric or obstetrics and gynaecology services. UHBFT is one of 12 NHS Trusts designated as an NHS Global Digital Exemplar by NHS England [129] .

2.2 Electronic Data Sources

Electronic information systems in healthcare have been evolving at a fast rate and are increasingly used in healthcare [122]. The richness and completeness of data held in EHR has been increasing with time as more information is being shared across healthcare organisations and paper-based patient records are being replaced by EHR. Increasingly, EHR are being used to conduct observational research and clinical trials. Patients can be pre-identified and followed up using routinely collected clinical data. For this study, data were collected from the EHR in use at UHBFT and linked to the HES and ONS databases for outcomes after discharge.

2.2.1 Patient Administration System

All NHS hospitals in England have a Patient Administration System (PAS). This allows patient details, activity and events to be recorded. Such systems evolved to collect the NHS data model that arose out of the work by Edith Korner in the late 1980s. PAS systems have adapted to coding data for clinical and financial purposes. UHBFT has developed its own bespoke in-house PAS system, OceanoPAS which forms part of the Oceano platform. The OceanoPAS has been live since July 2017 and replaced iPM Lorenzo.

2.2.2 Prescribing Information and Communication Systems

Prescribing Information and Communication Systems (PICS) is an in-house system developed by the PICS team at QEHB and is also commercially available. It records a vast amount of data including prescriptions, administrations of drugs, procedures, assessments, observations and inpatient and outpatient activity. Data extraction from the system is robust and supports all national clinical reports [127].

2.2.3 Hospital Episodes Statistics

Hospital Episodes Statistics (HES) is an administrative data set that collates information on all patients' attendances and admissions to all NHS hospitals in England. Each admission contains a primary diagnosis and up to 19 secondary diagnoses (recorded using the standard system of International Classification of Diseases, 10th edition), and up to 24 procedure fields. The HES database [130] can be used to calculate the Charlson comorbidity index. Derived from the secondary diagnoses codes, this is a marker of comorbidity and was originally formulated to predict mortality [131]. The English Index of Multiple Deprivation (IMD) 2015 is derived from the patient's postcode [132]. It is calculated using seven domain

indices to produce an overall measure of deprivation. As well as clinical information, each HES record will also contain demographic information about the patient (e.g. age, gender and ethnicity) and the episode of care (e.g. hospital name, admission method, date of admission and discharge). All hospitals in England are required to submit data to HES.

2.2.4 Office of National Statistics

All deaths in England must be notified by law and recorded by the Office for National Statistics (ONS). Deaths during the study period will be derived through linkage between HES records and death registry information via the ONS. This improves mortality capture by including deaths outside of hospitals.

2.3 Data extraction

Data were extracted using Microsoft SQL Server Management Studio 2012 (SSMS). Patients demographic and admission data was collected from the PAS and test results were extracted from PICS. A unique patient identifier was used to link the PAS and PICS datasets to HES and ONS to get data on patient readmissions and mortality data. SQL scripts were constructed for each database separately and coded in order to link all servers together (scripts attached in appendix).

2.4 Participants

Patients were included in the main cohort if they were over 65 and had an emergency admission to QEHB between 1st July and 31st December 2014. They were excluded if they had missing or invalid NHS numbers, or if they were a resident outside of England. This is due to follow up issues. Patients were followed up from the date of their index emergency

admission, until either death or they reached three years of follow up. For validation purposes, an additional two years of data was extracted for all emergency admissions between 1st January 2015 and 31st December 2016. This was in order to validate the performance of the model and ensure that the results are generalisable. Everyone in the validation cohort was followed up until death or for one year. The maximum follow up date for both cohorts was 31st December 2017.

2.5 Variables Collected

The normal ranges for these measurements are presented in Table 1.

2.5.1 Demographics

The following demographic information was collected:

- Age

- Sex

- Ethnicity – Patient ethnicity is categorised into 'White', 'Mixed', 'Asian or Asian British', 'Black or Black British', 'Other Ethnic Group' and 'Unknown'.

- Body Mass Index – BMI is used as a marker of a weight that is healthy dependent on sex and height. Older adults might benefit from a slightly higher BMI (between 25 and 27) in terms of mortality and protection from osteoporosis [133, 134].

2.5.2 Vital Signs

The following information related to vital signs was collected:

- Blood Pressure – Systolic blood pressure measures the pressure in blood vessels when the heart contracts (systole) and diastolic measures the pressure when the heart relaxes (diastole). Low blood pressure (hypotension) can be a sign of underlying

problems in older people and high blood pressure (hypertension) is one of the most common chronic conditions in older people and can cause strokes, heart attacks and heart failure [135].

- Heart Rate – is the number of heart beats per minute. Abnormally low (bradycardia) and high (tachycardia) heart rates are more common with increasing age [136].

- Oxygen Saturation - measures the amount of circulating haemoglobin that is saturated with oxygen. Older adults standardly have lower oxygen saturation levels than younger adults [137].

- Respiratory Rate - is the number of breaths taken per minute. It has been shown to provide predictive abilities for adverse events [135]. Changing respiratory rate is linked to increasing age [135].

- Temperature - Generally, older patients have a lower body temperature than younger people [138].

2.5.3 Blood tests

The following data related to blood tests was collected:

Haematology

- Haemoglobin – haemoglobin is a protein found in red blood cells which transports oxygen in the circulation [139, 140]. Low haemoglobin levels are a sign of anaemia and high haemoglobin levels could be caused by lifestyle factors such a smoking, or in the absence of any other abnormalities could be an indication of more severe diseases. Anaemia is very common in older adults and can have multiple underlying causes [139, 140].

- INR – International Normalized Ratio (INR) can also be referred to as standardized prothrombin time and is a measure of the ability of blood to clot [141].

- Mean Corpuscular Volume – MCV is the average volume of red cells [142]. MCV values tend to increase with age and could be due to the normal aging process [142]. High and low MCV can also be a feature of disease [143].

- Platelets – Platelet count and age have been shown to be correlated. Platelet count remains stable between the ages of 25 and 60, but falls from then on [144]. However, it is hard to determine whether it is age alone that causes this due to the level of confounders observed in older people.

- White Blood Cells – White blood cells (WBC) are a key component of the immune system [145]. High levels can be an indication of systemic inflammation whereas low WBC can be a feature of bone marrow dysfunction. WBC count has been shown to have strong prognostic ability in older people. The total WBC naturally increases in older people [145].

Serum Biochemistry

- Albumin – is synthesised by the liver and is the main protein found in the circulation preventing fluid from leaking out of the blood vessels [146]. Several hormones, drugs and ions (e.g calcium) circulate bound to albumin. Low levels of albumin can suggest liver disease and rarely kidney diseases (nephrotic syndrome). Patients with severe inflammation or shock could have low levels of albumin along with those with digestive conditions such as Crohn's disease. High levels of albumin could be an indication of dehydration. Mean serum albumin concentration decreases with every decade of age [147].

- Alkaline Phosphatase – ALP is an enzyme found in several tissues throughout the body. Abnormal results indicate problems with your liver, digestive system, kidneys or bones. There is some evidence to suggest elevated ALP levels with increasing age [148].

- ALT – High levels of alanine aminotransferase indicate probable liver disease or liver damage [146]. Low ALT levels have been found to be associated with an increase in frailty.

- Calcium –is one of the most important nutrients for bone health. Older people are especially susceptible to calcium deficiency due to the changes the body goes through, such as a decreased diet, a decrease in the kidney function and a decrease in the absorption of calcium by the intestines [147].

- Creatinine –is a waste product from dietary protein and muscle metabolism and is removed from the circulation by the kidneys [149]. Serum creatinine is influenced by age, sex, race and kidney function [146, 147, 150].

- CRP – C-reactive protein has been linked with an increase in vulnerability for disease and mortality in older people. It has been shown that there is a correlation between increased frailty and increase in CRP [151].

- eGFR – the estimated glomerular filtration rate (eGFR), and is a key indicator of renal function. The eGFR decreases with increasing age, even in healthy patients without kidney disease. There are several equations to calculate the eGFR, in this study the Modification of Diet in Renal Disease (MDRD) Equation [152] has been used. This is currently the most widely used equation across the NHS although it is slowly being replaced by the Chronic Kidney Disease Epidemiology (CKD-EPI) equation [153].

- Glucose – Blood glucose levels naturally tend to rise as we grow older, which can cause cognitive decline [154].

- Potassium – potassium is an essential mineral and electrolyte in the body. It is necessary in all cells, tissues and organs and for metabolism, normal heart, muscle and nerve function. Older individuals need an adequate amount of potassium in their diet each day to maintain optimum health. Normal physiological changes associated with aging can affect the potassium levels in the body, leading to a variety of serious health conditions [147].

- Sodium – Low sodium (hyponatremia) is very common in older people, especially those who are hospitalised or living in care facilities long term [147]. This is more common in these people because they are more likely to either take medications that put them at risk or have underlying medical conditions that could cause the disorder. Hypernatremia (high sodium) is common again due to medication or reduced total body water caused by dehydration [147].

- Total Protein – proteins are important for health and growth of the body's cells and tissues. Low results can indicate liver or kidney problems, or a sign of malnutrition [155]. Older people are at higher risk of muscle and bone loss, which increase with insufficient protein levels.

- Urea – The liver produces urea as a waste product of the digestion of protein. Elevated levels usually indicate renal impairment or dehydration [150]. It has been shown that there is an age-related increase in urea levels [156].

2.5.5 Derived Scores

The following data collected are scores derived locally within the QEHB data:

- AVPU – the AVPU scale is used as an assessment within hospitals to determine a patient's mental status. It stands for alert, response to verbal stimuli, response to painful stimuli or totally unresponsive [157].

- Charlson Co-morbidity Score – a score derived from the sum of 17 weighted diseases that are coded using International Classification of Diseases, Tenth Edition (ICD10)codes for secondary diagnoses [158].

- Dementia Score – the term dementia covers many illnesses, Alzheimer's disease being the most common [159]. Dementia causes people to be increasingly forgetful; they may become more confused and develop a difficulty for completing daily tasks. In the PICS database there is a dementia screening field where the question 'Has the patient been more forgetful in the past 12 months to the extent that it has significantly affected daily life?' This is marked as a deficit if the answer to this question was 'Yes'.

- Falls Score – A falls risk assessment is completed within PICS. It must be completed within 6 hours of admission. The Falls Score used at UHBFT is made up of 5 questions: 'History of one or more falls on or before admission', 'Falls since admission', 'Is unsteady/unsafe with/without walking aid/s and/or tries to walk alone', 'Patient or relatives anxious about risk of falling' and 'New Fall' [160].

- Movement Score – The patient movement score is used to assess the patient, determine their abilities at the time of the assessment and identify whether any help is needed. The score is measured using a scale of 1-7 and takes into consideration the following factors: Complete Independence (moves independently and does not need equipment – score 1), Modified Independence (patient moves independently and needs extra time or equipment – score 2), Supervision or set up (staff are present because of risk considerations but do not need to give physical help. They may give help by being reassuring – score 3), Minimal physical assistance (patient requires physical assistance from one or two staff to move. May use a frame or walking aid but can sit/stand and walk self reliably – score 4), Moderate assistance (requires more

help than physical assistance, equipment may be needed to move patient – score 5), Maximal assistance (patient is physically demanding but may be able to roll – can sit up in bed or on a chair – score 6), Total assistance (patient nursed in bed most of the time, physically demanding care needed – score 7).

- MUST Score – The Malnutrition Screening Tool (MUST) is used to identify adults that are malnourished, which older people are prone to. It is calculated using the patients BMI, the level of unplanned weight loss within the last 3-6 months and the 'acute illness effect', whether the patient is acutely ill and there has been no nutritional intake for more than 5 days. These markers are added together to create a score which identifies whether a patient is at low (0), medium (1) or high (2+) risk of malnutrition.

- Pain Score – The pain assessment score is recorded in PICS and is measured on a scale of 0-10. Patients who report a score of 0 have no pain at rest or movement, 1-3 have no pain at rest but mild pain at movement, 4-6 have mild pain at rest and moderate pain at movement. If a patient reports a pain score of 7 or more then this has been classed as a deficit within the frailty score due to the patients having either severe pain at rest and during movement or reporting the worst pain possible.

- SEWS - The Standardised Early Warning Score (SEWS) is used to detect patients who are becoming acutely unwell in order to speed up interventions for deteriorating patients [161]. It is made up of Respiratory (breaths per minute), Oxygen saturation (%), Temperature, Systolic Blood Pressure, Heart Rate (beats per minute) and responsiveness (unresponsive, painful stimuli, verbal stimuli and alert). A SEWS Score of 6 or above is classed as critical; therefore this is used as the cut off for 'deficit' in the frailty score development.

- Thrombosis Score – a score has been developed to assess the risk of developing deep vein thrombosis, called the 'Wells Score'[162]. Older patients are more likely to develop a deep vein thrombosis due to reduced mobility.

- Waterlow Score – The Waterlow score is calculated to estimate the risk of a patient developing a pressure ulcer [163]. It is made up of multiple observations, including age, gender, BMI, skin type (healthy, discoloured etc), continence, mobility, whether the patient has lost weight recently, tissue malnutrition, medication, neurological deficit and major surgery or trauma.

Table 1: Variables collected, reference ranges and units

Test	Reference Range	Units
Albumin	34 to 51	g/L
Alkaline Phosphate	35 to 105	U/L
ALT	5 to 41	U/L
AVPU	4	Scale (1-4)
BMI	18.5 to 24.9	kg/m²
Diastolic BP	60 - 80	mmHg
Systolic BP	90-120	mmHg
Corrected Calcium	2.1-2.6	mmol/L
CRP	<10	mg/L
Dementia Status	No	Scale
eGFR	>60	mL/min
Falls Score	<2	Scale
Glucose	3.5-11	mmol/L
Haemoglobin	135-180	g/L
Heart Rate	60 to 100	bpm
INR	0.8-1.2	ratio
Potassium	3.5-5.2	mmol/L
Mean Cell Volume	80-99	fL
MUST Score	0 or 1	Scale
O2 Sats	90+	%
Pain score	0-6	Scale
Movement Score	0-3	Scale
Platelets	150-450	10*9/L
Respiratory Rate	12 to 20	bpm
Sews Score	<5	Scale
Sodium	134-146	mmol/L
Temperature	36.1 - 37.2	°C
Thrombosis Score	0 to 2	Scale
Urea	3.4-7.8	mmol/L
WBC	4 to 11	10*9/L
Waterlow Score	0 to 14	Scale

2.6 FI-Baseline Development

Using a subset of the routinely collected tests results previously defined, the initial aim was to use the methods produced by Howlett et al [38] as a template, creating a frailty score to identify patients at increased risk of mortality, readmission and being discharged to a care home at the end of their emergency admission. In the study by Howlett et al where an FI-LAB was developed, they used 23 variables including 21 routinely collected blood tests and then systolic and diastolic blood pressure. Out of these 23 variables, 15 were included in the initial frailty score that was calculated using the QEHB data, and this frailty score will be referred to as the FI-Baseline.

2.6.1 Variables Used

The reason not all variables used in the FI-LAB were included in the FI-Baseline calculation was due to incompleteness of data; variables not included are RBC Folate, Inorganic Phosphorus, TSH, Thyroxine, T4 Free, VDRL and Vitamin B12. The tests that were used to develop the FI-Baseline are: Albumin, Systolic BP, Diastolic BP, Calcium, Creatinine, Glucose, Haemoglobin, MCV, Alkaline Phosphatase, Potassium, Total Protein, Sodium, Urea, WCC and ALT. At this stage, the additional variables that have been collected were not included in the FI-Baseline calculation as the initial aim was to validate the FI-LAB on the QEHB data. All test results were taken at the time closest to admission.

2.6.2 Reference Ranges and Deficit Definition

For blood results, the reference ranges of the variables have been taken from the QEHB laboratory handbook [164]. For the derived scores, clinical advice was used in order to determine the reference ranges. These ranges differ slightly to the FI-LAB ranges as the

'normal' thresholds can vary between countries and even between hospitals, and each reference range should be determined by each individual laboratory taking the tests. This is due to the fact that they are normally calculated based on a sample of the population in question, taking an average of the population and calculating 2 standard deviations above or below the average to allow for variation [165]. In order to calculate the FI-Baseline, a 'deficit' was defined for each variable, which was given a value of 1 if the result was outside of the reference range and 0 if not.

2.6.3 Calculation

The number of complete measurements for each patient was calculated, along with the total number of deficits. The FI-Baseline was then be calculated by taking the sum of the deficits divided by the total number of measurements. This produced a score between 0 and 1.

2.7 FI-QEHB Development

Once the FI-Baseline was developed, the wider collection of 31 variables from the QEHB databases was used to calculate a new frailty score, which will be referred to as the FI-QEHB. The measurements included in the FI-QEHB were: Albumin, ALP, ALT, AVPU, BMI, Diastolic BP, Systolic BP, Calcium, CRP, Dementia Status, eGFR, Falls Score, Glucose, Haemoglobin, Heart Rate, INR, Potassium, MCV, MUST Score, O2 Sats, Pain Score, Movement Score, Platelets, Respiratory Rate, SEWS Score, Sodium, Temperature, Thrombosis Score, Urea, WBC and Waterlow Score. This was in order to assess whether adding some extra routinely collected variables that are recorded at QEHB improved the predictive power for adverse events when included in the frailty score calculation.

2.8 FI-Baseline and FI-QEHB Analysis

2.8.1 Exploratory Analysis

Patients were excluded from the analysis of both the FI-Baseline and FI-QEHB if they had less than 70% complete data, following the missing data rule used for the FI-LAB development. Initial exploratory analysis was undertaken on the data after calculating the two frailty scores. For presentation and analysis purposes, the FI-Baseline and FI-QEHB were categorised into 4 groups, with the least frail group having a score of <0.10 to the most frail group with a score >0.45. Data were presented as median and IQR for non–normally distributed variables, mean and standard deviation for normally distributed variables and percentages for categorical variables. Demographic variables such as age and gender were examined to test whether there was any difference across the categories of both the FI-Baseline and FI-QEHB.

2.8.2 Model Development

To investigate whether using a frailty score added any power to a model used to predict adverse events, age and gender were individually included in univariate logistic regression models for all outcomes (mortality, emergency 30 day readmission and discharge to care home). Multivariable logistic regressions were built using age and gender to predict all outcomes. Separate models were then used to examine whether, after adjusting for age and gender, FI-Baseline or FI-QEHB were associated with mortality in hospital, within 30 days, 12 months or 3 years of the discharge from the index admission, emergency readmission within 30 days and whether a patient was discharged to a care home at the end of their admission. After the addition of the FI-Baseline and the FI-QEHB, the Area Under the Receiving Operating Characteristic (AUROC) curve values were compared to the models

with age and gender alone. In order to aid interpretation, the FI-Baseline and FI-QEHB were multiplied by 100 to more accurately assess the effect of each percentage increase of the index, for analysis purposes only.

2.8.3 Model performance

To measure the multivariable logistic regression model performance, the AUROC curve was used. The AUROC curve summarises the models performance by evaluating the sensitivity (true positive rate) vs 1-specificity (false positive rate). The higher the AUROC curve, the better the prediction power of the model. The AUROC curve can range between 0 and 1, however an AUROC curve of 0.5 suggests a predictor which makes random guesses and has no predictive power, so ideally the AUROC curve should be over 0.5 and as close to 1 as possible for a predictive model [166]. An AUROC curve of 0.9 is described as having high accuracy, between 0.7 and 0.9 moderate and 0.5-0.7 low accuracy [167]. The AUROC curve can also be referred to as the c-statistic or the AUC.

2.8.4 Kaplan Meier Analysis

Kaplan Meier curves are one of the most popular methods used as part of survival analysis. The curves are produced by calculating probabilities of a certain event at certain time points and multiplying them by earlier probabilities to get the final survival estimate [168]. They can be used alongside log-rank tests which are used to compare survival between groups. Kaplan Meier curves, adjusted for age and gender, were plotted for time to survival, split by the frailty score category for both FI-Baseline and FI-QEHB. Survival differences between the categories were tested using log-rank tests.

2.9 HerFI Development

As the FI-QEHB used 31 variables, the next aim was to increase the simplicity of the calculation of the frailty score, without having to rely on having complete data for 31 different measurements. However, the predictive power of the model still needs to be maintained or improved upon. In order to achieve this, machine learning techniques have been explored with the view of reducing the number of variables required.

2.9.1 Missing Data Techniques

As with all routinely collected healthcare data, one of the main restrictions is data completeness. A variety of techniques have been developed to handle missing data and attempt to overcome such restrictions. The data is assumed to be missing at random (MAR), which is common of data collected within a hospital setting, where results depend on information that has already been collected. For example, when studying weight, weight will be less likely to be recorded in younger individuals as they won't be monitored as closely as more elderly patients. The most common and simplest method of dealing with missing data is listwise deletion, meaning if a patient is missing any of the variables in the study, then their whole record is deleted from the data. Some statistical packages, including R which has been used for this analysis, employ a variety of machine learning algorithms that can handle missing data automatically. The advantage of this is that the data does not need to be treated ahead of the model fitting [169]. Multiple imputation is another approach that can be used to overcome the missing data problem.

Two of the three missing data techniques mentioned above were used in this analysis; the automatic missing data technique implemented by the machine learning package in R, which will be described below, and multiple imputations. The Multivariate Imputation via Chained

Equations (MICE) package in R was used as this is considered to be the most appropriate method for this analysis for many reasons due to its ability to handle the binary data in the datasets being used. Multiple imputations should help account for the statistical uncertainty in the imputations [170], as opposed to single imputations, and has been shown to improve the predictive power of the model [171]. This is achieved by creating multiple datasets with the missing values filled in multiple times, leaving multiple 'complete' datasets. The MICE package assumes that data is missing at random, and imputes the missing data based on the observed values. It runs a series of regression models where each variable with missing data is modelled by the other variables, so for this binary data a logistic regression is used. For practicality purposes 5 imputations were run, as Rubin [172] found this to be sufficient. All variables that were included in the rest of the analysis were used in the imputation. The MICE package was used to impute the 5 datasets, and 1 dataset was included as the baseline training dataset with missing values included, Therefore, 6 separate datasets were used for the rest of this analysis.

2.9.2 Training and Test Datasets

For machine learning models, data is split into testing and training datasets. This is a cross-validation technique that is used in order to minimise overfitting. Starting with a full dataset, this is then split into two datasets. Before any analysis can begin, the first decision to make is the proportion of data that should be used as the training set and therefore how big the test set will be. The training set is the dataset that will be used to train the model; the sample of data that is used to build the model. The performance of the model that has been built using the training dataset is evaluated on the test dataset.

The dataset in this analysis was split using the 80-20 rule, with 80% used for training and 20% for testing and validation. Each imputed dataset was split into training and test datasets for this analysis.

2.9.3 Classification and Regression Trees

The method that has been explored in order to increase the predictive power of the models and to identify the characteristics of the patients who are most at risk of mortality is Classification and Regression Trees (CART). This is becoming an increasingly popular technique within clinical research studies due to the interpretability of its output and its application to real world datasets. It is a method of analysis used in data-mining which aims to predict the outcome of future events based on the characteristics of past events. Classification and regression trees, also referred to as decision trees, are particularly advantageous when working with categorical data. One of the main benefits of using decision trees is that they automatically perform feature selection. Feature selection is the technique used to identify the most important variables that help to predict an outcome and reduce the dimensionality. Where there are a large number of features or variables, the model is at risk of overfitting which would in turn reduce the performance ability. [173]

Another reason that the feature selection technique could be useful is that it can improve the completeness of the dataset. If the number of predictors is reduced, the number of patients with missing data should decrease; therefore, there will be fewer deleted observations when using listwise deletion. A further advantage of decision trees is that they don't require much data preparation. The analysis package that was used has built in procedures to automatically handle missing data; it assigns the values to a branch based on the weighted probability of the outcomes of the branches.

A further advantage of using CART is that they also work well with interactions, which is relevant in this analysis due to the nature of the variables that are being included, for example someone who has abnormal (high or low) diastolic blood pressure will most likely have abnormal systolic blood pressure. It is advantageous in this situation to use the CART method over regressions due to the number of possible interactions within the dataset, the CART model will automatically include them if they are optimal without having to specify them. Furthermore, decision trees can handle nonlinear relationships whereas if there were nonlinear relationships in simple regression models, the results would be invalid. For this analysis, the C5.0 package in R has been used, which is an extension of the ID3 and C4.5 algorithm, developed by Ross Quinlan [174].

Although the main aim of classification trees is to predict the outcome of future events, the primary purpose of this analysis was to identify health deficits that contributed the most to adverse outcomes. The variable which maximised the information gain was chosen at each stage of the tree in order to create the next set of branches. The variable with the highest information gain is the 'root' of the tree of the first node from which the rest of the data stems from. All of the included variables are binary; therefore, branches represent either deficit or no deficit. The main focus of the classification tree is for feature selection, so the variable importance or 'attribute usage' for each dataset is of key interest. Once the decision trees were built, the variable importance was assessed to help decide which attributes were going to be included in the frailty score. The target variable of the decision tree is a categorical variable, whether the patient died during follow up or not, with the possible values of yes or no.

2.9.4 Calculation and Analysis

Once a subset of variables based on attribute importance was created, the HerFI was calculated using the same method as the FI-Baseline and FI-QEHB. This was created using a subset of the variables from the FI-QEHB, based on the variable importance calculated using the CART analysis. Exploratory data analysis was performed and multivariable logistic regressions were rebuilt in order to examine whether replacing the FI-QEHB with the HerFI improved the model when predict mortality in hospital, within 30 days, 12 months and 3 years of discharge, emergency readmissions within 30 days and whether the patient was discharged to a care home. The AUROC curve values were then used to assess the predictive power.

2.10 Validation

In order to examine whether the new HerFI is generalisable to a larger dataset over a longer period of time, the validation dataset was be used, for emergency admissions between 1st January 2015 and 31st December 2016. The descriptive statistics are reported in order to compare the two datasets, and then multivariable logistic regressions were produced to assess the effect of the HerFI on mortality outcomes (in hospital, 30 day and 12 months), emergency readmissions within 30 days of discharge and discharge to care home. Patients in this validation cohort had a maximum of one year of follow up; therefore mortality was only assessed in hospital and at 30 days and 12 months post discharge. The AUROC curves were then used to assess whether the HerFI is generalisable on a larger dataset.

2.11 Packages Used

Data extraction was performed used Microsoft SQL Server Management Analysis 2012 and analysis was performed using RStudio version 1.0.153 (2016) for Windows and Stata$^{®}$ version 14 (StataCorp. 2015. Stata Statistical Software: Release 14. College Station, TX: StataCorp LP).

2.12 Ethics Statement

All data used in this project was anonymised. Institutional Review Board authorisation was therefore not required. This project was registered as a Quality Improvement exercise within UHBFT. Copyright © 2019, the Health and Social Care Information Centre (NHS Digital). Re-used with the permission of the Health and Social Care Information Centre (NHS Digital). All rights reserved.

3 Results

3.1 Demographics

In total there were 6,521 patients, over the age of 65, admitted to QEHB as an emergency between 1st July and 31st December 2014 with 6,480 patients left for analysis post exclusions. Patients were excluded for invalid or missing NHS numbers, or if they were a resident outside of England (Figure 3). The median age of the patients was 79 (IQR 72-86, range 65 - 114), there were 46% males and 84% of the cohort were of white ethnicity. All demographics are shown in Table 2. Patients had a median length of stay (LOS) of 4 days (IQR 1-12 days) and 4,737 (73.1%) were admitted via the emergency department. One of the most common reasons for attendance to the emergency department was 'chest pain' (544 (11.5%)), with other common presenting complaints being 'difficulty in breathing/shortness of breath' (461 (9.7%)) and 'hip injury' (170 (3.6%)). Over half the patients (58.1%) had a Charlson Comorbidity Score of 5 or more, suggesting a highly co-morbid cohort.

Figure 3: Flowchart of Inclusions and Exclusions

6,521 patients admitted to UHB between 1st July and 31st December 2014

7 excluded due to missing or invalid NHS number

34 excluded due to living outside of England

6,480 patients left for analysis
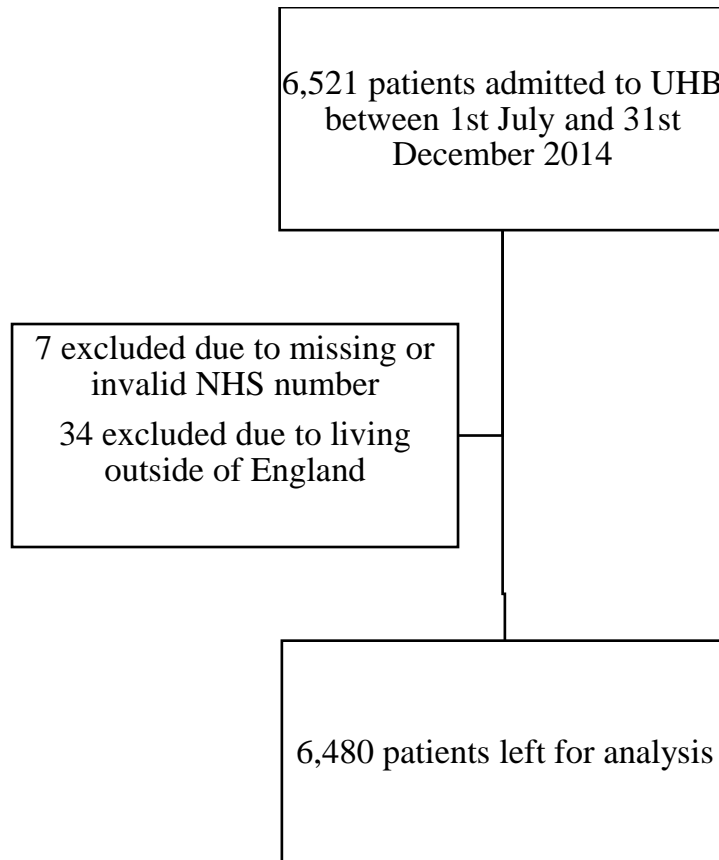
Table 2: Demographic Summary

Category	Subcategory	Value
Age	**(Median, IQR)**	79 (72-86)
Sex	**Male**	2978 (46.0%)
	Female	3502 (54.0%)
Deprivation (Quintiles)	**1 (Most Deprived)**	2619 (40.4%)
	2	1384 (21.4%)
	3	1455 (22.5%)
	4	688 (10.6%)
	5 (Least Deprived)	334 (5.2%)
Ethnic Group	**White**	5441 (84.0%)
	Mixed	27 (0.4%)
	Asian or Asian British	510 (7.9%)
	Black or Black British	179 (2.8%)
	Any Other Ethnic Group	97 (1.5%)
	Unknown	226 (3.5%)
Place of Residence	**North East**	*
	Yorkshire and the Humber	*
	London	6 (0.1%)
	South East	6 (0.1%)
	North West	9 (0.1%)
	East Midlands	12 (0.2%)
	South West	13 (0.2%)
	West Midlands	6428 (99.2%)
Charlson Comorbidity Category	**0**	1743 (26.9%)
	1 to 4	975 (15.0%)
	5+	3762 (58.1%)

3.2 Outcomes

3.2.1 Mortality

A total of 439 (6.8%) patients died during their index emergency admission, 689 (10.6%) died within 30 days post discharge and 1,713 (26.4%) within 12 months. Almost half of the cohort, 41.3%, died during the three years of follow up (figure 4).

Figure 4: Kaplan Meier for All-cause Mortality
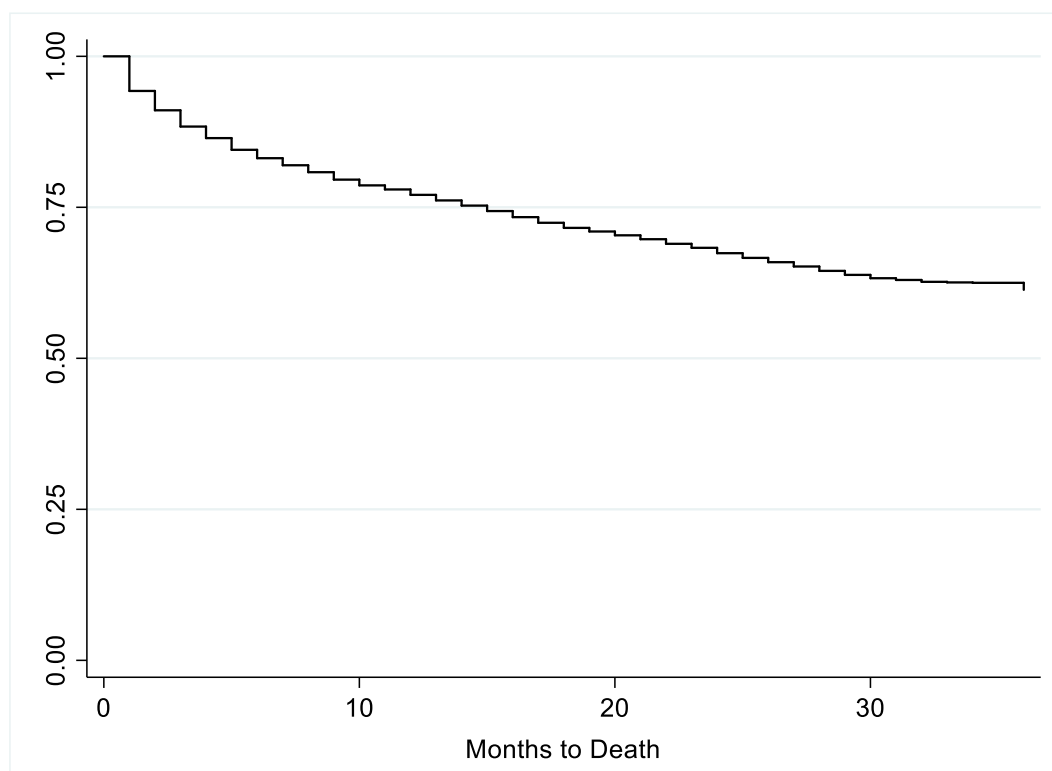
3.2.2 Discharge Destination

Of the 6,041 patients that survived the index emergency admission, 5,104 (84.5%) were discharged to their usual place of residence, with 349 (5.4%) patients being discharged to either an NHS funded or private care home having not being admitted from one.

3.2.3 Readmissions

After excluding those that died during their index admission, 1,263 (20.9%) patients were readmitted as an emergency within 30 days of their index admission discharge date. The median number of hospital days for emergency admissions within 30 days of their initial admission was 7 (IQR 2-18).

3.2.4 Modelling Outcomes

Univariate and multivariable logistic regression techniques were used to model outcomes (mortality, 30 day emergency readmissions and discharge to care home), adjusting for age and gender only, in order to assess the model performance before including any calculated frailty index. All results are presented in Table 3 and 4 with odds ratios (OR), 95% confidence intervals and their corresponding AUROC curve values. This was to evaluate whether the frailty index provides any additional information when predicting adverse outcomes.

Age vs Outcomes

The univariate regressions showed that each year increase in age increased the risk of in hospital mortality (OR 1.05, 95% CI 1.04 – 1.06, p <0.001), mortality within 30 days (OR 1.04, 95% CI 1.04 – 1.07, p<0.001) and 12 months post discharge (OR 1.05, 95% CI 1.05 – 1.06, p<0.001). There was no association with age and emergency readmission within 30 days (OR 1.00, 95% CI 1.00 – 1.01, p=0.611), however increasing age was associated with an increased risk of being discharged to a care home (OR 1.09, 95% CI 1.07 - 1.10, p<0.001). Age alone had a low predictive ability with an AUROC curve of 0.62 for mortality in hospital, within 30 days and 12 months of discharge. It is not predictive of emergency readmission within 30 days (AUROC curve 0.51), but the AUROC curve increased to 0.70 in

a univariate model to test for an association between age and whether the patient was discharged to a care home at the end of their admission.

Gender vs Outcomes

Gender alone was not associated with an increased risk of in hospital mortality (OR 0.88, 95% CI 0.72 – 1.07, p=0.189), mortality within 30 days (OR 0.88, 95% CI 0.72 – 1.07, p=0.196) or 12 months post discharge (OR 0.91, 95% CI 0.81 – 1.01, p=0.088). There was also no association between gender and emergency readmission within 30 days (OR 0.94, 95% CI 0.83 – 1.06, p=0.290), however females had an increased risk of being discharged to a care home (OR 1.73, 95% CI 1.38-2.18, p<0.001). There was no predictive power when modelling gender alone to predict mortality at all time points, with an AUROC curve of 0.52 for mortality in hospital and at 30 days post discharge and 0.51 at 12 months. Gender was not predictive of emergency readmission within 30 days (AUROC curve 0.51) and the AUROC curve for predicting whether a patient will be discharged to a care home at the end of their admission was 0.57.

Age and Gender Combined vs Outcomes

When adjusting for age and gender in a multivariable logistic regression, the conclusions stayed the same in the fact that increasing age is associated with mortality in hospital (OR 1.05, 95% CI 1.04 – 1.07, p<0.001), at 30 days (OR 1.05, 95% CI 1.04 – 1.07, p<0.001) and 12 months (OR 1.06, 95% CI 1.05 – 1.06, p<0.001). Females had a reduced risk of mortality at all time points, in hospital (OR 0.75, 95% CI 0.61 – 0.91, p=0.004), 30 days (OR 0.75, 95% CI 0.61 – 0.92, p=0.005) and 12 months (OR 0.77, 95% CI 0.68 – 0.86, p<0.001). In this multivariable model, neither age (OR 1.00, 95% CI 1.00 – 1.01, p=0.487) nor gender (OR 0.93, 95% CI 0.82 – 1.05, p=0.246) were predictive of 30 day emergency readmission

but increasing age (OR 1.08, 95% CI 1.07 – 1.10, p<0.001) and female gender (OR 1.37, 95% CI 1.09 – 1.74, p=0.008) were associated with an increased risk of being discharged to a care home. When age and gender were combined, the AUROC curve increased slightly when predicting mortality in hospital to 0.63, to 0.62 for 30 day mortality and 0.63 for 12 month mortality. The model was still not predictive of emergency readmissions within 30 days with an AUROC curve of 0.51; however the AUROC curve was 0.70 when predicting whether patients will be discharged to a care home.

Table 3: Modelling Age and Gender on Mortality Outcomes

		In Hospital Mortality			30 Day Mortality			12 Month Mortality		
		Odds Ratio (95% CI)	p-value	AUROC curve	Odds Ratio (95% CI)	p-value	AUROC curve	Odds Ratio (95% CI)	p-value	AUROC curve
Model 1	**Age**	1.05 (1.04 - 1.06)	<0.001	0.6202	1.04 (1.04 - 1.07)	<0.001	0.6157	1.05 (1.05 - 1.06)	<0.001	0.6206
Model 2	**Sex (Baseline = Male)**	0.88 (0.72 - 1.07)	0.189	0.5162	0.88 (0.72 - 1.07)	0.196	0.5162	0.91 (0.81 - 1.01)	0.088	0.5123
Model 3	**Age**	1.05 (1.04 - 1.07)	<0.001	0.6257	1.05 (1.04 - 1.07)	<0.001	0.6213	1.06 (1.05 - 1.06)	<0.001	0.6253
	Sex (Baseline = Male)	0.75 (0.61 - 0.91)	0.004		0.75 (0.61 - 0.92)	0.005		0.77 (0.68 - 0.86)	<0.001	

Table 4: Modelling Age and Gender on Emergency Readmissions and Discharge to a Care Home

		30 Day Emergency Readmission			Discharge to Care home		
		Odds Ratio (95% CI)	p-value	AUROC curve	Odds Ratio (95% CI)	p-value	AUROC curve
Model 1	Age	1.00 (0.99 - 1.01)	0.611	0.5038	1.09 (1.07 - 1.10)	<0.001	0.6950
Model 2	Sex (Baseline = Male)	0.94 (0.83 - 1.06)	0.290	0.5083	1.73 (1.38 - 2.18)	<0.001	0.5657
Model 3	Age	1.00 (1.00 - 1.01)	0.487	0.5113	1.08 (1.07 - 1.10)	<0.001	0.6986
	Sex (Baseline = Male)	0.93 (0.82 - 1.05)	0.246		1.37 (1.09 - 1.74)	0.008	

3.3 FI-Baseline Development and Evaluation

3.3.1 Distribution and Demographics

All routinely collected measurements that were closest to the patients' admission time and date were extracted. For the rest of the analysis only patients who had complete data for more than 70% of the variables were included. The completeness for all of the tests for the patients that have been included in the analysis is shown in table 5.

Table 5: Variables Completeness

Test	Completeness
Albumin	95.04%
Alkaline Phosphate	93.57%
ALT	93.10%
AVPU	90.03%
BMI	71.64%
Diastolic BP	98.07%
Systolic BP	98.07%
Corr Calcium	81.19%
CRP	84.54%
Dementia Status	60.18%
eGFR	96.31%
Falls Score	83.22%
Glucose	70.69%
Haemoglobin	95.14%
Heart Rate	98.04%
INR	75.48%
Potassium	93.10%
Mean Cell Volume	95.11%
MUST Score	76.47%
O2 Sats	97.92%
Pain score	91.91%
Movement Score	97.91%
Platelets	95.06%
Respiratory Rate	97.92%
Sews Score	97.84%
Sodium	96.33%
Temperature	97.94%
Thrombosis Score	85.11%
Urea	96.37%
WBC	95.03%
Waterlow Score	82.28%

A total of 5,970 (92.1%) of the 6,480 patients in the cohort had at least 70% complete data

for the measurements that were included in the FI-Baseline and this is the cohort that is to be

used for the rest of the analysis. The demographics of this cohort and the cohort that was used to derive the FI-LAB ([101]) are shown in table 6.

Table 6: Demographics of the FI-LAB and FI-Baseline

			Grade of the FI			
			<0.10	0.10 to 0.22	0.23 to 0.45	>0.45
FI-Baseline	*Total*		*630*	*1880*	*2660*	*800*
	Age (Median and IQR)		75 (69 - 83)	78 (71 -85)	80 (73 - 87)	80 (72 - 86)
	FI-Baseline (Mean and SD)		0.06 (0.03)	0.17 (0.03)	0.33 (0.06)	0.53 (0.07)
	Women (%)		42.5	53.8	56.8	53.5
	Mortality (%)		25.4	34.3	49.9	68
FI-LAB	*Total*		*56*	*255*	*645*	*57*
	Age (Mean and SD)		77.8 (6.6)	80.1 (7.3)	81.5 (7.1)	83.6 (6.8)
	FI-LAB (Mean and SD)		0.08 (0.02)	0.17 (0.03)	0.31 (0.06)	0.50 (0.04)
	Women (%)		60.7	67.8	60.5	47.4
	Mortality (%)		19.6	44.7	54.4	77.2

The FI-Baseline was plotted in order to examine the distribution which is shown in Figure 5, the FI-Baseline ranged from 0 for the least frail to 0.83 for the patients with the highest level of frailty.

After splitting the QEHB cohort into categories with the least frail patients having an FI-Baseline <0.10 and the most frail a FI-Baseline >0.45, the mean FI-Baseline was 0.06 (Standard Deviation (SD) 0.03) for the patients in the least frail category, increasing to 0.53 (SD 0.07) for the most frail category. The FI-Baseline increased with age (Figure 6), as with the cohort used to define the FI-LAB [101].

Figure 5: Distribution of FI-Baseline
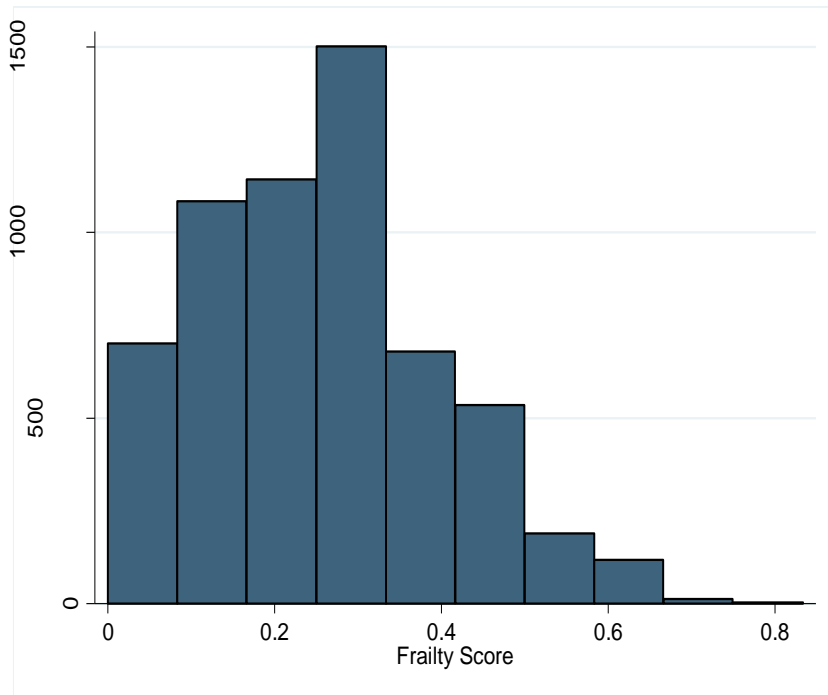
Figure 6: Distribution of age vs FI-Baseline
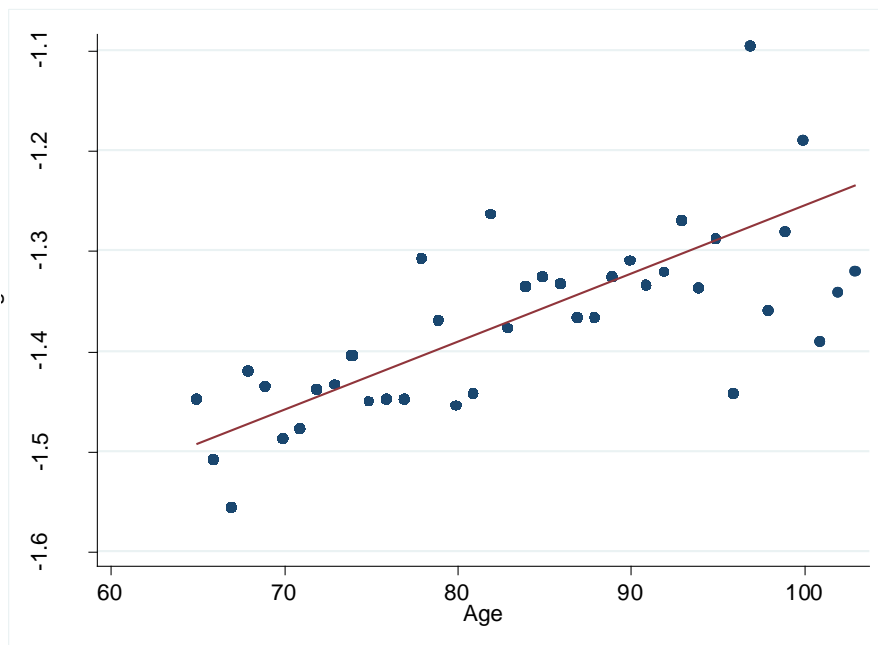
3.3.2 Mortality

Looking at a breakdown of mortality by time point and FI-Baseline categories (Table 7), as the FI- Baseline increased so did mortality rates.

Table 7: Mortality Rates by FI-Baseline Category

		Mortality			
		In Hospital	**30 Day**	**12 month**	**3 year**
FI-Baseline	**<0.10**	14 (2.2%)	22 (3.5%)	70 (11.1%)	160 (25.4%)
	0.10 - 0.22	59 (3.1%)	101 (5.4%)	372 (19.8%)	645 (34.3%)
	0.23 - 0.45	195 (7.3%)	311 (11.7%)	815 (30.6%)	1328 (49.9%)
	>0.45	163 (20.3%)	233 (29.1%)	396 (49.5%)	544 (68%)
	Total	430 (7.2%)	667 (11.2%)	1653 (27.7%)	2677 (44.8%)
	p-value	<0.001	<0.001	<0.001	<0.001

In Hospital Mortality

Out of the 5,970 patients that were included for this part of the analysis, 7.2% died during their admission. For patients in the least frail category, 2.2% of patients with an FI-Baseline <0.10 died during their admission, as opposed to 20.3% of patients dying who had an FI-Baseline over 0.45. This difference was statistically significant (p<0.001). In a multivariable logistic regression, adjusting for age, gender and FI-Baseline, it was found that with each increasing year of age there was an increased risk of in hospital mortality (OR 1.05, 95% CI 1.03 – 1.06, p<0.001), females had a reduced risk of mortality in hospital (OR 0.74, 95% CI 0.60 – 0.90, p=0.004) and with each 0.1 increase of the FI-Baseline there was an increase in the risk of mortality in hospital (OR 1.05, 95% CI 1.05 – 1.06, p<0.001). This model had good predictive power with an AUROC curve of 0.74. These results are detailed in table 8.

30 Day Mortality

Overall, 11.2% of patients in this cohort died within 30 days of their discharge. Only 22 (3.3%) of the patients with an FI-Baseline <0.10 died within 30 days of their discharge, compared to 29.1% in the most frail category (FI-Baseline >0.45). The difference is statistically significant with p<0.001. In the multivariable logistic regression, adjusting for age, gender and FI-Baseline, this showed that with each increasing year of age there was an increased risk of mortality within 30 days of discharge (OR 1.05, 95% CI 1.04 – 1.06, p<0.001), females had a lower risk of mortality (OR 0.78, 95% CI 0.66 – 0.92, p=0.004), and with each 0.1 increase in the FI-Baseline there was an increase in risk of mortality within 30 days of discharge (OR 1.05, 95% CI 1.05-1.06, p<0.001). This model had good predictive power with an AUROC curve of 0.74.

12 Month Mortality

Similarly, with the more long-term outcome of 12 month mortality, 11.1% of patients with an FI-Baseline of <0.10 died within 12 months of their admission, compared to 49.5% of patients with an FI-Baseline over 0.45 (p<0.001). The multivariable logistic regression, adjusting for age, gender and FI-Baseline, showed that with each increasing year of age there was an increased risk of mortality within 12 months of discharge (OR 1.05, 95% CI 1.05 – 1.06, p<0.001), females had a lower risk of mortality (OR 0.74, 95% CI 0.65 - 0.83, p<0.001) and with each 0.1 increase in the FI-Baseline there was an increased risk of mortality within 12 months of discharge (OR 1.04, 95% CI 1.-1.04, p<0.001). This model had good predictive power with an AUROC curve of 0.70.

3 Year Mortality

Over the 3 year follow-up period there were 2,677 (44.8%) deaths. More than two thirds (68%) of patients with an FI-Baseline over 0.45 died during follow up, dropping to 25.4% of the least frail patients. Kaplan Meier curves to show this data are shown in figure 7. The results of the multivariable logistic regression, adjusting for age, gender and FI-Baseline, showed that with each increasing year of age there was an increased risk of mortality within the 3 years of follow up (OR 1.07, 95% CI 1.07- 1.08, $p<0.001$), females had a lower risk of mortality (OR 0.72, 95% CI 0.65-0.81, $p<0.001$), and with each 0.1 increase in the FI-Baseline there was an increased risk of mortality within 3 years (OR 1.04, 95% CI 1.03-1.04, $p<0.001$). This model has good predictive power with an AUROC curve of 0.71.

Figure 7: Kaplan Meier for Mortality by FI-Baseline Category
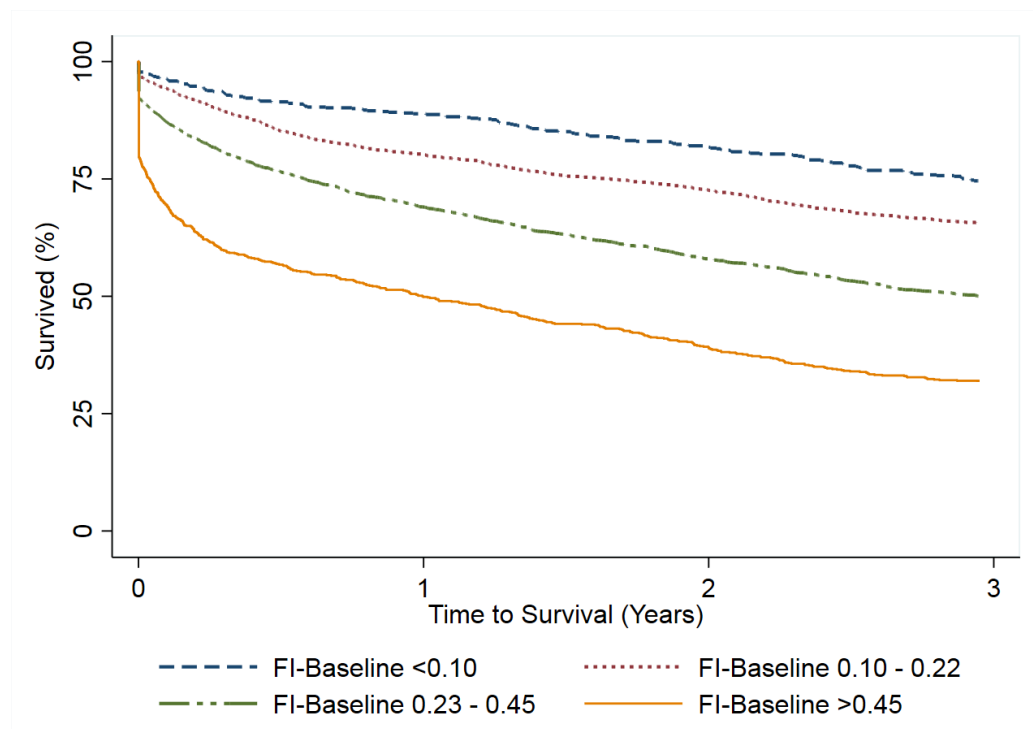
3.3.3 Readmission within 30 days of discharge

For the readmissions analysis, everyone who died during their admission has been excluded, leaving 5,540 patients. Out of these 5,540 patients that were eligible for analysis, 859 (15.5%) had an emergency readmission within 30 days of their discharge. The multivariable logistic regression results suggest that age is not associated with an increased risk of readmission, females have a reduced risk (OR 0.82, 95% CI 0.70 – 0.95, p=0.008 and as the FI-Baseline increases by 0.1, the risk of emergency readmission within 30 days increases (OR 1.02, 95% CI 1.01-1.02, p<0.001). The AUROC curve value for this model is 0.57.

3.3.4 Discharge to care home

After excluding patients who died during their admission, there were 5,540 patients left for this part of the analysis, of which 339 (6.1%) were discharged to a care home at the end of their index emergency admission. In the multivariable logistic regression, a yearly increase in age (OR 1.09, 95% CI 1.07 – 1.10, p<0.001), female gender (OR 1.33, 95% CI 1.04 – 1.68, p=0.021) and increasing FI-Baseline (OR 1.02, 95% CI 1.01 – 1.03, p<0.001) were all associated with an increased risk of being discharged to a care home, with an AUROC curve of 0.72.

Table 8: Multivariable Logistic Regression with FI-Baseline

	Variable		Odds Ratio (95% CI)	p-value	AUROC
In Hospital Mortality	**Age**		1.05 (1.03 - 1.06)	<0.001	0.74
	Sex	**Male**	1 (baseline)		
		Female	0.74 (0.60 - 0.90)	0.004	
	FI-Baseline		1.05 (1.05 - 1.06)	<0.001	
30 Day Mortality	**Age**		1.05 (1.04 - 1.06)	<0.001	0.74
	Sex	**Male**	1 (baseline)		
		Female	0.78 (0.66 - 0.92)	0.004	
	FI-Baseline		1.05 (1.05 - 1.06)	<0.001	
12 Month Mortality	**Age**		1.05 (1.05 - 1.06)	<0.001	0.7
	Sex	**Male**	1 (baseline)		
		Female	0.74 (0.65 - 0.83)	<0.001	
	FI-Baseline		1.04 (1.04 - 1.04)	<0.001	
3 Year Mortality	**Age**		1.07 (1.07 - 1.08)	<0.001	0.71
	Sex	**Male**	1 (baseline)		
		Female	0.72 (0.65 - 0.81)	<0.001	
	FI-Baseline		1.04 (1.03 - 1.04)	<0.001	
30 Day Readmission	**Age**		1.00 (0.99 - 1.01)	0.831	0.57
	Sex	**Male**	1 (baseline)		
		Female	0.82 (0.70 - 0.95)	0.008	
	FI-Baseline		1.02 (1.01 - 1.02)	<0.001	
Discharge to Care Home	**Age**		1.09 (1.07 - 1.10)	<0.001	0.72
	Sex	**Male**	1 (baseline)		
		Female	1.33 (1.04 - 1.68)	0.021	
	FI-Baseline		1.02 (1.01 - 1.03)	<0.001	

3.4 FI-QEHB Development

3.4.1 Demographics and Distribution

For the development of the FI-QEHB, after exclusions due to completeness, 5,519 patients, 85.2% of the original cohort, are included in this part of the analysis. The breakdown of the variables used, the deficit numbers and the completeness for each variable is listed are table 9. Overall, the completeness of the variables that have been selected is acceptable; they range from 100% complete for blood pressure and heart rate results to 75% complete BMI. Almost half of patients have an abnormal BMI result (either too high or low), around 34% have an abnormal falls score suggesting they are at risk of falls and less than 1% have an abnormal O2 Sats result. The demographic figures, split by FI-QEHB category, are detailed in table 10.

Table 9: FI-QEHB Deficits and Completeness

Test	Deficit	Missing
Albumin	597 (10.8%)	64 (1.2%)
Alkaline Phosphate	1667 (30.2%)	136 (2.5%)
ALT	560 (10.1%)	162 (2.9%)
AVPU	59 (1.1%)	358 (6.5%)
BMI	2607 (47.2%)	1396 (25.3%)
Diastolic BP	2592 (47.0%)	0 (0.0%)
Systolic BP	4308 (78.1%)	0 (0.0%)
Corr Calcium	324 (5.9%)	849 (15.4%)
CRP	2926 (53.0%)	640 (11.6%)
Dementia Status	273 (4.9%)	2405 (43.6%)
eGFR	2526 (45.8%)	6 (0.1%)
Falls Score	2015 (36.5%)	698 (12.6%)
Glucose	355 (6.4%)	1432 (25.9%)
Haemoglobin	3812 (69.1%)	67 (1.2%)
Heart Rate	614 (11.1%)	0 (0.0%)
INR	1147 (20.8%)	1179 (21.4%)
Potassium	612 (11.1%)	168 (3.0%)
Mean Cell Volume	865 (15.7%)	69 (1.3%)
MUST Score	416 (7.5%)	1071 (19.4%)
O2 Sats	43 (0.8%)	*
Pain score	59 (1.1%)	345 (6.3%)
Movement Score	1900 (34.4%)	812 (14.7%)
Platelets	914 (16.6%)	70 (1.3%)
Respiratory Rate	945 (17.1%)	*
Sews Score	214 (3.9%)	7 (0.1%)
Sodium	1076 (19.5%)	6 (0.1%)
Temperature	1760 (31.9%)	*
Thrombosis Score	553 (10.0%)	664 (12.0%)
Urea	2386 (43.2%)	23 (0.4%)
WBC	2034 (36.9%)	87 (1.6%)
Waterlow Score	1889 (34.2%)	760 (13.8%)

Table 10: Demographics by FI-QEHB Category

		Grade of the FI			
		<0.10	**0.10 to 0.22**	**0.23 to 0.45**	**>0.45**
	Total	*164*	*1780*	*3334*	*241*
FI-QEHB	**Age (Median and IQR)**	73 (69 - 79)	76 (70 - 83)	81 (74 - 87)	81 (73 - 88)
	FI-QEHB (Mean and SD)	0.07 (0.02)	0.17 (0.04)	0.31 (0.06)	0.51 (0.04)
	Women (%)	40.2	50.4	56.1	55.6
	Mortality (%)	12.2	26.2	52.9	78.8

3.4.2 Mortality

Table 11 details the mortality rates split by FI-QEHB category. As with the FI-Baseline, as

the FI-QEHB category increased, the mortality rate increased.

Table 11: Mortality Rates by FI-QEHB Category

		Mortality			
		In Hospital	**30 Day**	**12 month**	**3 year**
FI-QEHB	**<0.10**	1 (0.6%)	3 (1.83%)	9 (5.5%)	20 (12.2%)
	0.10 - 0.22	35 (2.0%)	52 (2.9%)	243 (13.7%)	467 (26.2%)
	0.23 - 0.45	229 (6.9%)	392 (11.8%)	1055 (31.6%)	1765 (52.9%)
	>0.45	73 (29.5%)	99 (41.1%)	152 (63.1%)	190 (78.8%)
	Total	338 (6.1%)	546 (9.9%)	1174 (26.4%)	2442 (44.2%)
	p-value	<0.001	<0.001	<0.001	<0.001

In Hospital Mortality

Only 0.6% of patients with a FI-QEHB <0.10 died during their admission, as opposed to

29.5% of patients who had a FI-QEHB over 0.45. This difference was statistically significant

($p < 0.001$). In the multivariable logistic regression, adjusting for age, gender and FI-QEHB, it

can be concluded that with each increasing year of age there was an increased risk of in

hospital mortality (OR 1.04, 95% CI 1.02 – 1.05, $p < 0.001$), females have a lower risk of

mortality (OR 0.68, 95% CI 0.54 – 0.87, p<0.001) and with each 0.1 increase in the FI-QEHB there was an increase in risk of mortality in hospital (OR 1.10, 95% CI 1.09 – 1.11, p<0.001). This model has good predictive power with an AUROC curve of 0.78. These results are detailed in table 12.

30 Day Mortality

Only 1.8% of patients with an FI-QEHB <0.10 died within 30 days of their discharge at the end of their emergency admission, as opposed to 41.1% of patients dying who had an FI-QEHB over 0.45. This difference was statistically significant (p<0.001). In the multivariable logistic regression, adjusting for age, gender and FI-QEHB, it can be concluded that with each increasing year of age there is an increased risk of mortality within 30 days (OR 1.04, 95% CI 1.03 – 1.05, p<0.001), females have a lower risk of mortality (OR 0.75, 95% CI 0.62 – 0.91, p=0.003) and with each 0.1 increase in the FI-QEHB there is an increase in risk of mortality in hospital (OR 1.09, 95% CI 1.08 – 1.10, p<0.001). This model has good predictive power with an AUROC curve of 0.77.

12 Month Mortality

Only 5.5% of patients with a FI-QEHB <0.10 died during their admission, as opposed to 63.1% of patients dying who had an FI-QEHB over 0.45. This difference was statistically significant (p<0.001). In the multivariable logistic regression, adjusting for age, gender and FI-QEHB, it can be concluded that with each increasing year of age there is an increased risk of in hospital mortality (OR 1.04, 95% CI 1.03 – 1.05, p<0.001), females have a lower risk of mortality (OR 0.73, 95% CI 0.64 – 0.83, p<0.001) and with each 0.1 increase in the FI-QEHB there is an increase in risk of mortality in hospital (OR 1.07, 95% CI 1.06 – 1.08, p<0.001). This model has good predictive power with an AUROC curve of 0.72.

3 Year Mortality

For the patients with a FI-QEHB <0.10, 12.2% had died by the end of the three years of follow up, compared to 78.8% in the highest group with a FI-QEHB over 0.45. Kaplan Meier analysis shows there is a difference in the survival of the patients in the different FI categories for the duration of follow up, up until a maximum of 3 years post index emergency admission (Figure 8). The results of the log-rank test indicate that this difference is significant (p<0.001). In multivariable logistic regression, adjusting for age, gender and FI-QEHB, it can be concluded that with each increasing year of age there is an increased risk of mortality (OR 1.06 95% CI 1.05 – 1.06, p<0.001), females have a lower risk of mortality (OR 0.71, 95% CI 0.63 – 0.80, p<0.001) and with each 0.1 increase in the FI-QEHB there is an increase in risk of mortality in hospital (OR 1.08, 95% CI 1.07 – 1.08, p<0.001). This model has good predictive power with an AUROC curve of 0.74. The AUROC curve values in these models for mortality show good predictive power and suggest that some of the routinely collected variables that have been added into the FI-QEHB improve the models when compared to the FI-Baseline.

Figure 8: Kaplan Meier Curve for mortality by FI-QEHB
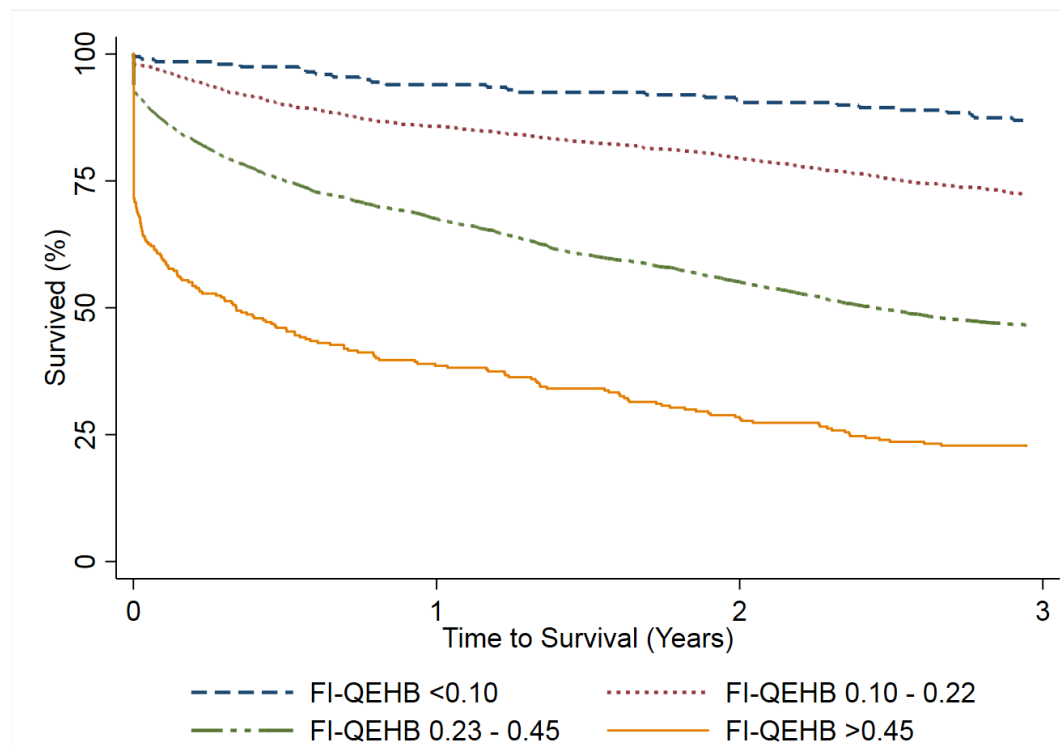
3.4.3 Readmission within 30 days of discharge

As with the FI-Baseline, everyone who died during their admission has been excluded, leaving 5,192 patients. Out of the patients that were eligible for analysis, 819 (15.8%) were readmitted as an emergency within 30 days of their discharge. The multivariable logistic regression results suggest that age is not associated with risk of readmission, females have a reduced risk of being readmitted as an emergency within 30 days (OR 0.82, 95% CI 0.70 – 0.95, p=0.008) and as the FI-QEHB increases by 0.1, the risk of emergency readmission within 30 days increases (OR 1.02, 95% CI 1.01-1.02, p<0.001). The AUROC curve value for this model is 0.58 showing a very slight improvement on the FI-Baseline.

3.4.4 Discharge to Care Home

At the end of their index emergency admission, excluding patients who died during the admission, 308 (5.93%) of the patients were discharged to a care home. Increasing age (OR 1.08, 95% CI 1.06 – 1.09, p<0.001), female gender (OR 1.35, 95% CI 1.05 – 1.73, p<0.001) and increasing FI-QEHB (OR 1.06, 95% CI 1.05 – 1.07, p<0.001) are all associated with an increased risk of being discharged to a care home. The AUROC curve for this model was 0.74, which shows this model has good predictive power.

Table 12: Multivariable Logistic Regression with FI-QEHB

	Variable		Odds Ratio (95% CI)	p-value	AUROC
In Hospital Mortality	Age		1.04 (1.02 - 1.05)	<0.001	0.78
	Sex	Male	1 (baseline)		
		Female	0.68 (0.54 - 0.87)	0.002	
	FI-QEHB		1.10 (1.09 - 1.11)	<0.001	
30 Day Mortality	Age		1.04 (1.03 - 1.05)	<0.001	0.77
	Sex	Male	1 (baseline)		
		Female	0.75 (0.62 - 0.91)	0.003	
	FI-QEHB		1.09 (1.08 - 1.10)	<0.001	
12 Month Mortality	Age		1.04 (1.03 - 1.05)	<0.001	0.72
	Sex	Male	1 (baseline)		
		Female	0.73 (0.64 - 0.83)	<0.001	
	FI-QEHB		1.07 (1.06 - 1.08)	<0.001	
3 Year Mortality	Age		1.06 (1.05 - 1.07)	<0.001	0.74
	Sex	Male	1 (baseline)		
		Female	0.71 (0.63 - 0.80)	<0.001	
	FI-QEHB		1.08 (1.07 - 1.08)	<0.001	
30 Day Readmission	Age		1.00 (0.99 - 1.00)	0.297	0.58
	Sex	Male	1 (baseline)		
		Female	0.81 (0.70 - 0.94)	0.007	
	FI-QEHB		1.03 (1.02 - 1.03)	<0.001	
Discharge to Care Home	Age		1.08 (1.06 - 1.09)	<0.001	0.74
	Sex	Male	1 (baseline)		
		Female	1.35 (1.05 - 1.73)	0.021	
	FI-QEHB		1.06 (1.05 - 1.07)	<0.001	

However, as the FI-QEHB relies on 31 different measurements being collected it would be useful if the number of variables included in the frailty score could be reduced, in order to decrease the complexity but improve the predictive power. This requires some more exploration of which of the 31 variables hold the most importance.

3.5 HerFI Development

3.5.1 Variable Importance using Classification and Regression Trees

In order to assess whether the number of variables used in the FI-QEHB could be reduced in order to create a less complex frailty index, which will be known as the HerFI, Classification and Regression Tree analysis was used. After constructing multiple regression trees in R using the C50 package, the number of variables to be included in the frailty score was reduced from 31 down to 8. For the first CART, which was produced using 'Training Dataset 1', without any data cleansing of the missing variables, 10 out of the 31 variables were kept in the tree as they were shown to be important when predicting the outcome of mortality. Albumin had the highest attribute usage percentage at 98.9%, followed by SEWS Score (88.7%) and Movement Score (74%). The full list of attribute importance is listed in table 13.

The five imputed datasets were then used to create five further regression trees. As the results that were produced by these five datasets varied in the number of attributes they included, it was of interest to see which variables the six different CART's had in common. Tree 2 used 14 out of the 31 attributes, Tree 3 used 9, Tree 4 used 13, Tree 5 used 21 and Tree 6 used 16. The variables that all six trees shared were Albumin, SEWS Score, Waterlow Score, Alkaline Phosphatase, CRP and Urea.

Table 13: Attribute contribution from CART analysis

Variable	Tree 1	Tree 2	Tree 3	Tree 4	Tree 5	Tree 6
Albumin	98.91%	100.00%	100.00%	100.00%	100.00%	100.00%
AVPU	0.00%	30.53%	0.00%	88.72%	85.48%	0.00%
SEWS	88.70%	88.65%	88.72%	87.84%	88.59%	88.65%
Waterlow Score	12.48%	85.53%	85.60%	84.94%	84.71%	85.53%
Alkaline Phosphate	21.63%	46.08%	56.23%	63.29%	59.60%	29.82%
MUST	0.00%	0.00%	0.00%	13.68%	54.19%	9.87%
Fall Score	0.00%	0.00%	0.00%	0.00%	18.73%	6.82%
Thrombosis Score	0.00%	0.00%	8.94%	30.10%	0.00%	9.15%
CRP	4.82%	36.10%	40.47%	25.23%	15.63%	26.97%
Dementia Score	0.00%	0.00%	0.00%	4.42%	32.22%	15.31%
Pain Score	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
INR	0.00%	5.41%	0.00%	7.38%	3.01%	0.00%
Haemoglobin	0.00%	1.86%	7.65%	0.00%	0.61%	0.00%
BMI	0.00%	14.88%	0.00%	18.41%	25.11%	7.72%
White Blood Cells	0.00%	0.00%	0.00%	0.00%	1.18%	0.00%
eGFR	39.38%	9.96%	0.00%	0.00%	9.49%	9.26%
Sodium	0.00%	0.00%	0.00%	0.00%	3.87%	0.00%
Respiratory Rate	21.63%	0.00%	0.00%	5.30%	0.00%	8.38%
Potassium	7.45%	10.82%	0.00%	0.00%	15.60%	4.87%
Movement Score	73.96%	58.45%	9.01%	0.00%	57.40%	62.18%
Urea	57.81%	31.32%	30.39%	34.01%	31.91%	75.66%
Glucose	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ALT	0.00%	0.00%	0.00%	0.00%	2.26%	0.00%
Diastolic BP	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Platelets	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
MCV	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Corr Calcium	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Temperature	0.00%	0.00%	0.00%	0.00%	0.50%	1.36%
Systolic BP	0.00%	0.00%	0.00%	0.00%	6.88%	0.00%
Heart Rate	0.00%	4.17%	0.00%	0.00%	0.00%	0.00%

The training dataset regression tree correctly predicted 69.4% of deaths, with an error rate of 30.6%. When evaluating the data on the test dataset, the model was shown to correctly predict 68% of the deaths, which follows the logic that a model performs worse on an unseen dataset. The results of the classification trees are on shown in Figures 9a – 9f. At each 'node'

is a variable, a different routinely collected test from the data and each variable in the dataset is binary; deficit or no deficit. Each 'node' is followed by two branches which lead to the next node. For example, the first node in tree one is whether the patient has an abnormal albumin measurement or not and this splits into two branches. The nodes and branches continue until a 'leaf' is reached, which is the outcome of mortality, and a ratio is given for that particular leaf. For tree one, the interpretation of the first branch is that 499 patients who had albumin recorded as a deficit died within the three years of follow up, whereas 135 patients did not. Likewise, for patients who had a normal albumin result recorded, but an abnormal SEWS score, 138 out of 172 died within three years of follow up. Therefore, patients that met these criteria would be predicted to be more likely to die if these abnormalities were observed when these routine tests were collected. Based on these classification and regression trees, the number of variables has been reduced down to 6.

Figure 9: Classification Trees

Figure 9a: Classification Tree 1
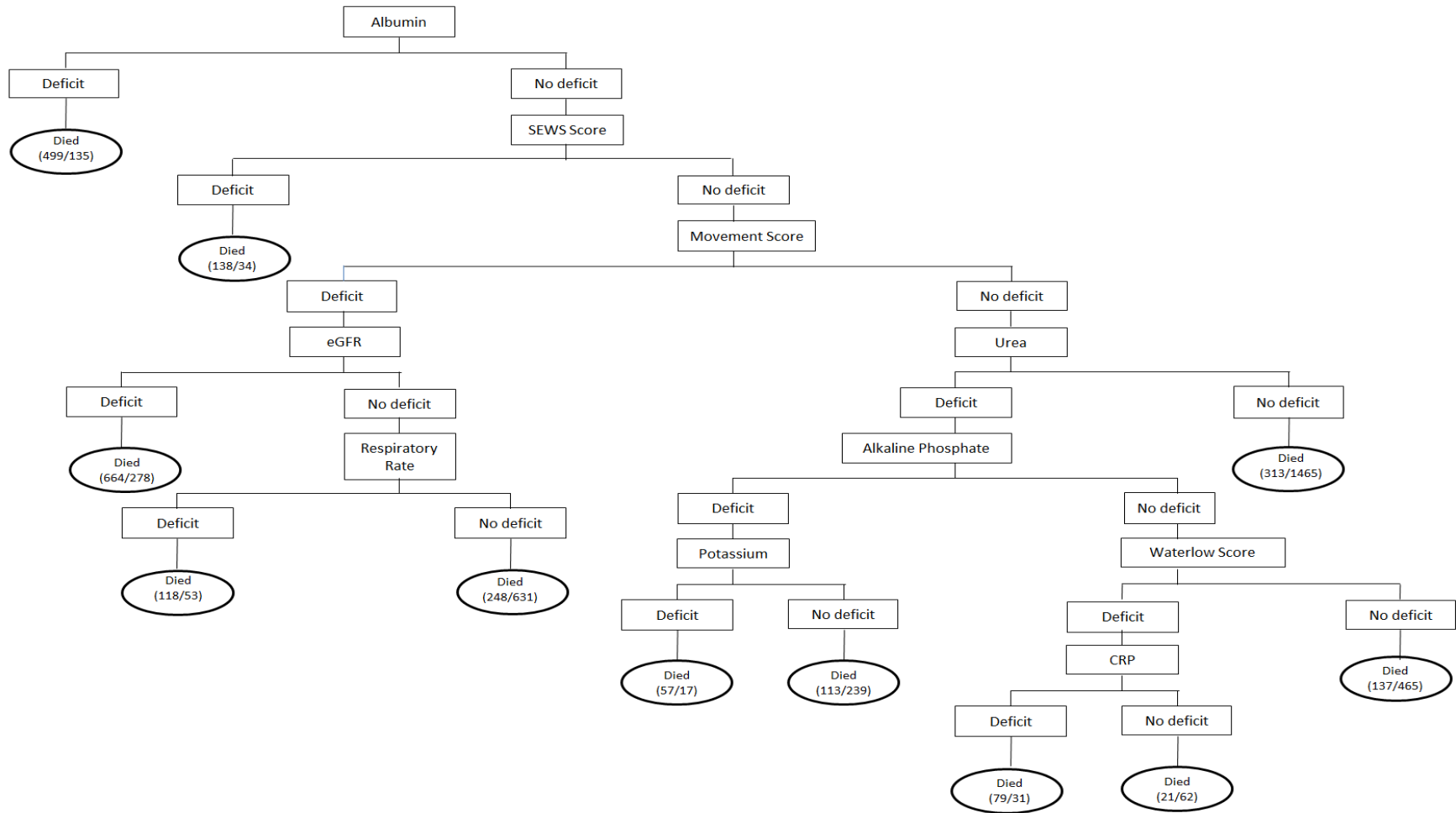
Figure 9b: Classification Tree
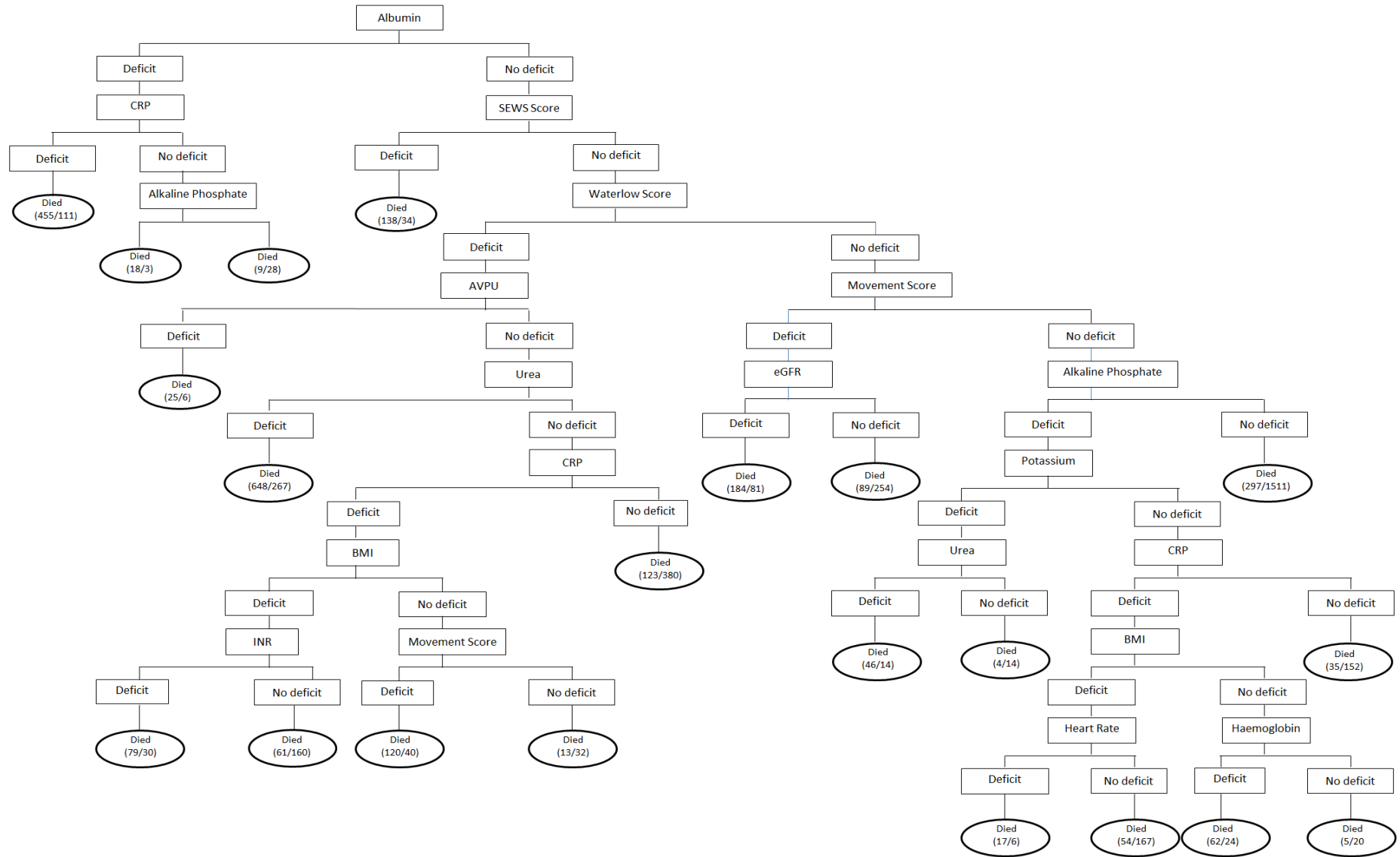
Figure 9c: Classification Tree 3
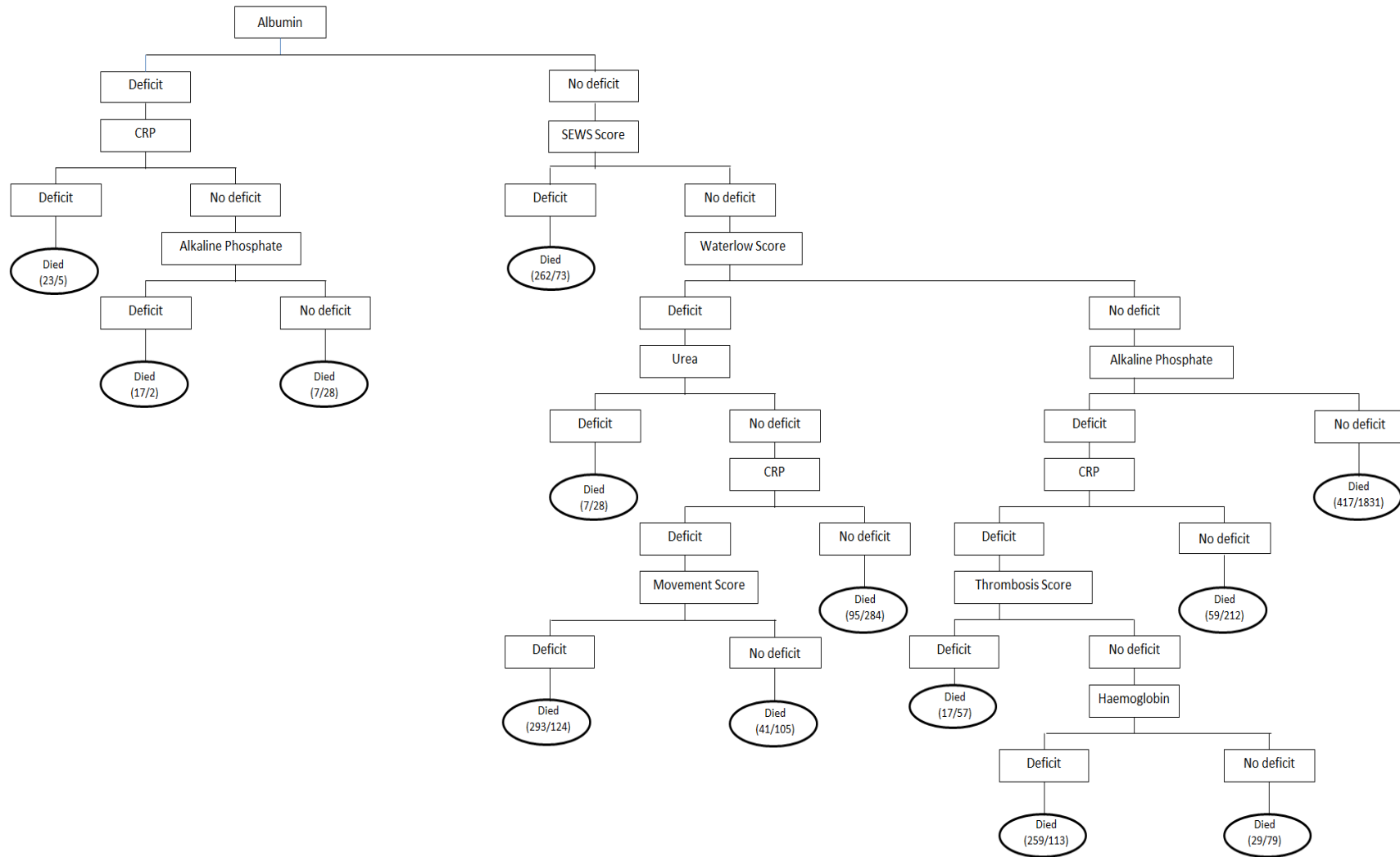
Figure 9d: Classification Tree 4
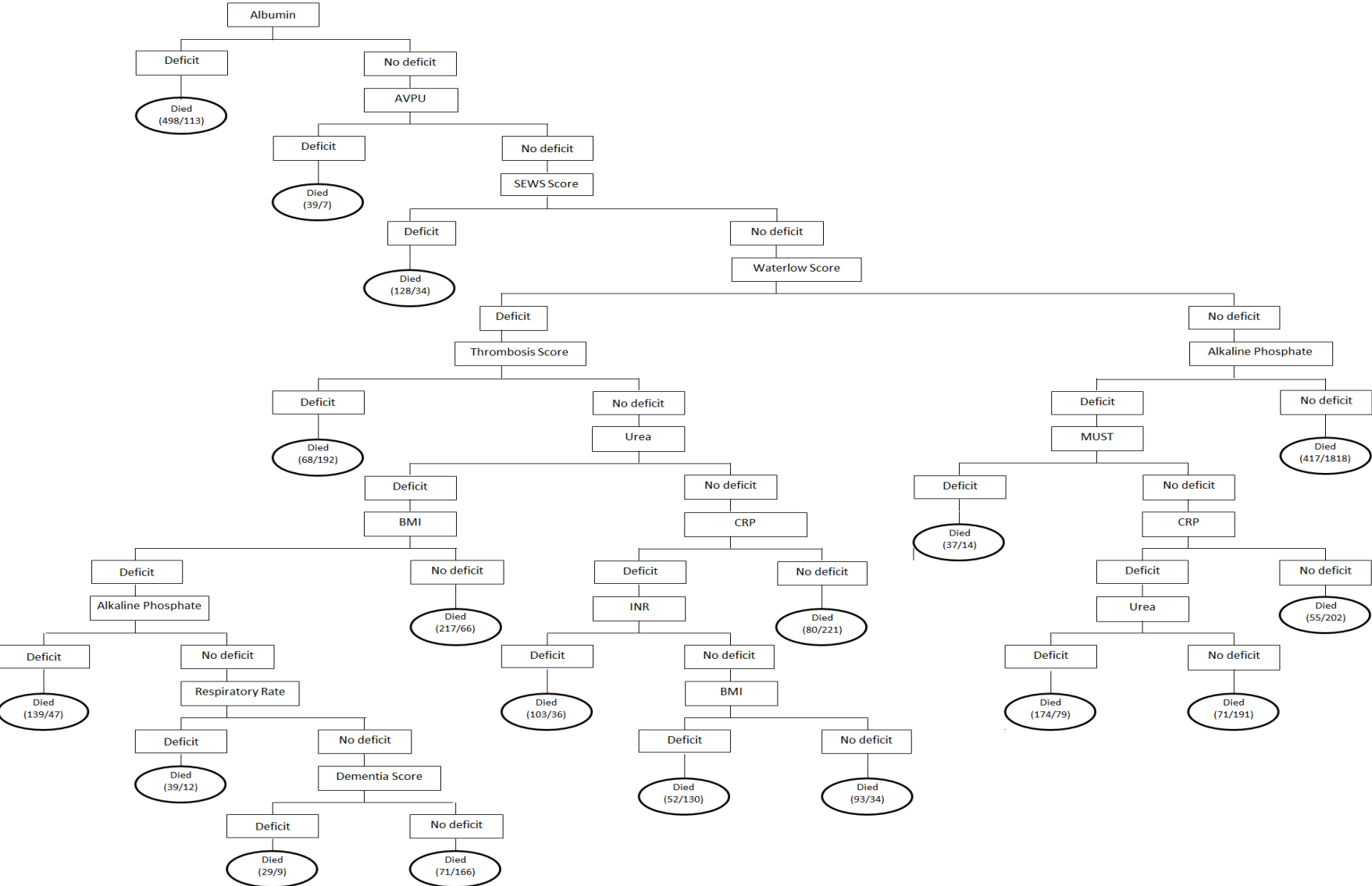
Figure 9e: Classification Tree 5
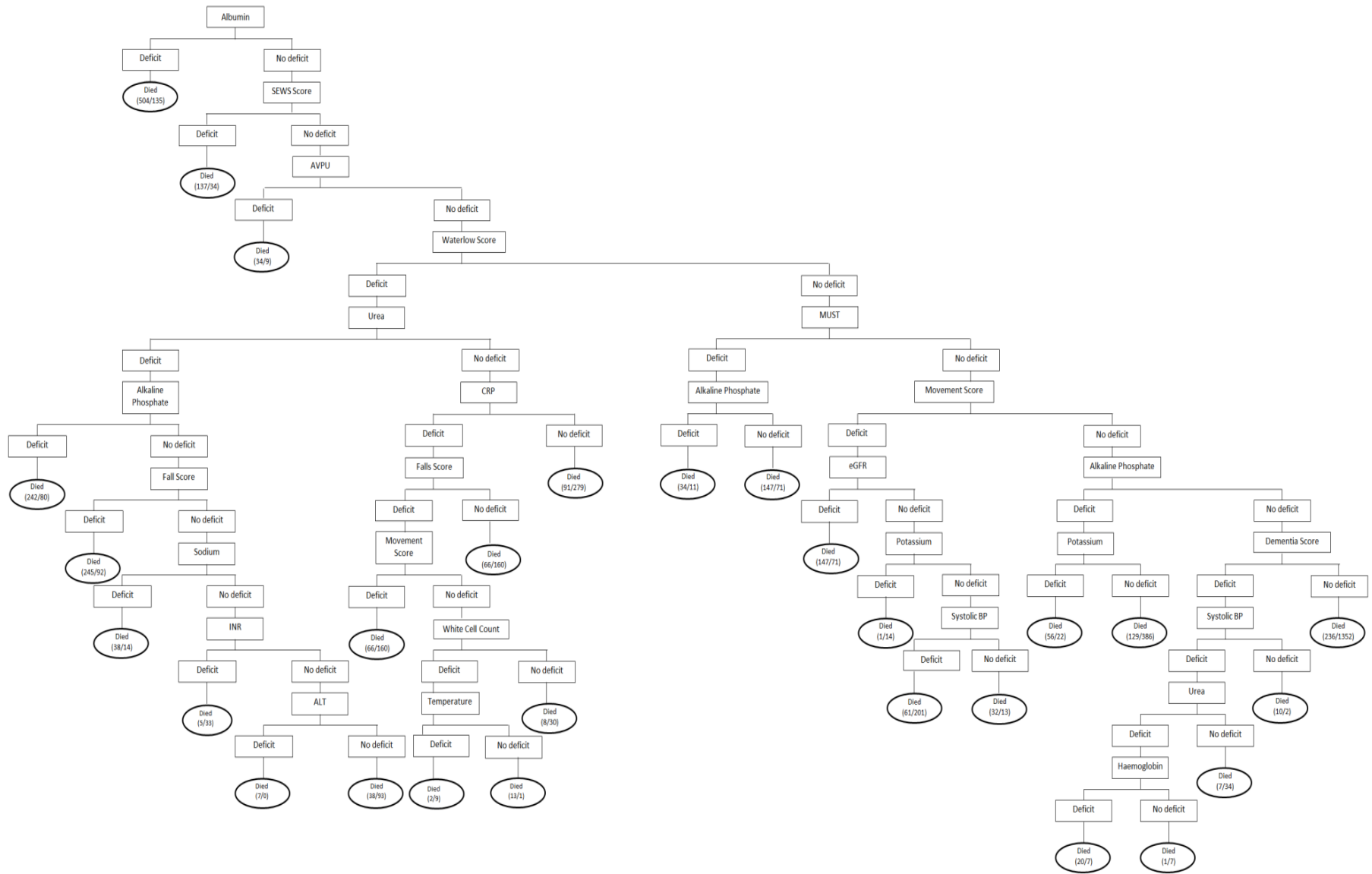
Figure 9f: Classification Tree 6
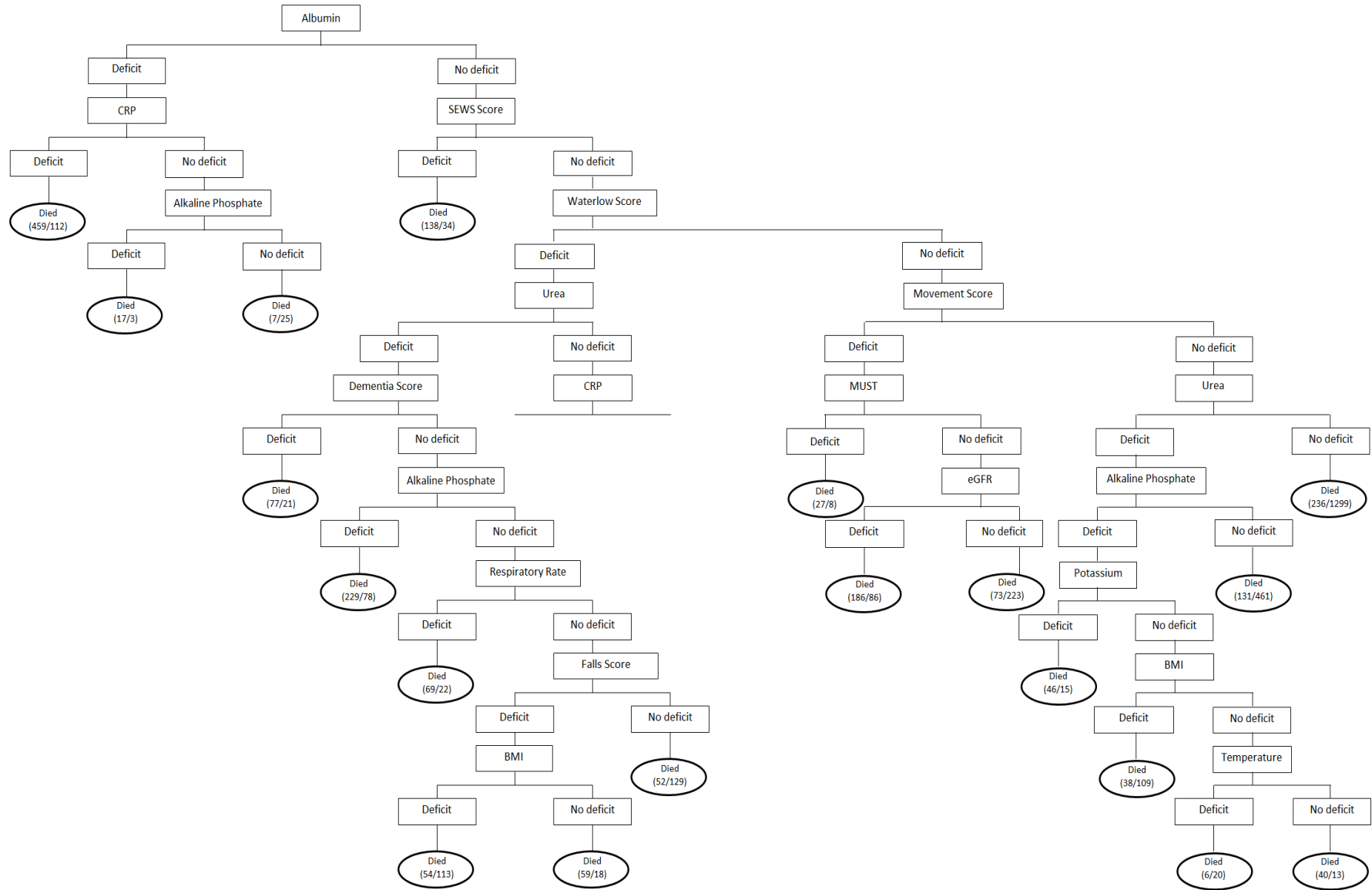
3.5.2 Demographics and Distribution

After recalculating the frailty score with just these variables, and reducing the dataset to only those who have 70% of tests as before, there were 5,386 patients left for analysis. The demographics of each HerFI category are outlined in table 14. The median age in the lowest HerFI group with a score <0.10 is 76 (IQR 70-82) compared to 82 (IQR 75-88) in the patients with a HerFI above 0.45. The completeness of the tests used in the HerFI are listed in table 15.

Table 14: Completeness and Deficits of HerFI Variables

Test	Deficit	Missing
Albumin	1868 (10.0%)	12 (0.1%)
Alkaline Phosphate	5417 (28.9%)	358 (1.9%)
CRP	9307 (49.7%)	2278 (12.2%)
Sews Score	596 (3.2%)	165 (0.9%)
Urea	7847 (41.9%)	3 (0.0%)
Waterlow Score	4977 (26.6%)	3559 (19.0%)

Table 15: Demographics by HerFI Category

		Grade of the FI			
		<0.10	**0.10 to 0.22**	**0.23 to 0.45**	**>0.45**
	Total	*972*	*1453*	*1401*	*1560*
HerFI	Age (Median and IQR)	76 (70-82)	78 (71-85)	81 (73 - 87)	82 (75-88)
	HerFI (mean and SD)	0 (0)	0.18 (0.01)	0.35 (0.03)	0.59 (0.12)
	Women (%)	51.4	53.1	54.3	54.9
	Mortality (%)	17.3	32.6	49	70.1

3.5.3 Mortality

The distribution of mortality at all time points split by HerFI Category is detailed in table 16.

Table 16: Mortality by HerFI Category

		Mortality			
		In Hospital	**30 Day**	**12 month**	**3 year**
HerFI	**<0.10**	12 (1.2%)	20 (2.1%)	81 (8.3%)	168 (17.3%)
	0.10 - 0.22	32 (2.2%)	55 (3.8%)	229 (15.8%)	476 (32.8%)
	0.23 - 0.45	86 (6.1%)	133 (9.5%)	385 (27.5%)	687 (49.0%)
	>0.45	221 (14.2%)	347 (22.2%)	754 (48.3%)	1094 (70.1%)
	Total	351 (6.5%)	555 (10.3%)	1,449 (21.7%)	2,425 (45.0%)
	p-value	<0.001	<0.001	<0.001	<0.001

In Hospital Mortality

The lowest mortality rate was again seen in the lowest HerFI category with 12 (1.2%) patients with a HerFI of <0.10 dying during their admission. When compared to the most frail group with a HerFI of >0.45 (14.2%) this difference was statistically significant (p<0.001). In multivariable logistic regression, adjusting for age, gender and HerFI, it can be concluded that with each increasing year of age there is an increased risk of in hospital mortality (OR 1.04, 95% CI 1.02 – 1.05, p<0.001), females have a lower risk of mortality (OR 0.75, 95% CI 0.59 – 0.94, p=0.014) and with each 0.1 increase in the HerFI there is an increase in risk of mortality in hospital (OR 1.04, 95% CI 1.04 – 1.05, p<0.001). This model has good predictive power with an AUROC curve of 0.78 (Figure 10). These results are detailed in table 17.

Figure 10: ROC for In Hospital Mortality

Area under ROC curve = 0.7791
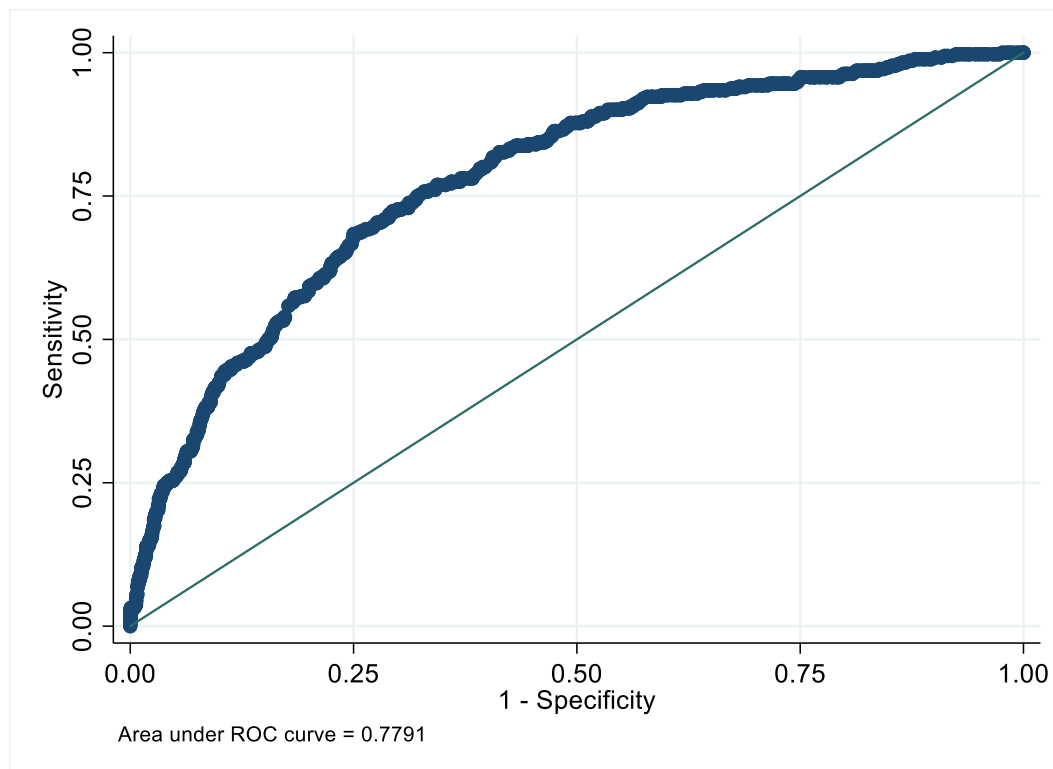
30 Day Mortality

The lowest mortality rate was again seen in the lowest HerFI category with 20 (2.1%) patients with a HerFI of <0.10 dying during their admission. When compared to the most frail group with a HerFI of >0.45 (22.2%) this difference was statistically significant (p<0.001). In multivariable logistic regression, adjusting for age, gender and HerFI, it can be concluded that with each increasing year of age there is an increased risk of in hospital mortality (OR 1.04, 95% CI 1.02 – 1.05, p<0.001) and with each 0.1 increase in the HerFI there is an increase in risk of mortality within 30 days of discharge (OR 1.04, 95% CI 1.04 – 1.05, p<0.001). The association between gender and mortality within 30 days of discharge is not significant (OR 0.83, 95% CI 0.69-1.00, p=0.056). This model has good predictive power with an AUROC curve of 0.78.

12 Month Mortality

The lowest mortality rate was again seen in the lowest HerFI category with 81 (8.3%) patients with a HerFI of <0.10 dying during their admission. When compared to the most frail group with a HerFI of >0.45 (48.3%) the difference was statistically significant (p<0.001).

In multivariable logistic regression, adjusting for age, gender and HerFI, it can be concluded that with each increasing year of age there is an increased risk of in hospital mortality (OR 1.04, 95% CI 1.03 – 1.05, p<0.001), females have a lower risk of mortality (OR 0.78, 95% CI 0.68 – 0.89, p<0.001) and with each 0.1 increase in the HerFI there is an increase in risk of mortality within 30 days of discharge (OR 1.04, 95% CI 1.03 – 1.04, p<0.001). This model has good predictive power with an AUROC curve of 0.74.

3 Year Mortality

Out of the 5,386 patients that met the criteria for the HerFI analysis, 45.0% had died by the end of the three years of follow up. The lowest mortality rate was again seen in the lowest HerFI category with 168 (17.3%) patients with a HerFI of <0.10 dying during their admission. When compared to the most frail group with a HerFI of >0.45 (70.1%) the difference was statistically significant (p<0.001). The Kaplan Meier curve demonstrates that there is a difference between the mortality rates of the HerFI categories (p<0.001) (Figure 11). In multivariable logistic regression, adjusting for age, gender and HerFI, it can be concluded that with each increasing year of age there is an increased risk of mortality within 3 years post discharge (OR 1.06, 95% CI 1.05 – 1.07, p<0.001), females have a lower risk of mortality (OR 0.76, 95% CI 0.67 – 0.86, p<0.001) and with each 0.1 increase in the HerFI

there is an increase in risk of mortality within 3 years of discharge (OR 1.04, 95% CI 1.04 – 1.04, p<0.001). This model has good predictive power with an AUROC curve of 0.76.

Figure 11: Kaplan Meier curve for mortality split by HerFI category
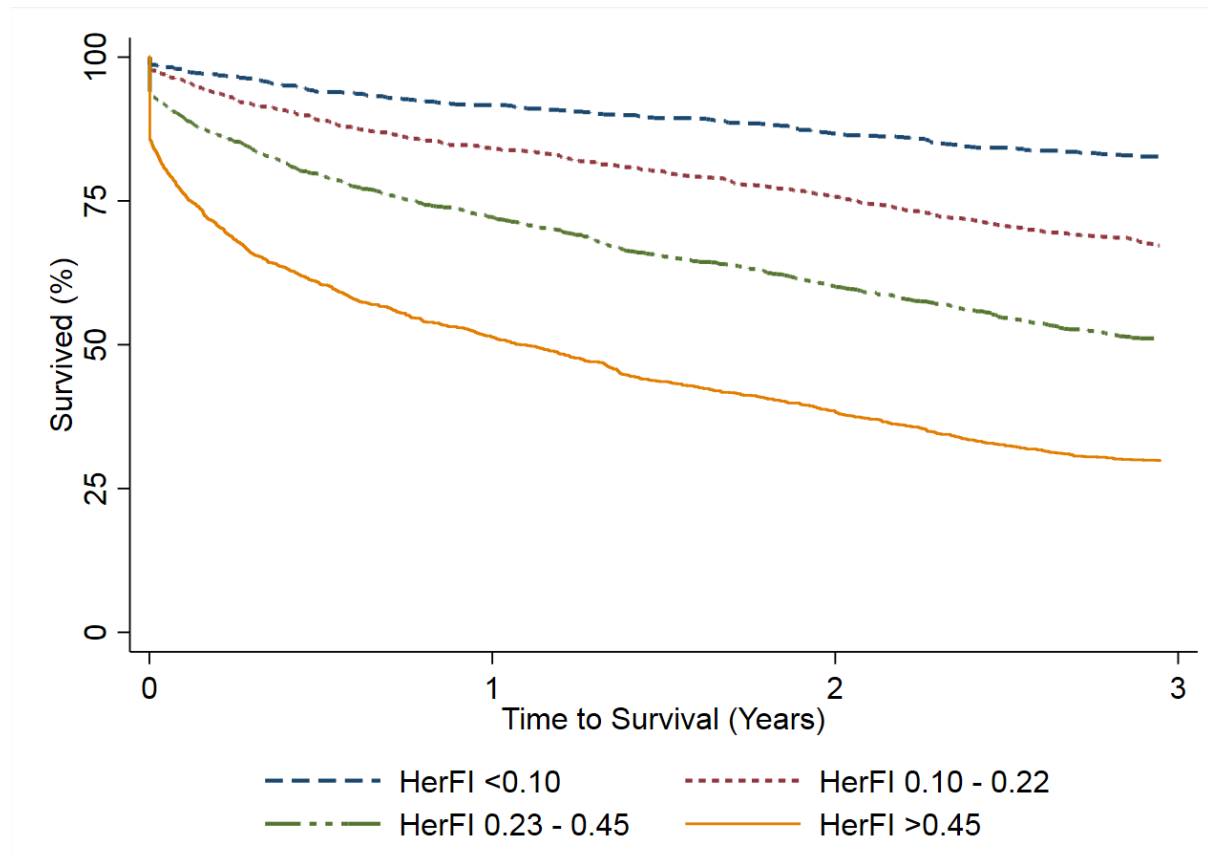
3.5.4 Readmissions

After excluding the 351 patients who died during their admission, the dataset was reduced to 5,035 patients for this part of the analysis. Out of the patients that were discharged from hospital at the end of their initial emergency admission, 809 (16.1%) patients were readmitted to hospital as an emergency within 30 days of their discharge date. The results of the multivariable logistic regression demonstrate that age is not a significant risk factor when predicting emergency readmissions, however females have a lower risk of being readmitted within 30 days than males (OR 0.83, 95% CI 0.71 – 0.97, p=0.016) and increasing HerFI is

associated with an increased risk of emergency readmission within 30 days (OR 1.01, 95% CI 1.01 – 1.02), p<0.001). There is a slight improvement to the AUROC curve when using these measurements to predict emergency readmission. It has increased from 0.57 to 0.59 for 30 day readmission, however even though this is an improvement, this is not powerful enough to be reliable to make clinical decisions.

3.5.5 Discharge to care home

Out of the 5,035 patients that were used for this part of the analysis, 302 (6%) were discharged to a care home at the end of their index emergency admission. Similarly to the FI-Baseline and FI-QEHB, increasing age (OR 1.07, 95% CI 1.06 – 1.09, p<0.001), female gender (OR 1.40, 95% CI 1.08 – 1.80, p=0.010) and increasing HerFI (OR 1.02, 95% CI 1.02 – 1.03, p<0.001) are all associated with an increased risk of being discharged to a care home. No predictive power was lost when comparing the model including the HerFI to the models with FI-Baseline and FI-QEHB, with an AUROC curve of 0.74.

Table 17: Multivariable Logistic Regression with HerFI

	Variable		Odds Ratio (95% CI)	p-value	AUROC
In Hospital Mortality	Age		1.04 (1.02 - 1.05)	<0.001	0.78
	Sex	Male	1 (baseline)		
		Female	0.75 (0.59 - 0.94)	0.014	
	HerFI		1.04 (1.04 - 1.05)	<0.001	
30 Day Mortality	Age		1.04 (1.02 - 1.05)	<0.001	0.78
	Sex	Male	1 (baseline)		
		Female	0.83 (0.69 - 1.00)	0.056	
	HerFI		1.04 (1.04 - 1.05)	<0.001	
12 Month Mortality	Age		1.04 (1.03 - 1.05)	<0.001	0.74
	Sex	Male	1 (baseline)		
		Female	0.78 (0.68 - 0.89)	<0.001	
	HerFI		1.04 (1.03 - 1.04)	<0.001	
3 Year Mortality	Age		1.06 (1.05 - 1.07)	<0.001	0.76
	Sex	Male	1 (baseline)		
		Female	0.76 (0.67 - 0.86)	<0.001	
	HerFI		1.04 (1.04 - 1.04)	<0.001	
30 Day Readmission	Age		0.99 (0.98 - 1.00)	0.146	0.59
	Sex	Male	1 (baseline)		
		Female	0.83 (0.71 - 0.97)	0.016	
	HerFI		1.01 (1.01 - 1.02)	<0.001	
Discharge to Care Home	Age		1.07 (1.06 - 1.09)	<0.001	0.74
	Sex	Male	1 (baseline)		
		Female	1.40 (1.08 - 1.80)	0.01	
	HerFI		1.02 (1.02 - 1.03)	<0.001	

3.6 Validation Cohort

3.6.1 Data Extraction

To further examine whether the HerFI is generalisable to a larger dataset over a longer period of time, data has been extracted for patients who have an emergency admission over a period of two years, between 1st January 2015 and 31st December 2016. There were 19,486 patients

aged over 65 that were admitted to QEHB as an emergency during this time period. All demographics were extracted and 95 patients that were missing gender or NHS number data were excluded, leaving 19,391 patients for analysis.

For these patients, measurements of Albumin, Alkaline Phosphatase, CRP, Sews Score, Urea and Waterlow Score that were closest to their admission date and time were collected in order to calculate the HerFI. The outcome variables that were extracted were mortality (in hospital, 30 day and 12 month), 30 day emergency readmission and discharged to care home. All patients were followed up for one year, with the maximum follow up date being 31st December 2017.

3.6.2 Demographics and Distribution

After the calculation of the HerFI on the validation cohort, patients who had less than 70% complete data were excluded. This left 15,258 patients for the rest of the analysis after excluding 4,133. When testing the significance of any differences between the main cohort and the validation cohort, the main cohort is slightly older overall, (median 79 (IQR 72 − 86) vs median 78 (IQR 71 − 85), p<0.001), they have a slightly higher HerFI (mean 0.31 (SD 0.22) vs mean 0.28 (SD 0.22), p<0.001) and there isn't a significant difference in the gender distribution between the two cohorts, (53.7% vs 52.4%, p =0.115).

3.6.3 Mortality

In Hospital Mortality

A total of 1,006 (6.6%) of patients in the validation cohort died during their admission

In multivariable logistic regression, adjusting for age, gender and HerFI, it can be concluded that with each increasing year of age there is an increased risk of in hospital mortality (OR

1.04, 95% CI 1.03 – 1.05, p<0.001), females have a lower risk of mortality (OR 0.78, 95% CI 0.68 – 0.89, p<0.001) and with each 0.1 increase in the HerFI there is an increase in risk of mortality in hospital (OR 1.05, 95% CI 1.05 – 1.05, p<0.001). This model has good predictive power with an AUROC curve of 0.81. These results are detailed in table 18.

30 Day Mortality

A total of 1,489 (9.8%) patients in the validation cohort died within 30 days of their discharge. In multivariable logistic regression, adjusting for age, gender and HerFI, it can be concluded that with each increasing year of age there is an increased risk of mortality within 30 days of discharge (OR 1.04, 95% CI 1.04 – 1.05, p<0.001), females have a lower risk of mortality (OR 0.80, 95% CI 0.71 – 0.90, p<0.001) and with each 0.1 increase in the HerFI there is an increase in risk of mortality within 30 days (OR 1.05, 95% CI 1.05 – 1.05, p<0.001). This model has good predictive power with an AUROC curve of 0.80.

12 Month Mortality

A total of 3,652 (23.9%) patients in the validation cohort died within 12 months of their discharge. In multivariable logistic regression, adjusting for age, gender and HerFI, it can be concluded that with each increasing year of age there is an increased risk of mortality within 12 months of discharge (OR 1.04, 95% CI 1.04 – 1.05, p<0.001), females have a lower risk of mortality (OR 0.73, 95% CI 0.67 – 0.80, p<0.001) and with each 0.1 increase in the HerFI there is an increase in risk of mortality within 12 months (OR 1.04, 95% CI 1.04 – 1.04, p<0.001). This model has good predictive power with an AUROC curve of 0.75.

3.6.4 Readmissions

After removing the patients that died during their admission, 2,061 (14.5%) were readmitted as an emergency within 30 days of their discharge. Increasing age showed a slightly reduced risk of readmission (OR 0.99, 95% CI 0.99 – 1.00, p=0.032), Female gender showed a reduced risk when compared to males (OR 0.86, 95% CI 0.78 – 0.94, p<0.001) and increasing HerFI was again associated with a significant increased risk of readmission (OR 1.01, 95% CI 1.01 -1.02, p<0.001). The AUROC curve for readmissions has stayed the same at 0.58.

3.6.5 Discharge to care home

Out of the 14,252 patients that were discharged at the end of their index emergency admission, 426 (3.0%) were discharged to a care home. Increasing age was found to be a risk factor of being discharged to a care home (OR 1.09, 95% CI 1.08 – 1.10, p<0.001), as was female gender when compared to males (OR 1.33, 95% CI 1.08 – 1.63, p=0.007). There was an increased risk of being discharged to a care home with each 0.1 increase of the HerFI (OR 1.02, 95% CI 1.02 – 1.03, p<0.001). The AUROC curve has increased to 0.76 when assessing risk factors of being discharged to a care home, which shows that the increase in the size of the dataset improves the power of the model. This validation exercise has shown that the model including the HerFI is valid and can be applied to a wider cohort.

Table 18: Multivariable Logistic Regression models with HerFI for validation cohort

	Variable		Odds Ratio (95% CI)	p-value	AUROC
In Hospital Mortality	Age		1.04 (1.03 - 1.05)	<0.001	0.81
	Sex	Male	1 (baseline)		
		Female	0.78 (0.68 - 0.89)	<0.001	
	HerFI		1.05 (1.05 - 1.05)	<0.001	
30 Day Mortality	Age		1.04 (1.04 - 1.05)	<0.001	0.80
	Sex	Male	1 (baseline)		
		Female	0.80 (0.71 - 0.90)	<0.001	
	HerFI		1.05 (1.05 - 1.05)	<0.001	
12 Month Mortality	Age		1.04 (1.04 - 1.05)	<0.001	0.75
	Sex	Male	1 (baseline)		
		Female	0.73 (0.67 - 0.80)	<0.001	
	HerFI		1.04 (1.04 - 1.04)	<0.001	
30 Day Readmission	Age		0.99 (0.99 - 1.00)	0.032	0.58
	Sex	Male	1 (baseline)		
		Female	0.86 (0.78 - 0.94)	0.001	
	HerFI		1.01 (1.01 - 1.02)	<0.001	
Discharge to Care Home	Age		1.09 (1.08 - 1.10)	<0.001	0.76
	Sex	Male	1 (baseline)		
		Female	1.33 (1.08 - 1.63)	0.007	
	HerFI		1.02 (1.02 - 1.03)	<0.001	

4 Discussion

4.1 Key Findings

The study of routinely collected hospital data for emergency admissions in the over 65's has shown that we can create a model with relatively good predictive power based on a frailty index calculated from routinely collected data without having to rely on collecting too many variables. The number of variables has been able to be reduced from 31 down to 6, whilst also increasing the AUROC curve value when predicting the outcomes of mortality, readmissions and discharge to a care home. Table 19 displays the AUROC of all models and outcomes that have been included in the analysis.

Table 19: AUROC values for all models and outcomes

	FI-Baseline	FI-QEHB	HerFI	HerFI - Validation
In Hospital Mortality	0.74	0.78	0.78	0.81
30 Day Mortality	0.74	0.77	0.78	0.80
12 Month Mortality	0.70	0.72	0.74	0.75
3 Year Mortality	0.71	0.74	0.76	N/A
30 Day Readmission	0.57	0.58	0.50	0.58
Discharge to care home	0.72	0.74	0.74	0.76

After classification and regression tree analysis, the six measurements that were found to be the most important when predicting mortality and that were used in the HerFI were Albumin, Alkaline Phosphatase, CRP, SEWS Score, Urea and the Waterlow Score. While the AUROC curve for predicting mortality and discharge to a care home are high, the ROC for predicting 30-day readmission does not reach above 0.6 which suggests this may not be the correct model to predict readmissions.

4.2 What do these findings mean for clinical practice?

Approximately, people aged over 65 account for over half of admissions to hospital. Age is one factor that influences the patients' risk of experiencing adverse events such as death, but the level of risk that these over 65's have varies per person. This is where a frailty measure is potentially useful. The ability to predict adverse outcomes with a high level of confidence (i.e. high sensitivity and specificity) would allow targeted interventions aimed at improving outcomes. The measurements included in the HerFI are all taken at the start of a patient's admission. Its application could therefore be used shortly after admission right at the start of the acute care journey to highlight patients at risk of in-patient and 30-day mortality, as well as those at high risk of being discharged to a care home. The only other attempt at producing such a frailty index in the UK (The Hospital Frailty Risk Score) [120] predicts mortality. However, it is derived from information at the time of discharge. It therefore has absolutely no value if the aim is to prevent in-patient mortality or to prevent discharge to a care home. It is also of limited value in preventing short-term (e.g 30-day) mortality given the limited amount of time available to institute any intervention. Intuitively, it would seem much more likely that any such intervention would be more likely to succeed if steps are taken to implement it at any point during the in-patient stay rather than waiting for the decision to be made at the time of discharge. The HerFI presented here thus has several advantages over the Hospital Frailty Risk Score. It's key advantage being that it is available at the time of admission and therefore measures can be taken shortly after admission and as well as targeting both short and long-term mortality, it can be used to attempt to prevent discharge to a care home and increase the chances of the patient being discharged back to their own home.

This study does not address what interventions would improve the outcomes of patients identified by HerFI to be at high risk. Potential options include physiotherapy [115], CGA

[7], or social services review. However, their effectiveness would need to be addressed in future trials before being introduced into clinical practice. The developed HerFI does allow for studies to be able to identify, and direct interventions at, higher risk patients making them more efficient and requiring lower numbers. Any investment in new research or a clinical intervention reduces the resources that are available for other investigations or interventions [175]. Any potential research study or clinical intervention needs to have a very careful evaluation for their potential to achieve the required outcomes and the potential health-economic impact. The developed HerFI therefore goes some way to achieving both these outcomes by identifying high risk patients allowing studies to be adequately powered and the potential health-economic gains to be modelled [176-179].

4.3 Using the AUROC curve to measure predictive power

Receiver Operating Characteristic curves are used to measure how well a predictive model can distinguish between true positives and negatives, by plotting sensitivity (probability that predicting a real positive will be a positive) against 1- specificity (probability that predicting a real negative will be a positive) [180, 181]. Ultimately the best models are those that are high on sensitivity and low on 1-specificity giving an AUROC curve close to 1. That is, stratify individual patients into different risk categories. In this situation, the better the model is at distinguishing between patients who die or do not, who get readmitted or do not and who get discharged to a care home or do not.

The developed HerFI models for predicting mortality and discharge to a care home have produced AUROC curve at 0.7 or above giving them good predictive power. An AUROC curve of 0.9 is described as having high accuracy, between 0.7 and 0.9 moderate and 0.5-0.7 low accuracy [167]. It should also be noted that even perfectly calibrated models, that is models in which the predicted risk equals the observed risk in all sub-groups, cannot achieve

an AUROC curve of 1 in usual settings [182]. However, there are some arguments that the AUROC curve is not a reliable measure of predictability. Some reasons that have been argued are that it "ignores the predicted probability values and the goodness of fit of the model" and it "does not give information about the spatial distribution of model errors" [183]. An alternative method to test model accuracy could be measuring calibration, which measures how well predicted probabilities agree with the actual observed risk. Proportions are calculated for the expected people at risk and the actual proportion that develop the disease. The Hosmer-Lemeshow test can be used to compare the proportions and assess the level of calibration [181]. Nevertheless, the AUROC curve is regularly used and has the benefit of being completely objective with no subjective input from the researcher needed, and its interpretation is widely understood by both researchers and non-researchers.

However, it should be recognised that the HerFI developed performs well compared to other risk scores routinely used in clinical practice. For example, a systematic review looking at including the widely used CHADS2 [184] and CHA2DS2-VASc [185] in models to predict the risk of stroke and thromboembolism in patient with atrial fibrillation found that $CHADS_2$ has a median AUROC curve of 0.683 and 0.673 for $CHA_2DS_2\text{-}VASc$ [186]. Many studies have used these two tools to model outcomes and reported their predictive power, which at most is described as 'acceptable' performance [186]. Another clinical decision score that has been developed is the European Registry for Patients with Mechanical Circulatory Support (EUROMACS). This has been used in a study to identify patients at risk for early right-sided heart failure (RHF) [187]. They gave this the name of EUROMACS-RHF, and using the AUROC curve of 0.70 on the derivation cohort and 0.67 on the validation cohort they concluded that this score outperforms other RHF risk scores.

The Tangri score is described as 'the best performing kidney failure risk equation' and has also been assessed in many studies [188]. The original score reported an AUROC curve of 0.863 which can be described as having excellent discriminative power. The score has been developed into an 8-variable model, using complex and expensive proteomic variables that are not routinely available, from a 4-variable model and reached an AUROC curve of 0.917[188]. Thus, although the HerFI appears to be comparable in predictive power to other commonly used scores, at least in terms of the AUROC curve, it could potentially still be improved, with the use of additional non-routinely collected variables such as grip strength.

4.4 Is the HerFI a true measure of frailty or is it an acute illness score?

The developed HerFI uses values obtained on an acute admission and as such it is possible that it is an acute illness score rather than a true measure of frailty. Figure 1 highlights the fact that patients who are increasingly frail and experience even a minor illness, adverse event or change will deteriorate rapidly and require extra care as opposed to patients that are overall in better health. It would, therefore, seem likely that the HerFI is both an acute illness score and a measure of frailty combined. Whether this is an important consideration is far from clear. From a pragmatic clinical viewpoint the important considerations are whether HerFI reliably and accurately identifies patients at high risk of the outcome of interest and perhaps even more importantly, whether it identifies high risk patients whose outcome can be improved by an intervention. The AUROC curve values greater than 0.7 suggests that the HerFI is able to identify high risk patients. Whether it identifies patients whose outcome can be improved cannot be determined from this work and would need to be identified in future interventional studies. Potential interventions need to be determined, but as already discussed a targeted CGA with multidisciplinary/multispecialty involvement would be a reasonable starting point.

4.5 Would a clinical alert system be a reasonable intervention?

Many hospitals across the UK and worldwide have been using computer generated alert systems to inform clinicians of patients who are potentially at risk for many years and assist in decision making [189-194]. Some studies have found that computer-based alerts do improve patients' outcomes when compared to no alerts [195]. They generally found that computer reminders achieve moderate improvements in provider behavior when it comes to patient care, interventions, prescribing and test ordering [196].

The concern with the alerts on electronic healthcare systems is that clinicians have the potential to experience 'alert fatigue' where they may choose to override the recommendations and warnings without paying attention to the content [197-199]. Indeed, a study about black-box warnings regarding medications with serious risks concluded that the alerts did not improve clinicians' adherence [200]. Currently, multiple alerts appear on the electronic healthcare systems which are not always relevant to the patient. Solutions have been proposed in order to reduce alert fatigue such as ensuring the alerts are patient specific so the clinicians are more likely to pay attention to them because they would be relevant and also the number of alerts would reduce. Therefore, the addition of an additional Frailty alert may not actually improve patient outcomes if it is ignored anyway. Introduction of such an alert would need to be extensively evaluated if it is to be introduced into clinical practice to ensure acceptability and usability.

4.6 Strengths and Limitations

This analysis is based on a single centre study and therefore the results may not be generalisable to the rest of the UK. However, QEHB is a very large teaching hospital serving a large and ethnically diverse population. Nevertheless the HerFI needs to be validated in other Trusts across the UK. As with all collected data sets using routinely collected data it is entirely reliant on the data required being complete. Despite the data set being relatively complete, several missing data techniques have also been used in the development of HerFI to mitigate as much as possible the potential influence of this missing data on the results. However, it remains possible that patients with missing data could be sicker than those who have complete data. This is the one of the major reasons that simple case deletion was not used in this study as this would potentially skew the population towards a generally healthier cohort.

The IT team at QEHB developed PICS in-house. Changes are continuously being made within the system that is used in the trust; therefore adding in a new frailty alert within trust would be feasible. The data that we have used requires linkage to the Secondary Uses Service (SUS) which stores the patient level data. Not all trusts in England are as highly computerised as QEHB therefore this level of detail may not be possible all over the country. However, the components of the HerFI are all simple and routinely collected throughout the UK. Development and use of HerFI would require no further time or additional resource to perform tests that are not usually carried out, provided the most basic of computer systems are in use.

5 Future Work

Even though this study has been successful in determining key variables that contribute to a strong model predict adverse events of mortality and discharge to a care home, there are more areas that could be explored further. Currently, the final HerFI has only been tested on an acutely ill population, who have a high level of comorbidities which is evident in the distribution of the Charlson Comorbidity Score where 58% of the patients included have a score of 5 or above. In order to validate the model further, it may be of interest to see whether this can be used on all admissions, both elective and emergency. Further to this, the age of the population has been restricted to over 65's only. By testing the model on the whole population of all ages, it could help to determine whether this is solely a model to predict adverse events, or whether in fact it is a measure of degree of frailty. Similarly, the model could be used to investigate patients aged over 85, for example or a new model developed.

The developed HerFI proved not to be particularly predictive of readmissions. The reason for this is unclear, therefore this is an area that needs further exploration given the importance of preventing patients from coming back into hospital, both from socio-economic and patient specific perspectives. Alternative Machine Learning methods for feature selection could be applied to the data in order to assess whether they produce different results. For example, Random Forest analysis could be explored [201]. Random Forest analysis is an extension of decision trees, in the way that it is simply a collection of decision trees, all aggregated into one result. They are efficient at limiting overfitting and reducing errors due to bias. Therefore, it would be of interest to explore whether the important features selected in a random forest are the same or different to those that we have found using classical decision trees.

Currently the 'deficits' explored only take into account whether the test results is abnormal, and does not differentiate between whether it is too high or too low. Therefore, further analyses could explore whether having three categories, 'high', 'low' and 'normal' makes a difference instead of just 'deficit' and 'no deficit'.

One of the strengths of this study is that it is using routinely collected data that does not add additional clinical time to collect. However, it would be of interest to see whether non-routinely collected parameters add any value to the HerFI and improve the model. For example, many studies have found that grip strength is a good and easily collectable measure of frailty [202]. The non-routinely collected frailty measures that are used in the Clinical Frailty Score from Rockwood, the Edmonton Frail Scale and the Fried Frailty Scale could be combined with our routinely collected tests in order to assess whether they together produce a predictive model.

Once the full model has been developed and has achieved the optimum performance it can with the data available, it would be of interest to implement a frailty alert which could influence interventions from appropriate medical teams. In order to do this, it would be of interest to set a cut-off for the degree of frailty at which the alert would be activated. There are different methods currently in the literature that are used to produce an optimal cut-off value, including using Youden's index [203] which is a summary measure of the ROC curve helps determine which point the best sensitivity and 1-specificity is achieved. However, such techniques should be used with caution when making clinical decisions.

In the development of this HerFI only data obtained at a single time point, which is on admission, has been used to develop the score. It is possible that using more dynamic

measures, such as change over time, peak result or minimum values as examples might have improved the model. Although perhaps of interest it would probably limit the clinical applicability of the tool as it would not be able to be used from the point of admission to influence immediate patient selection to start potentially outcome altering interventions. However, the concept of having an evolving "score" may be an attractive one although it would need a great deal of thought and work to develop such a system.

6 Conclusions

With an increasingly ageing population, older people account for the majority of UK healthcare use and spend. However, the severity of health status and the number of adverse outcomes in older people is varied. Therefore, frailty is a highly topical measure of interest in order to quantify the need for intervention in order to prevent adverse outcomes such as mortality, readmissions and more long-term care such as a care home admission.

Many studies have used a variety of measures in order to define frailty. However, the aim of this study was to use solely routinely collected data to predict in hospital mortality, 30 day mortality, 12 month mortality, emergency readmissions and discharge to care home. Most published studies in the literature using frailty measures require additional resource or cost to collect. By using routinely collected data, use of the HerFI would not add any extra burdens onto the healthcare services.

Using exploratory data analysis techniques and also machine learning methods, the number of variables to be included was reduced down to 6, while maintaining a high level of predictability. Three out of the final six final measurements were included in the initial Rockwood model: albumin, urea and alkaline phosphatase. The addition of the Waterlow Score, SEWS Score and CRP and not including any others, was the combination that ended in the optimum performance achievable with the data.

The proposed HerFI is therefore a simple but efficient way of identifying high risk patients aged over 65 on admission to hospital. Although more work remains to be done, this is an important first step to improve the outcome of this vulnerable group of patients.

7 Appendices and References

Appendix 1 – SQL Script for Data Extraction

---Extract all patients aged 65+ who were admitted to hospital betweeen July and December 2014

```
drop table #frailty
select * into #frailty from (
select a.UNITNO,
       spellno,
       convert (datetime, a.epistart,112) as 'Ep_st_date',
       convert (datetime, (a.epiend),112) as 'Ep_dis_dat',
       epino,
       a.SEX_CDS as 'Sex',
       am_cds as 'Admission_method',
       a.Adm_Source_CDS as 'Admission_source',
       a.DD_CDS as 'Discharge_destination',
       a.ETH_GROUP_CDS as 'Ethnos',
       left(a.postcode, 3) as postcode,
       a.age,
       a.DIAG1 as 'Primary_diag',
       a.DIAG2 as 'Secondary_diag',
       mainspec as 'Spec_code',
       Tfunc as 'Treatment_function'
From [Inpatient table] a
     where admdat between '20140701' and '20141231' and age>=65) as a
```

---Find full details of the spells by joining on the spell ID

```
select * into #frailty_2 from (
select a.UNITNO,
       spellno,
       convert (datetime, a.epistart,112) as 'Ep_st_date',
       convert (datetime, (a.epiend),112) as 'Ep_dis_dat',
       epino,
       a.SEX_CDS as 'Sex',
       am_cds as 'Admission_method',
       a.Adm_Source_CDS as 'Admission_source',
       a.DD_CDS as 'Discharge_destination',
       a.ETH_GROUP_CDS as 'Ethnos',
       a.postcode,
       a.age,
       a.DIAG1 as 'Primary_diag',
       a.DIAG2 as 'Secondary_diag',
       mainspec as 'Spec_code',
       Tfunc as 'Treatment_function'
from [Inpatient table] a
     where SPELLNO in (select distinct spellno from #frailty)) as a
```

---Now to get spell details first

```
drop table #tmp_spells
select *  into #tmp_spells from
(select b.pasid,
       a.UNITNO,
       a.SPELLNO,
       min(a.Ep_st_date) as 'Spell_adm_date',
       max(a.Ep_dis_dat) as 'Spell_dis_date',
       max(a.EPINO) as 'Number_Episodes'
from #frailty_2 as a
```

```
left join
     #frailty_unitnos as b
on left(a.UNITNO,7)=left(b.pasminor,7)
where a.Ep_dis_dat is not null
group by b.pasid, a.SPELLNO, a.UNITNO) as a
```

---Add in discharge destination

```
alter table #tmp_spells
add discharge_destination char(2)

update #tmp_spells
set discharge_destination = b.Discharge_destination
from #tmp_spells a inner join #frailty_2 b
on a.unitno = b.unitno and
   a.spellno = b.spellno and
   a.Number_episodes = b.epino
```

---Inserting into permanent table from #tmp_spells and #frailty_2

```
drop table [Frailty Data 1]
select * into [Frailty Data 1] from
(select a.pasid,
        a.unitno,
        a.spellno,
        a.Spell_adm_date,
        a.Spell_dis_date,
        a.Number_Episodes,
        a.Sex,
        a.Admission_method,
        a.Admission_source,
        a.Discharge_destination,
        a.Ethnos,
        a.age,
        case when a.imd is null then a.[imd score] else a.imd end as 'IMD_score'
from
(select a.*, b.Sex, b.Admission_method, b.Admission_source, b.Discharge_destination,
b.Ethnos, b.age, b.POSTCODE, c.LSOA01, d.IMD, e.[IMD SCORE] from #tmp_spells as a
left join
(select *, row_number() over (partition by a.pasid, a.spellno order by a.sex,
a.ep_st_date) as 'Row_no' from #frailty_2 as a) as b
on left(a.pasid,7)=left(b.pasid,7) collate database_default and
   a.spellno=b.spellno and
   b.row_no=1
left join [Postcode table] as c on b.POSTCODE=c.PCD2
left join [LSOA Table] as d on c.LSOA01=d.lsoa
left join [IMD Table]  as e on c.LSOA01=e.[LSOA CODE]) AS A) as a
```

---Expanding into episodes rather than spells to get more information
```
select * into [Frailty Episodes Data]
from (
select a.UNITNO,
       a.pasid,
       a.SPELLNO,
       a.Ep_st_date,
       a.Ep_dis_dat,
       a.EPINO,
       a.Spec_code,
       a.Treatment_function,
       a.primary_diag,
       b.CCS_CATEGORY,
       b.CCS_LABEL,
```

```
            a.secondary_diag from #frailty_2 as a
left join [ICD10 table] as b on a.Primary_diag=b.ICD10_CODE) as a
```

---Adding days to next emergency admission

```
select a.pasid,
        a.SPELLNO as 'Init_spell',
        b.SPELLNO,
        b.No_episodes,
        b.am_cds,
        a.Spell_adm_date,
        b.epistart,
        datediff (dd, a.Spell_adm_date, b.epistart) as 'date_diff',
        ROW_NUMBER() over (partition by a.pasid, a.spellno order by datediff (dd,
a.Spell_adm_date, b.epistart)) as 'Row_no'
  into #tmp_post_spells_2
from [Frailty Data 1] as a
left join
(select a.SPELLNO,
        a.pasid,
        a.AM_CDS,
        min(a.Epistart) as 'Epistart',
        max(a.Epiend) as 'Epiend',
        max(a.epino) as 'No_episodes'
from (select a.spellno,
            convert (datetime, a.epistart,112) as 'Epistart',
            convert (datetime, a.epiend,112) as 'Epiend',
            a.EPINO,
            a.AM_CDS,
            a.UNITNO,
            b.pasid,
            case when a.UNITNO = b.pasid then 1 else 0 end as 'Flag'
from [Frailty Data 1] a
        left join #frailty_unitnos as b
on left(a.unitno,7)= left (b.pasminor,7)
where left(a.unitno,7) in (select distinct left(pasminor,7) from #frailty_unitnos)
and pclass =1 ) as a
group by a.SPELLNO, a.pasid, a.AM_CDS) as b
on a.Spell_dis_date <= b.epistart and
    a.spellno <> b.SPELLNO and
    a.pasid = b.pasid
where b.AM_CDS like '2%'
```

---Adding this data to the main table

```
alter table [Frailty Data 1]
add Days_to_next_non_elec_adm int

update [Frailty Data 1]
set Days_to_next_non_elec_adm = b.Date_diff
from [Frailty Data 1] as a inner join #tmp_post_spells_2 as b
on a.spellno=b.Init_spell and
    a.pasid=b.pasid collate database_default and b.Row_no = 1
```

---Add times of admission and episodes

```
alter table [Frailty Data 1]
add spell_adm_date_time datetime,
    spell_dis_date_time datetime;


update [Frailty Data 1]
set spell_adm_date_time = [Admdat_Dttm],
```

```
        spell_dis_date_time = [Disdat_Dttm]
from [Frailty Data 1] as a inner join
(select b.unitno,
        b.spellno,
        [Admdat_Dttm],
        [Disdat_Dttm]
 from [Daily Inpatient Table] as b
where spellno in
(select distinct spellno
 from [Frailty Data 1] as a)
group by b.unitno,
      b.spellno,
     [Admdat_Dttm],
     [Disdat_Dttm]) as b
on left(a.spellno,9)=left(b.spellno,9) and
   left(a.unitno,7)=left(b.unitno,7)

alter table [Frailty Episodes Data]
add EPI_adm_date_time datetime,
    EPI_dis_date_time datetime;

update [Frailty Episodes Data]
set EPI_adm_date_time = [Epistart_Dttm],
    EPI_dis_date_time = [Epiend_Dttm]
from [Frailty Episodes Data] as a
inner join
(select b.unitno,
        b.spellno,
        [Epistart_Dttm],
        [Epiend_Dttm],
        EPINO
from [Daily Inpatient Table] as b
where left(spellno,9) in
(select distinct left(spellno,9)
from [Frailty Data 1] as a)
group by b.unitno,
         b.spellno,
         [Epistart_Dttm],
         [Epiend_Dttm],
         EPINO) as b
on left(a.spellno,9)=left(b.spellno,9) and
   left(a.unitno,7)=left(b.unitno,7) and
   a.EPINO=b.epino;
```

---Add in discharge method

```
alter table [Frailty Data 1]
add dismeth varchar(2);

update [Frailty Data 1]
set dismeth = b.DM_CDS
from [Frailty Data 1] as a
inner join
(select a.spellno,
        a.unitno,
        a.DM_CDS
from [Inpatient Table] as a
where spellno in
(select distinct spellno
from [Frailty Data 1] as a)
group by a.spellno,
         a.unitno,
```

```
        a.DM_CDS) as b
on left(a.spellno,9)=left(b.spellno,9) and
   left(a.unitno,7)=left(b.unitno,7);
```

---Adding comorbidities into the table

```
set concat_null_yields_null off
alter table [Frailty Data 1]
add AMI int,
    Cerebro_vasc int,
    CHF int,
    ConnTissueD int,
    Dementia int,
    Diabetes int,
    Liver_dis int,
    Peptic_ulcer int,
    PVD int,
    Pulmonary_dis int,
    Cancer int,
    Diab_comp int,
    paraplegia int,
    met_ca int,
    HIV int,
    sev_liv int,
    Renal_dis int,
    TB_flag int,
    Charlson_score_nwt int;

update [Frailty Data 1]
set AMI= b.AMI,
    Cerebro_vasc = b.Cerebro_vasc,
    CHF = b.CHF,
    ConnTissueD = b.ConnTissueD,
    Dementia = b.Dementia,
    Diabetes = b.Diabetes,
    Liver_dis = b.Liver_dis,
    Peptic_ulcer = b.Peptic_ulcer,
    PVD = b.PVD,
    Pulmonary_dis = b.Pulmonary_dis,
    Cancer = b.Cancer,
    Diab_comp = b.Diab_comp,
    Paraplegia = b.paraplegia,
    met_ca = b.met_ca,
    HIV = b.HIV ,
    sev_liv = b.sev_liv,
    Renal_dis = b.Renal_dis,
    Charlson_score_nwt = b.Charlson_score_nwt
from [Frailty Data 1] as a
inner join (
select a.SPELLNO,
       a.EPINO,
AMI+Cerebro_vasc+CHF+ConnTissueD+Dementia+Diabetes+Liver_dis+Peptic_ulcer+PVD+Pulmonar
y_dis+Cancer+Diab_comp+paraplegia+met_ca+HIV+sev_liv+Renal_dis
as 'Charlson_score_nwt',
AMI,
Cerebro_vasc,
CHF,
ConnTissueD,
Dementia,
Diabetes,
Liver_dis,
```

```
        Peptic_ulcer,
        PVD,
        Pulmonary_dis,
        Cancer,
        Diab_comp,
        paraplegia,
        met_ca,
        HIV,
        sev_liv,
        Renal_dis
        from
        (
select a.spellno,
        a.epino,
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 +        b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 +
b.diag16 + b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%I2[123]%' then 5
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%I25[28]%' then 5 else 0 end as 'AMI',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%I6%' then 11
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%G45[012489]%' then 11
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%G46%' then 11 else 0 end as
'Cerebro_vasc',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%I50%' then 13 else 0 end as 'CHF',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%M05%' then 4
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%M06[039]%' then 4
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%M3[24]%' then 4
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%M332%' then 4
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%M353%' then 4 else 0 end as
'ConnTissueD',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%F0[0123]%' then 14
     when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%F051%' then 14 else 0 end as
'Dementia',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%E1[0134][15689]%' then 3 else 0 end
as 'Diabetes',
```

```
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K70[23]%' then 8
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K717%' then 8
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K7[34]%' then 8 else 0 end as
'Liver_dis',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K2[5678]%' then 9 else 0 end as
'Peptic_ulcer',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17+ b.diag18 + b.diag19 + b.diag20 like '%I739%' then 6
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%I790%' then 6
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%Z958%' then 6
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%Z959%' then 6
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%I71%' then 6
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 +  b.diag18 + b.diag19 + b.diag20 like '%R02%' then 6 else 0 end as 'PVD',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%J4[01234567]%' then 4
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%J6[01234567]%' then 4 else 0 end as
'Pulmonary_dis',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%C[01234589]%' then 8
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%C7[0123456]%' then 8
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%C6[023456789]%' then 8 else 0 end as
'Cancer',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%E1[0134][2347]%' then -1 else 0 end
as 'Diab_comp',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%G041%' then 1
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%G820%' then 1
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%G821%' then 1
```

```
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%G822%' then 1
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%G81%' then 1 else 0 end as
'Paraplegia',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%C7[789]%'  then 14 else 0 end as
'Met_ca',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%B2[01234]%'  then 2 else 0 end as
'HIV',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K721%' then 18
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K729%' then 18
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K766%' then 18
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%K767%' then 18 else 0 end as
'Sev_liv',
case when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%I1[23]%' then 10
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 +  b.diag18 + b.diag19 + b.diag20 like '%N0[13]%' then 10
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%N1[89]%' then 10
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%N25%' then 10
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%N05[23456]%' then 10
    when b.diag2 + b.diag3 + b.diag4 + b.diag5 + b.diag6 + b.diag7 + b.diag8 +
b.diag9 + b.diag10 + b.diag11 + b.diag12 + b.diag13 + b.diag14 + b.diag15 + b.diag16 +
b.diag17 + b.diag18 + b.diag19 + b.diag20 like '%N07[234]%' then 10 else 0 end as
'Renal_dis'
from [Frailty Episodes Data] as a
left join [Inpatient table] as b
on a.SPELLNO=b.SPELLNO
```

---Adding diagnosis 1 and 2 to episodes table
```
alter table [Frailty Episodes Data]
add diag1 varchar(10),
    diag2 varchar(10)

update [Frailty Episodes Data]
set diag1 = b.diag1,
    diag2 = b.diag2
from [Frailty Episodes Data] a inner join [Inpatient Table] b
on a.spellno = b.spellno and
   a.epino = b.epino
```

---Making sure everyone is treated at QEHB

```
alter table [Frailty Episodes Data]
add treatment_site varchar(8)

update [Frailty Episodes Data]
set treatment_site = b.treatment_site
from [Frailty Episodes Data] a inner join [Inpatient table] b
on a.unitno= b.unitno and
   a.spellno = b.spellno
```

---Calculating length of admission
```
alter table [Frailty Data 1]
add los int

update [Frailty Data 1]
set los = datediff(dd, spell_adm_date, spell_dis_date)
```

---Selecting only the patients who had an emergency admission and getting their demographics
```
drop table [Frailty Data 2]
select distinct a.unitno,
               a.spellno,
               a.spell_adm_date,
               a.spell_dis_date,
               datediff(dd,a.spell_adm_date,a.spell_dis_date) as los,
               a.newpkey,
               a.age,
               a.sex,
               b.eth_group_cds as ethnos,
              (case when b.eth_group_cds = 'A' or b.eth_group_cds = 'B' or
b.eth_group_cds = 'C' then 'White'
               when b.eth_group_cds = 'D' or b.eth_group_cds = 'E' or b.eth_group_cds =
'F' or b.eth_group_cds = 'G' then 'Mixed'
               when b.eth_group_cds = 'H' or b.eth_group_cds = 'J' or b.eth_group_cds =
'K' or b.eth_group_cds = 'L' then 'Asian or Asian British'
               when b.eth_group_cds = 'M' or b.eth_group_cds = 'N' or b.eth_group_cds =
'P' then 'Black or Black British'
               when b.eth_group_cds = 'R' or b.eth_group_cds = 'S' then 'Any Other Ethnic
Group'
               when b.eth_group_cds = 'Z' or b.eth_group_cds = 'X' or b.eth_group_cds is
null or b.eth_group_cds = '99' then 'Unknown/Other' end) as ethnic_group,
               a.IMD_Score,
               b.Postcode,
              (case when d.GOR = 'E12000001' then 'North East'
                when d.GOR = 'E12000002' then 'North West'
                when d.GOR = 'E12000003' then 'Yorkshire and the Humber'
                when d.GOR = 'E12000004' then 'East Midlands'
                when d.GOR = 'E12000005' then 'West Midlands'
                when d.GOR = 'E12000006' then 'East of England'
                when d.GOR = 'E12000007' then 'London'
                when d.GOR = 'E12000008' then 'South East'
                when d.GOR = 'E12000009' then 'South West'
                when d.GOR = 'M99999999' then 'Isle of Man'
                when d.GOR = 'W99999999' then 'Wales'
                when d.GOR = 'S99999999' then 'Scotland'
                when d.GOR = 'N99999999' then 'Northern Ireland'
                when d.GOR = '' then 'Unknown/Foreign/Nofixedabode' end)
               as [county of residence],
                c.[quintile_1_is_most_deprived] as Quintiles,
                d.GOR
```

```
into [Frailty Data 2]
 from [Frailty Data 1] a
 left join [Inpatient table] b
on a.unitno = b.unitno and a.spellno = b.spellno
 left join [IMD Scores] c on left(a.IMD_score,5) = left(c.[IMD SCORE],5) and
            a.unitno = b.unitno
 left join [Postcode table] d on left(b.postcode,8) = left(d.PCD2,8) and
            a.unitno = b.unitno
where a.ep_type <> 'D' and a.row = 1 and a.admission_method like '2%'
        group by  a.unitno,
                  a.spellno,
                  a.spell_adm_date,
                  a.spell_dis_date,
                  a.los,
                  a.newpkey,
                  a.age,
                  a.sex,
                  b.eth_group_cds,
                  a.IMD_Score,
                  b.Postcode,
                  c.[quintile_1_is_most_deprived],
                  d.GOR
            order by unitno
```

----Updating the deprivation quintiles
```
update [Frailty Data 2]
set quintiles = case when imd_score between 0.476955 and 8.371959
                  then 5
                  when imd_score between 8.372283 and 13.922229
                   then 4
                   when imd_score between 13.923681 and 21.431307
                   then 3
                   when imd_score between 21.432324 and 33.870696
                   then 2
                   when imd_score >33.872607
                  then 1
                   end
```

---Where patients were admitted from
```
alter table [Frailty Data 2]
add adm_source_cds varchar(3)

update [Frailty Data 2]
set adm_source_cds = b.adm_source_cds
from [Frailty Data 2] a inner join final.dbo.all_IP b
on a.spellno = b.spellno
```

---Extracting diagnoses ICD10 codes
```
alter table [Frailty Data 2]
add all_diag varchar(150)

update [Frailty Data 2]
set all_diag = b.all_diag
from [Frailty Data 2] a inner join [Inpatient table] b
on a.unitno = b.UNITNO and
   a.SPELLNO = b.SPELLNO
```

---Adding the exclusion column
```
alter table [Frailty Data 2]
add drop_record int

update [Frailty Data 2]
set drop_record = case when [county of residence] = 'Northern Ireland' or
```

```
                              [county of residence] = 'Isle of Man' or
                              [county of residence] = 'Scotland' or
                              [county of residence] = 'Wales' or
                              [county of residence] = 'Unknown/Foreign/Nofixedabode' then 1
                     when unitno like '1%' or unitno like '2%' then 1 else 0 end
```

----Adding in diagnosis ICD10 codes for admission

```
alter table [Frailty Data 2]
add all_diag varchar(150)

update [Frailty Data 2]
set all_diag = b.all_diag
from [Frailty Data 2] a inner join final.dbo.all_IP b
on a.unitno = b.UNITNO and
   a.SPELLNO = b.SPELLNO
```

---Adding admission source

```
alter table [Frailty Data 2]
add adm_source_cds varchar(3)

update [Frailty Data 2]
set adm_source_cds = b.adm_source_cds
from [Frailty Data 2] a inner join final.dbo.all_IP b
on a.spellno = b.spellno
```

---Getting admission information

```
drop table [Frailty Data 3]
select distinct a.unitno,
                a.spellno,
                b.start_ward,
                a.spell_dis_date,
                c.Description as ward_name,
                b.DD_CDS as Discharge_Destination_code,
                e.Description as Discharge_Destination,
                b.DM_CDS as Discharge_Method_code,
                f.Description as Discharge_Method,
                d.comp_time,
                d.reason_text as admission_reason,
                row_number () over (partition by a.unitno order by d.comp_time asc) rn,
                case when DM_CDS = 4 then 1 else 0 end as 'in_hosp_death',
                case when DD_CDS in (54, 86, 88) then 1 else 0 end as 'dis_to_care_home',
                b.MainSpec
into [Frailty Data 3]
from [Frailty Data 2] a
   left join [Inpatient table] b on a.unitno = b.unitno and
                                    a.spellno = b.spellno and
                                    a.spell_dis_date = b.DISDAT
   left join [Ward table] c on b.start_ward = c.Ward_Number
   left join [Admission reason] d on a.newkey = d.pkey and d.comp_time between
a.spell_adm_date and a.spell_dis_date and d.seq =1
   left join [DisDestLookup] e on b.dd_cds = e.code
   left join [Dismethlookup] f on b.dm_CDS = f.code
 group by a.unitno,
          a.spellno,
          b.start_ward,
          b.DD_CDS,
          c.Description,
          e.description,
          d.reason_text,
          d.comp_time,
          f.Description,
          b.dm_CDS,
          b.MainSpec
```

```
order by unitno
```

---Flag for if they went to the ED
```
alter table [Frailty Data 3]
add [ED] int

update [Frailty Data 3]
set [ED] = 1
from [Frailty Data 3] a inner join [AETable] b
on left(a.unitno,7) = left(b.unitno,7) and
 datediff(dd, b.assessment_time_dttm, a.spell_adm_date) between 0 and 2
```

---More info on ED
```
alter table [Frailty Data 3]
add [ED_Disposal_Meth] nvarchar(80),
    [presenting_complaint] nvarchar(50),
    attendance_no nvarchar(50)

update [Frailty Data 3]
set [ed_disposal_meth] = b.[Disposal_method]
from [Frailty Data 3]  a inner join [AETable] b
on left(a.unitno,7) = left(b.unitno,7) and
   datediff(dd, b.assessment_time_dttm, a.spell_adm_date) between 0 and 2

update [Frailty Data 3]
set presenting_complaint = b.presenting_complaint
from [Frailty Data 3] a inner join [AETable]  b
on left(a.unitno,7) = left(b.unitno,7) and
   datediff(dd, b.assessment_time_dttm, a.spell_adm_date) between 0 and 2

update [Frailty Data 3]
set attendance_no = b.attendance_no
from [Frailty Data 3] a inner join [AETable] b
on left(a.unitno,7) = left(b.unitno,7) and
   datediff(dd, b.assessment_time_dttm, a.spell_adm_date) between 0 and 2

alter table [Frailty Data 3]
add ED_datetime_assessment datetime

update [Frailty Data 3]
set ed_datetime_assessment = b.assessment_time_dttm
from [Frailty Data 3] a inner join [AETable] b
on left(a.unitno,7) = left(b.unitno,7) collate database_default and
   a.attendance_no = b.attendance_no collate database_default
```

---Death Information from local data
```
alter table [Frailty Data 3]
add death_flag int,
    dod datetime

update [Frailty Data 3]
set death_flag = case when b.dod is not null then 1 else 0 end
from [Frailty Data 3] a inner join [Local Patient Table] b
on a.unitno = b.reg collate database_default


update [Frailty Data 3]
set dod = b.dod
from [Frailty Data 3] a inner join [Local Patient Table] b
on a.unitno = b.reg collate database_default
```

---Adding mortality at different time points

```
alter table [Frailty Data 3]
add mort_30_day int,
    mort_6_month int,
    mort_12_month int

update [Frailty Data 3]
set mort_30_day = case when datediff(dd, spell_dis_date, death_check) between 0 and 30 and
death_flag = 1 then 1 else 0 end

update [Frailty Data 3]
set mort_6_month = case when datediff(dd, spell_dis_date, death_check) between 0 and 183
and death_flag = 1 then 1 else 0 end

update [Frailty Data 3]
set mort_12_month = case when datediff(dd, spell_dis_date, death_check) between 0 and 366
and death_flag = 1 then 1 else 0 end
```

---Extracting blood test results

```
drop table #testit
drop table #baselinevalues
; With Data as
(
select
a.pkey,
d.unitno,
a.ikey as test_id,
a.comp_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
b.inv as test,
[status],
b.value,
datediff (d,a.comp_time,d.BloodsLink_DTTM) [Date_Difference],
case when b.inv = 'NA' then 'Sodium'
when b.inv = 'K' then 'Potassium'
when b.inv = 'TCO2' then 'Bicarbonate'
when b.inv = 'UR' then 'Urea'
when b.inv = 'CREAT' then 'Creatinine'
when b.inv like 'EGFR' then 'eGFR'
when b.inv like 'URATE' then 'Urate'
when b.inv = 'CRP' then 'CRP'
when b.inv = 'ALT' then 'ALT'
when b.inv = 'ALKP' or b.inv = 'ALPI' or b.inv = 'ALP1' then 'Alkaline Phosphate'
when b.inv = 'BILI' then 'Bilirubin'
when b.inv = 'GGT' then 'Gamma GT'
when b.inv = 'CA' or b.inv = 'ACA' then 'Calcium'
when b.inv = 'CCA' then 'CorrCalcium'
when b.inv = 'PP' then 'Phosphate'
when b.inv = 'ALB' then 'Albumin'
when b.inv = 'TP' then 'Total_Protein'
when b.inv = 'TRANS' then 'Transferrin'
when b.inv = 'FERR' then 'Ferritin'
when b.inv like 'B12%' then 'B12'
when b.inv = 'FOL' then 'Folate'
when b.inv like 'FT4' then 'FreeT4'
when b.inv like 'FT3' then 'FreeT3'
when b.inv like 'TSH' then 'TSH'
when b.inv like 'GLUC' then 'Glucose'
when b.inv in ('HB', 'HGB') then 'Haemoglobin'
when b.inv like 'HCT' then 'Haematocrit'
when b.inv = 'MCV' then 'MCV'
when b.inv like 'WBC' then 'WCC'
```

```
when b.inv like 'NEUTS' then 'Neutrophils'
when b.inv like 'BASOS' then 'Basophils'
when b.inv like 'EOSINS' then 'Eosinophils'
when b.inv like 'LYMPHS' then 'Lymphocytes'
when b.inv like 'MONOS' then 'Monocytes'
when b.inv like 'PLATS' then 'Plats'
when b.inv like 'INR' then 'INR'
when b.inv = 'WLAPPT' then 'Appt'
when b.inv = 'VDRL' then 'VDRL'
when b.inv = 'CMV' then 'CMV'
when b.inv = 'VITD' then 'Vit_D'
when b.inv like '%PTH%' then 'PTH'
end as [Full Name]
from
#patients d
INNER JOIN [PICStimesdata] a ON d.newpkey = a.pkey
INNER JOIN [PICSresults] b ON a.ikey = b.ikey
where ((datediff(dd, a.comp_time, d.spell_adm_date) between 0 and 2) or
       (convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date)) or
       (datediff(dd, d.spell_dis_date, a.comp_time) between 0 and 2))),
d2 as
(
select distinct pkey, unitno, test_id, test_time, spell_adm_date, spell_dis_date, labno,
ward, test, [status],value, [full name] from data
where UPPER(test) collate latin1_general_ci_as
IN ('NA','K', 'TCO2', 'UR','CREAT', 'EGFR', 'URATE' , 'CRP', 'ALT', 'ALP1', 'ALKP ',
'ALPI', 'BILI', 'GGT', 'CA', 'CCA', 'PP', 'ALB', 'TP', 'TRANS', 'FERR', 'B12', 'B12A',
'FOL', 'FT4','FT3', 'TSH', 'GLUC', 'HB', 'HGB', 'HCT', 'MCV', 'WBC', 'NEUTS',  'BASOS',
'EOSINS', 'LYMPHS', 'MONOS','PLATS', 'INR','WLAPPT', 'VDRL', 'CMV', 'VITD', 'PTH', 'PTH4',
'PTH5') and
 [status] = 'C' and
 test IS NOT NULL
----------------------------------------------------------
SELECT distinct * into #TestIT FROM
d2
```

----Getting test results closest to admission

```
;with Data as
(select *, abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT
),
d2 as (select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew
asc) rn  from data),
D3 AS
(select * from d2 where rn = 1 and  Value <> 'NA')
select [UnitNo],
        Sodium,
        Potassium,
        Bicarbonate,
        Urea,
        Creatinine,
        GFR,
        Urate,
        CRP,
        ALT,
        [Alkaline Phosphate],
        Bilirubin,
        [Gamma GT],
        Calcium,
        CorrCalcium,
        Phosphate,
        Albumin,
        Total_Protein,
```

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```
                Transferrin,
                Ferritin,
                B12,
                Folate,
                ThyroxineT4,
                FreeT4,
                FreeT3,
                TSH,
                Glucose,
                Haemoglobin,
                Haematocrit,
                MCV,
                WCC,
                Neutrophils,
                Basophils,
                Eosinophils,
                Lymphocytes,
                Monocytes,
                Plats,
                INR,
                Appt,
                VDRL,
                CMV,
                Vit_D,
                PTH
into #BaselineValues
from
(select [UnitNo], [Full Name], [Value] from  d3)
p pivot (max ([Value]) for [Full Name]
in (Sodium,
        Potassium,
        Bicarbonate,
        Urea,
        Creatinine,
        GFR,
        Urate,
        CRP,
        ALT,
        [Alkaline Phosphate],
        Bilirubin,
        [Gamma GT],
        Calcium,
        CorrCalcium,
        Phosphate,
        Albumin,
        Total_Protein,
        Transferrin,
        Ferritin,
        B12,
        Folate,
        ThyroxineT4,
        FreeT4,
        FreeT3,
        TSH,
        Glucose,
        Haemoglobin,
        Haematocrit,
        MCV,
        WCC,
        Neutrophils,
        Basophils,
        Eosinophils,
        Lymphocytes,
        Monocytes,
        Plats,
        INR,
```

```
        Appt,
        VDRL,
        CMV,
        Vit_D,
        PTH)) as pvt


Drop table #Minmax

Select n.UnitNo,
        n.[Full Name],
        min(CONVERT(FLOAT,(n.[value]))) as min_Num,
        max(Convert(FLOAT,(n.[value]))) as max_Num
into #MinMax
from    -- Numerator
        (Select UnitNo,
                [Full Name],
                [value],
                row_number() over(partition by UnitNo, [Full Name] order by [value] asc) +
0e0 as ord
from #TestIT) as n,
            -- Denominator
            (Select UnitNo,
                    [Full Name],
                     count(*)+1e0 as nplus1
from #TestIT
        group by UnitNo,
                  [Full Name]) as d
where n.UnitNo = d.UnitNo and
        n.[Full Name] = d.[Full Name] and
        [Value] not in ('NA','<3','<5', '<1.0', '>90', '<60', '>2000', '>20.00',
'<0.02','.', '<14') and ISNUMERIC (n.[value]) = 1
group by n.UnitNo, n.[Full Name]
ORDER BY UnitNo
```

---Creating table with baseline blood results
```
drop table [Blood Results]
create table [Blood Results]
([UnitNo] varchar(20),
 baseline_num_sodium varchar(100),
 baseline_num_potassium varchar(100),
 baseline_num_bicarbonate varchar(100),
 baseline_num_urea varchar(100),
 baseline_num_creatinine varchar(100),
 baseline_num_GFR varchar(100),
 baseline_num_Urate varchar(100),
 baseline_num_CRP varchar(100),
 baseline_num_ALT varchar(100),
 baseline_num_Alkaline_Phosphate varchar(100),
 baseline_num_Bilirubin varchar(100),
 baseline_num_Gamma_GT varchar(100),
 baseline_num_calcium  varchar(100),
 baseline_num_corr_calcium varchar(100),
 baseline_num_phosphate varchar(100),
 baseline_num_albumin varchar(100),
 baseline_num_total_protein varchar(100),
 baseline_num_transferrin varchar(100),
 baseline_num_ferritin varchar(100),
 baseline_num_B12 varchar(100),
 baseline_num_folate varchar(100),
 baseline_num_thyroxine_T4 varchar(100),
 baseline_num_FreeT4 varchar(100),
 baseline_num_FreeT3 varchar(100),
 baseline_num_TSH varchar(100),
```

```sql
    baseline_num_Glucose varchar(100),
    baseline_num_haemoglobin varchar(100),
    baseline_num_haematocrit varchar(100),
    baseline_num_MCV varchar(100),
    baseline_num_WCC  varchar(100),
    baseline_num_Neutrophils  varchar(100),
    baseline_num_Basophils  varchar(100),
    baseline_num_Eosinophils  varchar(100),
    baseline_num_lymphocytes  varchar(100),
    baseline_num_monocytes  varchar(100),
    baseline_num_Plats  varchar(100),
    baseline_num_INR  varchar(100),
    baseline_num_Appt  varchar(100) ,
    baseline_num_VDRL  varchar(100),
    baseline_num_CMV  varchar(100),
    baseline_num_Vit_D  varchar(100),
    baseline_num_PTH  varchar(100))

insert into [Blood Results]
select pvt.[UnitNo],
        a.baseline_num_sodium,
        a.baseline_num_potassium,
        a.baseline_num_bicarbonate,
        a.baseline_num_urea,
        a.baseline_num_creatinine,
        a.baseline_num_GFR,
        a.baseline_num_Urate,
        a.baseline_num_CRP,
        a.baseline_num_ALT,
        a.baseline_num_Alkaline_Phosphate,
        a.baseline_num_Bilirubin,
        a.baseline_num_Gamma_GT,
        a.baseline_num_calcium,
        a.baseline_num_corr_calcium,
        a.baseline_num_phosphate,
        a.baseline_num_albumin,
        a.baseline_num_total_protein,
        a.baseline_num_transferrin,
        a.baseline_num_ferritin,
        a.baseline_num_B12,
        a.baseline_num_folate,
        a.baseline_num_thyroxine_T4,
        a.baseline_num_FreeT4,
        a.baseline_num_FreeT3,
        a.baseline_num_TSH,
        a.baseline_num_Glucose,
        a.baseline_num_haemoglobin,
        a.baseline_num_haematocrit,
        a.baseline_num_MCV,
        a.baseline_num_WCC,
        a.baseline_num_Neutrophils,
        a.baseline_num_Basophils,
        a.baseline_num_Eosinophils,
        a.baseline_num_lymphocytes,
        a.baseline_num_monocytes,
        a.baseline_num_Plats,
        a.baseline_num_INR,
        a.baseline_num_Appt,
        a.baseline_num_VDRL,
        a.baseline_num_CMV,
        a.baseline_num_Vit_D,
        a.baseline_num_PTH
from (select [UnitNo], [Full Name], [NewMax_Num] from  d7) as p
pivot
(max ([NewMax_Num]) for [Full Name]
in (Sodium,
```

```sql
            Potassium,
            Bicarbonate,
            Urea,
            Creatinine,
            GFR,
            Urate,
            CRP,
            ALT,
            [Alkaline Phosphate],
            Bilirubin,
            [Gamma GT],
            Calcium,
            CorrCalcium,
            Phosphate,
            Albumin,
            Total_Protein,
            Transferrin,
            Ferritin,
            B12,
            Folate,
            ThyroxineT4,
            FreeT4,
            FreeT3,
            TSH,
            Glucose,
            Haemoglobin,
            Haematocrit,
            MCV,
            WCC,
            Neutrophils,
            Basophils,
            Eosinophils,
            Lymphocytes,
            Monocytes,
            Plats,
            INR,
            Appt,
            VDRL,
            CMV,
            Vit_D,
            PTH)) as pvt
    left join
    (select [UnitNo],
            Sodium as baseline_num_sodium,
            Potassium as baseline_num_potassium,
            Bicarbonate as baseline_num_bicarbonate,
            Urea as baseline_num_urea,
            Creatinine as baseline_num_creatinine,
            GFR as baseline_num_GFR,
            Urate as baseline_num_Urate,
            CRP as baseline_num_CRP,
            ALT as baseline_num_ALT,
            [Alkaline Phosphate] as baseline_num_Alkaline_Phosphate,
            Bilirubin as baseline_num_Bilirubin,
            [Gamma GT] as baseline_num_Gamma_GT,
            Calcium as baseline_num_calcium,
            CorrCalcium as baseline_num_corr_calcium,
            Phosphate as baseline_num_phosphate,
            Albumin as baseline_num_albumin,
            Total_Protein as baseline_num_total_protein,
            Transferrin as baseline_num_transferrin,
            Ferritin as baseline_num_ferritin,
            B12 as baseline_num_B12,
            Folate as baseline_num_folate,
            ThyroxineT4 as baseline_num_thyroxine_T4,
            FreeT4 as baseline_num_FreeT4,
```

```
            FreeT3 as baseline_num_FreeT3,
            TSH as baseline_num_TSH,
            Glucose as baseline_num_Glucose,
            Haemoglobin as baseline_num_haemoglobin,
            Haematocrit as baseline_num_haematocrit,
            MCV as baseline_num_MCV,
            WCC as baseline_num_WCC,
            Neutrophils as baseline_num_Neutrophils,
            Basophils as baseline_num_Basophils,
            Eosinophils as baseline_num_Eosinophils,
            Lymphocytes as baseline_num_lymphocytes,
            Monocytes as baseline_num_monocytes,
            Plats as baseline_num_Plats,
            INR as baseline_num_INR,
            Appt as baseline_num_Appt,
            VDRL as baseline_num_VDRL,
            CMV as baseline_num_CMV,
            Vit_D as baseline_num_Vit_D,
            PTH as baseline_num_PTH
from (select [UnitNo],
             [Full Name],
             BaselineValue from d7) p
 pivot
 (max (BaselineValue) for [Full Name]
 in (Sodium,
      Potassium,
      Bicarbonate,
     Urea,
     Creatinine,
     GFR,
     Urate,
     CRP,
     ALT,
     [Alkaline Phosphate],
     Bilirubin,
     [Gamma GT],
     Calcium,
     CorrCalcium,
     Phosphate,
     Albumin,
     Total_Protein,
     Transferrin,
     Ferritin,
     B12,
     Folate,
     ThyroxineT4,
     FreeT4,
     FreeT3,
     TSH,
     Glucose,
     Haemoglobin,
     Haematocrit,
     MCV,
     WCC,
     Neutrophils,
     Basophils,
     Eosinophils,
     Lymphocytes,
     Monocytes,
     Plats,
     INR,
     Appt,
     VDRL,
     CMV,
     Vit_D,
     PTH)) as pvt) a
```

```
on pvt.UnitNo = a.UnitNo
```

---Extracting waterlow score
```
drop table #testit
; With Data as
(
select
a.pkey,
d.unitno,
a.ikey as test_id,
a.start_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
b.inv as test,
[status],
b.value,
case when b.inv = 'WLSCORE' then 'Waterlow_Score'
        when b.inv = 'WLSKBS'  then 'Broken Spot'
        when b.inv = 'WLSKDC'  then 'Discoloured'
        when b.inv = 'WLSKDRY' then 'Dry'
        when b.inv = 'WLSKHEAL'then 'Healthy'
        when b.inv = 'WLSKOED' then 'Oedematous'
        when b.inv = 'WLSKTP'  then 'Tissue Paper'
        when b.inv = 'WLSMOKE' then 'Smoking'
        when b.inv = 'WLNDIAB' then 'Diabetes'
        when b.inv = 'WLULCER' then 'Grade of most sev PU'
        when b.inv = 'WLUNUMB' then 'No. PU'
        when b.inv = 'WLCONT'  then 'Continence'
end as [Full Name],
f.line,
f.txt
from [Frailty Data 2] d
INNER JOIN [PICStimesdata] a ON d.newpkey = a.pkey
INNER JOIN [PICSresults] b ON a.ikey = b.ikey
left join [PICSannotatedinv] as ikey on a.ikey = ikey.ikey and b.inv = ikey.inv
left join [PICSannotatedtext] f on ikey.agkey = f.agkey
where convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date)),
d2 as
(select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno,
                ward,
                test,
                [status],
                case when value = 'Yes' then 1
                    when value = 'No'  then 0
                    when value = 'N/A' then 0
                    when test like 'WLULCER' and value = 'No' then 0
                    when test like 'WLULCER' and value = '1' then 1
                    when test like 'WLULCER' and value = '2' then 2
                   when test like 'WLULCER' and value = '3' then 3
                    when test like 'WLULCER' and value = '4' then 4
                    when test like 'WLULCER' and value = 'DTI' then 5
                    when value = '.'   then 0
                    when value = '00' then 0
                    when value = '01' then 1
                    when value = 'NA' then 0 else value end as 'Value',
```

```
                            [full name],
                            line,
                            txt from data
 where upper(test) collate latin1_general_ci_as
IN ('WLSCORE','WLSKBS','WLSKCL','WLSKDC', 'WLSKDRY', 'WLSKHEAL', 'WLSKOED', 'WLSKTP',
'WLSMOKE', 'WLULCER','WLNDIAB', 'WLUNUMB', 'WLCONT') and
[status] = 'C' and
test IS NOT NULL)
SELECT distinct * into #TestIT FROM
d2

drop table #data
drop table #BaselineValues
;with Data as
(select pkey, unitno, test_id, test_time, spell_adm_date, spell_dis_date, value, [full
name], abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT),
d2 as
(select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew asc) rn
from data),
d3 AS
(select * from d2 where rn = 1)

select [UnitNo],
       [Waterlow_Score],
       [Broken Spot],
       [Clammy, Pyrexia],
       [Discoloured],
       [Dry],
       [Healthy],
       [Oedematous],
       [Tissue Paper],
       [Smoking],
       [Diabetes],
       [Pressure Ulcer Locations],
       [Grade of most sev PU],
       [No. PU],
       [Continence]
into #BaselineValues
from
(select [UnitNo], [Full Name], [Value]
       from d3) p
pivot (max([Value]) for [Full Name]
       in
       ([Waterlow_Score],
        [Broken Spot],
        [Clammy, Pyrexia],
        [Discoloured],
        [Dry],
        [Healthy],
        [Oedematous],
        [Tissue Paper],
        [Smoking],
        [Diabetes],
        [Pressure Ulcer Locations],
        [Grade of most sev PU],
        [No. PU],
        [Continence])
) as pvt
```

---Creating table for waterlow

```
drop table [Waterlow Table]
create table [Waterlow Table]
(unitno varchar(20),
pkey varchar(20),
```

```
[baseline_Waterlow_Score] int,
[baseline_Broken Spot] int,
[baseline_Clammy, Pyrexia] int,
[baseline_Discoloured] int,
[baseline_Dry] int,
[baseline_Healthy] int,
[baseline_Oedematous] int,
[baseline_Tissue Paper] int,
[baseline_Smoking] int,
[baseline_Diabetes] int,
[baseline_Grade of most sev PU] int,
[baseline_No. PU] int,
[baseline_Continence] int
)

insert into [Waterlow Table]
(unitno,
pkey,
[baseline_Waterlow_Score],
[baseline_Broken Spot],
[baseline_Clammy, Pyrexia],
[baseline_Discoloured],
[baseline_Dry],
[baseline_Healthy],
[baseline_Oedematous],
[baseline_Tissue Paper],
[baseline_Smoking],
[baseline_Diabetes],
[baseline_Grade of most sev PU],
[baseline_No. PU],
[baseline_Continence])

select
t1.unitno,
t1.newpkey as pkey,
t2.[Waterlow_Score],
t2.[Broken Spot],
t2.[Clammy, Pyrexia],
t2.[Discoloured],
t2.[Dry],
t2.[Healthy],
t2.[Oedematous],
t2.[Tissue Paper],
t2.[Smoking],
t2.[Diabetes],
t2.[Grade of most sev PU],
t2.[No. PU],
t2.[Continence]
from [Frailty Data 2] t1 left join #BaselineValues t2
on t1.unitno = t2.unitno
```

---Extracting Thrombosis Score
```
drop table #testit
; With Data as
(
select
a.pkey,
d.unitno,
a.ikey as test_id,
a.start_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
```

```sql
b.inv as test,
[status],
b.value,
datediff (d,a.comp_time,d.spell_adm_date) [Date_Difference],
case when b.inv = 'THRSCORE'  then 'Thrombosis_score'
        end as [Full Name]
into #datatest
from
#patients d
INNER JOIN PICSaudit.dbo.Ikey_date_range a ON d.newpkey = a.pkey
INNER JOIN PICSaudit.dbo.IkeyResult b ON a.ikey = b.ikey
where convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date) and
        b.tst in ('THRSCORE')),
d2 as
(select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno,
                ward,
                test,
                [status],
                value,
                [Date_Difference],
                [full name]
from data where UPPER(test) collate latin1_general_ci_as
IN
('THRSCORE') and
[status] = 'C' and
test IS NOT NULL
union all
select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno,
                ward,
                test,
                [status],
case when left(value,1) = '<' then replace(value, '<','') when Value = 'NA' then null else
value end,
[Date_difference],
[full name]
from data
where UPPER(test) collate latin1_general_ci_as
IN
('THRSCORE') and
[status] = 'C' and test IS NOT NULL)


select distinct * into #TestIT FROM data

;with Data as
(select *, abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT),
d2 as
(select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew asc) rn
from data),
d3 as (select * from d2 where rn = 1 and  Value <> 'NA')

select [UnitNo],
       Thrombosis_score
```

```
into #BaselineValues
from
(select [UnitNo],
        [Full Name],
        [Value]
from d3) p
pivot (max ([Value]) for [Full Name] in (Thrombosis_score)) as pvt


drop table [Thrombosis Table]
create table [Thrombosis Table]
 (Unitno varchar(20),
  thrombosis_score varchar(250))

insert into [Thrombosis Table]
 (unitno,
 thrombosis_score)
select * from #BaselineValues
```

---Extracting MUST score
```
drop table #testit
; With Data as
(
select
a.pkey,
d.unitno,
a.ikey as test_id,
a.start_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
b.inv as test,
[status],
b.value,
datediff (d,a.comp_time,d.spell_adm_date) [Date_Difference],
case when b.inv = 'MUSTSCORE'  or b.inv like 'PNUTSCORE' then 'MUST_Score'
     when b.inv = 'HAEWTLOSS' or b.inv like 'MUSTWLOSS' or b.inv like 'PNUTWGHT' then
'Weight_loss'
     when b.inv like 'MUSTILL' then 'Acute_Illness_Effect'
     end as [Full Name]
into #datatest
from
#patients d
INNER JOIN PICSaudit.dbo.Ikey_date_range a ON d.newpkey = a.pkey
INNER JOIN PICSaudit.dbo.IkeyResult b ON a.ikey = b.ikey
where convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date) and b.tst in ('MUSTSCORE', 'PNUTSCORE', 'HAEWTLOSS',
'MUSTWLOSS', 'PNUTWGHT', 'MUSTILL')),
d2 as (select distinct pkey,
                       UnitNo,
                       test_id,
                       test_time,
                       spell_adm_date,
                       spell_dis_date,
                       labno,
                       ward,
                       test,
                       [status],
                       value,
                       [Date_Difference],
                       [full name]
from data where UPPER(test) collate latin1_general_ci_as
```

```
IN
('MUSTSCORE', 'PNUTSCORE', 'HAEWTLOSS', 'MUSTWLOSS', 'PNUTWGHT', 'MUSTILL') and
 [status] = 'C' and
 test IS NOT NULL
union all
select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno, ward,
                test,
                [status],
case when left(value,1) = '<' then replace(value, '<','') when Value = 'NA' then null else
value end,
                [Date_difference],
                [full name]
from data where  UPPER(test) collate latin1_general_ci_as
IN
('MUSTSCORE', 'PNUTSCORE', 'HAEWTLOSS', 'MUSTWLOSS', 'PNUTWGHT', 'MUSTILL')
        and [status] = 'C'
        and test IS NOT NULL)

select distinct * into #TestIT FROM data


;with Data as
(select *, abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT),
d2 as
(select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew asc) rn
from data),
d3 AS
(select * from d2 where rn = 1 and  Value <> 'NA')

select [UnitNo],
        MUST_score,
        Weight_loss,
        Acute_Illness_Effect
into #BaselineValues
from
(select [UnitNo], [Full Name], [Value] from  d3)   p
pivot (max ([Value])  for [Full Name] in
        (MUST_score,
         Weight_loss,
         Acute_Illness_Effect)) as pvt


drop table [MUSTTable]
create table [MUSTTable]
(Unitno varchar(20),
 [MUST_score] varchar(250),
 [Weight_loss] varchar(250),
 Acute_Illness_Effect varchar(250)
 )

insert into [MUSTTable]
(unitno,
 [MUST_score],
 [Weight_loss],
 Acute_Illness_Effect)
select * from #BaselineValues
```

---Extracting Movement Score

```sql
drop table #testit
; With Data as
(
select
a.pkey,
d.unitno,
a.ikey as test_id,
a.start_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
b.inv as test,
[status],
b.value,
datediff (d,a.comp_time,d.spell_adm_date) [Date_Difference],
case when b.inv = 'PHAMOVE'  then 'Movement_Score' end as [Full Name]
into #datatest from #patients d
INNER JOIN [PICStimesdata] a ON d.newpkey = a.pkey
INNER JOIN [PICSresults] b ON a.ikey = b.ikey

where convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date) and b.tst in ('PHAMOVE')),
d2 as
(select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno,
                ward,
                test,
                [status],
                value,
                [Date_Difference],
                [full name]
from data where UPPER(test) collate latin1_general_ci_as
IN ('PHAMOVE') and
    [status] = 'C' and
     test IS NOT NULL
union all
select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno,
                ward,
                test,
                [status],
case when left(value,1) = '<' then replace(value, '<','') when Value = 'NA' then null else
value end,
                [Date_difference],
                [full name]
from data where UPPER(test) collate latin1_general_ci_as
IN ('PHAMOVE') and
    [status] = 'C' and
    test IS NOT NULL)


select distinct * into #TestIT FROM data

;with Data as
(select *, abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT),
```

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```
d2 as (select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew
asc) rn from data),
d3 AS
(select * from d2 where rn = 1 and  Value <> 'NA')

select [UnitNo],
       Movement_Score
into #BaselineValues
from
(select [UnitNo], [Full Name], [Value] from d3) p
pivot (max ([Value])  for [Full Name] in (Movement_score)) as pvt


drop table [MovementScoreTable]
create table [MovementScoreTable]
(Unitno varchar(20),
 movement_score varchar(250))

insert into [MovementScoreTable]
(unitno,
 movement_score)
select * from #BaselineValues
```

---Extracting haemodynamics data

```
drop table #baselinevalues
drop table #testit
; With Data as
(
select
a.pkey,
d.unitno,
a.ikey as test_id,
a.start_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
b.inv as test,
[status],
b.value,
datediff (d,a.comp_time,d.spell_adm_date) [Date_Difference],
case when b.inv = 'BPSYS'  then 'Systolic_BP'
when b.inv = 'BPDIA'  then 'Diastolic_BP'
when b.inv = 'HR' then 'Heart_Rate'
end as [Full Name]
into #datatest
from
#patients d
INNER JOIN [PICStimesdata] a ON d.newpkey = a.pkey
INNER JOIN [PICSresults] b ON a.ikey = b.ikey
where convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date) and
      b.tst in ('BPSYS','BPDIA','HR')),
d2 as
(select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno,
                ward,
                test,
                [status],
```

```
                    value,
                    [Date_Difference],
                    [full name]
from data where UPPER(test) collate latin1_general_ci_as
IN ('BPSYS','BPDIA','HR') and
    [status] = 'C' and
    test IS NOT NULL
union all
select distinct pkey,
                    UnitNo,
                    test_id,
                    test_time,
                    spell_adm_date,
                    spell_dis_date,
                    labno,
                    ward,
                    test,
                    [status],
case when left(value,1) = '<' then replace(value, '<','') when Value = 'NA' then null else
value end,
                    [Date_difference],
                    [full name]
from data where UPPER(test) collate latin1_general_ci_as
IN ('BPSYS','BPDIA','HR') and
    [status] = 'C' and
    test IS NOT NULL)


select distinct * into #TestIT FROM data

;with Data as
(select *, abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT),

d2 as
(select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew asc) rn
from data),
d3 as
(select * from d2 where rn = 1 and  Value <> 'NA')

select [UnitNo],
       Systolic_BP,
       Diastolic_BP,
       Heart_Rate
into #BaselineValues
from
(select [UnitNo],
        [Full Name],
        [Value] from d3) p pivot
(max ([Value]) for [Full Name] in
       (Systolic_BP,
        Diastolic_BP,
        Heart_Rate)) as pvt

Drop table #Minmax

Select n.UnitNo,
       n.[Full Name],
       min(CONVERT(FLOAT,(n.[value]))) as min_Num,
       max(Convert(FLOAT,(n.[value]))) as max_Num
into #MinMax
from    -- Numerator
       (Select UnitNo,
               [Full Name],
               [value],
```

```sql
                row_number() over(partition by UnitNo, [Full Name] order by [value] asc) +
0e0 as ord
    from #TestIT) as n,
          -- Denominator
          (Select UnitNo,
                [Full Name],
                count(*)+1e0 as nplus1
        from #TestIT group  by UnitNo,[Full Name]) as d
where n.UnitNo = d.UnitNo and
      n.[Full Name] = d.[Full Name] and
      [Value] NOT IN ('NA','<3','<5', '<1.0', '>90', '<60', '>2000', '>20.00',
'<0.02','.', '<14') and
      ISNUMERIC (n.[value]) = 1
group by n.UnitNo, n.[Full Name]
ORDER BY UnitNo

drop table [BPHRTable]
create table BPHRTable
(Unitno varchar(20),
 baseline_num_Systolic_BP int,
 baseline_num_Diastolic_BP int,
 baseline_num_HR int)


 drop table #Data
Select t1.*,
       t2.Systolic_BP,
       t2.Diastolic_BP,
       t2.Heart_Rate
into #Data
from #MinMax t1 left join #BaselineValues t2 on t1.UnitNo = t2.unitno


; with data as
(select *,
case when [Full Name] = 'Systolic_BP' THEN
convert(int,pics.dbo.udf_GetNumeric([Systolic_BP])) END AS RealNumberSystolicBP,
case when [Full Name] = 'Diastolic_BP' THEN
convert(int,pics.dbo.udf_GetNumeric([Diastolic_BP])) END AS RealNumberDiastolicBP,
case when [Full Name] = 'Heart_Rate' THEN
convert(int,pics.dbo.udf_GetNumeric([Heart_Rate])) END AS RealNumberHeartRate
from #Data
),

d2 as
(select *,
case when RealNumberSystolicBP > Max_Num and [Full Name] = 'SystolicBP'  then
convert(float,RealNumberSystolicBP/10.0) end as NewRealNumberSystolicBP,
case when RealNumberDiastolicBP > Max_Num and [Full Name] = 'DiastolicBP'  then
convert(float,RealNumberDiastolicBP/10.0) end as NewRealNumberDiastolicBP,
case when RealNumberHeartRate > Max_Num and [Full Name] = 'HeartRate'  then
convert(float,RealNumberHeartRate/10.0) end as NewRealNumberHeartRate
from data),
d3 as
(select UnitNo,
       [Full Name],
       Min_Num,
       Max_Num,
        [RealNumberSystolicBP],
       NewRealNumberSystolicBP,
        [RealNumberDiastolicBP],
       NewRealNumberDiastolicBP,
        [RealNumberHeartRate],
       NewRealNumberHeartRate from d2),
d4 as
(select UnitNo,
```

```
        [Full Name],
        Min_Num,
        Max_Num,
case when [Full Name] = 'Systolic_BP' and NewRealNumberSystolicBP is null then
[RealNumberSystolicBP] else NewRealNumberSystolicBP end as Systolic_BP,
case when [Full Name] = 'Diastolic_BP' and NewRealNumberDiastolicBP is null then
[RealNumberDiastolicBP] else NewRealNumberDiastolicBP end as Diastolic_BP,
case when [Full Name] = 'Heart_Rate' and NewRealNumberHeartRate is null then
[RealNumberHeartRate] else NewRealNumberHeartRate end as Heart_Rate
from d3),
d5 as
(select UnitNo,
        [Full Name],
        Min_Num,
        Max_Num,
case when Systolic_BP is not null then Systolic_BP
        when Diastolic_BP is not null then Diastolic_BP
        when Heart_Rate is not null then Heart_Rate
        end as [BaselineValue]
from d4),
d6 as
(select *, Max_num - BaselineValue as PeakIncrease
from d5),
d7 as
(select *, case when  PeakIncrease <0 then  BaselineValue else Max_Num end as NewMax_Num
from d6),
d8 as
(select UnitNo,
        [Full Name],
        Min_Num,
        NewMax_Num,
        BaselineValue,
case when BaselineValue < Min_Num then Min_Num when BaselineValue > NewMax_Num then
NewMax_Num else BaselineValue end as NewBaseline
from d7)


insert into [BPHRTable]
select pvt.[UnitNo],
      a.baseline_num_Systolic_BP,
       a.baseline_num_Diastolic_BP,
       a.baseline_num_Heart_Rate,
from
(select [UnitNo], [Full Name], [NewMax_Num] from  d7) as p
pivot
(max ([NewMax_Num]) for [Full Name] in
      (Systolic_BP,
       Diastolic_BP,
       Heart_Rate)) as pvt
left join
(select [UnitNo],
        Systolic_BP as baseline_num_Systolic_BP,
        Diastolic_BP as baseline_num_Diastolic_BP,
        Heart_Rate as baseline_num_Heart_Rate
from (select [UnitNo],
            [Full Name],
            BaselineValue from d7) p
 pivot
(max (BaselineValue)  for [Full Name]
in (Systolic_BP,
    Diastolic_BP,
    Heart_Rate)) as pvt) a
              on pvt.UnitNo = a.UnitNo
```

---Falls score

```
drop table #baselinevalues
drop table #testit
; With Data as
(select
a.pkey,
d.unitno,
a.ikey as test_id,
a.start_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
b.inv as test,
[status],
b.value,
datediff (d,a.comp_time,d.spell_adm_date) [Date_Difference],
case when b.inv = 'FLHIST'  or b.inv like 'NUHISFALL' then 'Hx 1 or more falls'
     when b.inv = 'FLFALL' then 'Fall since adm'
         when b.inv like 'FLWALK' then 'Is unsteady'
         when b.inv like 'FLFEAR' then 'anxious about falling'
         when b.inv like 'FLNEW' or b.inv like 'NEWFALL' then 'New Fall'
         when b.inv like 'FLSCORE' then 'Fall score'
end as [Full Name]
into #datatest
from #patients d
INNER JOIN PICSaudit.dbo.Ikey_date_range a ON d.newpkey = a.pkey
INNER JOIN PICSaudit.dbo.IkeyResult b ON a.ikey = b.ikey
where convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date)
and b.tst in ('FLHIST', 'NUHISFALL', 'FLFALL', 'FLWALK', 'FLFEAR', 'FLNEW', 'NEWFALL',
'FLSCORE')),
d2 as
(select distinct pkey,  UnitNo, test_id, test_time, spell_adm_date, spell_dis_date, labno,
ward, test, [status],value, [Date_Difference], [full name] from data where
UPPER(test) collate latin1_general_ci_as IN
('FLHIST', 'NUHISFALL', 'FLFALL', 'FLWALK', 'FLFEAR', 'FLNEW', 'NEWFALL', 'FLSCORE') and
[status] = 'C' and
test IS NOT NULL
union all
select distinct pkey,
                UnitNo,
                test_id,
                test_time,
                spell_adm_date,
                spell_dis_date,
                labno,
                ward,
                test,
                [status],
                case when left(value,1) = '<' then replace(value, '<','') when Value = '
'NA' then null else value end, [Date_difference], [full name]
                from data
where UPPER(test) collate latin1_general_ci_as
IN ('FLHIST', 'NUHISFALL', 'FLFALL', 'FLWALK', 'FLFEAR', 'FLNEW', 'NEWFALL', 'FLSCORE') and
[status] = 'C'
and test IS NOT NULL)

select distinct * into #TestIT FROM data

;with Data as
(select *, abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT),
d2 as
(select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew asc) rn
from data),

d3 AS
```

```
(select * from d2 where rn = 1 and  Value <> 'NA')

select [UnitNo],
       [Hx 1 or more falls],
       [Fall since adm],
       [Is unsteady],
       [anxious about falling],
       [New Fall],
       [Fall score]
into #BaselineValues
from
(select [UnitNo], [Full Name], [Value] from  d3) p
 pivot (max ([Value]) for [Full Name]
in     ([Hx 1 or more falls],
       [Fall since adm],
       [Is unsteady],
       [anxious about falling],
       [New Fall],
       [Fall score])) as pvt




drop table [Falls Table]
create table [Falls Table]
 (Unitno varchar(20),
 [Hx 1 or more falls] varchar(250),
 [Fall since adm] varchar(250),
 [Is unsteady] varchar(250),
 [anxious about falling] varchar(250),
 [New Fall] varchar(250),
 [Fall score] varchar(250))




insert into [Falls Table]
 (unitno,
 [Hx 1 or more falls],
 [Fall since adm],
 [Is unsteady],
 [anxious about falling],
 [New Fall],
 [Fall score])

alter table [Falls Table]
add history_of_falls int

update [Falls Table]
set history_of_falls = case when [Hx 1 or more falls] = 'at risk of falls' then 1
                           when [Hx 1 or more falls] = 'fall at home' then 1
                           when [Hx 1 or more falls] = 'Falls risk indicated' then 1
                           when [Hx 1 or more falls] = 'high risk of falls' then 1
                           when [Hx 1 or more falls] = 'Indicated at risk of falls,
family assisting with mobilisation on discharge for safety' then 1
                           when [Hx 1 or more falls] = 'patient is at risk of falls'
then 1
                           when [Hx 1 or more falls] = 'Patient is at risk of falls,
admitted due to a fall however no falls on this admission.' then 1
                           when [Hx 1 or more falls] = 'Patient is mobile with his
stick.  He is at risk of falls.' then 1
                           when [Hx 1 or more falls] = 'previous falls' then 1
                           when [Hx 1 or more falls] = 'Pt admitted post fall, no falls
during admission. No concerns with mobilising.' then 1
                           when [Hx 1 or more falls] = 'Pt is at risk of falls.' then 1
                           when [Hx 1 or more falls] = 'The lastest fall assessment
suggests that patient is at risk of fall.' then 1
                           when [Hx 1 or more falls] like 'Y%' then 1
```

```
                                                                 else 0 end
```

---Extracting data for dementia

```
drop table #baselinevalues
drop table #testit
; With Data as
(select
a.pkey,
d.unitno,
a.ikey as test_id,
a.start_time as test_time,
d.Spell_adm_date,
d.spell_dis_date,
a.specimen_id as labno,
a.location as ward,
b.inv as test,
[status],
b.value,
datediff (d,a.comp_time,d.spell_adm_date) [Date_Difference],
case when b.inv = 'DEMFOROTH'  then 'Dementia'
end as [Full Name]
into #datatest
from
#patients d
INNER JOIN PICSaudit.dbo.Ikey_date_range a ON d.newpkey = a.pkey
INNER JOIN PICSaudit.dbo.IkeyResult b ON a.ikey = b.ikey
where convert(DATE,a.start_time) BETWEEN CONVERT(DATE,d.spell_adm_date) and
CONVERT(DATE,d.spell_dis_date) and
b.tst in ('DEMFOROTH')),
d2 as
(select distinct pkey,
               UnitNo,
               test_id,
               test_time,
               spell_adm_date,
               spell_dis_date,
               labno,
               ward,
               test,
               [status],
               value,
               [Date_Difference],
               [full name]
from data where UPPER(test) collate latin1_general_ci_as
IN ('DEMFOROTH') and
[status] = 'C' and
test IS NOT NULL
union all
select distinct pkey,
               UnitNo,
               test_id,
               test_time,
               spell_adm_date,
               spell_dis_date,
               labno,
               ward,
               test,
               [status],
               case when left(value,1) = '<' then replace(value, '<','') when Value = 'NA'
then null else value end,
               [Date_difference],
               [full name]
from data where
UPPER(test) collate latin1_general_ci_as
```

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```
IN ('DEMFOROTH') and
    [status] = 'C' and
     test IS NOT NULL)

select distinct * into #TestIT FROM data

;with Data as
(select *, abs(convert(int,test_time - spell_adm_date)) as DatediffNew from #TestIT),
d2 as
(select *, row_number() over (partition by UnitNo, [Full Name] order by Datediffnew asc) rn
from data),

d3 AS
(select * from d2 where rn = 1 and  Value <> 'NA')

select [UnitNo],
       Dementia
into #BaselineValues
from
(select [UnitNo], [Full Name], [Value] from  d3) p
pivot (max ([Value])  for [Full Name] in
       (Dementia)) as pvt

drop table [Dementia Table]
create table [Dementia Table]
 (Unitno varchar(20),
 Dementia varchar(250),
 Dementia_diag int)

insert into [Dementia Table]
(unitno,
dementia)
select * from #BaselineValues
```

---Creating a table with reference ranges

```
drop table [reference range table]
create table [reference range table]
(Inv nvarchar(255),
 Full_Name nvarchar(255),
 unit nvarchar(255),
 sex char(2),
 lower_age float,
 upper_age float,
 lower_boundary numeric(10,2),
 upper_boundary numeric(10,2),
 abnormal decimal(2,2))

 insert into [reference range table]
 values    ('N', 'Sodium', 'mmol/L', 'M', '0', '120', 134, 147, 0),
           ('N', 'Sodium', 'mmol/L', 'F', '0', '120', 134, 147, 0),
           ('K', 'Potassium', 'mmol/L', 'M', '0', '120', 3.4, 5.2, 0),
           ('K', 'Potassium', 'mmol/L', 'F', '0', '120', 3.4, 5.2, 0),
           ('UR', 'Urea', 'mmol/L', 'M', '60','120', 3.4, 8.0, 0),
           ('UR', 'Urea', 'mmol/L', 'F', '60','120', 3.4, 8.0, 0),
           ('CREAT', 'Creatinine', 'µmol/L', 'M', '0', '120', 60, 126, 0),
           ('CREAT', 'Creatinine', 'µmol/L', 'F', '60', '120', 50, 111, 0),
           ('EGFR', 'GFR', 'mL/min', 'M', '0', '120', 60, 105, 0),
           ('EGFR', 'GFR', 'mL/min', 'F', '0', '120', 60, 105, 0),
           ('CRP', 'CRP', 'mg/L', 'M', '0', '120', 0, 10, 0),
           ('CRP', 'CRP', 'mg/L', 'F', '0', '120', 0, 10, 0),
           ('ALT', 'ALT', 'U/L', 'M', '0', '120', 5, 41, 0),
           ('ALT', 'ALT', 'U/L', 'F', '0', '120', 5, 41, 0),
           ('ALKP', 'Alk Phos', 'U/L', 'M', '18', '120', 40, 130, 0),
           ('ALKP', 'Alk Phos', 'U/L', 'F', '18', '120', 35, 105, 0),
           ('CA', 'Calcium', 'mmol/L', 'M', '0', '120', 2.1, 2.6, 0),
```

```
('CA', 'Calcium', 'mmol/L', 'F', '0', '120', 2.1, 2.6, 0),
('CCA', 'Corr_Calcium', 'mmol/L', 'M', '0', '120', 2.1, 2.6, 0),
('CCA', 'Corr_Calcium', 'mmol/L', 'F', '0', '120', 2.1, 2.6, 0),
('ALB', 'Albumin', 'g/l', 'M', '0', '120', 34, 51, 0),
('ALB', 'Albumin', 'g/l', 'F', '0', '120', 34, 51, 0),
('TP', 'Total_Protein', 'g/l', 'M', '0', '120', 60, 80, 0),
('TP', 'Total_Protein', 'g/l', 'F', '0', '120', 60, 80, 0),
('BMI', 'BMI', 'kg/m', 'M', '0', '120', 18.5, 24.9, 0),
('BMI ', 'BMI', 'kg/m', 'F', '0', '120', 18.5, 24.9, 0),
('GLUC', 'Glucose', 'mmol/L', 'M', '0', '120', 3.5, 11, 0),
('GLUC', 'Glucose', 'mmol/L', 'F', '0', '120', 3.5, 11, 0),
('HGB', 'New_Haemoglobin', 'g/L', 'M', '0', '120', 135, 180, 0),
('HGB', 'New_Haemoglobin', 'g/L', 'F', '0', '120', 115, 165, 0),
('HB', 'Old_Haemoglobin', 'g/L', 'M', '0', '120', 135, 180, 0),
('HB', 'Old_Haemoglobin', 'g/L', 'F', '0', '120', 115, 165, 0),
('MCV', 'MCV', 'fL', 'M', '0', '120', 80, 99, 0),
('MCV', 'MCV', 'fL', 'F', '0', '120', 80, 99, 0),
('WBC', 'White Blood Count', 'fL', 'M', '0', '120', 4, 11, 0),
('WBC', 'White Blood Count', 'fL', 'F', '0', '120', 4, 11, 0),
('INR', 'INR', 'ratio', 'M', '0', '120', 0.8, 1.2, 0),
('INR', 'INR', 'ratio', 'F', '0', '120', 0.8, 1.2, 0),
('HR', 'Heart Rate', 'pmol/L', 'M', '0', '120', 60, 100, 0),
('HR', 'Heart Rate', 'pmol/L', 'F', '0', '120', 60, 100, 0),
('WLSCORE', 'Waterlow_score', '-', 'M', '0', '120', 0, 15, 0),
('WLSCORE', 'Waterlow_score', '-', 'F', '0', '120', 0, 15, 0),
('FLSCORE', 'Falls Score', '-', 'M', '0', '120', 0, 2, 0),
('FLSCORE', 'Falls Score', '-', 'F', '0', '120', 0, 2, 0),
('PHAMOVE', 'Movement_Score', '-', 'M', '0', '120', 0, 3, 0),
('PHAMOVE', 'AMT_'Movement, '-', 'F', '0', '120', 0, 3, 0),
('MUSTSCORE', 'MUST_Score', '-', 'M', '0', '120', 0, 0, 0),
('MUSTSCORE', 'MUST_Score', '-', 'F', '0', '120', 0, 0, 0),
('BPSYS', 'Systolic_BP', '-', 'M', '0', '120', 90, 140, 0),
('BPSYS', 'Systolic_BP', '-', 'F', '0', '120', 90, 140, 0),
('BPDIA', 'Diastolic_BP', '-', 'M', '0', '120', 60, 80, 0),
('BPDIA', 'Diastolic_BP', '-', 'F', '0', '120', 60, 80, 0)
('O2SATS', 'O2Sats', '-', 'M', '0', '120', 90, 100, 0),
('O2SATS', 'O2Sats', '-', 'F', '0', '120', 90, 100, 0)
('PAINSCORE10', 'PainScore', '-', 'M', '0', '120', 0, 6, 0),
('PAINSCORE10', 'PainScore', '-', 'F', '0', '120', 0, 6, 0)
('RESP', 'RespRate', '-', 'M', '0', '120', 12, 20, 0),
('RESP', 'RespRate', '-', 'F', '0', '120', 12, 20, 0),
('SEWSSCORE', 'Sews_Score', '-', 'M', '0', '120', 0, 5, 0),
('SEWSSCORE', 'Sews_Score, '-', 'F', '0', '120', 0, 5, 0)
('THRSCORE', 'Thrombosis_Score', '-', 'M', '0', '120', 0, 2, 0),
('THRSCORE', 'Thrombosis_Score, '-', 'F', '0', '120', 0, 2, 0)
```

---Creating script with deficits

```
select distinct a.unitno,
                a.age,
                a.sex,
                a.albumin,
max(case when b.full_name = 'Albumin' and (a.albumin <= b.lower_boundary or a.albumin >=
b.upper_boundary) then 1
when b.full_name = 'Albumin' and  a.albumin between b.lower_boundary and b.upper_boundary
then 0 end) as albumin_deficit,
                a.Systolic_BP,
max(case when b.full_name = 'Systolic_BP' and (a.Systolic_BP <= b.lower_boundary or
a.Systolic_BP >= b.upper_boundary) then 1
when b.full_name = 'Systolic_BP' and a.Systolic_BP between b.lower_boundary and
b.upper_boundary then 0 end) as Systolic_deficit,
                a.Diastolic_BP,
max(case when b.full_name = 'Diastolic_BP' and (a.Diastolic_BP <= b.lower_boundary or
a.Diastolic_BP >= b.upper_boundary) then 1
```

```sql
when b.full_name = 'Diastolic_BP' and a.Diastolic_BP between b.lower_boundary and
b.upper_boundary then 0 end) as Diastolic_deficit,
                a.calcium,
max(case when b.full_name = 'Calcium' and (a.calcium <= b.lower_boundary or a.calcium >=
b.upper_boundary) then 1
when b.full_name = 'Calcium' and a.calcium between b.lower_boundary and b.upper_boundary
then 0 end) as Calcium_deficit,
                a.creatinine,
max(case when b.full_name = 'Creatinine' and (a.creatinine <= b.lower_boundary or
a.creatinine >= b.upper_boundary) then 1
when b.full_name = 'Creatinine' and a.creatinine between b.lower_boundary and
b.upper_boundary then 0 end) as Creatinine_deficit,
                a.Glucose,
max(case when b.full_name = 'Glucose' and (a.Glucose <= b.lower_boundary or a.Glucose >=
b.upper_boundary) then 1
when b.full_name = 'Glucose' and a.Glucose between b.lower_boundary and b.upper_boundary
then 0 end) as Glucose_deficit,
                a.haemoglobin,
max(case when b.full_name = 'New_Haemoglobin' and (a.haemoglobin <= b.lower_boundary or
a.haemoglobin >= b.upper_boundary) then 1
when b.full_name = 'New_Haemoglobin' and a.haemoglobin between b.lower_boundary and
b.upper_boundary then 0 end) as Haemoglobin_deficit,
                a.MCV,
max(case when b.full_name = 'MCV' and (a.MCV <= b.lower_boundary or a.MCV >=
b.upper_boundary) then 1
when b.full_name = 'MCV' and a.MCV between b.lower_boundary and b.upper_boundary then 0
end) as MCV_deficit,
                a.[Alkaline Phosphate],
max(case when b.full_name = 'Alk Phos' and (a.[Alkaline Phosphate] <= b.lower_boundary or
a.[Alkaline Phosphate] >= b.upper_boundary) then 1
when b.full_name = 'Alk Phos' and a.[Alkaline Phosphate] between b.lower_boundary and
b.upper_boundary then 0 end) as Alk_phos_deficit,
                a.potassium,
max(case when b.full_name = 'Potassium' and (a.potassium <= b.lower_boundary or a.potassium
>= b.upper_boundary) then 1
when b.full_name = 'Potassium' and a.potassium between b.lower_boundary and
b.upper_boundary then 0 end) as Potassium_deficit,
                a.total_protein,
max(case when b.full_name = 'Total_Protein' and (a.total_protein <= b.lower_boundary or
a.total_protein >= b.upper_boundary) then 1
when b.full_name = 'Total_Protein' and a.total_protein between b.lower_boundary and
b.upper_boundary then 0 end) as Tot_Protein_deficit,
                a.sodium,
max(case when b.full_name = 'Sodium' and (a.Sodium <= b.lower_boundary or a.Sodium >=
b.upper_boundary) then 1
when b.full_name = 'Sodium' and a.Sodium between b.lower_boundary and b.upper_boundary then
0 end) as Sodium_deficit,
                a.urea,
max(case when b.full_name = 'Urea' and (a.urea <= b.lower_boundary or a.urea >=
b.upper_boundary) then 1
when b.full_name = 'Urea' and a.urea between b.lower_boundary and b.upper_boundary then 0
end) as Urea_deficit,
                a.WCC,
max(case when b.full_name = 'White Blood Count' and (a.WCC <= b.lower_boundary or a.WCC >=
b.upper_boundary) then 1
when b.full_name = 'White Blood Count' and a.WCC between b.lower_boundary and
b.upper_boundary then 0 end) as WCC_deficit,
                a.ALT,
max(case when b.full_name = 'ALT' and (a.ALT <= b.lower_boundary or a.ALT >=
a.upper_boundary) then 1
when b.full_name = 'ALT' and a.ALT between b.lower_boundary and b.upper_boundary then 0
end) as ALT_deficit
into #deficits
from [Blood Results] a
left join [reference range table] b
on a.sex = b.sex collate database_default and
```

```
        a.age between b.lower_age and b.upper_age
where a.droprecord = 0
group by a.unitno,
        age,
        a.sex,
        albumin,
        Systolic_BP,
        Diastolic_BP,
        Calcium,
        Glucose,
        creatinine,
        haemoglobin,
        MCV,
        [Alkaline Phosphate],
        potassium,
        sodium,
        urea,
        wcc,
        total_protein,
        alt
order by unitno

alter table #deficits
add number_of_measurements int

select a.unitno,
       a.albumin_deficit,
       a.systolic_deficit,
       a.diastolic_deficit,
       a.calcium_deficit,
       a.creatinine_deficit,
       a.glucose_deficit,
       a.Haemoglobin_deficit,
       a.mcv_deficit,
       a.Alk_phos_deficit,
       a.potassium_deficit,
       a.Tot_Protein_deficit,
       a.sodium_deficit,
       a.urea_deficit,
       a.wcc_deficit,
       a.alt_deficit,
(select count(*) from (values (a.albumin_deficit),
                              (a.systolic_deficit),
                              (a.diastolic_deficit),
                              (a.calcium_deficit),
                              (a.creatinine_deficit),
                              (a.glucose_deficit),
                              (a.haemoglobin_deficit),
                              (a.mcv_deficit),
                              (a.alk_phos_deficit),
                              (a.potassium_deficit),
                              (a.Tot_Protein_deficit),
                              (a.sodium_deficit),
                              (a.urea_deficit),
                              (a.wcc_deficit),
                              (a.alt_deficit)) as v(col)
where v.col is not null) as number_of_measurements,
(select sum(isnull(a.albumin_deficit,0)) +
            isnull(a.systolic_deficit,0) +
            isnull(a.diastolic_deficit,0) +
            isnull(a.calcium_deficit,0) +
            isnull(a.creatinine_deficit,0) +
            isnull(a.glucose_deficit,0) +
            isnull(a.haemoglobin_deficit, 0) +
            isnull(a.mcv_deficit,0) +
            isnull(a.alk_phos_deficit,0) +
```

```
                isnull(a.potassium_deficit, 0) +
                isnull(a.Tot_Protein_deficit, 0) +
                isnull(a.sodium_deficit, 0) +
                isnull(a.urea_deficit, 0) +
                isnull(a.wcc_deficit, 0) +
                isnull(a.alt_deficit, 0)) as total_deficits
into [FILABDeficit Table]
from #deficits a
group by a.unitno,
        a.albumin_deficit,
        a.systolic_deficit,
        a.diastolic_deficit,
        a.calcium_deficit,
        a.creatinine_deficit,
        a.glucose_deficit,
        a.Haemoglobin_deficit,
        a.mcv_deficit,
        a.Alk_phos_deficit,
        a.potassium_deficit,
        a.Tot_Protein_deficit,
        a.sodium_deficit,
        a.urea_deficit,
        a.wcc_deficit,
        a.alt_deficit


alter table [FILABDeficit Table]
add FI_score decimal(10,2)

update [FILABDeficit Table]
set FI_score = case when number_of_measurements > 0 then
                cast(total_deficits as decimal(4,2))/cast(number_of_measurements
                as decimal(4,2)) end
```

---Readmissions Data
---Putting all readmissions into a big table

```
drop table [Readmissions Table]
select distinct a.unitno,
                b.spellno,
                a.spell_dis_date,
                datediff(dd, a.spell_dis_date, b.admdat) as time_to_readm,
                b.admdat,
                b.disdat,
                datediff(dd, b.admdat, b.disdat) as readm_los,
                left(b.am_cds,1) as admimeth
into [Readmissions Table]
from [Frailty Data 2] a left join [Inpatient Table] b
on a.unitno = b.unitno and
   a.spell_adm_date < b.admdat and
   a.spellno <> b.spellno and
   b.disdat is not null


drop table [Readmission Summary Table]
 create table [Readmission Summary Table]
 (unitno varchar(20),
  [emerg_readm_30_days_UHB] int,
  [emerg_readm_12_months_UHB] int,
  [total_emerg_hosp_days_30_days_UHB] int,
  [total_emerg_hosp_days_12_months_UHB] int,
  any_readm_30_days_UHB int,
  any_readm_12_months_UHB int,
  total_hosp_days_30_days_UHB int,
  total_hosp_days_12_months_UHB int,
  total_hosp_days_all_follow_up_UHB int)
```

```
insert into [Readmission Summary Table]
(unitno)
select distinct unitno from [Readmission Summary Table]

update [Readmission Summary Table]
set emerg_readm_30_days_UHB = 1
from [Readmission Summary Table] a inner join (select * from [Readmissions Table]
where datediff(dd, spell_dis_date, admdat) between 0 and 30 and admimeth = 2) b
on a.unitno = b.unitno collate database_default


update [Readmission Summary Table]
set [emerg_readm_30_days] = case when timetoadm <= 1 and admimeth like '2%' then 1 else 0
end
from [Readmission Summary Table] a inner join [HES Readmission Table] b
on a.unitno = b.unitno collate database_default
```

----extracting all years patients

```
drop table [Validation patients]
create table  [Validation patients]
 (unitno varchar(10),
 spellno varchar(12),
 forename varchar(35),
 surname varchar(35),
 epistart_dttm datetime,
 epiend_dttm datetime,
 sex varchar(7),
 Admission_method varchar(10),
 Admission_source varchar(10),
 Discharge_destination varchar(10),
 ethnic_group varchar(25),
 age int,
 primary_diag varchar(6),
 Secondary_diag varchar(6),
 all_diag varchar(250),
 all_op varchar(250),
 Spec_code varchar(5),
 Treatment_function varchar(5),
 spell_adm_date datetime,
 spell_dis_date datetime,
 IMD varchar(50),
 quintile_IMD int,
 [county of residence] varchar(50),
 pkey int,
 drop_record int)

insert into [Validation patients]
select a.unitno,
       a.spellno,
       a.forename,
       a.surname,
       a.epistart_dttm,
       a.epiend_dttm,
       a.sex,
       a.Admission_method,
       a.Admission_source,
       a.Discharge_destination,
       a.ethnic_group,
       a.age,
       a.primary_diag,
       a.Secondary_diag,
       a.all_diag,
       a.all_op,
```

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```
            a.Spec_code,
            a.Treatment_function,
            b.spell_adm_date,
            b.spell_dis_date,
            e.IMD,
            e.quintile_IMD,
            (case when d.GOR = 'E12000001' then 'North East'
                  when d.GOR = 'E12000002' then 'North West'
                  when d.GOR = 'E12000003' then 'Yorkshire and the Humber'
                  when d.GOR = 'E12000004' then 'East Midlands'
                  when d.GOR = 'E12000005' then 'West Midlands'
                  when d.GOR = 'E12000006' then 'East of England'
                  when d.GOR = 'E12000007' then 'London'
                  when d.GOR = 'E12000008' then 'South East'
                  when d.GOR = 'E12000009' then 'South West'
                  when d.GOR = 'M99999999' then 'Isle of Man'
                  when d.GOR = 'W99999999' then 'Wales'
                  when d.GOR = 'S99999999' then 'Scotland'
                  when d.GOR = 'N99999999' then 'Northern Ireland'
                  when d.GOR = '' then 'Unknown/Foreign/Nofixedabode' end) as [county of
residence],
        f.pkey end as 'pkey',
        case when d.GOR in ('M99999999', 'W99999999', 'S99999999', 'N99999999', '') then 1

        else 0 end as 'Drop_record'
from (select UNITNO,
            spellno,
            forename,
            surname,
            epistart_dttm,
            epiend_dttm,
            SEX_CDS as 'Sex',
            am_cds as 'Admission_method',
            Adm_Source_CDS as 'Admission_source',
            DD_CDS as 'Discharge_destination',
(case when eth_group_cds = 'A' or eth_group_cds = 'B' or eth_group_cds = 'C' then 'White'
      when eth_group_cds = 'D' or eth_group_cds = 'E' or eth_group_cds = 'F' or
eth_group_cds = 'G' then 'Mixed'
      when eth_group_cds = 'H' or eth_group_cds = 'J' or eth_group_cds = 'K' or
eth_group_cds = 'L' then 'Asian or Asian British'
      when eth_group_cds = 'M' or eth_group_cds = 'N' or eth_group_cds = 'P' then 'Black or
Black British'
      when eth_group_cds = 'R' or eth_group_cds = 'S' then 'Any Other Ethnic Group'
      when eth_group_cds = 'Z' or eth_group_cds = 'X' or eth_group_cds is null or
eth_group_cds = '99' then 'Unknown/Other' end) as ethnic_group,
            postcode,
            age,
            DIAG1 as 'Primary_diag',
            DIAG2 as 'Secondary_diag',
            All_Diag,
            all_op,
            mainspec as 'Spec_code',
            Tfunc as 'Treatment_function'
from [Inpatient Table]
where admdat between '20150101' and '20161231' and
      age between 65 and 110 and
      AM_CDS like '2%' and
      ep_type = 'M') as a
left join
(select unitno,
        spellno,
        min(Epistart_Dttm) as spell_adm_date,
        max(Epiend_Dttm) as spell_dis_date
from [Inpatient Table] group by unitno, spellno) b
on a.unitno = b.unitno and
   a.spellno = b.spellno
```

```
left join [Postcode Table] as d on left(a.POSTCODE,8)=left(d.PCD2,8)
left join [LSOA Table] as e on d.LSOA01=e.lsoa
left join [Patient Number Table] f on left(a.unitno, 7) = left(f.regno, 7) collate
database_default


drop table [Validation Patient Blood Tests]
create table [Validation Patient Blood Tests]
(pkey varchar(15),
 unitno varchar(10),
 ikey bigint,
 comp_time datetime,
 spell_adm_date datetime,
 spell_dis_date datetime,
 specimen_id varchar(200),
 location varchar(7),
 inv varchar(13),
 [status] char(1),
 value varchar(988))


insert into [Validation Patient Blood Tests]
select distinct a.pkey,
                d.unitno,
                a.ikey as test_id,
                a.comp_time as test_time,
                d.Spell_adm_date,
                d.spell_dis_date,
                a.specimen_id as labno,
                a.location as ward,
                a.inv as test,
                a.[status],
                a.value
from [Validation patients]  d
INNER JOIN [PICS Results Table] a ON d.pkey = a.pkey
where a.inv in ('AKI', 'ALB', 'ALPI', 'ALKP', 'ALP1', 'ALT', 'AMY', 'AVPU', 'B12A',
'BASOS', 'BILI', 'BLDFLW', 'BMI', 'BPDIA', 'BPSYS', 'BSA', 'BSA2', 'CA', 'CCA', 'CHOL',
'CK', 'CREAT', 'CRP', 'DEMFORGET', 'DEPEND', 'EEGFR', 'EGFR', 'EOSINS', 'EPATPAIN', 'FE',
'FERR', 'FLFALL', 'FLFEAR', 'FLHIST', 'FLNEW', 'FLSCORE', 'FLWALK', 'FOL', 'FT4', 'GFR',
'GLUCBM', 'GLUCBMA', 'HB', 'HCT', 'HGB', 'HGHT', 'HR', 'IHBA1', 'INR', 'K', 'LYMPHS',
'MAP', 'MCH', 'MCHC1', 'MCV', 'MONOS', 'MUSTILL', 'MUSTPLAN', 'MUSTSCORE', 'MUSTWLOSS',
'NA', 'NEUTS', 'NEWFALL', 'NRBC', 'O2FLOW', 'O2SATS', 'OBSUBLD', 'OBSUGLU', 'OBSULEU',
'OBSUNIT', 'OBSUPH', 'OBSUPRO', 'PAINSCORE', 'PAINSCRE10', 'PHABATHS', 'PHAMIBS',
'PHAMOVE', 'PHATOILETS', 'PHATRANSS', 'PHAWALKS', 'PLATS', 'PP', 'RBC', 'RDW', 'RESP',
'SEWSSCORE', 'TEMPTR', 'THRSCORE', 'TP', 'TSH', 'UR', 'URINE', 'WBC', 'WGHT', 'WLACTION',
'WLANAEM', 'WLAPPT', 'WLBLD', 'WLCARD', 'WLCONT', 'WLEQUIP', 'WLMED', 'WLMOB', 'WLNCVST',
'WLNDEME', 'WLNDIAB', 'WLNMSCL', 'WLNPATE', 'WLORTHO', 'WLSCORE', 'WLSKBS', 'WLSKCL',
'WLSKDC', 'WLSKDRY', 'WLSKHEAL', 'WLSKOED', 'WLSKTP', 'WLSMOKE', 'WLTABLE', 'WLTERM',
'WLULCER', 'WLULCLOC', 'WLUNUMB', 'WLVASC') and
((datediff(dd, a.comp_time, d.spell_adm_date) between 0 and 366) or
 (datediff(dd, d.spell_dis_date, a.comp_time) between 0 and 366)) and a.[status] = 'C'
```

---Getting first admission for validation patients
```
drop table #row_number
select unitno, spell_adm_date, row_number() over (partition by UnitNo order by
spell_adm_date) as [row]
into #row_number
from [Validation patients]

alter table [Validation patients]
add [row] int

update [Validation patients]
set [row] = b.[row]
from [Validation patients] a inner join #row_number b
```

```
on a.unitno = b.unitno and
    a.spell_adm_date = b.spell_adm_date
```

---Extracting time from admission to blood test

```
alter table [Validation Patient Blood Tests]
add date_diff int

update [Validation Patient Blood Tests]
set date_diff = datediff(dd, spell_adm_date, comp_time)
```

---Pivot table of bloods

```
drop table [Validation Bloods Pivot Table]
;with Data as
(select *, abs(convert(int, spell_adm_date-comp_time)) as DatediffNew from
pics.[dbo].[jm_20180320_Frailty_Patients_Bloods_years]  where [row] = 1 and spell_adm_date
> '20150101'),
d2 as
(select *, row_number() over (partition by UnitNo, inv order by Datediffnew asc) rn  from
data),
D3 AS
(select * from d2 where  Value <> 'NA')

select distinct pkey,
                [UnitNo],
                spell_adm_date,
                DatediffNew,
                AKI,
                ALB,
                ALKP,
                ALPI,
                ALP1,
                ALT,
                AMY,
                AVPU,
                B12A,
                BASOS,
                BILI,
                BLDFLW,
                BMI,
                BPDIA,
                BPSYS,
                BSA,
                BSA2,
                CA,
                CCA,
                CHOL,
                CK,
                CREAT,
                CRP,
                DEMFORGET,
                DEPEND,
                EEGFR,
                EGFR,
                EOSINS,
                EPATPAIN,
                FE,
                FERR,
                FLFALL,
                FLFEAR,
                FLHIST,
                FLNEW,
                FLSCORE,
                FLWALK,
                FOL,
                FT4,
                GFR,
```

GLUCBM,
GLUCBMA,
HB,
HCT,
HGB,
HGHT,
HR,
IHBA1,
INR,
K,
LYMPHS,
MAP,
MCH,
MCHC1,
MCV,
MONOS,
MUSTILL,
MUSTPLAN,
MUSTSCORE,
MUSTWLOSS,
NA,
NEUTS,
NEWFALL,
NRBC,
O2FLOW,
O2SATS,
OBSUBLD,
OBSUGLU,
OBSULEU,
OBSUNIT,
OBSUPH,
OBSUPRO,
PAINSCORE,
PAINSCRE10,
PHABATHS,
PHAMIBS,
PHAMOVE,
PHATOILETS,
PHATRANSS,
PHAWALKS,
PLATS,
PP,
RBC,
RDW,
RESP,
SEWSSCORE,
TEMPTR,
THRSCORE,
TP,
TSH,
UR,
URINE,
WBC,
WGHT,
WLACTION,
WLANAEM,
WLAPPT,
WLBLD,
WLCARD,
WLCONT,
WLEQUIP,
WLMED,
WLMOB,
WLNCVST,
WLNDEME,
WLNDIAB,

```
                    WLNMSCL,
                    WLNPATE,
                    WLORTHO,
                    WLSCORE,
                    WLSKBS,
                    WLSKCL,
                    WLSKDC,
                    WLSKDRY,
                    WLSKHEAL,
                    WLSKOED,
                    WLSKTP,
                    WLSMOKE,
                    WLTABLE,
                    WLTERM,
                    WLULCER,
                    WLULCLOC,
                    WLUNUMB,
                    WLVASC
into [Validation Bloods Pivot Table]
from
(select distinct pkey,
                    [UnitNo],
                    spell_adm_date,
                     inv,
                    [Value],
                    Datediffnew from d3) p
pivot (max([Value]) for inv in
      (AKI,
       ALB,
       ALKP,
       ALPI,
       ALP1,
       ALT,
       AMY,
       AVPU,
       B12A,
       BASOS,
       BILI,
       BLDFLW,
       BMI,
       BPDIA,
       BPSYS,
       BSA,
       BSA2,
       CA,
       CCA,
       CHOL,
       CK,
       CREAT,
       CRP,
       DEMFORGET,
       DEPEND,
       EEGFR,
       EGFR,
       EOSINS,
       EPATPAIN,
       FE,
       FERR,
       FLFALL,
       FLFEAR,
       FLHIST,
       FLNEW,
       FLSCORE,
       FLWALK,
       FOL,
       FT4,
```

GFR,
GLUCBM,
GLUCBMA,
HB,
HCT,
HGB,
HGHT,
HR,
IHBA1,
INR,
K,
LYMPHS,
MAP,
MCH,
MCHC1,
MCV,
MONOS,
MUSTILL,
MUSTPLAN,
MUSTSCORE,
MUSTWLOSS,
NA,
NEUTS,
NEWFALL,
NRBC,
O2FLOW,
O2SATS,
OBSUBLD,
OBSUGLU,
OBSULEU,
OBSUNIT,
OBSUPH,
OBSUPRO,
PAINSCORE,
PAINSCRE10,
PHABATHS,
PHAMIBS,
PHAMOVE,
PHATOILETS,
PHATRANSS,
PHAWALKS,
PLATS,
PP,
RBC,
RDW,
RESP,
SEWSSCORE,
TEMPTR,
THRSCORE,
TP,
TSH,
UR,
URINE,
WBC,
WGHT,
WLACTION,
WLANAEM,
WLAPPT,
WLBLD,
WLCARD,
WLCONT,
WLEQUIP,
WLMED,
WLMOB,
WLNCVST,
WLNDEME,

```
        WLNDIAB,
        WLNMSCL,
        WLNPATE,
        WLORTHO,
        WLSCORE,
        WLSKBS,
        WLSKCL,
        WLSKDC,
        WLSKDRY,
        WLSKHEAL,
        WLSKOED,
        WLSKTP,
        WLSMOKE,
        WLTABLE,
        WLTERM,
        WLULCER,
        WLULCLOC,
        WLUNUMB,
        WLVASC)) as pvt
```

--Creating table for distinct patients
```
create table #distinctpatients
(pkey varchar(15),
 unitno varchar(10),
 spell_adm_date datetime,
alb varchar(988),
alkp varchar(988),
alt varchar(988),
avpu varchar(988),
bmi varchar(988),
bpdia varchar(988),
bpsys varchar(988),
ca varchar(988),
cca varchar(988),
crp varchar(988),
egfr varchar(988),
demforget varchar(988),
flscore varchar(988),
glucbm varchar(988),
glucbma varchar(988),
hgb varchar(988),
hr varchar(988),
inr varchar(988),
k varchar(988),
mcv varchar(988),
mustscore varchar(988),
na varchar(988),
o2sats varchar(988),
painscore varchar(988),
phamove varchar(988),
plats varchar(988),
resp varchar(988),
sewsscore varchar(988),
temp varchar(988),
thrscore varchar(988),
ur varchar(988),
wbc varchar(988),
wlscore varchar(988))

insert into #distinctpatients
(pkey)
(select distinct pkey from [Validation Bloods Pivot Table])

update #distinctpatients
set alb = b.alb,
```

```
        alkp = b.alp1,
        alt= b.alt,
        avpu = b.avpu,
        bmi = b.bmi,
        bpdia = b.bpdia,
        bpsys = b.bpsys,
        ca = b.ca,
        cca = b.cca,
        egfr = b.egfr,
        demforget = b.demforget,
        flscore = b.flscore,
        glucbm = b.glucbm,
        hgb = b.hgb,
        hr = b.hr,
        inr = b.inr,
        k = b.k,
        mcv = b.mcv,
        mustscore = b.mustscore,
            na = b.na,
            o2sats = b.o2sats,
            painscore = b.painscore,
            phamove = b.phamove,
            plats = b.plats,
            resp = b.resp,
            sewsscore = b.sewsscore,
            temp = b.temptr,
            thrscore = b.thrscore,
            ur = b.ur,
            wbc = b.wbc,
            wlscore  = b.wlscore
from #distinctpatients a inner join [Validation Bloods Pivot Table] b
on a.unitno = b.unitno collate database_default and
    datediffnew = 0
```

--Flag if the validation cohort went to a care home
```
alter table [Validation Patient Blood Tests]
add dis_dest_care_home int

update [Validation Patient Blood Tests]
set dis_dest_care_home = 1
from [Validation Patient Blood Tests] a inner join [Validation patients]  b
on a.unitno = b.unitno and
    a.spellno = b.spellno collate database_default and
    b.discharge_destination in ('54', '65', '85')
```

---Flag if they were readmitted to UHB within 30 days
```
alter table [Validation Patient Blood Tests]
add readmission30days int

update [Validation Patient Blood Tests]
set readmission30days = 1
from [Validation Patient Blood Tests] a inner join [Inpatient Table] b
on a.unitno = b.unitno collate database_default and
    a.spellno <> b.spellno and
    b.am_cds like '2%' and
    datediff(dd, a.spell_dis_date, b.epistart_dttm) between 0 and 30
```

---Linking to HES for readmissions
```
drop table [All Readmissions Table]
select a.patient_ID,
            a.unitno ,
        a.spell_adm_date,
            a.spell_dis_date,
```

```
        b.admimeth,
        b.admidate,
        b.disdate,
        b.dismeth
into [All Readmissions Table]
from [Table for Linking] a inner join [HES Spells] b
on a.patient_ID = b.PATIENT_ID and
   a.spell_dis_date <= b.ADMIDATE and
   b.admimeth like '2%'


alter table [All Readmissions Table]
add readmission30days int

alter table [All Readmissions Table]
add timetoreadmission int

update [All Readmissions Table]
set timetoreadmission = datediff(dd, spell_dis_date, admidate)

update [All Readmissions Table]
set readmission30days = case when timetoreadmission <=30 then 1 else 0 end
```

Appendix 2 – STATA Analysis Script

---Importing data set
import excel – Data for FI_Baseline

---exclude patients with less than 70% of tests
drop if proportionoftests<0.7

---Generating variable for FI_Baseline categories
gen FI_cat = 1 if FrailtyScore<0.10
replace FI_cat = 2 if FrailtyScore>=0.10 & FrailtyScore <=0.22
replace FI_cat = 3 if FrailtyScore >=0.23 & FrailtyScore <=0.45
replace FI_cat = 4 if FrailtyScore >0.45

--Getting summary of age and FI_Baseline by Category
by FI_cat, sort : summarize age, detail
by FI_cat, sort : summarize FrailtyScore , detail

---Producing histogram of FI_Baseline
histogram FrailtyScore, discrete frequency

---Log FI_Baseline for scatter plot
gen logFI = log(FrailtyScore)
egen m_logFI = mean(logFI)
twoway (scatter m_logFI age, sort) || lfit m_logFI age

---Mortality Data by FI_Baseline category chi-squared
tabulate FI_cat Inhospitaldeath , chi2
tabulate FI_cat death30, chi2
tabulate FI_cat death12months, chi2
tabulate FI_cat death3years, chi2

---Set survival data for 3 year mortality
stset MonthstoDeath, failure(death) scale(12)

---KM Curve by FI_Baseline category
sts graph, by(FI_cat)

---Log-rank test for difference between FI_Baseline category
sts test FI_cat

---Multiply FI_Baseline by 100 for analysis
gen FI_100 = FrailtyScore*100

---Univariate logistic regressions for age and sex individually
xi: logit Inhospitaldeath age, or
lroc
xi: logit mort30day age, or
lroc
xi: logit mort12month age, or

lroc
xi: logit mort3year age, or
lroc
xi: logit readmission30days age, or
lroc
xi: logit carehome age, or
lroc
xi: logit Inhospitaldeath i.sex, or
lroc
xi: logit mort30day i.sex, or
lroc
xi: logit mort12month i.sex, or
lroc
xi: logit mort3year i.sex, or
lroc
xi: logit readmission30days i.sex, or
lroc
xi: logit carehome i.sex, or
lroc

---Multivariable logistic regression with age and sex
xi: logit Inhospitaldeath age i.sex, or
lroc
xi: logit mort30day age i.sex, or
lroc
xi: logit mort12month age i.sex, or
lroc
xi: logit mort3year age i.sex, or
lroc
xi: logit readmission30days age i.sex, or
lroc
xi: logit carehome age i.sex, or
lroc

---Multivariable logistic regression with age, sex and FI_Baseline
xi: logit Inhospitaldeath age i.sex FI_100, or
lroc
xi: logit mort30day age i.sex FI_100, or
lroc
xi: logit mort12month age i.sex FI_100, or
lroc
xi: logit mort3year age i.sex FI_100, or
lroc
xi: logit readmission30days age i.sex FI_100, or
lroc
xi: logit carehome age i.sex FI_100, or
lroc

---Importing data set
import excel – Data for FI_QEHB

---exclude patients with less than 70% of tests
drop if proportionoftests<0.7

---Generating variable for FI_QEHB categories
gen FI_cat = 1 if FrailtyScore<0.10
replace FI_cat = 2 if FrailtyScore>=0.10 & FrailtyScore <=0.22
replace FI_cat = 3 if FrailtyScore >=0.23 & FrailtyScore <=0.45
replace FI_cat = 4 if FrailtyScore >0.45

--Getting summary of age and FI_QEHB by Category
by FI_cat, sort : summarize age, detail
by FI_cat, sort : summarize FrailtyScore , detail

---Mortality Data by FI_QEHB category chi-squared
tabulate FI_cat Inhospitaldeath , chi2
tabulate FI_cat death30, chi2
tabulate FI_cat death12months, chi2
tabulate FI_cat death3years, chi2

---Set survival data for 3 year mortality
stset MonthstoDeath, failure(death) scale(12)

---KM Curve by FI_QEHB category
sts graph, by(FI_cat)

---Log-rank test for difference between FI_QEHB category
sts test FI_cat

---Multiply FI_QEHB by 100 for analysis
gen FI_100 = FrailtyScore*100

---Multivariable logistic regression with age, sex and FI_QEHB
xi: logit Inhospitaldeath age i.sex FI_100, or
lroc
xi: logit mort30day age i.sex FI_100, or
lroc
xi: logit mort12month age i.sex FI_100, or
lroc
xi: logit mort3year age i.sex FI_100, or
lroc
xi: logit readmission30days age i.sex FI_100, or
lroc
xi: logit carehome age i.sex FI_100, or
lroc

---Importing data set
import excel – Data for HerFI

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---exclude patients with less than 70% of tests
drop if proportionoftests<0.7

---Generating variable for HerFI categories
gen FI_cat = 1 if FrailtyScore<0.10
replace FI_cat = 2 if FrailtyScore>=0.10 & FrailtyScore <=0.22
replace FI_cat = 3 if FrailtyScore >=0.23 & FrailtyScore <=0.45
replace FI_cat = 4 if FrailtyScore >0.45

--Getting summary of age and HerFI by Category
by FI_cat, sort : summarize age, detail
by FI_cat, sort : summarize FrailtyScore , detail

---Mortality Data by HerFI category chi-squared
tabulate FI_cat Inhospitaldeath , chi2
tabulate FI_cat death30, chi2
tabulate FI_cat death12months, chi2
tabulate FI_cat death3years, chi2

---Set survival data for 3 year mortality
stset MonthstoDeath, failure(death) scale(12)

---KM Curve by HerFI category
sts graph, by(FI_cat)

---Log-rank test for difference between HerFI category
sts test FI_cat

---Multiply HerFI by 100 for analysis
gen FI_100 = FrailtyScore*100

---Multivariable logistic regression with age, sex and HerFI
xi: logit Inhospitaldeath age i.sex FI_100, or
lroc
xi: logit mort30day age i.sex FI_100, or
lroc
xi: logit mort12month age i.sex FI_100, or
lroc
xi: logit mort3year age i.sex FI_100, or
lroc
xi: logit readmission30days age i.sex FI_100, or
lroc
xi: logit carehome age i.sex FI_100, or
lroc

----**Importing data set**
import excel – Data for Validation

---exclude patients with less than 70% test
drop if proportionoftests<0.7

---Generating variable for Validation categories
gen FI_cat = 1 if FrailtyScore<0.10
replace FI_cat = 2 if FrailtyScore>=0.10 & FrailtyScore <=0.22
replace FI_cat = 3 if FrailtyScore >=0.23 & FrailtyScore <=0.45
replace FI_cat = 4 if FrailtyScore >0.45

--Getting summary of age and Validation by Category
by FI_cat, sort : summarize age, detail
by FI_cat, sort : summarize FrailtyScore , detail

---Mortality Data by Validation category chi-squared
tabulate FI_cat Inhospitaldeath , chi2
tabulate FI_cat death30, chi2
tabulate FI_cat death12months, chi2

---Multiply Validation by 100 for analysis
gen FI_100 = FrailtyScore*100

---Multivariable logistic regression with age, sex and Validation
xi: logit Inhospitaldeath age i.sex FI_100, or
lroc
xi: logit mort30day age i.sex FI_100, or
lroc
xi: logit mort12month age i.sex FI_100, or
lroc
xi: logit readmission30days age i.sex FI_100, or
lroc
xi: logit carehome age i.sex FI_100, or
lroc

Appendix 3 – R Script for Analysis

---import data into R
MyData <- read.csv(MyData)

---Convert all variables into factors
MyData$alb_deficit<-as.factor(MyData$alb_deficit)
MyData$alkp_deficit<-as.factor(MyData$alkp_deficit)
MyData$alt_deficit<-as.factor(MyData$alt_deficit)
MyData$AVPU.deficit<-as.factor(MyData$AVPU.deficit)
MyData$BMI_deficit<-as.factor(MyData$BMI_deficit)
MyData$bpdia_deficit<-as.factor(MyData$bpdia_deficit)
MyData$bysys_deficit<-as.factor(MyData$bysys_deficit)
MyData$cca_deficit<-as.factor(MyData$cca_deficit)
MyData$crp_deficit<-as.factor(MyData$crp_deficit)
MyData$egfr_deficit<-as.factor(MyData$egfr_deficit)
MyData$demforget_deficit<-as.factor(MyData$demforget_deficit)
MyData$flscore_deficit<-as.factor(MyData$flscore_deficit)
MyData$glucbma_deficit<-as.factor(MyData$glucbma_deficit)
MyData$hgb_deficit<-as.factor(MyData$hgb_deficit)
MyData$hr_deficit<-as.factor(MyData$hr_deficit)
MyData$INR_deficit<-as.factor(MyData$INR_deficit)
MyData$potassium_deficit<-as.factor(MyData$potassium_deficit)
MyData$mcv_deficit<-as.factor(MyData$mcv_deficit)
MyData$MUST_deficit<-as.factor(MyData$MUST_deficit)
MyData$Sodium_deficit<-as.factor(MyData$Sodium_deficit)
MyData$osats_deficit<-as.factor(MyData$osats_deficit)
MyData$painscore10_deficit<-as.factor(MyData$painscore10_deficit)
MyData$phamove_deficit<-as.factor(MyData$phamove_deficit)
MyData$plats_deficit<-as.factor(MyData$plats_deficit)
MyData$resp_deficit<-as.factor(MyData$resp_deficit)
MyData$Sews_deficit<-as.factor(MyData$Sews_deficit)
MyData$temp_deficit<-as.factor(MyData$temp_deficit)
MyData$thrscore_deficit<-as.factor(MyData$thrscore_deficit)
MyData$urea_defict<-as.factor(MyData$urea_defict)
MyData$wbc_deficit<-as.factor(MyData$wbc_deficit)
MyData$wl_deficit<-as.factor(MyData$wl_deficit)
MyData$death<-as.factor(MyData$death)

---Install the MICE package
install.packages("mice")
library(mice)

---Create 5 imputations on training data
dataset_impute_<- mice(train_data, print = FALSE, m=5, method = "logreg")
summary(dataset_impute_)

---Dataset 1
completeData1<-complete(dataset_impute_,1)
summary(completeData1)

---Dataset 2
completeData2<-complete(dataset_impute_,2)
summary(completeData2)

---Dataset 3
completeData3<-complete(dataset_impute_,3)
summary(completeData3)
---Dataset 4
completeData4<-complete(dataset_impute_,4)
summary(completeData4)

---Dataset 5
completeData5<-complete(dataset_impute_,5)
summary(completeData5)

---Splitting main dataset into test and train
in_train <- sample(1:nrow(MyData), size = 4416)
train_data <-MyData[in_train,]
test_data <-MyData[-in_train,]
summary(train_data)
summary(test_data)

---Building decision trees on all datasets
---Tree 1
buildtree_train2 <- C5.0(train_data[-32], train_data$death)
buildtree_train2
summary(buildtree_train2)

---Tree 2
buildtree_completedata1<-C5.0(death~.,data=completeData1)
summary(buildtree_completedata1)
plot(buildtree_completedata1)

---Tree 3
buildtree_completedata2<-C5.0(death~.,data=completeData2)
summary(buildtree_completedata2)
plot(buildtree_completedata2)

---Tree 4
buildtree_completedata3<-C5.0(death~.,data=completeData3)
summary(buildtree_completedata3)
plot(buildtree_completedata3)

---Tree 5
buildtree_completedata4<-C5.0(death~.,data=completeData4)
summary(buildtree_completedata4)
plot(buildtree_completedata4)

---Tree 6
buildtree_completedata5<-C5.0(death~.,data=completeData5)
summary(buildtree_completedata5)
plot(buildtree_completedata5)

---Testing on the test dataset
death_pred <- predict(buildtree_train2, test_data)
install.packages("gmodels")
library(gmodels)
CrossTable(test_data$death, death_pred,
        prop.chisq = FALSE, prop.c = FALSE, prop.r = FALSE,
        dnn = c('actual default', 'predicted default'))

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