Exploring measures of multimorbidity in predicting health and social care outcomes using administrative and survey data

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Abstract

Background: Multimorbidity is associated with adverse health and care outcomes, particularly in older populations. When quantifying multimorbidity, the appropriate measure varies by population, outcome under study and data available. Integrated health/social care, with a focus on the individual, improves patient satisfaction and health. In Scotland, clarity as to which measures/conditions are most strongly associated with health and care outcomes will help anticipate integrated care.

Aim: To identify which multimorbidity measures, conditions and comorbidities predict health and care outcomes in an older Scottish population.

Methods: Demographics, social care, admissions, and prescribing data for individuals 65+/resident in Scotland 2010-16 comprised three panel cohorts: for health (n=5,579,492), social (n=4,374,662) and informal care outcomes (n=2,449,229). Survey data linked to admissions were used for co-resident care (n=8,334). Panel logistic regression, using the receiver operating curve (ROC), identified the most predictive measures of multimorbidity for health/care. Further modelling was used to identify the strongest associated conditions/comorbidities, the impact of multimorbidity on social care by deprivation, and whether administrative outperforms survey data in predicting informal/co-resident care.

Results: The Charlson Comorbidity Index (CCI) performed best (ROC >0.8) in predicting mortality, proxy measures for other health outcomes (ROC >0.7 and <0.9), the Henery Chronic Disease Score 2 for social care (ROC >0.7 and <0.8) and informal care (ROC >0.8), and self-report measure (ROC >0.75) for co-resident care. Dementia is strongly associated with care, while comorbid interactions varied. An inverse effect between the relationship between multimorbidity and social care was found for local authority deprivation. Administrative data outperforms survey data at predicting informal care.

Conclusions: The varying performance of multimorbidity measures highlight the importance of a wide range of data when predicting use of health and care services. A national index tailored to a Scottish population derived from both diagnosis-based and medication-based data may have better precision. This, and findings regarding individual and comorbid conditions, such as dementia, as well as macro- and micro-level effects of deprivation on the relationship between multimorbidity and care, have the potential to improve existing risk predicting algorithms within Scotland.

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Chapter One - Introduction

1.1. Background to multimorbidity and PhD project

Multimorbidity, the presence of multiple conditions within an individual, is associated with multiple adverse health outcomes and complex care needs worldwide, particularly in older people (Marengoni et al 2011). The definition of what constitutes multimorbidity has varied throughout literature, often as a result of subjective interpretation of what a condition or disease is (Conrad & Barker 2010) and what data is available and techniques for identifying these conditions (Ho et al 2021). This presents challenges in ascertaining the true burden of multimorbidity in at-risk populations. The term "multimorbidity" has evolved in contemporary literature as a counterpart to the related term "comorbidity." Comorbidity refers to additional conditions or complications co-existing with a particular condition of interest, or "index" condition (Feinstein 1970); this term was also used broadly to refer to what is now known as multimorbidity, prior to a paper by van den Akker et al (1996) adapting a word priorly exclusively used in German literature (Le Reste et al 2013) into an unambiguous definition referring to multiple conditions within one person at one time. However, many contemporary studies still erroneously refer to multimorbidity as comorbidity; this presents barriers toward collating and evaluating prior research.

Contemporary appraisals of multimorbidity expand on or refine van den Akker's original definition dependent on the context. The relationship between co-occurring conditions, as well as chronology, is important. For example, particular combinations of conditions may be common because one causes the other, or they have common risk factors but are otherwise unrelated (Valderas et al 2009); a landmark report by the Academy of Medical Sciences (2018) defines the latter as concordant and discordant multimorbidity, respectively. A number of papers including Valderas et al also suggest that patient complexity such as socio-economic circumstances and environmental characteristics, and patient characteristics e.g. age and frailty (the "morbidity burden") be taken into account when developing a multimorbidity profile.

The National Institute for Health and Clinical Excellence or NICE (2016) defines multimorbidity as two or more long-term health conditions; this can include typical physical and mental health conditions as well as other ongoing health problems including learning disabilities, pain, sensory impairment, or substance dependence. More recently, the Academy of Medical Sciences (2018) proposes a definition of two or more co-existing chronic conditions, which can be one of a physical non-communicable disease, a mental health condition or a long-term infectious disease. Multimorbidity will hereafter be discussed in reference to these operational definitions throughout this thesis, unless otherwise stated.

Prevalence of and complications from multimorbidity are typically higher in the older population. From 2017 to 2041, the proportion of people in Scotland aged 65 and above (hereafter referred to as "older people") is projected to increase from 19% to 25% (NRS Scotland 2018). For older age groups the relative change is higher; those aged 75 and above are estimated to see a 79% increase in population. This demographic change presents current and future challenges for health and social care services.

In Scotland health care is largely provided by the Scottish National Health Service (NHS), a single payer funded system devolved from the wider UK administration. People aged 65 and above are more likely to be admitted to hospital in an emergency, and have longer emergency lengths of stay ("bed days") than the general population (Audit Scotland 2016). Older people comprise the majority of admissions, bed days and costs; this burden will increase exponentially with the increasing ageing population. The majority of older people in Scotland have multimorbidity (Barnett et al 2012); multimorbid populations are highly heterogeneous, with different combinations of conditions requiring varying healthcare needs, which presents obstacles to developing wide-ranging solutions to reduce health care costs. Table 1.1 below outlines common conditions and groups of conditions in older people in Scotland and the UK. Hypertension, pain, arthritis, cardiovascular disease, heart disease and obesity are prevalent in approximately over one in four in the Scottish or UK older population, with many other conditions likely prevalent in over one in ten. There is slight variation in figures between the studies, with lower prevalence of depression (and to a lesser extent, heart disease) in survey derived cohorts, likely as a result of underreporting from survey respondents or design constraints. Regardless, given these conditions will frequently co-exist with each other, the "single-disease" model – where each condition is treated as a separate, distinct entity, with individual guidelines including general practice appointments, treatment, and prescribing – may prove to be ineffective, or elevate patient management burden beyond acceptable limits. It is suggested that for multimorbidity – for whom single disease care pathways can be complex and uncoordinated (NIHR 2021) – specific guidelines for management which follow a generalist approach will have the greatest benefit (Marengoni et al 2011).

Social care, provided at local authority (LA) level in Scotland, allows older people with complex needs greater autonomy in later years of life such as staying at home longer, independent living and continued community participation (Scottish Government 2022). Through this, there is potential to reduce emergency interventions in worsening status of older people, such as emergency admissions or lengthy stays in hospital. Whilst the rate of emergency admissions in individuals over 65 is not increasing, the overall number is, as a result of increases in population (ISD Scotland 2016). An emergency admission can be interpreted as an intervention on the part of primary care when care

services are not sufficient (Scottish Government 2016). The Scottish Government has integrated health and social care, with two models – one with a joint board overseeing both services (which has been used in the majority of cases), and a "lead agency" model where one of either the health board or the local authority takes the initiative in planning and delivering services – this was the model adopted in the Highlands (Scottish Government 2014). The success of integration since it was implemented has varied by target (Audit Scotland 2018) – whilst acute emergency bed days and delayed discharges from hospital have fallen in the general population, key indicators of success of integrated care have risen, such as emergency admissions or palliative care spent at home. The proportion of people aged 75 and above living in the community (compared to an institutional setting) has risen slightly – however, these mixed results show that much more work is to be done to ensure that integration is a success, with a recent review proposing the establishment of a National Care Service (Scottish Government 2021).

However, there are a number of challenges regarding effectively providing social care, particularly to older people with complex needs. Despite broad consensus on the operational definition of multimorbidity (NICE 2016), more complex measures (such as inclusion of specific conditions as well as how to define or identify disease), for the purpose of risk prediction or association with poor health, vary considerably in contemporary research (Ho et al 2021), with optimum measures of multimorbidity dependent on population, health outcome and data available. In Scotland, local authorities have access to linked health and social care data comprising a number of characteristics of older people receiving social care (Audit Scotland 2016). This PhD project uses this data to identify types of multimorbidity which best predict need for both adverse health outcomes (such as mortality, admissions to hospital, or hospital days) and care outcomes (receipt of government-provided social care or informally provided care from family or friends).

Table 1.1: Prevalence of common chronic conditions in older people and whole population, in Scotland and UK

		Condition prevalence				
ICD-10 chapter		**65-74, Scotland, primary care***	**75+, Scotland, primary care***	**65-74, Scotland, survey data****	**75+, Scotland, survey data****	**65+, UK, survey data*****
Infectious disease	*All*			1%		
Neoplasms	*All*			6%	6%	
	Cancer					12.6%
Blood & immune	*All*			1%	3%	
Endocrine & metabolic	*All*			22%	16%	
	Diabetes	21.1%		14%	16%	14.7%
	Obesity			37%	30%	
	Thyroid disorders	14.5%	15.9%			
Mental & behavioural	*All*			8%	3%	
	Dementia					6.8%
	Depression	18.5%	17.2%			2.3%
Nervous system	*All*			5%	7%	
Eye/vision	*All*			5%	10%	
Ear/hearing	*All*			3%	5%	
	Hearing loss		15.5%			
Heart & circulatory	*All*			25%	32%	
	Cardiac arrythmia			10%	13%	
	Cardiovascular disease			19%	34%	
	Heart disease	26.1%	31.2%	16%	27%	18.3%
	Hypertension	58.3%	61.9%	50%	57%	49.0%
	Stroke	10.5%	16.6%	5%	11%	7.5%

Respiratory	*All*			16%	10%	18.0%
	Asthma			12%	9%	
	Chronic obstructive pulmonary disease	14.6%		9%	11%	
Digestive	*All*			8%	9%	
	Constipation		17.0%			
	Dyspepsia	15.9%				
Skin complaints	*All*			1%	1%	
Musculoskeletal	*All*			33%	45%	
	Arthritis					48.6%
	Inflammatory poly-arthropathy	13.7%				
Genitourinary	*All*			3%	5%	
	Chronic kidney disease		18.5%			
Other	*All*			<1%	1%	
	Pain	30.0%	23.6%			

* McLean et al (2014); primary care data, general practice diagnosis. Rounded to one decimal place. Ten most prevalent conditions per age group.

** Bromley et al (2013); survey data, self-reported or doctor diagnosed. Rounded to nearest whole number

*** Kingston et al (2018); survey data, self-reported, doctor diagnosed or probabilistic matching. Rounded to one decimal place

1.2. Conceptual and disciplinary background of PhD

Whilst based in social science, this PhD has cross-disciplinary and cross-industry involvement from the Economics department within the University of Stirling and the Health and Social Care team of the Scottish Government. A cross-disciplinary team from all the above departments put together the initial application for the project and were involved in the initial acquisition of access to the data as well as the development of supplementary forms for further years of data. This involvement is part of a wider cross-collaboration between the University of Stirling and the Scottish Government using linked health and social care data on multiple projects such as admission to hospital, care costs and length of stay. Representatives from the Scottish Government were involved in a number of stages of the PhD project such as supervision and review of draft pieces of work, maintaining the cross-collaborative nature of the project.

The Scottish Government's involvement in the project is reflected in the policy-driven approach of a number of aspects of this thesis; the findings from this PhD project originate from and are intended to influence the relationship between integrated health and social care and health outcomes for those with multimorbidity. Whilst the methodological origins of a number of aspects of the analysis within the project originate from a wider discussion regarding quantifying multimorbidity, the overall goal was to adapt these methods and use them to identify people within the multimorbid population who were most at risk of particular health outcomes in order to provide better care.

The Scottish Government's involvement in the project assisted in validating whether the overall direction of this thesis was valid in a policy context. Appropriate policy documents, recommended by the Government, helped frame the methodological approach and identify policy gaps, and regular meetings with Government officials ensured that the direction of the thesis was appropriate. This cross-disciplinary approach has led to development, implementation, and production of findings relevant in both an academic and public sector context.

It should also be noted that despite this PhD's subject matter, which adapts methodologically and thematically from a number of disciplines, including medical sciences and public health, it is still at its core a social policy thesis. The project was funded for and is primarily focused on alleviating demand on social care and emergency medical services through health professionals, via identifying risk factors for health and social care demand. The discipline has therefore impacted the approach taken to a number of areas of the thesis which would otherwise be found in medical or public health PhDs.

The greatest impact of the discipline of this PhD on its content was the approach taken to coding and interpreting multimorbidity as a construct. A number of the multimorbidity measures in this study, particularly those adapted from American medication classifications, do not entirely accurately capture national prevalence of the conditions they flag for. Whilst one of the main focuses of the thesis was identifying and comparing different aspects of multimorbidity, the primary goal was risk prediction, and as such developing precise multimorbidity measures in which all condition prevalence aligns with national statistics (as would be required in a medical or public health PhD), whilst preferred, was not the over-arching aim; however, care was taken to limit any divergence from other sources, with explanations provided and limitations acknowledged where this was not possible. The findings from this thesis satisfy the primary demand of adding to existing risk prediction models for older people in Scotland; the new multimorbidity measures, while informative, will need further refining beyond the thesis author's expertise to reliably identify every condition within. Whilst this is still a major limitation, and discussed to that end in chapter 8, the multimorbidity measures developed for this thesis produce reliable estimates of risk and care outcomes in an older population, as demonstrated by predictive ability of models, and confidence intervals of individual conditions within the models.

1.3. Aims and research questions of PhD

At its core, the aim of the PhD is to improve risk prediction for demand for care among older people with complex needs. The literature and policy review in chapter 2 identified three key research objectives stemming from this primary aim, for which appropriate analyses were conducted to answer questions posed by this research. These are summarised in table 1.2.

Table 1.2: Aims and research questions of PhD

Aims	Accompanying research questions
To develop tools to enable providers to provide integrated care more reliably and quickly to older people with multimorbidity.	*All*
To determine which measures of multimorbidity, based on source data, identification methods and included conditions, best predict mortality and healthcare utilisation outcomes, and how strongly individual components of multimorbidity are associated.	• Which multimorbidity measure(s) best predict mortality & healthcare utilisation outcomes in older people in Scotland using linked administrative data? • What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes? • Which multimorbidity measure(s) best predict transitions into social care in older people in Scotland using linked administrative data?
To determine which measures of multimorbidity, based on source data, identification methods and included conditions, best predict use of social care, how strongly individual components of multimorbidity are associated, and whether the strength of this association differs by geography and/or socio-economic circumstances.	• What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care? • Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?
To determine which measures of multimorbidity, based on source data, identification methods and included conditions, best predict use of informal care, whether transitioning into local authority provided (henceforth "informal care") or provided by a co-resident (henceforth "co-resident care"), in both administrative and survey data, and how strongly individual components of multimorbidity are associated.	• Which multimorbidity measure(s) best predict informal/co-resident care uptake in older people in Scotland using linked administrative data and linked survey data? • What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal care? • Is linked administrative or linked survey data able to better predict informal/co-resident care in older people in Scotland?

1.4. By-chapter summary of PhD

The below table contains a list of each subsequent chapter in the thesis (minus supplementary chapter such as the references and appendix) and presents a short description of the type of chapter as well as a summary of the contents.

Table 1.3: Summary of all chapters in thesis and main contents

Title	Type of chapter	Summary of contents
Literature review	Literature review	After reviewing ~150 papers, the literature review was split into three key areas: multimorbidity and health outcomes, deprivation, and transitions into social care, and multimorbidity and informal care.
Methods of measuring multimorbidity	Literature review Methodology	Discusses both literature behind multimorbidity in general and introduces and justifies selected multimorbidity methods used in the analyses. Consists of a discussion of multimorbidity in the context of social care, how to measure multimorbidity in a quantitative setting, and an overview of the chosen multimorbidity scores.
Methods of analysis	Methodology	Consists of four main sections: an overview of the data used for the analyses, how the datasets were constructed, the main analyses for each of the three analysis chapters, and ethical considerations.
Multimorbidity & health outcomes	Results Discussion	Examines the best multimorbidity measure for predicting health outcomes (mortality, admissions, emergency admissions, hospital days) as well as at what score that measure is particularly associated with each outcome. Also examines within the most predictive score what individual conditions are most strongly associated with these outcomes. This is done using panel regression modelling as detailed in the methods section. Discusses the results of these findings.
Multimorbidity, deprivation and transition into social care	Results Discussion	Determines the most predictive multimorbidity measure of transitioning into social care as well as how this varies by score of this measure as well as the most predictive individual conditions from that score index, in the same way as chapter 5. Also examines regional differences in depth by examining how the relationship between multimorbidity and social care varies by local authority, ordering each LA by average Scottish Index of Multiple

		Deprivation (SIMD) score. Finally, also examines how social care varies in SIMD quintile 1 of each LA, again ordered by average SIMD. Discusses the results of these findings.
Multimorbidity & informal care	Results Discussion	Determines the most predictive multimorbidity measure of transitioning into informal care/receipt of co-resident care in administrative and survey datasets, as well as how this varies by score of this measure as well as the most predictive individual conditions from that score index, in the same way as chapter 5. Also compares how predictors of transition into informal care in administrative data and receipt of co-resident care in survey data vary. Discusses the results of these findings.
Conclusion	Discussion	Summarises the key overall findings from the study, discusses limitations of research and steps that can be taken when considering these, and offers concluding remarks.

Chapter Two – Literature review

The process of identifying relevant papers for literature review consisted of three phases. At the inception of this PhD, the author was inexperienced with the topic subject, and thus searching for literature consisted of using keywords relating to health outcomes, social care, multimorbidity and ageing to search literature databases such as Google Scholar and ProQuest, as well as collating additional papers from colleagues within both academia and policy. Exhaustive details on the results of these searches such as hit counts and search dates were not retained, but some information on the search strings and papers found was kept, with examples given in Appendix A1. The aim of this initial review was to gain an understanding of multimorbidity as well as its relationship with health and social care, and decide on a direction for the project supported by gaps in the existing literature.

The second phase of this review began following a decision on the research focus of the project (comparing multimorbidity measures in predicting health and care outcomes). Refined keyword strings were used to identify papers which matched the topic subject, with the keywords used changing as the author became more familiar with the language used, and methodology of papers comparing multimorbidity in predicting health, such as use of the area under the receiver operating characteristic (ROC) curve (AUROC, or AUC) or c-statistic. Examples of keywords and papers reviewed as a result of these searches are given in Appendix A1. Papers were reviewed until the author was satisfied that key measures of multimorbidity and how these measures related to outcomes of interest had been identified. Prior to the submission of the initial thesis, a top-up search was also run for relevant policy or key literature.

The third phase of this review commenced following feedback regarding weaknesses in the original review's thoroughness and purpose. To this end, a more meticulous search along the lines of Phase 2 was conducted, using refined keywords based on those used in prior reviewed papers as well as phrases used in a similar search by Stirland et al (2019) to search PubMed, Web of Science and Medline, with a further search with identical parameters run close to submission. The aim of this was to capture any papers not found in the initial search which compared existing measures of multimorbidity in predicting health and care outcomes, in a general population. Studies using a population restricted to those with a particular condition (i.e. comorbidity studies) or in acute care (e.g. admissions to hospital or in a care home) were excluded, as were studies which compared a novel or author-developed index to existing scores; the purpose of this review was to compare predictive ability of existing scores (preferably the ones selected for inclusion in this study based on Phase 2), not document all scores as was the purpose of the Stirland review.

In Phase 3, titles of every paper found in each database were checked, followed by abstracts and (if necessary) full-texts or potentially relevant papers following inclusion in the literature review. Papers were also retained if they were not specifically relevant to the intention of the search, but were potentially relevant to the thesis more broadly (such as policy recommendations). Details of the dates of each search, keywords used, hits, papers screened, and papers selected for review can be found in Appendix A2. To test the validity of the searches, results were checked to see if four previously reviewed key papers (Brilleman and Salisbury 2012, Diederichs et al 2010, Huntley et al 2012 and Wallace et al 2016) had been found; all of which appeared in at least one search.

Once selected for review, papers were read, annotated, and scanned for compartmentalised information relating to methodology (study design, participants, analysis), key topic areas (multimorbidity e.g. indices used or definition, social care, health outcomes and what they were) and key messages/relevance to this study. Papers were also assigned one or more category depending on their content such as "deprivation" or "informal care." This information was extracted and placed in a summary table; column headings and examples of reviewed papers are provided in Appendix A3.

At the outset of the literature review, a grading system was implemented and maintained throughout. Given the wide range of literature reviewed, and changes in scope throughout the lifetime of the project, the primary purpose of the rating system was to prioritise study inclusion in the final thesis, and identify key papers, rather than systematically evaluating literature. As a result, criteria for grade placement were loosely defined, with some overlap; given this, validity checking was not appropriate. Grades were allocated based on relevance relating to five domains: multimorbidity, social care, health outcomes, older people and study design (quantitative or non-quantitative), ranging from A (relevant in all five domains and particularly high quality, or a key reference fundamental to the topic), to E (met very little of the five domains but included a nominal reference). Most papers of grades A and B were included in the final literature review, while papers of grades C to E were included if contributing anything further. Papers were also given grade X (excluded) post-review if they were of no relevance. Further details of this grading system, as well as examples of papers for each grade and justification, can be found in Appendix A3. The aim of the literature review, in phases 1 and 2 was to guide study and methodological development, rather than synthesise all available evidence in a particular area. The aim of phase 3 (and any additional top-up searches) was to capture any key literature not already found in phases 1 and 2; given that this took place after the analyses were performed, synthesis of any literature which was substantially different or replicated the findings of this PhD may have resulted in further analyses; this proved not to be the case. Approximately 250 studies were reviewed, with circa 100 referenced in this chapter.

Whilst the strategy used for this literature review was not as exhaustive as other methods typically required in Medical or Public Health disciplines such as a systematic or scoping review, the author is satisfied that this approach (an initial exploration of the topic subject, followed by reviewing of literature with increasingly refined search terms until key messages were evident) is typical of the narrative literature review (UAB 2022) and is consistent with what is expected within Social Science and Humanities (NYU 2022), particularly given that there were no clearly defined research questions at the outset of the PhD.

Based on the main findings from the papers, the review was split into five sections, the final three forming the three main focuses of the thesis:

- A "key outcomes" section examining the overall findings from the literature review, relevant to the entire thesis.
- A policy review section specifically focusing on the Scottish government's approach to integrated health and social care for older people with multimorbidity
- **Focus 1:** Multimorbidity in predicting health outcomes using administrative data
- **Focus 2:** Multimorbidity and transitions into social care using administrative data, and how this interacts with deprivation
- **Focus 3:** Multimorbidity and informal care using administrative and survey data

At the end of each section, the gaps found in the literature are summarised – this forms the basis of the research questions summarised in the table at the end of the literature review, and how this thesis can address these gaps.

2.1. Key outcomes

This first section looks at the main themes of this thesis, which are relevant to all sub-chapters. These themes are the following: that multimorbidity and use of care consistently predict adverse health outcomes, that integrated care is beneficial for people with multimorbidity (but care needs should be predicted more effectively), and that multimorbidity is a difficult concept to quantitatively measure.

2.1.1. Multimorbidity and social care associated with health outcomes

The main predictors of interest (multimorbidity and social care) are consistently associated with adverse health outcomes. These health outcomes can be sorted into two broad categories: overall health and quality of life (mortality, self-rated health) and measures of healthcare utilisation or HCU (admissions to hospital, healthcare costs, physician appointments and bed days).

A systematic review of ageing and multimorbidity by Marengoni et al (2011) found that increasing conditions (Wolff et al 2002) and diagnosis groups (Condelius et al 2008) resulted in a higher number of hospitalisations. The review found fewer papers examining mortality, with varying outcome measurement periods from 2- to 10-year mortality – binary outcomes such as 2+ or 7+ conditions were associated with increased risk in some studies (Menotti et al 2001, Byles et al 2005) but not in others (Marengoni et al 2009). The reviewers noted, however that variance in multimorbidity measurement may have led to inconsistency in results. A longitudinal study by Pot et al (2009) examining people aged 55-85 in Amsterdam with linked survey and mortality data found that a count-based multimorbidity variable predicted healthcare utilisation as well as being in an "end-of-life" group. Badia et al (2013) also found that multimorbidity predicted one-year mortality, when linking health assessment data to deaths for patients in Catalonia aged 65 and above; this study only included people receiving home care. In terms of costs, Kasteridis et al (2015) used linked health and social care data comprising the entire population of South Somerset in England in 2012/13, operationalising multimorbidity as a count of 8 "clinically significant" conditions as well as a binary "three conditions or more" variable. They found that multimorbidity predicted almost all costs for different kinds of healthcare, including inpatient and accident and emergency (A&E). This study in particular noted that the number of conditions was just as important as the type of conditions, indicating an exponential effect in which individual conditions, when multimorbid, impact health more than each condition individually.

The literature reviewed also found evidence of association between receipt of home care and likelihood of adverse health outcomes, not as a direct effect (i.e. that receipt of care worsens health) but as an indicator that receipt of care implies poorer health status. Pot et al (2009) found that those in the "end-of-life" group were more likely to use both "professional" care and informal care – however, the effect disappeared when adjusting for frailty. A study by Deschodt et al (2015) which examined a small cohort of patients (n=442) admitted to hospital in Belgium looked at a number of different subsets of care, such as home nursing care, meal delivery, cleaning help and shopping assistance. The latter two were identified as the strongest predictors of both one-month and three-month readmission. They suggest that these among other results show clear differences in the wellbeing of older people admitted to the emergency department compared to those who do not, and that those who fit this profile should be identified for provision of good quality care to avoid adverse health that could lead to further admissions.

All the literature reviewed in this section suggests that people with multimorbidity – however defined – are at a greater risk of mortality, admissions, and increased healthcare utilisation than those who do

not. As introduced in chapter one, integrated social and health care may reduce this risk. This is another key area found within the literature review

2.1.2. Integrated & generalist care and predicting need

Integrated care, in the context of this study, refers to social care that is administered under a joint body that is also responsible for delivering primary care, to ensure common goals and easier communication between both types of care providers. Integrated care is particularly important for people with multimorbidity because it makes it easier to deliver what is called "person-centred" or "generalist" care that takes a holistic approach to delivery focused on the individual as a whole in contrast to the "disease-focused" approach commonly favoured by primary care, in which each disease is treated individually according to established guidelines.

In primary care, disease-focused approaches for medication can result in, but are not the sole cause of, "polypharmacy" i.e. overprescribing of multiple medications for multiple conditions. The exact definition of polypharmacy can vary, but is commonly accepted to be ten or more distinct medications (Scottish Government 2015). Medication for one condition can exacerbate another (Health and Social care Alliance Scotland 2014); for example, psychotropic drugs can increase risk of obesity or diabetes (NIHR 2021). In addition, polypharmacy can lead to higher likelihood of potentially harmful drug-drug interactions (DDIs). According to a longitudinal Tayside-based study by Guthrie et al (2015) examining prescription rates over time in adults, DDIs rose from 1995 to 2010. Guthrie et al recommend that in part to reduce this, clinical guidelines for specific conditions (which are increasingly more focused on prescribing large numbers of medication) should include sections on stopping drug treatment when potential risks or impacts of quality of life outweigh benefits. A literature review looking at papers suggesting a generalist care approach to multimorbidity by Boyd & Lucas (2014) found that people with multimorbidity take large numbers of medications, make an unreasonable amount of lifestyle changes and are at risk of harmful DDIs if following a disease-focused approach. They argue that if a medication carries a high individual risk of DDI, then it should not be considered. Guidance on approaching polypharmacy by the Scottish Government (2015), updated in 2018, makes the distinction between "appropriate" polypharmacy – purposeful prescribing when there is an expectation that treatment goals be met – and inappropriate, when there is a risk of adverse drug reactions (ADR).

A number of studies examine how integrated care can help facilitate an environment in which social care can be more easily delivered due to greater co-operation between primary and social care providers. A case study synthesis by Wodchis et al (2015) examined seven case studies in English-speaking Western countries delivering integrated care for older people with complex needs. They

found that common characteristics of these programs included a holistic assessment and a named manager to oversee care. Outcomes in these studies included in a reduction of emergency admissions in four and a reduction of hospital days/length of stay in three, suggested that if delivered correctly integrated care can reduce emergency health care costs. It was also noted that days spent at home increased in one study, and mortality decreased in another. Kasteridis et al (2015) mentions that people with multimorbidity stand to benefit most from integrated care, as numbers of conditions, rather than specific conditions, are more strongly associated with care costs. A systematic review and population study by Salive (2012), whilst primarily investigating prevalence of multimorbidity, also recommended approaches that are patient-centred and recognise that multimorbidity is complex and varies by individual.

However, it is important to point out the difficulties in integrating care to begin with; whilst increasingly crucial to meeting complex needs of an ageing population, integration requires system-wide change, and is proving difficult to implement in Scotland (Mercer et al 2021, Scottish Government 2021). Wodchis et al (2015) found that whilst integration did result in improved health outcomes, primary care providers were at times reluctant to engage with the programs due to the focus on generalist care. A qualitative study by Rosstad et al (2013) invited social care workers and health professionals in Norway to develop a cross-disciplinary approach to generalist care and found similar issues. Both sets of providers found it difficult to agree on how best to deliver care for people with multimorbidity, with care workers favouring a generalist approach and health care professionals favouring a disease-focused approach. The authors noted discrepancies in how those from both professions approached multimorbidity, but noted that the outcome of the focus groups was agreement on a patient-centred approach which included input from primary and social care.

The literature strongly suggests that integrated care is beneficial to people for multimorbidity, but this brings us back to the issue of heterogeneity within multimorbidity and how no single person with a particular condition has the same needs or prognosis. Whilst many studies find that integrated care helps people with complex needs, few examine what characteristics within people with complex needs are most predictive of need for care. A cross-sectional study of a large section of the Scottish population by Barnett et al (2012), highly relevant to this thesis in a number of areas, addresses how multimorbidity in the Scottish population varies by deprivation and age. Looking at individual conditions the authors found that the prevalence of particular conditions, particularly mental health-related, vary by deprivation level. Boyd & Lucas (2014) mention that multimorbidity measurement depends on what conditions are considered and how they are identified, but as a literature review this was not actively investigated.

The conditions chosen for Barnett et al (2012) and Kasteridis et al (2015)'s studies were identified via physician review, but it would be helpful to compare multiple measures to see which perform best at predicting care need, of which literature is scarce. This is further compounded by the fact that multimorbidity is difficult to quantify dependent on context.

2.1.3. Difficulties involved in quantifying multimorbidity

While progress has been made in recent years as outlined in chapter one, the definition of multimorbidity still varies throughout literature. The report by the Academy of Medical Sciences (2018) put forward, at the simplest level, that multimorbidity should encompass two or more co-existing conditions; however, data on all relevant conditions may not always be available. A systematic review on studies reporting prevalence of multimorbidity by Fortin et al (2012) found that observed prevalence was not consistent between studies (from 3.5% to 98.5%), with inconsistent population recruitment and design, and that definition of multimorbidity (usually two or more conditions, but sometimes three or four) was principally responsible for this variance rather than actual population prevalence. A similar systematic review by Ho et al (2021) found that in studies measuring multimorbidity, only eight conditions were used from which to define multimorbidity in over half of the studies, suggestion considerable variation in not just the population, and definition, but also the pool of conditions for which multimorbidity is defined.

A number of studies investigating multimorbidity use more complex parameters than two or more conditions. Examples of this include a composite score via either a count of identified conditions or a weighted condition index (Charlson et al 1987), individual conditions compared to each other (Ferrer et al 2017), specific combinations of individual conditions (of two and up) (Brilleman et al 2013), or clusters of conditions determined via statistical methods such as factor analysis (Prados-Torres et al 2021). A number of established methods for measuring multimorbidity exist; whilst cross-comparison of these is still subject to the limitations mentioned above, it is accepted that which methods is most appropriate varies depending on the population under study, the health outcome being studied in relation to multimorbidity, and data available (Academy of Medical Sciences 2018).

There are many existing studies which compare both condition combinations and different multimorbidity scores. A study by Brilleman & Salisbury (2012) used a number of count-based and weighted condition scores to predict mortality and consultations using GP and prescription data in a sample of patients registered at English general practices. Similarly, Wallace et al (2016) performed a similar approach using a smaller Irish cohort to predict emergency admissions, the scores in both of these studies drawing on data from either administrative records or prescription data. Another study by Brilleman et al (2013) used an alternative approach, interacting seventeen conditions from the

Quality and Outcomes Framework (QOF) together to make two-way interactions and analysing how each of these predicted primary care costs. Both of Brilleman's studies used data from the General Practice Research Database; the majority of multimorbidity scores are derived from administrative data (such as admissions or GP consultations).

The above demonstrates how varied and complex the process of measuring multimorbidity is, and provides pointers on the best approach to both measuring multimorbidity and using it to identify particularly at-risk groups.

2.2. Policy review

Given that this PhD was partly developed with and supported by Scottish Government input, and primarily to provide assistance in predicting social care use using available multimorbidity data, it is necessary to understand the policy background to integrating social care for older people with multimorbidity: how policymakers plan to implement person-centred care, how providers interpret and aim to use data on multimorbidity and how the current research can help achieve those aims.

The review on policy is split into two main areas – the constraints of the data in evaluating integrated care, and how multimorbidity is approached in policy documents.

2.2.1. Project data and integrated care

Outside of care provided in care homes, local authority-funded, or "formal" or "social" care in Scotland, as defined in the Social Care Survey (SCS), can be classified as – "home" or "personal" care. Home care can refer to services around the house that the individual requires assistance with – such as help with shopping, doing laundry or house cleaning – as well as technology-provided care such as community alarm (a panic button the care recipient can press when requiring urgent help). Personal care refers to tasks that the individual requires assistance with, such as preparing meals or personal hygiene such as cleaning oneself. In Scotland, one can usually receive either home care or both types of care. Normally, personal care alone is not an option as those receiving personal care will have diminished functional ability and will almost certainly require home care too – however, demand in some areas is so great that only personal care is provided.

Free personal and nursing care (FPNC) was seen as a "flagship" policy of the then-Scottish Executive when the Scottish Parliament was first opened in 1999 and was implemented in 2002. This policy guaranteed personal and nursing care for those aged 65 and over, subject to assessment of need by their local authority. If an individual is eligible for social care, they can either receive it directly from

the local authority or instead choose a number of "self-directed support" options (such as receiving a direct payment for care for them to make the arrangements themselves, choose their care plan but have the LA manage the payments, or a combination of the two) (Bell 2018). There are many policy papers on what is termed "joined-up" care, all in agreement that it is required and particularly for people with complex needs, but with varying views on how it should be delivered.

Integration is the focus of the Scottish Government (2014) paper regarding the "route map to the 2020 vision of health and social care", which summarises and sets out plans for improving health and social care in the following years. The reason for this is a focus on providing care in a home setting, and primary and social care services working in partnership, as well as developing local solutions for problems such as relative inequalities. A report by the Health and Social Care Alliance Scotland (2014) emphasises a holistic approach, empowering care recipients to make their own decisions. A "multimorbidity action plan" by the Scottish Government (2014) advocates integration as a way of moving away from a clinician-dependent disease-focused system and avoid fragmented care. On the more technical side, as mentioned previously the health and social care integration narrative by the Scottish Government (2014) discusses how integration can be taken forward, with either an "integration joint board" directing the process or either the health board or local authority taking overall responsibility for delivering the program.

The process of integration officially began on 1st April 2016 via the Public Bodies Joint Working Act (though some bodies had already begun integrating services prior) and reviews have been published on the policy to date. A joint review on the integration process by COSLA and the Scottish Government (2019) suggests that whilst planning and service delivery is improving as a result of integration, further improvements, such as in partnership working, are required. In particular, the development of a COSLA-wide integration framework has been suggested. An update on progress with integration by Audit Scotland (2018) comments that while some targets have been met (such as an increase in days spent at home during palliative care, and a reduction in emergency bed days), emergency admissions are still rising and there have been issues around joint leadership and governance agreements. A further review (Scottish Government 2021) identified similar issues and lack of progress, prompting the recommendation for a National Care Service (NCS).

Some of the aims of integrated care as defined by the review of progress by COSLA & The Scottish Government (2019) include improving healthy life expectancy, reducing health inequalities via health and social care, and supporting independent home living for those with disabilities or long-term conditions. Those with multimorbidity have by definition multiple long-term conditions, and many people with disabilities will also have multiple conditions. Both will benefit in this regard from integrated care.

2.2.2. Policy documents and multimorbidity

The majority of policy literature on integrated care highlight those with multimorbidities as a key demographic to benefit from this policy, whether directly or as the more general designation of people with "complex needs" or "long term conditions." The implication is that a disease-focused short-term treatment care model is not as effective as one that takes account of the individual as a whole, including condition interactions and long-term prognosis irrespective of the care given.

The health and social care vision by the Scottish Government (2014) frequently refers to older people with multimorbidity as particularly benefitting from integrated care. The multimorbidity action plan by the Scottish Government (2014) focuses on delivering integrated care for those with multimorbidity, and mentions that multimorbidity is associated with increased likelihood of emergency admissions – frequently used to outline that social care in its current form is ineffective at prevention of emergency interventions. An advice paper by the Joint Improvement Team (2014) also notes that emergency admissions are rising year-on-year, particularly for people with high numbers of coexisting conditions. A paper on national clinical strategy, also by the Scottish Government (2016) mentions that admissions, care uptake and bed days are all higher amongst people with long-term conditions, and suggests that social support (either from relatives, friends, or social care providers) is required more for people in this demographic than just primary care. The NICE guidelines (2016) for assessment and management of multimorbidity stress individualised management plans, and improvement of holistic assessment for people with multimorbidity, and mentions that emergency health service use is greater for this demographic.

However, in the majority of the papers reviewed, there is an absence of a consistent definition of multimorbidity. As mentioned previously, people with multimorbidity can have a wide array of both conditions and impacts of conditions on their health depending on their age and socioeconomic status among other factors. Papers refer to "multimorbidity" or "long term conditions" as a whole but do not explore this concept further. Identification of multimorbidity is a key step in delivering care that takes account of the individual's specific needs, but this is one area that a number of the policy documents have missed out. Guidance for the Scottish Health Survey (SHeS) by the Scottish Government (2016) (a cross-sectional nationally representative health survey of the Scottish population) provides a number of different examples of operationalising multimorbidity (such as recoding into International Classification of Disease (ICD) categories).

Throughout policy documents, people with multimorbidity are often treated as one homogeneous population, with little exploration of differential care requirements from different kinds of multimorbidity. Some papers do mention this to an extent – the route map for health and social care

(Scottish Government 2014) does mention that one particular avenue to explore is the most frequent combinations of particular conditions. However, this still does not address the issue of how those conditions can be reliably assessed in the population. Of all policy documents regarding multimorbidity and long-term conditions in Scotland, one (ISD 2008) compares prevalence of a selected list of conditions within general practice, Quality Outcomes Framework, survey, and admissions data, finding that a number of conditions such as dementia and hypertension are under-reported and under-diagnosed across some of the datasets (in particular admission and survey data). A paper on comorbid conditions (particular combinations of conditions as opposed to combinations of any conditions) by the UK Department of Health (2014) refers to some comorbidities as being dominant (in which one condition has a greater effect on the health of the individual than the other), synergistic (in which the conditions are related to each other) and coincidental (where there is no relationship). This paper in particular considers the nature of conditions in considerably greater detail than the Scottish papers mentioned. The absence of a unified definition of multimorbidity has been discussed earlier in this thesis, and whilst the Academy of Medical Sciences (2018) paper provides a solution, it is stressed that population and outcome should be taken into account. There needs to be a greater understanding of not just that people with multimorbidity are different, but how they are different, how this can be measured with available data, and how observable differences are fed back into the assessment and care planning process. A data-driven approach will allow care providers and health professionals to assign each person care that is specifically tailored to their needs as identified by their multimorbidity profile.

The closest approximation of an algorithm for identifying those at risk of adverse health outcomes in Scotland, with adjustment for multimorbidity, is the Scottish Patients at Risk of Readmission and Admission (SPARRA) tool, developed by ISD in 2006 and updated in 2008 and 2011. Designed to identify those at particular risk of emergency readmission, the most recent version of the tool uses one year of admission, prescribing and outpatient data (with three years of emergency admissions) to calculate emergency admission risk scores from age, sex, area deprivation, location, prior healthcare utilisation, prescribing for specific medication groups or conditions, and diagnosis of a select number of condition groups from previous admissions. Combinations of these variables are used in three cohorts (frail elderly, long term conditions, and younger emergency department), which together capture approximately 95% of the Scottish population who have emergency admissions each year. Whilst SPARRA is a useful screening tool which allows care providers to make informed decisions on anticipatory care, it would benefit from refinement. The list of conditions identified are now ten years old, were derived primarily through an algorithm-based approach as opposed to theory-based, and consist largely of broad condition groups rather than specific conditions; a paper by Wallace et al (2016) notes that five conditions in particular are responsible for most urgent admissions within the UK. More recently, the High Health Gain Potential (pHHG), developed by ISD successor Public

Health Scotland (2020) uses multiple routine health datasets to identify who in the population would benefit from anticipatory care planning.

In addition, it should be noted that the majority of the literature reviewed in this section specifically focusing on multimorbidity is from before integrated health and social care was implemented. The majority of policy documents added post-implementation focus on evaluating integrated care as a whole, as opposed to multimorbidity in particular. Again, there are mentions that people with complex needs will particularly benefit from integration (COSLA & The Scottish Government 2019, NHS Scotland 2017) but this does not sufficiently address how this is going to be achieved, and indeed if it has since integration. Finally, the policy documents – whilst stressing the importance of integrated care in particular for older people with multimorbidity – do not put in place a plan for how multimorbidity can best be identified. The SPARRA tool (ISD 2011) ensures that there is a form of anticipatory care provision based on risk prediction, but as mentioned its definitions of multimorbidity are somewhat rudimentary and only address one type of health outcome (admissions).

2.2.3. Gaps in literature

As elaborated on in 2.2.2, multimorbidity is at the forefront of the Scottish Government's mind in terms of who can most benefit from integrated care, and in this regard, it is important to find a way to classify who does and does not have multimorbidity in order to best provide care. However, the latter is something that the literature does not mention.

- ***The review of policy documents would recommend there is a need to reliably use multimorbidity to identify individuals at risk of adverse health outcomes or transitions into social care, but current work uses limited or dated strategies to achieve this.***

2.3. Multimorbidity and health outcomes

This section focuses on the predictive ability of different multimorbidity measures for health outcomes. Three key areas are covered here: an overview of what determines the best multimorbidity method to use and what existing literature says regarding the best multimorbidity measures for particular health outcomes, that these outcomes often conflict with each other largely due to demographic discrepancies, and that no study has evaluated the predictive ability of multiple multimorbidity measures on the entire Scottish older population.

2.3.1. Selection of multimorbidity measures and existing studies

There are a number of different methods used in literature to measure multimorbidity, typically chosen based on study focus, the population used and data available. Composite multimorbidity measures generally consist of a pre-developed "index" based on flags in data for specific conditions, usually from self-reported data or administrative records (Ho et al 2021). The score developed by this index can either be a flat count of conditions such as the Elixhauser Index or EI (Elixhauser et al 1998) or one where certain conditions are "weighted" according to disease severity following physician review, such as the Charlson Comorbidity Index or CCI (Charlson et al 1987). Most studies will either use an already established index, develop their own list of conditions as in Kasteridis et al (2015) or Barnett et al (2012) or (particularly when using multimorbidity as a control variable) use a simple count of conditions or macro-level categories (as a "proxy" measure).

Which of these approaches to use is still highly contested. The overriding view is that the optimum multimorbidity measure varies by the outcome being examined (Brilleman & Sailsbury 2012), and the demographics of the study population (Huntley et al 2012). This is the recommendation in the Academy of Medical Sciences (2018) report, which suggests that the optimal measure of multimorbidity for any given study is dependent on population studied and outcome under study. The effectiveness of a multimorbidity measure within these parameters is primarily derived from its data source. Diagnosis-based measures, typically derived from health care utilisation data such as admissions or GP attendance, tend to overestimate condition prevalence, whilst medication-based measures, derived primarily from issued prescriptions, perform better at monitoring long-term health conditions but contain limited diagnostic information (Fortin et al 2012) and are further limited by the fact they identify medication used to potentially treat a specific condition, not the condition itself.

A systematic review on existing multimorbidity indices by Diederichs et al (2011) found that multimorbidity scores based on administrative data or medical records (such as the CCI, Medication-Based Disease Burden Index or Incalzi Index) were usually developed for predicting mortality (or admissions, in the case of the Chronic Disease Score or Seattle Index of Comorbidity) whilst scores based on survey data were developed for predicting functional status or self-rated health (such as the Comorbidity Symptom Scale). However, there is some overlap – the Self-Administered Comorbidity Questionnaire by Sangha et al (2003) was developed for admissions, medical costs, and quality of life. The study also mentions that most of these indices do not provide any particular justification for including specific diseases.

There are many studies which examine the predictive power of multimorbidity scores and compare different measures against each other, in order to recommend the optimum multimorbidity measure

for a specific outcome using a data driven approach. Most do this by way of comparing parameters of non-nested models such as the Akaike or Bayesian Information Criterion (AIC/BIC) or the AUC. The majority of comparison studies look at health outcomes such as general health status (i.e. mortality or rated health) or HCU (i.e. admissions, costs, or physician consultations). Brilleman & Salisbury (2012) used GP and prescription data to predict mortality and GP consultations, whilst Wallace et al (2016) used a mixture of administrative and survey data to predict emergency admissions and functional decline.

Almost all studies which compare multimorbidity measure prediction are clinically or public health based. All of the outcomes examined are health-based; an example is Brilleman & Salisbury (2012) who look at consultation rates but only GP rates; not social care receipt. This study, and others, do not control for social care; likely as most of the data sources for these studies do not have access to social care data which is largely census-based and held by local as opposed to national providers. However, it should be noted that even when using the same selection of multimorbidity scores, between-study performance is subject to high variance. This is typically as a result of data sources, the population involved, and the outcome under study.

2.3.2. Variable cross-performance of multimorbidity measures by population and outcome

A systematic review by Fortin et al (2012) on studies reporting multimorbidity prevalence, and further research by Lefevre et al (2014), has found wide variation in recruitment of participants, collection of diagnostic information and cohort size; variance in condition prevalence was most likely explained by methodological differences. For example, Brilleman & Salisbury (2012) do not restrict their study population to older people, with the sample containing anyone aged 18 and above. Wallace et al (2016) on the other hand only included people aged 70 and up. Studies can be drawn from a general population (Stanley & Sarfati 2017), or an acute care sample such as admissions to hospital (Holman et al 2005); the latter may present misleading findings especially when generalising the results to the population as a whole.

Variance in measure effectiveness by outcome under study can occur even within similar populations. Generally, however, diagnosis-based indices (such as the CCI and EI) perform better at predicting mortality, whilst medication-based measures (Chronic Disease Score or CDS, CDS-2, RxRisk) fare better with healthcare utilisation outcomes (admissions, appointments, hospital days). A systematic review of systematic reviews measuring multimorbidity (Johnston et al 2018) found that the CCI or diagnosis-based measures typically performed best for mortality, as did other systematic reviews (Sharabiani et al 2012, Yurkovich et al 2015) and numerous other studies (Brilleman & Salisbury 2012, Lu et al 2010, Perkins et al 2004, Schneeweiss et al 2004). Whilst medication-based measures

are relatively underused compared to diagnosis-based, the systematic reviews (Johnston et al 2018, Sharabiani et al 2012, Yurkovich et al 2015) also found that medication-based measures outperformed diagnosis-based for healthcare utilisation, as well as did some other studies (Brilleman & Salisbury 2012, Fan et al 2008, Park 2016, Wallace et al 2016). Some exceptions do exist, such as the medication-based Rx-Risk-V outperforming the CCI in predicting mortality in one study (Johnson et al 2006); however, this is rare and against the overall trend.

Whilst performances of multimorbidity measures by source of data are generally consistent for each outcome, studies have shown mixed results when cross-comparing different measures from the same data source. For example, among the two most frequently used diagnosis-based measures (the CCI and EI), the CCI outperforms the EI in some studies, and populations within studies for mortality, particularly long-term (Corrao et al 2017, Fernando et al 2019, Sharabiani et al 2012, Snow et al 2020) whilst in others the opposite was found, especially short-term mortality (Austin et al 2011, Fernando et al 2019, Mnatzaganian et al 2012, Quail et al 2011, Sharabiani et al 2012, Snow et al 2020, Yurkovich et al 2015); the EI generally performs better when predicting healthcare utilisation (Fernando et al 2019, Huang et al 2020). Studies have also compared different versions of specific indices, for example a self-reported CCI performing identically to the original in predicting mortality (Chaudhry et al 2005) and a weighted adaptation of the EI outperforming the original unweighted version, also in predicting mortality (van Walraven et al 2009). Cross-comparison of medication-based indices is rarer, and as a result it is difficult to infer any trends. Most have found the RxRisk (Wallace et al 2016 and Yurkovich et al 2015) or CDS (Park 2016) to be the strongest predictor of healthcare utilisation, and one study in the Yurkovich et al (2015) systematic review found the CDS performs best at predicting mortality.

In addition to variation in cross-comparison of multimorbidity measures within the same population, it must also be taken into account that the objective predictive ability of each measure varies between each study. The preferred measure of cross-comparison is the AUC, a measure of model performance from 0 to 1 which plots sensitivity and specificity of individual values. An AUC of 0.8 is considered good, 0.7 acceptable, 0.6 poor and 0.5 indicates no precision (Mandrekar 2010). The systematic review by Yurkovich et al (2015) reports wide variation in the AUC across all studies, measures, and outcomes, from 0.5 to above >0.8. Specifically, for one-year mortality, CCI AUCs ranged from 0.650 to 0.906 and EI AUCs from 0.690 to 0.909. The Quail et al (2011) study, in an over 65 population, found AUCs ranging from acceptable (0.7) to good (0.8) for diagnosis-based and medication-based measures in predicting mortality; conversely, Quan et al (2005) found that variations of the CCI and EI all performed at above 0.8 AUC in predicting in-hospital mortality. Information on AUCs of healthcare utilisation outcomes is more scarce, though are generally more similar; both Quail et al (2011) and Wallace et al (2016) found a range of measures uniformly poor (0.6) in predicting

hospitalisation. Quail et al (2011) noted that whilst there was some degree of overlap in which measures performed best by outcome, greater disparity was observed with different study populations. In particular, measures were usually worse performing in older cohorts.

The above highlights the wide variance in predictive ability of multimorbidity measures, both within- and between-studies and outcomes. As mentioned previously, this is likely as a result of differences in study populations, and as a result the most appropriate measure for each population and outcome is not immediately obvious. Evidence from studies based in other countries, whilst helpful, may not reliably anticipate health and care use domestically. In Scotland, reliable prediction of health and care uptake is required to address an escalation in social care and emergency health service use; validation of multimorbidity measures in a national population can improve this. However, at present there are no studies in Scotland which cross-compare multimorbidity measures within an older population.

2.3.3. No studies examining national older Scottish population

As gaps in policy show, there is a need to find both the most predictive measure of specific outcomes and within those measures the people most at risk for these outcomes within the older Scottish population. Whilst there is common consensus of the type of data from which multimorbidity measures are developed to predict specific health outcomes (diagnosis-based for mortality, medication-based for healthcare utilisation), there is less agreement over whether there is a common predictor for specific outcomes. It is more than likely that there is no universally applicable measure regardless of population, and as a result separate research will have to be conducted for each when available.

Specifically, the Academy for Medical Sciences (2018) report notes that effectiveness of multimorbidity measures differ with respect to population. To the author's knowledge, and after carefully searching a number of literature databases for studies matching the required criteria, there have been no studies comparing the predictive power of multimorbidity indices using Scottish data on an entirely older (65+) general population. The closest approximation to studies meeting these criteria is Robertson et al (2019), which compares the Charlson Index with the Tonelli Index (TI; a diagnosis-based measure derived from the Barnett count) in a population of all adult admissions to hospital in the Grampian region in 2014, finding that the CCI outperforms the TI for mortality and vice-versa for length of stay and readmission. This study, while welcome, uses an admission-only sample (and therefore excludes the general population), is not restricted to the older population, and only compares two diagnosis-based measures as opposed to measures from multiple data sources. Additionally, Robertson et al (2017), which while evaluating the precision of allostatic load (a biomarker-based measure of physiological health), only compared its precision to individual components of the

allostatic load scale rather than to other multimorbidity measures, and did not use an objective measure of predictive ability (i.e. via the AIC, BIC or c-statistic) which would have allowed cross-comparison with other studies.

2.3.4. Gaps in literature

Whilst some trends in multimorbidity prediction have been observed (such as a tendency for diagnosis-based measures to perform better at predicting mortality and medication-based indices for healthcare utilisation), results for specific scores differ considerably. This suggests that multimorbidity indices differ widely in predictive power depending on the study population.

- ***Previous research on comparing multimorbidity measures to predict outcomes have conflicting outcomes, largely due to the heterogeneous study populations.***

Given that the predictive power of multimorbidity indices is in part determined by the study population, to accurately predict health and care outcomes in older people in Scotland it is necessary to compare both diagnosis-based and medication-based scores using a Scottish population. To date, bar one study looking at a regional, age-inclusive cohort, this is not the case.

- ***There are no studies comparing predictive ability of multiple multimorbidity measures for health outcomes in older people in a national Scottish sample.***

2.4. Multimorbidity, deprivation and transition into social care

The Scottish Government has prioritised looking at pathways into care for people with multimorbidity; examining literature on the relationship between multimorbidity and social care will help in making an informed decision regarding policy for care pathways. Research exists in Scotland examining the relationship between multimorbidity and deprivation, but again this is largely clinical. In contrast, much of the literature on social care, multimorbidity and deprivation are policy documents. Within people who have multimorbidity, current policy is to focus care provision to more deprived areas of Scotland, with the Scottish Government (2014) in their route map for delivering health and social care prioritising reducing health inequalities. This section focuses on three main areas: that little literature exists on using multiple multimorbidity measures to predict care outcomes, the "inverse care law" in Scotland and its effect on primary and social care in deprived areas, and the difficulty of providing consistent levels of care by local authority.

2.4.1. Lack of studies comparing multimorbidity measures in predicting care uptake, particularly with administrative data

As shown in section 2.3, there are many studies that compare the predictive power of various multimorbidity scores for a number of different health outcomes, and studies exist examining the effect of multimorbidity on care outcomes. Most of these use self-report data; for example, Pot et al (2009), the aforementioned study looking at a Dutch cohort of older people found that increasing numbers of conditions was associated with professional home care (but not informal care). However, to the author's knowledge there are no studies which compare multiple measures of multimorbidity in predicting care outcomes, and none that use a national Scottish population.

One of the objectives of this study is to examine the relationship between multimorbidity and a needs-assessment-based decision to receive social care from one year to the next, from this point onward referred to as "transition into social care." Part of this is identifying what multimorbidity measures predict transitions into social care most effectively, and within these scores what people are most at risk. Previous literature has typically used small survey-based datasets linked to administrative records. For example, Pot et al (2009) uses survey data linked to mortality data only and the study investigating a cohort of people using care by Badia et al (2013) uses only nurse assessments and mortality data. A study by Bradshaw et al (2013) examining six-month outcomes (both health and care related) for people admitted to hospital in England with comorbid conditions uses a small sample of 250, consisting of admissions data and a follow up interview, and a study by Picco et al (2016) investigating the impact of multimorbidity on care costs also uses survey data for its multimorbidity measures, which are self-reported. Care uptake is generally not included in administrative data, and as a result studies with care as a focus which use national cohorts are rate. In addition, multimorbidity measures used in these studies are typically derived via assessment or are self-reported.

Challenges involving linking care data to other administrative datasets may partially explain why there are few care-based studies with access to large national cohorts. In Scotland, social care census data is held by local authorities whilst health data is held by the NHS. Therefore, linkage of a full national dataset must be done either via consent of all 32 local authorities or via probabilistic matching. However more recently, Henderson et al (2020) found an increased risk of using social care in Scotland from an administrative-derived multimorbidity score (a count of unique medications), persisting after adjustment for age and socio-economic circumstances. Whilst this finding is welcome, the study did not compare the predictive ability of different measures.

The absence of studies which compare multimorbidity indices for a non-clinical outcome such as social care means that limited inference can be made on expected results. However, given that social

care too implies diminished health status or functional capacity, as do health outcomes such as admissions to hospital, it is expected that there will be variance in predictive ability of multimorbidity measures for social care. As discussed in section 2.3.2 medication-based indices perform better at predicting healthcare utilisation outcomes such as admissions, so it is possible that the same could apply to social care.

However, it should be noted that social care differs from HCU measures in that the decision to provide social care is made over a longer period of time, and requires lengthy assessment of individual circumstances. The decision to admit to hospital is made in order to assess and potentially treat a problem and can be planned in advance in the short-term or happen instantaneously (in the case of emergency admissions) – for transitioning into social care the assessment of the individual is made before social care is received, and as such there may be variance in predictive ability of multimorbidity measures not seen for other health outcomes. Differential impact of social care provision by deprivation must also be taken into account when examining interactions with multimorbidity, particularly in the context of the inverse care law.

2.4.2. Multimorbidity and the inverse care law in Scotland

Deprivation is a universal predictor of almost every health outcome (Salmond & Crampton 1999), and is commonly used as a covariate in a number of multimorbidity studies, particularly in Scotland. One of the most cited papers regarding multimorbidity in Scotland is Barnett et al (2012)'s cross-sectional study which uses its own set of 40 conditions, derived from a list of recommendations in the Diederichs et al (2011) systematic review, from a report on long-term conditions in Scotland, and conditions in the NHS Quality and Outcomes Framework (QOF), a system used to monitor and evaluate GP performance. The paper examined prevalence of these conditions by deprivation level on a population of 1.8 million patients at 341 general practices across the country. It was found that multimorbidity increased with deprivation and that the incidence of particular conditions such as coronary heart disease (CHD), diabetes and cancer were higher in deprived areas. In addition, the study found that mental health conditions, in particular depression, were higher in deprived areas. Within the UK, a cohort study by Charlton et al (2013) investigating the impact of deprivation on multimorbidity used data from 600 clinical practices among people aged 30 and over. This study found that multimorbidity was higher in more deprived areas and that an interaction between deprivation and number of conditions was predictive of mortality. However a systematic review by France et al (2011) on multimorbidity in primary care found that none of the six papers reviewed focused on deprivation, suggesting that outside of Scotland this relationship is not as commonly studied.

The challenges associated with this caring for people with multimorbidity in deprived areas in Scotland is complicated by what is known as the "inverse care law;" in which general practices and GP staff are flatly distributed by population rather than need (Blane et al 2012, Mercer et al 2012). This creates a situation in which there are more patients with complex needs per general practitioner in deprived areas, with less available time and resources to address these issues; consultations are generally shorter and there is less expectation of shared decision making (Mercer et al 2021). People in deprived areas may have comparatively poorer self-management (Marengoni et al 2011) and therefore require more help, which is already compounded by a higher prevalence of conditions; given this, ending the inverse care law should be central to any policy-focused approach toward integrating health and social care (Mercer et al 2021). However, a study looking at deprivation and multimorbidity by Orueta et al (2014) using a national sample of the population of the Basque Country, where investment in socialised medicine is proportional to inequality, found that deprivation was associated with more multimorbid conditions, and that both were predictive of higher healthcare costs.

Mercer & Watt (2007) examined a cross-section of 3,000 patients of 26 general practices in Scotland (split between practices in the least and most deprived areas), finding that in addition to lower overall health and higher numbers of conditions, patients at the most deprived practices reported longer waits for services, shorter consultation times and more encounters at "drop-in" clinics. Of particular concern was the higher incidence of social problems in tandem with physiological conditions – a qualitative study by O'Brien et al (2011) based on interviews with GP staff in practices in deprived areas in Scotland mentions the "endless struggle" of coping with multiple conditions as well as social problems such as poverty or poor housing. Given that social care is typically delivered by local providers, with varying approaches and eligibility criteria, the regional differences in the relationship between multimorbidity and social care may also be pertinent.

2.4.3. Multimorbidity and delivery of care by local authority

As mentioned in the policy review, in Scotland (and a number of other developed countries) social care is delivered locally, in this case by one of 32 Scottish council areas or local authorities. Each LA has individual control over how to spend its budget in a number of different areas, including provision of social care.

The FPNC policy in Scotland ensures that people over the age of 65 receive free home and personal care subject to eligibility for some services – however, due to the policy being implemented by local authorities there are large variations in how many people receive services. National standardised eligibility criteria groups potential care recipients as "critical," "substantial," "moderate" and "low"

risk following assessment of physical/mental health, environmental circumstances, participation in the community and informal carer support, with care required to be provided to those with "critical" or "substantial" risk according to eligibility guidance produced by Inverclyde Council (2016). It is whether or not councils choose to provide care to those with "moderate" or "low" risk that leads to differences in uptake rates, usually as a result of budget decisions; the recent review of social care has highlighted the perceived high threshold for receipt of care in many local authorities (Scottish Government 2021).

A paper examining free personal care (FPC) uptake in Scotland by Lemmon & Bell (2019) mentions that there is variation in FPC uptake rates at LA level and notes that local authorities carry out the assessment themselves – as a result, people assessed to be at "substantial" risk in one LA may only be assessed to be at "moderate" risk in another. It is also important to point out that these local authorities will all have varying levels of deprivation – Glasgow, for example, is on average the most deprived LA in Scotland but borders East Renfrewshire, the least deprived. This may have an effect on the budget as well as internal politics of these LAs and lead to changes in delivery – Lemmon & Bell (2019) suggest that more deprived LAs and data zones may have a lower care uptake rate, which is in conflict with care need.

In this respect, it is important to consider the effect of both macro and micro area level deprivation. For census purposes, Scotland is split evenly by population into circa 6,500 "data zones" (DZs) – geographical areas adjudged to be similar in population characteristics within each local authority. It is within these DZs that area level measures of deprivation such as the SIMD are derived. It is also possible to calculate the average level of deprivation by LA from all the component DZs, giving two area-level measures. Similar work has been done using this particular classification by Bywaters et al (2015), applied to Child Protection Plan (CPP) rates in the Midlands of England. England delivers child protection services at LA level and area deprivation (the Index of Multiple Deprivation or IMD) is calculated for lower super output areas (LSOAs), roughly analogous to DZs. Bywaters examined the "inverse intervention paradox" by examining CPP intervention rates in the most deprived 10% of English LSOAs within each LA in the Midlands, and how they varied by the average IMD of each LA. It was found that while CPP rates are higher in more deprived areas overall, they are higher in the most deprived areas of LAs that are on average less deprived. Bywaters et al (2015) suggested reasons for this paradox, such as more visible deprivation in more affluent LAs, or greater community support in more deprived LAs and therefore less need for care. Lemmon & Bell (2019) explored care rates in Scotland, finding that FPC uptake is lower in deprived areas.

2.4.4. Gaps in literature

As established in the policy section it is important not just to use multimorbidity to predict health outcomes but transition into social care use as well, in order to look at care "pathways" for people with multimorbidity and identify multimorbid characteristics which are most predictive of care uptake. However no prior research (in Scotland or otherwise) has compared predictive ability of different multimorbidity measures for social care.

- ***There are no studies which compare the predictive power of multimorbidity measures for transition into social care.***

Section 2.4.2 describes the "inverse care law" and how general practices in Scotland are allocated based on population and not need. Section 2.4.3 outlines that this may lead to differing impacts of multimorbidity on social care uptake rates in Scotland, both by relative deprivation and by local authority level. This is something that has not yet been looked at in literature.

- ***There is a lack of research into the effect of multimorbidity on social care uptake in Scotland by deprivation level.***

2.5. Multimorbidity and informal care

The policy review identified that the Scottish Government views formally provided care as integral to ensuring that older people with complex needs remain in a home setting and to prevent emergency primary care interventions. However, many people who receive local authority care will also receive what is known as unpaid or "informal" care, supplementary care usually provided by friends and family such as help with day-to-day tasks (Rutherford & Bu 2017). Informal care in this regard is very different to formally-provided care but is still an important part of the care process – a Canadian qualitative study by (Naganathan et al 2016) which interviewed both caregivers and care recipients found that informal care recipients prefer the more personal nature of informal care to formally-provided support. This section will focus on two specific areas – the difficulty of measuring informal care for health-related outcomes (particularly in administrative data), and a lack of studies comparing the predictive ability of multimorbidity measures for informal care outcomes.

2.5.1. Difficulty of measuring informal care

Informal care receipt is by nature dependent on individual circumstances, and typically provided by someone close to the individual, usually a live-in spouse or children if no spouse is present. Pot et al

(2009) found that having a partner was the most strongly associated variable in the study with being in receipt of informal care. A study by Kuzuya et al (2011) examining the relationship between informal care and a number of health outcomes in Japan amongst just under 2,000 respondents to an ageing survey found that those who receive "insufficient" informal care tend to be younger and live alone with poorer economic status. It is evident that informal care cannot be "targeted" to those who need it the most in the same way as formal care but is just as important in allowing people with multimorbidity to live independent lives.

Informal care is difficult to measure in quantitative research, primarily due to ambiguity from carers when asked if they consider informal care a service. Rutherford & Bu (2017) examined how informal care is measured in the English Longitudinal Study of Ageing and found that people gave inconsistent answers when care is referred to in different terms, such as "cared for" or "looked after". The authors speculate that recipients may not consider that they are providing informal care, or give inconsistent answers depending on the wording of the question. Studies that do use surveys to measure informal care include a Swedish study by Condelius et al (2010) which used the Good Ageing in Skane (GAS) survey to predict healthcare utilisation among just under 700 people aged 65 and above, with the study population restricted to those receiving some kind of formally provided care. Picco et al (2016) also operationalised both informal care and formal care as cost outcome variables. Another Swedish survey by Kristensson et al (2007) used the Swedish National Study of Ageing to predict healthcare consumption using a number of variables including informal care use, but in common with a number of these studies the sample size was very small (<400). A number of these studies (Condelius et al 2010, Kristensson et al 2007) also split informal care into Personal Activities of Daily Living (PADL) and Instrumental Activities of Daily Living (IADL) – PADLs refer to self-care aspects such as meal preparation, whilst IADLs refer to non-personal care, such as shopping or laundry.

The above highlights that measurement of informal care is problematic primarily due to the ambiguity of the definition as well as inconsistent self-labelling among informal care providers. Perhaps as a result of this there is currently no research comparing multimorbidity measures in predicting informal care outcomes.

2.5.2. No studies comparing multiple multimorbidity measures in predicting informal care

Sections 2.3 and 2.4 outline that the only studies comparing predictive power of multiple multimorbidity scores use health-based variables as the outcomes, with none looking at formal care uptake. The same is true for informal care. This is especially more difficult given that most comparison studies use administrative data, and as shown informal care is usually measured in surveys which have small populations occasionally linked to some administrative outcomes such as

mortality. One example is Karlsson et al (2008), which was limited to one region of Sweden (Skane) and linked questionnaire and Swedish register data to example the relationships between different kinds of healthcare including informal care – this was one of the larger samples, with just under 2,000 cases. Ultimately, when looking at informal care, multimorbidity and health outcomes it would be preferable to use a mixture of administrative data and survey data.

There are no studies which compare predictive ability of multimorbidity scores for informal care; indeed, there are very few studies which focus on the relationship between informal care and multimorbidity at all. Most studies (such as Kristensson et al 2007 and Kuzuya et al 2011) use multimorbidity as a control variable as opposed to a main focus. In Pot et al (2009)'s end-of-life study, multimorbidity is one of several measures of interest and is represented as a self-reported condition count from a list of seven, a common type of measure used in survey-based studies; however, this variable was not predictive of informal care uptake (but was of formal care). Picco et al (2016) was the only study reviewed to explore this in-depth, examining how informal and formal care costs (as well as primary care costs) increased by numbers of conditions (again a self-reported count). The cost increases for informal care per condition were higher than for formal care.

2.5.3. Gaps in literature

The difficulty of measuring informal care in both survey and administrative data, low sample sizes in studies examining it in conjunction with multimorbidity and a lack of application of methods normally used in medical studies mean that to date there have been no studies comparing the ability of different multimorbidity measures to predict informal care.

- ***There are no studies which compare the predictive power of multimorbidity measures for informal care uptake, using either survey or administrative data.***

Informal care is very difficult to measure and does not normally appear in administrative datasets; studies that use it as a predictor or an outcome often have low sample sizes. This is not necessarily an issue if surveys can reliably predict informal care use; however, there are no studies comparing informal care measurement in administrative or survey data.

- ***There are no studies that have compared whether administrative-based or survey-based data are better predictors of informal care uptake.***

2.6. Summary and research questions

A summary of each sub-section of the literature review is outlined here, followed by an explanation of how this thesis can address questions posed after synthesising the literature. Following this, the gaps outlined in prior sections are summarised, with accompanying research questions.

2.6.1. Summary of literature review and how thesis can add to existing research

The synthesis of key areas of research in section 2.1.1 outlines that multimorbidity and receipt of social care are associated with increased risk of adverse health outcomes, and section 2.1.2 expands on this by demonstrating how integrated care is particularly beneficial to the multimorbid population. In the context of this study, what is important is more effectively predicting health outcomes and understanding how multimorbidity and care provision interact. This study examines not just multimorbidity as a stand-alone concept, but also different ways of measuring and categorising multimorbidity. This will help to understand not just that multimorbidity is associated with poor health, but explore differential impact of multimorbidity severity on poor health.

The policy review in section 2.2 illustrates the evolution of provision of social care in Scotland, and that one of the main aims of integration is to make it easier for primary and social care providers to deliver generalist, person-centred care to people with complex needs. As the legislation-defined integration of health and social care began in 2016 (before the period for which the study author has access to data), this cannot be directly evaluated. In lieu of this, the data available can evaluate how best to identify individuals in need of care, specifically different types of multimorbidity and associated risk. Part of the Scottish Government's work within care provision looks at the different types of pathways that people take in and out of care. The findings from this project will aid national and local government, care providers and the wider sector in predicting care transitions and delivering integrated care for those who need it the most via potential development of risk prediction algorithms.

It was also noted that there is an absence of a focus on identifying multimorbidity within most of the policy documents. The data available in this project, outlined in chapter 4, allows for comparison and contrast of different measures of multimorbidity in order to determine which is the most predictive of health and care outcomes. It is necessary to identify who in the older Scottish population is multimorbid, and within that their individual characteristics. There are a variety of different multimorbidity measures, both score-based and for individual conditions – all from different sources of administrative and survey-based data. These findings could be used to improve risk prediction tools, such as SPARRA, for local authorities and inform needs assessments, as the same data will be

made available to local councils for this purpose (Audit Scotland 2016). The outcomes of this study and prediction models developed can be replicated by local councils using the same data to deliver integrated care to those who need it the most.

Section 2.3 outlines the large number of existing measures used to measure multimorbidity, their data sources (such as diagnosis-based and medication-based), types (such as weighted and unweighted, condition-based and proxy) and finds that studies comparing performance of multimorbidity measures often have conflicting results as a result of differential study cohorts, the outcome under study, and data sources/measures. There are no multimorbidity comparison studies for any outcome in an older Scottish population, and findings existing research may not necessarily apply to this cohort for the reasons outlines above. One aim of this PhD is to establish risk of health and care outcomes among older people with multimorbidity in Scotland, and part of this is establishing the best performing condition-based measure for these outcomes – this will ensure that, in accordance with this study's recommendations, each health or care outcome has an appropriate weighted measure for an older Scottish population. This study uses health and social care data for the entire Scottish population aged 65 and above, elaborated on in chapter 4. This would allow local authorities to use a verified risk-prediction tool to provide care to those who require it the most within people who have multimorbidity. Results from a national sample would also be applicable to other European countries with similar demographic trajectories, such as those mentioned in Kluge et al (2019).

It should also be mentioned in the context of the location of this study that none of the predominant medication indices outlined in section 2.3 (CDS and its adaptations the CDS-2 and RxRisk) use the British National Formulary (BNF) notation system. All three were developed for the North American prescription notation system (von Korff et al 1992, Clark et al 1995, Fishman et al 2003) and the majority of studies that use them are based in North America (Park 2016, Quail et al 2011, Ou et al 2012). Wallace et al (2016) uses an adaptation of the RxRisk for the Anatomical Therapeutic Chemical (ATC) notation system used in most of Europe but not the UK. This study is also to the author's knowledge the first to use condition-based multimorbidity indices adapted for use with the BNF, and therefore provides a valuable insight into the predictive ability of medication-based indices in the UK.

Section 2.4 builds on previous discussion regarding multimorbidity and social care by noting the lack of studies which contrast predictive ability of multimorbidity measures in predicting transition into social care, as all look at health outcomes exclusively. In addition to this, the additional impact of relative deprivation on the relationship between multimorbidity and social care is discussed, as well as how this in turn may vary at regional level. This PhD adapts a previously clinically dominated

methodology and applies it to a non-clinical outcome in a large administrative and social care census dataset. There are no prior indications of what multimorbidity measures are most predictive of transition into social care, and as such this research will contribute to the existing body of literature. The thesis also examines the relationship between deprivation and multimorbidity on transition into social care, in particular whether the effect of multimorbidity on transitions into care varies by deprivation both at local and regional level. Finally, the regional impact can be assessed by looking at whether multimorbidity is more or less strongly associated with transitions into social care both by overall deprivation and in the most deprived DZs by average LA deprivation.

Section 2.5 discusses the relationship between multimorbidity and social care, specifically that informal care provision is recorded poorly in routine data and that, similarly to social care, no studies exist which cross-compare multimorbidity performance in predictive transition into informal care. The current study is unlike a number of others in that there is an identifier for receipt of informal care within the health and social care data, but it would also be helpful to use survey data too. To this end, this thesis uses both the linked H/SC dataset as well as the SHeS to examine analyses involving informal care data. This will allow for examining informal care and multimorbidity in greater detail than a number of the studies reviewed in section 2.5. Additionally, accounting for the difficulties observed in measuring informal care, this PhD identifies the best measures to predict uptake using both administrative and linked administrative-survey data, given that the former allows for greater predictive power and the latter is the most frequent context in which informal care uptake is analysed. Prediction of whether or not someone is likely to be in receipt of or need informal care is important in a policy context, especially if it can be established that those receiving informal care have different health needs than those who are receiving formal care.

2.6.2. Summary of gaps in literature, and research questions

The gaps, and research questions are split into three sections within table 2.1, each of which is a separate chapter in this thesis.

Table 2.1: Summary of gaps and research questions by literature review chapter

Chapter	**Gaps in literature**	**Research questions**
Multimorbidity and health outcomes	• The review of policy documents would recommend there is a need to reliably use multimorbidity to identify individuals at risk of adverse health outcomes or transitions into	• Which multimorbidity measure(s) best predict mortality & healthcare utilisation outcomes in older people in Scotland using linked administrative data?

	social care, but current work uses limited or dated strategies to achieve this. • Previous research on comparing multimorbidity measures to predict outcomes have conflicting outcomes, largely due to the heterogeneous study populations. • There are no studies comparing predictive ability of multiple multimorbidity measures for health outcomes in older people in a national Scottish sample, and no medication-based multimorbidity score has been developed for use with the British National Formulary notation system.	• What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?
Deprivation and transitions into social care	• There are no studies which compare the predictive power of multimorbidity measures for transitions into social care. • There is a lack of research into the effect of multimorbidity on social care uptake in Scotland by deprivation level.	• Which multimorbidity measure(s) best predict transitions into social care in older people in Scotland using linked administrative data? • What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care? • Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?
Multimorbidity and informal care	• There are no studies which compare the predictive power of multimorbidity measures for informal care uptake, using either survey or administrative data. • There are no studies that have compared whether administrative-based or survey-based data are better predictors of informal care uptake.	• Which multimorbidity measure(s) best predict transition into informal care in older people in Scotland using linked administrative data, and co-resident care using linked survey data? • What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal/co-resident care?

	• Is linked administrative or linked survey data able to better predict informal or co-resident care in older people in Scotland?

The policy review identifies a need to best predict multimorbidity in a Scottish population for a number of different outcomes. Given that the best performing multimorbidity measures differ by population even within the same outcome, this cannot be answered by previous literature. As such, the three key areas of focus (health outcomes, social care, and informal care) all contain research questions which focus on the best performing multimorbidity measure to predict each outcome, as well as supplemental questions on specific conditions/combinations of conditions. The social and informal care sections also contain questions which relate to delivery of social care and deprivation and exploration of predictors of informal care in survey data (as this outcome is more readily and reliably available in survey data).

Chapter Three – Methods of measuring multimorbidity

The literature review outlines the importance of multimorbidity in predicting health and social care outcomes, and the problems in choosing particular measures. Given the fundamental importance of measuring multimorbidity to this study it is also crucial to engage in a thorough discussion regarding conceptualising, quantifying, and analysing multimorbidity.

This chapter consists of the following sections:

- A more detailed discussion to the definition of multimorbidity and conditions and its relationship to social care
- A discussion of measuring multimorbidity in a quantitative context, and an overview of the chosen multimorbidity methods for this study

3.1. Introduction to multimorbidity

In this section multimorbidity is described in terms of its operational definition and how this changes depending on context, the relationship between multimorbidity and social care, and a discussion of the social construction of multimorbidity and long-term conditions.

3.1.1. Defining multimorbidity

The empirical definition of multimorbidity changes between and within disciplines, with much depending on the study components of the discipline or research in question. The distinction between multimorbidity and the sister term "comorbidity" has been discussed previously in chapter 1. Whilst the two phrases were initially used interchangeably in research, "multimorbidity" has come to mean two or more conditions in general, whilst "comorbidity" refers to one or more conditions in addition to a main, or "index" disease. A number of indices such as the CCI (Charlson et al 1987) or the EI (Elixhauser et al 1998) were developed with comorbid populations in mind but were later used extensively in research looking at multimorbidity. Research on comorbidity can either focus on one specific index condition – such as a scoping review by Bunn et al (2014) on comorbidity and dementia – or comorbidity in general, such as Yurkovich et al (2014)'s systematic review of how indices compare in predicting health outcomes, excluding an index condition.

This study focuses specifically on multimorbidity and not comorbidity because in the context of provision of care, all conditions must be considered when developing an individual's profile. Development of care provision methods which can be applied to all individuals does not require identification of an "index" condition – to do so would be attempting to fit individuals into disease-

specific groups and would therefore circumvent the person-centred approach of acknowledging all those with multimorbidity as a diverse, heterogeneous group.

The recommendation for a universal definition of multimorbidity by the Academy of Medical Sciences (2018), as covered earlier, is two or more co-existing chronic conditions, which can be any of a long-term non-communicable disease, a mental health condition, or a long-term infectious disease. This is further expanded into "discordant" and "concordant" multimorbidity, when the conditions coexist by chance or association, respectively. Whilst this definition is straightforward, and covers the majority of long-term ailments, there is still the issue of what is considered a "condition" is in the first place, taking into account the subjective nature of classifying and compartmentalising observable symptoms into conditions, and how what is considered a disease has changed over time due to changes in medical practice or cultural attitudes. This will be covered in detail in the next section.

As covered previously, there is no "gold standard" for measuring multimorbidity, either in quantitative or qualitative research, and conditions included in studies measuring multimorbidity show considerable heterogeneity (Ho et al 2021). Much depends on the data available, the study population, and the outcome being measured. Whilst attempts have been made to develop guidelines for selection of conditions and indices (Fortin et al 2012), this is often ignored, and in many studies which do not use a pre-existing index no explanation is given for the importance (and therefore selection of) of each condition. In particular, mental health conditions are often excluded despite being a common component of multimorbidity profiles and contributing strongly to adverse health outcomes (Ho et al 2021). Researchers can use admissions data, prescription data or self-report data to code for multimorbidity, all of which have separate methods of noting and operationalising this information. The effect of one's multimorbidity "value" (whatever this might be) is dependent on the relative effects of the individual conditions that comprise that value, and as such some measures weight particular conditions to give them a higher score. Weightings may potentially vary based on demographics of the cohort (and within this, the individual) under study. Different demographics are more susceptible to particular conditions – for example, cardiovascular disease in older people 75+ compared to 65-74 (Bromley et al 2013) – and as a result multimorbidity measures must take account of which conditions fit and which do not. In addition, weightings will vary depending on the outcome under study. For example, a condition such as dementia may be highly predictive of placement in a long-term care facility but less predictive of mortality, and vice versa for conditions such as metastatic cancer. One of this study's primary aims is to investigate the relationship between multimorbidity and social care, one of these potential outcomes.

3.1.2. Multimorbidity in the context of social care

People with multimorbidity often have complex care needs which can only be satisfactorily met with integrated or person-centred care; social care is part of a holistic approach which differs from the traditional disease focused model used in clinical settings. This PhD explores this relationship between the two, specifically what measures of multimorbidity are predictive of one's likelihood to transition into social care. Prior to exploring this relationship quantitatively, it is important to explore further the dynamics underpinning the relationship between multimorbidity and care.

In many countries where social care is provided by or funded the government, allocation of social care for older people is based on functional assessment – this is to determine whether or not someone requires social care to maintain their daily lives without being placed into a care home. People who can still function adequately without outside help would not be allocated care. The policy review in chapter two notes that eligibility for FPNC in Scotland is determined by a single shared assessment (Inverclyde Council 2016) which determines the individual's functional capacity in a number of different areas. This is consistent with approaches elsewhere – a review by Wodchis et al (2015) found that most countries who adopted integrated care programs also use eligibility criteria. As a consequence, most people in receipt of care will have lower functional ability and less independence respective to the general population, including but not limited to increasing age, frailty and multimorbidity.

Assessment of functional status will result in a more multimorbid population in receipt of social care than not. This is backed up by literature. Gott et al (2007) found in a sample of older people in England that people who had more contact with social service were more likely to have two or more conditions than people who are not receiving any social services. Another study using English data by Kasteridis et al (2014) found that in predicting use of and cost of social care, multimorbidity is the strongest predictor of both outcomes, with the strength of association increasing with more conditions. A study by Kuzuya et al (2012) examined the likelihood of being placed into long-term care amongst older people in Japan and found that those who used care had a significantly higher multimorbidity score than those who did not. Landi et al (2001) in a study evaluating the effectiveness of a newly developed home care program in Italy used a sample consisting of people deemed eligible for inclusion in the program – the average number of medical conditions per case in the sample was 3.5, indicating people eligible had more conditions than those who did not. It is likely that people in care programs as defined in the Landi study, given associations between social care and multimorbidity, are more likely to have all the accompanying difficulties such as polypharmacy as well as conflicting treatment and management regimes.

A principal reason why multimorbidity in particular is of interest in terms of integrated care is that the current system of health care and social care does not best fit the needs of this particular demographic. A multimorbid patient's clinical pathway (such as seeing a GP, being referred to a specialist, being prescribed medicine for their conditions and making further appointments) has historically been separate to their care pathway (such as a needs assessment, allocation to specific types of care and meetings with care providers). When they are separate this can result in conflicting information, mixed messages, and fragmented care for the individual (Lupari et al 2011), particularly if both use different approaches. The literature review earlier mentioned the advantages that "generalist" approaches have over "disease-focused" approaches to people with multimorbidity, in that it reduces the likelihood of polypharmacy and potentially harmful DDIs (Guthrie et al 2015) and that the Scottish Government has identified those with multimorbidity as particularly benefitting from integrated care (Scottish Government 2014). A generalist approach, in focusing primarily on the individual, should also take into account the individual's subjective experience of multimorbidity and disease, and beyond this, the social construction of what is considered a disease, or illness.

3.1.3. Multimorbidity and long-term conditions as a social construct

Regardless of the methodological approach to defining multimorbidity in this thesis, is it important to consider multimorbidity and disease as a social construct. The medical definition of multimorbidity is the coexistence of two or more conditions. However, the concept of what a "condition" is, and social construction of disease itself, will help shape underlying understanding of multimorbidity and its interactions with health and social care.

When defining one's multimorbidity in a medical context, the components that make up this measure are referred to as "diseases." In this context, disease refers to objective components that make up a condition such as biological changes, the presence of a particular bacteria or virus or particular symptoms in the individual. Diseases are diagnosed by medical professionals using a predefined set of criteria, and provide a certain degree of certainty as to how one matching specific objective phenomenon should be treated. Conrad & Barker (2010) make a distinction between disease as defined above and "illness" – the subjective experience of a disease, and how the individual experiences the disease in a social context.

Individuals may experience illness differently to others with the same condition, and the cultural response to them may also differ. Conrad & Barker (2010) bring up the concept of "contested illnesses", where symptoms are present, but no biological explanation can be given. If a patient is ill but their symptoms meet no empirically defined disease, they may simply have one that is not, or will never be defined. Some conditions may be experienced differently by individuals – Brown (1995) in

writing about experience of illness suggests that people may not associate symptoms with a particular disease, or interpret them in different ways (such as spiritually). Disease is relatively consistent, but illness is not.

If subjective experience is variable with one condition or disease, experience of more conditions at once may be even more varied. It could be argued that the individual experiences of one person with multiple conditions will be a shared "illness" rather than multiple illnesses at one time, with only the number of diagnosed diseases defining multimorbidity. The likelihood of individuals having varying experiences of illness and different cultural perceptions and interpretations of their situation may increase exponentially with multimorbidity. O'Brien et al (2011) write of the "endless struggle" of those who have multimorbidity living in deprived areas in terms of juggling multiple appointments and prescriptions as well as managing at-times difficult personal lives. Patient complexity, which takes into account characteristics related to, but not encompassing, multimorbidity, such as socio-economic status, age, and frailty (Valderas et al 2009) will also impact a patient's subjective and symptomatic experience of a disease.

A holistic approach, led by integrated person-focused care, will not only take account of the diseases one has but also their subjective experience of the illness or illnesses. The disease-based pathway treats individuals based on their diagnoses and besides the previously discussed problems regarding polypharmacy and conflicting approaches, this may not be appropriate, given limited personal resources individuals have to manage multiple conditions at once (Morris et al 2011). An integrated, person-centred approach will focus more on the individual and how they react to their particular combinations of conditions, and hopefully lead to better health outcomes.

Differing subjective experiences presents difficulties in translating into empirical quantitative measures of multimorbidity. Any measure of multimorbidity will be constrained by the fact that whilst one may have the same combinations of conditions or multimorbidity "score," their subjective experience will be different. It may be that some combinations have very different experiences from person to person, whilst others will not; this should be considered when interpreting any analyses based on objective positivist interpretations of multimorbidity.

The concepts of illness and disease are part of a wider school of thought in sociology referred to as "social constructivism." This goes beyond one's subjective experience of a particular disease, rather questioning how it is that a particular combination of objective phenomena is defined as a disease, whilst others are not. All definitions of disease that exist today did not come about by their own accord; they were defined, labelled, and associated with a set of symptoms – i.e. they were "socially constructed." Definitions of what is considered disease have changed over time – osteoporosis, for

example, was once considered an unavoidable consequence of ageing, but is now classified as a disease (Scully 2004). Systematic reviews of multimorbidity, for example Salive (2012), find wide variance in what is included as a condition or disease by paper; whilst this in some circumstances is due to information available, subjective interpretation or importance of particular diseases will also impact inclusion. Salive notes that obesity, usually omitted from studies measuring multimorbidity, is under consideration as a chronic condition; obesity (and weight loss) is included in some multimorbidity indices including the EI (Elixhauser 1998).

It is here that Conrad & Barker's (2010) idea of "contested illnesses" is pertinent. They write that people prefer to categorise general health complaints as specific diseases as it gives them an innate feeling of control over the progression of and treatment of the disease. For example, "general complaints" could be considered a condition; if it contributes to the individual's subjective perception of illness then it may well have an effect on health outcomes, whether directly (as symptoms of an underlying disease which is having an effect on the individual's health) or indirectly (via contributing to a perception of illness which negatively affects the individual's mental health). It is possible that some of these "contested illnesses" are symptoms of either a disease (and wrongly diagnosed), or in another situation would be defined as a new, previously unknown construction of "disease."

Data-derived measures, based on the above, may potentially exclude information on illness whether via disease that has been misdiagnosed or has not yet been diagnosed or as part of a "general complaint" that may affect the individual's health outcomes and subjective illness. Conversely, overdiagnosis of disease may also contribute to a misleading physiological profile (Brodersen et al 2018), whether via overdetection (in which a multitude of tests detects a condition which is has no obvious symptoms or a negligible impact on the individual) or overdefinition, which refers to either lowering the threshold for disease risk or classifying symptoms as a condition even when they are ambiguous, or mild. When symptoms are temporary, or require no long-term or immediate management, overdiagnosis (whilst distinct from misdiagnosis) is not helpful, and in some cases may adversely impact the patient via unnecessary treatment for a condition that does not contribute to morbidity burden (referred to by Brodersen as "overtreatment"). In the context of multimorbidity, overdiagnosis and subsequently overtreatment may further compound already-complex multi-condition management programmes.

Another aspect of social constructivism is whether specific conditions have a social dimension to them, i.e. if they are stigmatised. This can have large bearings on whether or not a condition is reported or even acknowledged by the individual or family/friends. Stigmatised conditions can vary by community, or the characteristics of the individual as can the nature of the stigmatisation. An example is mental illness, which can carry stereotypes of being perceived as distant, or more likely to

be violent towards others than people without mental illness (Link et al 1999). As a result, people are far more likely to underreport suspected mental illness, especially men. Dementia in particular is also associated with stigma. As a diagnosis of dementia means the individual may later have to take on a large degree of social support (including possible relocation into a care home), people with dementia may be stigmatised as not taking pleasure in life or having their wants and needs ignored or dismissed (Benbow & Jolley 2012). As a result of this (and due to the life choices associated with progression of the condition) both the individual and family members, who may potentially be responsible for informal care provision, may not contact health care providers despite symptoms. Partly as a consequence of this dementia is consistently underreported in data, including in Scotland (ISD 2008). This is further compounded by the lack of effectiveness of drugs used for dementia, all of which only alleviate symptoms (Casey et al 2010). This can lead to under-provision of treatment and care at state level for those undiagnosed in addition to potential lack of informal care, particularly for those with no other diagnosed underlying conditions.

The social constructivist approach to identifying and defining disease is contrasted to positivism and identifying disease or conditions using big data i.e. large-scale linked datasets. A positivist approach places emphasis on observable data or proof derived from experience or hypothesis testing and less on subjective experience, theory, or interpretation (ScienceDirect 2021). A positivist approach to diagnosis, using big data, would be to identify a condition solely on a set of pre-existing parameters (such as admission codes, or a set of medications) which are identified by a trained, neutral observer (i.e. a doctor or hospital worker) and applied based on phenotypes which are always present if the condition or disease in question is also present. Any errors in identification of disease or conditions would be as a result of methodological issues, such as the omission of a particular admission or medication code, failure to link a particular dataset, or guidelines which omit a particular symptom of disease.

However, the positivist approach fails to take account of a number of factors mentioned above. Many symptoms of disease are not always present in all cases, and vary by patient and sociodemographic characteristics such as gender (Kroenke & Spitzer 1998); alternatively, two co-occurring diseases may have identical symptoms causing one to remain undiagnosed (Feinstein 1970). In addition, personal or subjective experience on behalf of both “neutral” observer and patient will impact diagnosis of a condition; overdefinition occurs when the threshold for defining disease is reduced, or when diagnosis occurs even when ambiguous or mild symptoms are present (Brodersen et al 2018). A patient may not attend an appointment for a complaint either via a belief that their symptoms are benign, or to avoid perceived stigmatisation of being diagnosed with a condition such as dementia (Benbow & Jolley 2012); additionally, a doctor or patient may disagree over symptoms, particularly unobservable ones.

Finally, disease or conditions are at their origin socially constructed; as discussed above, a set of symptoms and phenotypes are classed as a "condition" and treated accordingly.

The approach taken in this thesis, whilst methodologically taking a positivist approach to defining disease using big data, should consider the limitations inherent in this approach when interpreting and reporting findings, and discussing implications for reporting research. Prevalence of particular conditions will be discussed and compared to other national estimates (such as those in table 1.1), and potential stigma or underreporting of disease (such as dementia) will be taken into account.

3.2. A quantitative approach to multimorbidity

As covered previously both in this chapter and earlier in the thesis, any data-driven approach to multimorbidity should take into account the advantages and disadvantages to using a particular approach or scale, the study population, and any other contextual circumstances such as data available or outcome under study. This section collates the evidence and recommendations thus far and outlines the methodological approach to multimorbidity in this thesis, specifically:

- The suitability of a quantitative approach to identifying and analysing multimorbidity in this study
- Optimal use of the longitudinal cohort constructed for the study
- Development and selection of optimal multimorbidity measures for this study based on the parameters outlined above
- An overview of this study's chosen multimorbidity measures, and methodological and contextual basis

3.2.1. The advantages of measuring multimorbidity quantitatively

Qualitative approaches usually focus on the experience of multimorbidity, not the way it is measured. For example, Morris et al (2011) state that their sample consists of people with two of three specific conditions but do not mention how these conditions were identified. As previously touched upon, determining multimorbidity depends on the data available, the study population and the outcome measure. It may only be possible to use specific methods with specific datasets, and the efficacy of a multimorbidity measure may vary by the population parameters and the outcome measure. As a result, it is important to understand the most predictive measure to use in any given situation, depending on what is available and the aims of the study.

A quantitative approach to measuring multimorbidity enables identification of different sources of data and use of scales that correspond to these sources, such as admission-based, prescription-based, or self-report scales. Any outcomes can be converted into a format suitable for analysis, with different parameters and statistical tests available to estimate the predictive power of different scales. Through this, the best multimorbidity measure for a particular outcome within a specific population can be determined, depending on what data is available. This study presents an opportunity to conduct research on a population-wide Scottish dataset spanning multiple years in the last decade and with a number of linked datasets including demographic information, admissions, prescription uptake and social care status. This has only become possible in recent years as a result of increased levels of population-wide data collection, progress in data sharing and development of technology that can both work with this data and provide a safe, secure environment for researchers to work with data without compromising the anonymity of the individuals contained within. This data can be used for a number of different projects given its scale – as well as the variables of interest there is also information on healthcare and social care costs, types of admissions, length of stay and individual care packages.

Another advantage to a quantitative approach to multimorbidity ties in with the previous aspect of being able to look at multiple measures, and that is avoiding bias or limitations associated to using just one measure. As mentioned, most qualitative research into multimorbidity does not in any case look at multiple measures by nature, but what is also important is the method they eventually choose to use. More often than not, qualitative research usually defers to a self-report or doctor-diagnosed measure (Naganathan et al 2016). Using one method on its own will result in no way to control for the limitations associated with that measure.

As mentioned in the previous chapter, the stigma or taboo associated with some conditions such as dementia means that it is likely for individuals to underreport these conditions. Illness itself may be seen as a sign of weakness, resulting in some demographic groups underreporting illnesses completely, such as men (Kroenke & Spitzer 1998). This is one of the main weaknesses of self-report scales. People who are receiving treatment for a particular condition may be reluctant to disclose this, even in an anonymous survey. These conditions may even be ones that close friends and family do not know about. Individuals may also be unaware of underlying conditions, either due to lack of symptoms or no clinical examination as a result of poor attendance at primary care.

If an individual has been diagnosed with a condition but is reluctant to disclose this, prescription-based measures will provide an indication of conditions the individual is likely to have via matching the type of prescription to a list of likely conditions (should the condition be prescribed for). In the event that the individual is not taking prescriptions due to noncompliance with treatment, not attending the doctor or having an as-yet unidentified condition, diagnosis codes based on either doctor

diagnoses or admissions to hospital can again identify underlying conditions. In some cases prescription measures may identify conditions that diagnosis-based measures may not (due to the individual not having health problems severe enough to merit an admission to hospital, should the diagnosis-based measure be derived entirely from admissions data); a quantitative approach can identify predictors of adverse health or care use those other measures do not. However, there are also advantages to self-report conditions – for example, conditions that do not require treatment nor are severe enough to warrant an admission to hospital will be picked up by a self-report scale. They can also detect loosely defined "illnesses" (as mentioned in section 3.1.3) that may not necessarily be flagged for by administrative data.

Use of quantitative data also allows large-scale study of people with specific comorbidity or multimorbidity profiles, especially if rare (though still medically significant) within a general population. Examples of this include estimating whether the risk of adverse health outcomes for those specific two-condition combinations (such as mental health and physiological comorbidity) is greater than the risk associated with each condition individually (Brilleman et al 2012 used a similar approach for costs of condition combinations) or the impact of condition clusters, derived using an automated approach grouping commonly co-occurring conditions together (Prados-Torres et al 2014).

In relation to this project, a quantitative approach is best for looking at which aspects of multimorbidity are particularly associated with health and social care outcomes – such as severity of multimorbidity via a condition score, individual conditions, or combinations of conditions. This analysis can find clear indicators of relationships between particular aspects of multimorbidity and health outcomes, such as which specific condition is most predictive of emergency admissions into hospital. The findings from this can be relayed back to policymakers and provide evidence as to which groups of people care should be provided to. Beyond simply choosing a quantitative approach, however, a number of contextual parameters should be considered, beginning with the time frame in which to measure multimorbidity.

3.2.2. Developing a multimorbidity profile using longitudinal data

Before determining the optimum method for measuring multimorbidity, the longitudinal nature of the data must be considered – specifically, whether a condition that was present but has no longer been recorded for a long period of time should be considered "part" of someone's multimorbid profile. This study measures outcomes for individuals immediately following an index date, necessitating a decision on how far back to collect multimorbidity data – whether via admissions or prescriptions – to complete both someone's multimorbidity "score" and indicators of individual conditions. This is known in research as the "lookback period."

Studies looking at comparing multimorbidity indices had lookback periods that varied considerably, with no apparent consensus on a standardised measure (Willadsen et al 2016). Some scores are only taken on the "index" admission to hospital i.e. the original study for the Quan et al (2005) adaptation of the CCI, whilst the Brilleman & Salisbury (2012) study uses all available historical data. Some studies have looked at this; an Australian study by Preen et al (2006) found that when using the Multipurpose Australian Comorbidity Scoring System (MACSS) in administrative data to predict one-year mortality and 30-day readmission, a one-year lookback period performed best for mortality, and whilst a five-year period worked best for readmission the authors felt the small difference in predictive power between five years and one year was not worth the extra data required. A study by Chu et al (2010) compared one-year and index-admission lookback periods with the EI and CCI, finding that one year is best for one-year mortality – the argument being that for long-term health a more complete disease profile is required including less severe conditions which may not be recorded for all admissions. However, both of these studies looked at comorbidity as opposed to multimorbidity and did not restrict their study population to older people. Fortin et al (2012)'s systematic review of disease measurement recommends either one year of lookback if historical data is not available, though notes that this may underestimate complex disease. Beyond the time period under study, however, it is also important to consider a number of other contextual circumstances relating to the data and study itself.

3.2.3. Development of an optimum measure of multimorbidity

No measure of multimorbidity has been developed which is universally applicable to most health-related settings, compounded further by the fact that the data source and data available does not remain consistent from study-to-study. Multiple multimorbidity measures are used, taking account of the three key criteria: the data available, the study population and the outcome to be measured.

Multimorbidity measures, like all composite variables require an original source of data for construction. As a result, the multimorbidity measures available to specific studies may differ depending on the data that is available. Given that different sources of data vary in both what conditions can be identified as well as the accuracy of identification, including in Scotland (ISD 2008), multiple sources of data will prove most effective at capturing a wide range of conditions, and should be used if available (Fortin et al 2012). This study will focus on three sources of data for multimorbidity scores, which are invariably the most widely-used – diagnosis-based, medication-based, and self-reported.

Administrative data such as hospital admissions or GP surgery data normally provide a disease code (at admission or at appointment), which can be used to construct diagnosis-based condition indices. The most well-known of this is the CCI (Charlson et al 1987), whilst other indices such as the EI (Elixhauser et al 1998) are also used. Multiple appointments or admissions over time allow for construction of a score based on a predefined timescale, such as one year. Whilst ICD codes are universally available, frequently updated (the most recent version being ICD-10), and usually correspond to a particular condition, diagnosis and completeness of records can vary by hospital and practice (Fortin et al 2012). In addition, diagnosis-based indices primarily or exclusively derived from admission data will exclude less severe or more easily managed illnesses, which while less likely to impact on short-term health may have unaccounted for long-term impact on overall health (Shadmi et al 2011).

Data derived from primary care, for example general practice attendance, may alleviate the above concerns regarding admissions somewhat by capturing disease in an earlier, less severe stage, for example at first point of contact with a practitioner rather than in an inpatient emergency, or conditions less strongly associated with old age such as mental health (Crooks et al 2016). Primary care-derived versions of the CCI and EI have been shown to perform well in predicting mortality (Crooks et al 2016); however, primary care data was not available at national level in Scotland at the time of study.

Medication or pharmaceutical data is also frequently used, with a number of existing measures available. Prescription codes can be used to create common scores such as the CDS (von Korff et al 1992), Chronic Disease Score 2 or CDS-2 (Clark et al 1995) or RxRisk (Fishman et al 2003) which diagnose conditions based on flags from medication classes. This ensures reliable monitoring of conditions for which regular prescribing is needed, but would not otherwise result into an admission to hospital or regular GP consultations (Fortin et al 2012) at the cost of potentially missing more severe conditions, particularly ones that occur near the end of life when preventative medication is typically not prescribed (Schneeweiss et al 2004). Further compounding this is that medication prescribing does not directly map to a particular condition unlike ICD-10 or Read codes; the condition being prescribed for is not always immediately apparent, introducing margin for error.

In addition, prescription identifiers for specific medication classes vary from country to country (for example, ATC in Europe and BNF in the UK) and as a result developing methodology which creates these scores can be more problematic than that used for diagnosis-based indices. Medication classes are frequently updated, meaning medication-based indices may lose value more quickly than diagnosis-based (Schneeweiss et al 2004), and are typically harder to map to specific diseases, meaning developing a definitive multimorbidity profile is less clear-cut (Fortin et al 2012); ISD

(2008) did not estimate prevalence indicators of conditions in Scotland from medication data for this reason. Interpretation of medication-based scores should also consider the impact of polypharmacy, particularly one facet of "inappropriate" prescribing in which medication is prescribed for a condition for which it is not required or may cause an adverse drug reaction (ADR), or redundant prescribing for a condition which is no longer present (Scottish Government 2015). Even given this, however, high medication use is indicative of multimorbidity (NICE 2016) even when the exact illnesses cannot be definitely ascertained, and in this respect a score- or count-based measure is still helpful.

The final main source of data is self-reported – this is usually used in survey-based studies when access to medical or pharmaceutical data is not available. These are used to construct self-report multimorbidity scores, with respondents to surveys asked to list conditions, or pick conditions from a list. In the case of the former, responses are retroactively assigned to a condition from a pre-prepared list. Lists can be based on ICD codes or the Quality Outcomes Framework (QOF). There is limited evidence of self-reported indices performing comparably to diagnosis-based measures, for example in predicting short-term functional capacity and quality of life (Olomu et al 2012); a self-reported CCI compared similarly to its diagnosis-based counterpart in a small hospital population study (Susser et al 2008).

Different multimorbidity measures constructed from different sources of data have different levels of effectiveness depending on a number of different factors, one of the more prominent being the outcome measure, as covered in chapter 2. One potential explanation for this is that diagnosis-based and medication-based indices show varying prevalence for different conditions; migraines, renal disease and hepatitis are underdiagnosed in medication data compared to other sources, and vice versa for epilepsy, glaucoma, and Parkinson's disease (Chini et al 2011).

The six outcomes of choice for this study consisted of mortality, three healthcare utilisation outcomes (admissions, emergency admissions, hospital days) transition into social care and informal care. As covered in the literature review, the general trend is that diagnosis-based measures better predict mortality (Brilleman & Salisbury 2012, Perkins et al 2004) whilst medication-based indices better predict healthcare utilisation (Fan et al 2006, Wallace et al 2016); no studies have yet examined multiple multimorbidity measures in predicting use of social or informal care. However, a consensus is lacking as to which individual measure within these data classes performs best, primarily as a result of varied study populations. The parameters of the study population inform how likely the individuals are to satisfy a particular outcome measure, as well as whether they are more likely to provide data that is used to construct a particular score. In addition to this, it should be considered whether a certain population is more likely to have, or be impacted more severely by, specific conditions.

This study's cohort is all people over 65 in Scotland. Older people are more likely to undergo admissions to hospital (NHS Digital 2016), to be prescribed medication (NHS Digital 2017) and receive care (DWP 2022); this will provide more data for diagnosis-based indices and medication-based indices. Survey data will usually take account of the whole population, but older people may not be able to provide accurate answers for a self-report scale due to conditions impacting memory such as dementia.

On the subject of individual conditions, older people are more likely to have conditions in general but some in particular are associated with ageing such as dementia, hypertension, arthritis, and stroke. In addition, conditions which are usually non-fatal to the overall population such as influenza can be far more serious in people over the age of 65. This and all other methodological complexities above were considered when selecting and evaluating multimorbidity measures in the current study; the measures chosen as a result are summarised in the following section.

3.2.4. Chosen multimorbidity measures and methodological context

Six multimorbidity measures were selected for comparative and further analyses in this study (Fig. 3.1 and below), three each derived from diagnosis-based data (in this case, the Scottish Morbidity Record or SMR01 and 04) and three from medication-based data (in this case, the PIS). One of each of the three diagnosis- and medication-based measures were proxy indicators of multimorbidity, i.e. derived from indicators of multimorbidity burden as opposed to specific conditions, and were primarily intended for comparison to more complex measures. These six measures are listed below; a more detailed explanation of each, including structure and methodological basis, are outlined in sections 3.2.4.1 (diagnosis-based measures) and 3.2.4.2 (medication-based).

- Charlson Comorbidity Index, Quan adaptation (CCI) – diagnosis-based
- Elixhauser Index, Quan adaptation (EI) – diagnosis-based
- Unique ICD-10 codes – diagnosis-based, proxy
- Chronic Disease Score, Henery adaptation (CDS-H1) – medication-based
- Chronic Disease Score 2, Henery adaptation (CDS-H2) – medication-based
- Count of unique prescriptions – medication-based, proxy

It should be noted that all multimorbidity scores when adapted for this study were derived solely from condition flags, and not demographic variables such as age or sex, as the primary consideration was to solely compare the predictive ability of the conditions used in each measure. If variables other than those specifically derived from conditions were originally included in a measure (such as the CDS-2), they were excluded for this study. To circumvent any potential erroneous impacts of this decision,

demographic covariates (age, sex, and deprivation) were controlled for separately within regression models outlined in chapter 4.

There are a number of approaches to quantifying multimorbidity and as a result a wide variety of potential scores available. In this study, the approach described above (six multimorbidity measures, three derived from admissions data and three from prescribing data) was considered a healthy balance between the majority of previous research, which typically compare two or three scores derived from only one data source such as admission records or medication (Yurkovich et al 2014) and more exhaustive comparison studies such as Park (2016), which compared fourteen different indices. Many other studies compare adaptations of the same "base" index, such as the Quan and Romano CCI (Yurkovich et al 2014), rather than distinct measures. Whilst comparison of prediction of multimorbidity scores was a focal point of this thesis, it was not the sole objective (compares to Park or similar studies), with more in-depth analyses of high-performing indices following on from model comparison. The decision was also made not to compare different versions of the same index to ensure greater heterogeneity of measures chosen and of further analyses.

Given the shorter list of indices chosen, care was taken to ensure that each included score was both frequently used in prior research (to provide an optimum reference point for comparison) and generally outperformed similar scores in studies in which it appeared. The CCI, as one of the first multimorbidity scores developed, is the principal measure to which other diagnosis-based scores are usually compared, and the EI is the second most common after this. Medication-based measures are less frequent overall (particularly in UK-based studies, where proxy medication counts are the only measures used), but when considered the CDS-1 & 2 are among the most frequent. Though relative performance did play a part in score selection, this was less important than frequency; as discussed in section 2.3.2, performance is heavily dependent on the data and outcome measure and may not necessarily translate to a Scottish population.

The ease of construction for each chosen score in this study varied by measure. The diagnosis-based measures used in this study (CCI and EI) are derived from ICD-10 codes, present in Scottish admissions data; as such, the CCI and EI can be adapted as-is and are commonplace in much previous research. The medication-based indices were derived from American classes which do not map perfectly to the BNF medication classification system; as a result, author-derived versions (the Henery CDS-1 and CDS-2, hereafter CDS-H1 and CDS-H2) were used, containing a number of modifications based on both availability of prescription drugs within the UK and the demographics of the cohort. This is described in further detail in section 3.2.4.2.

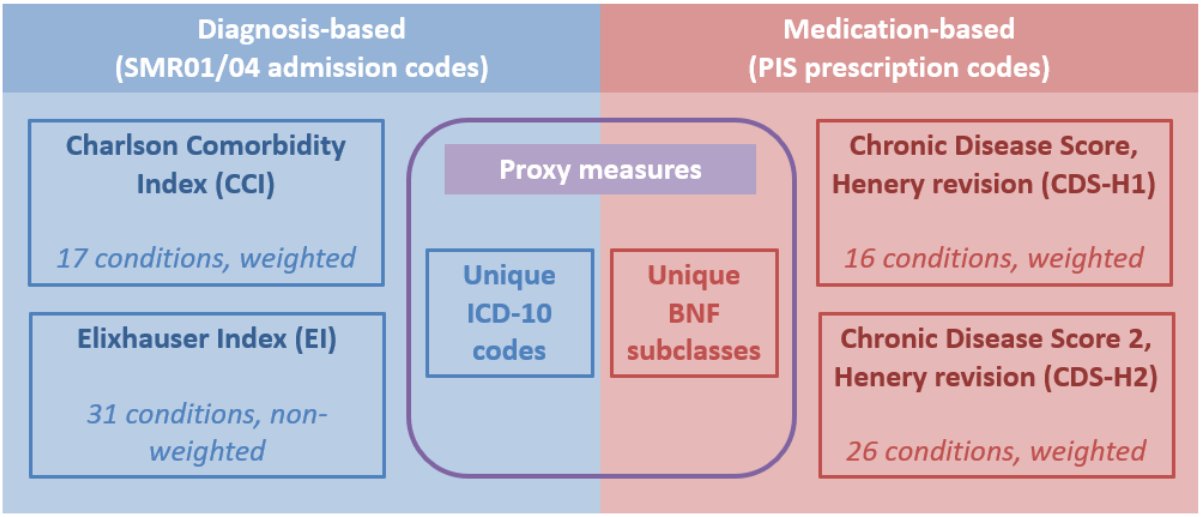

Fig. 3.1: Overview of the multimorbidity scores used in the administrative dataset

For the informal care analysis using survey data, two diagnosis-based measures, three self-report measures (derived from responses to a survey question on health complaints) and one (diagnosis-based) proxy measure were used:

- Limited Charlson Comorbidity Index, seven conditions (CCI-7) (diagnosis-based)
- Limited Elixhauser Index, eight conditions (EI-8) (diagnosis-based)
- Unique initial SMR admissions for specific conditions (diagnosis-based, proxy)
- Count of self-reported conditions (self-report)
- Count of ICD-10 categorised self-reported conditions (self-report)
- Weighted count of self-reported conditions (self-report)

A list of all conditions and accompanying scores for each index can be found in Appendix A4. Each of the measures are elaborated on in detail below, categorised by source of data and beginning with the diagnosis-based measures.

3.2.4.1. Diagnosis-based indices

The first diagnosis-based condition index chosen for the study was the Charlson Comorbidity Index (Charlson 1987), commonly known as the Charlson Index or CCI. This was first developed as a comorbidity tool to predict in-hospital mortality, and identifies up to 19 different conditions via condition flags which have since been adapted multiple times for changing classification systems. Each ICD codes for a particular condition – the scores for each condition are then added together to form an overall score. The CCI is what is known as a "weighted" condition index – the score is not based on a flat number of conditions; rather, each condition carries its own score, or "weight" based on either prior research, the author's judgement on which conditions are most heavily associated with

the outcome, or in the case of the CCI and others, regression modelling. For example, diabetes would carry a score of one whilst metastatic cancer carries a score of six.

Adaptations of the CCI given its age are common, with examples being the D'Hoore, Deyo, Quan and Romano CCIs (Park 2016). This study uses the Quan adaptation (Quan et al 2005), which was developed specifically to adapt the CCI and EI (see below) for use with ICD-10 classification codes (the measures available for this study) and performs well in cross-comparisons of Charlson adaptations (Sundararajan et al 2007). In the Quan adaptation leukaemia and lymphoma are included in the cancer diagnosis rather than separately; this reduces the condition count from 19 to 17. Many versions of the CCI also weight for age (Charlson et al 2022), including the original; separate weights for age were not included in the calculation of the CCI for this study, given that age is controlled for in regression analyses (as per earlier discussion in section 3.2.4).

Despite being over thirty years old, the CCI still performs well especially when predicting mortality and is frequently used as a comparison measure for newly developed scores. A study by Perkins et al (2004) compared a number of multimorbidity measures in predicting various health outcomes and found the CCI was joint best at predicting mortality (but was least effective at predicting healthcare costs or emergency readmission). Another comparison study by Brilleman & Salisbury (2012) also found that the CCI performed well at predicting mortality, as do reviews by de Groot et al (2003) and Yurkovich et al (2015). A systematic review by Sharabiani et al (2012) found that the CCI performs best at predicting short-term mortality. For healthcare utilisation outcomes the CCI is usually outperformed by prescription-based measures (Park 2016, Wallace et al 2016, Yurkovich et al 2015), in common with other diagnosis-based measures.

The EI (Elixhauser et al 1998) was developed 10 years after the CCI, with the aim of developing an index that could be applied to length of stay and cost outcomes as well as mortality. In contrast to the CCI, the EI increases the number of possible conditions from 19 to 30 and is a "non-weighted" index, in the sense that each condition gives a score of one and no conditions are scored differently. This study again uses the Quan adaptation of the EI (Quan et al 2005) developed for ICD-10 codes; this adaptation has separate flags for complicated and uncomplicated hypertension, increasing the condition count to 31.

The EI is second to the CCI in frequency of use in studies comparing indices, and on balance generally outperforms it – particularly for healthcare outcomes, though variance in study population may influence this. A study by Quail et al (2011) found the EI performed better than the CCI at predicting mortality and hospitalisation (with no difference when cohort was modified to include only 65-year-olds), whilst another systematic review by Sharabiani et al (2012) found it again performed

better when predicting long-term in-hospital mortality. Yurkovich et al (2014) finds the EI performs comparably to the CCI when predicting mortality.

The final diagnosis-based measure using administrative data is what is known as a "proxy" score – a measure that is indicative of multimorbidity but does not calculate its score based on specific conditions. Instead, the score is a count of aspects related to conditions, in this case a count of unique ICD-10 codes on admission. This is not specifically a count of all unique codes, rather a count of each "chapter" of the ICD-10 – this means that similar conditions within the same chapter will not be counted twice. In this case, all chapter letters up to "Q" were used, as letters R-Z refer to special codes that do not correspond to potential conditions. Proxy comparators have been shown to outperform condition-based methods in some studies (Brilleman & Salisbury 2012). The majority of these proxy scores are derived from prescription data, but one study by Condelius et al (2010) used a similar scale as a control when examining healthcare utilisation amongst a sample population receiving care either at home or in a care home – those with a higher score were more likely to be admitted to hospital.

In the survey dataset three similar measures were used. The first two were also the CCI and EI, but due to the limited nature of the SMR (in that only the first admissions for a limited predetermined list of conditions are given an ICD-10 code) these were both reduced indices, limited to seven and eight conditions respectively (as no other ICD-10 codes for other conditions were present within the study population). The proxy measure used was a count of the fourteen specific conditions specified in the limited SMR dataset. It was hoped that this score would obtain more data as it was based on variables already existing within the dataset. As only one initial admission was dated for each specific condition, it could be summarised that each individual admission would be for a different type of condition (albeit similar, given that a majority of the admissions were for cancer or heart-related morbidities). The purpose of this specific measure was to test the predictive ability of the limited admissions data in its simplest form, whilst also providing a base to measure it against some of the more complex measures.

The next set of measures used in this study, as outlined below, were derived from medication data.

3.2.4.2. Medication-based scores

The two condition-based medication-based scores chosen for this study were the CDS by von Korff et al (1992) and a derived measure, the CDS-2 by Clark et al (1995), adapted in this study into Henery revisions (CDS-H1 and CDS-H2). The CDS and CDS-2 are used in a number of studies comparing indices which include medication-based scores, and generally outperform diagnosis-based measures in predicting healthcare utilisation according to Yurkovich et al (2014)'s systematic review.

The original CDS consists of seventeen conditions, with flags in this case corresponding to specific medication classes. Like the CCI it is also weighted, but the scoring system differs slightly in that some conditions (such as heart disease) have weights dependent on how many medication sub-classes are flagged – for example, if only one is flagged the score is 3 but if all three are flagged it is 5. The CDS was developed as an alternative to diagnosis-based measures with increased availability of medication data, and like other medication-based measures in Yurkovich et al (2015)'s systematic review on comorbidity it outperformed the CDS-2 in predicting both mortality and hospitalisations, and in Park (2016)'s thesis on cancer survivors it was the best performing measure for admissions to the emergency department.

The CDS-2 was developed three years later by Clark et al (1995) and added a number of conditions to bring the total up to 28. It also took a different approach to deriving weights for these conditions, basing them on regression coefficients from a model predicting six-month costs rather than on physician opinion – this approach was taken in order to evaluate whether empirically derived weights presented a viable alternative to manual scoring of conditions. As a result, scores for age and gender are also included when deriving the final score, as well as a baseline score for the constant. As a result, the scores in the CDS-2 are markedly different from the other measures in this study, ranging from 64.3 (hypertension) to 16579 (renal failure). In Park (2016)'s study the CDS-2 performs better than the CDS at predicting mortality, but worse at predicting emergency visits, whilst in Yurkovich et al (2015)'s systematic review it performs worse at healthcare utilisation outcomes than the CDS.

The CDS and CDS-2 were developed in America, and use local classification systems which do not map directly to the BNF. Studies looking at medication-based outcomes in the UK have used prescription counts (Brilleman & Salisbury 2012) as a proxy for multimorbidity as opposed to derived scores. As a result, adaptations of the CDS/CDS-2 which could be used with BNF codes were derived specifically for this study. The resultant CDS-H1 and CDS-H2 were developed with a two-step process with the help of two pharmacists (Chris Johnson, of NHS Glasgow, and Catriona Matheson, of the University of Stirling) and one clinical academic (Vittal Katikiteddi, of the University of Glasgow). Step one of the adaptations involved a direct translation of the original scores via mapping the original medication classes as close as possible to equivalent BNF chapters, sub-chapters, paragraphs or individual medications as required. This was double-checked by Johnson with an overall consensus reached. At this stage, cancer was omitted from both indices as tumour suppression drugs are not supplied in the UK via prescription and are instead administered in a hospital setting. In addition, liver failure was removed from the CDS-H2 as the drug which codes for this (ammonia detoxicants) does not exist in the BNF – this reduced the number of conditions from 17 for the CDS and 28 for the CDS-2 to 16 and 26 in the CDS-H1 and CDS-H2 respectively. In addition, the

adjustments for age and sex, a composite of the original CDS-2, were removed from the CDS-H2 as this was adjusted for separately in regression analysis (as detailed earlier in section 3.2.4).

Step two of this adaptation commenced following a discussion with Prof. Matheson regarding the applicability of the CDS-H2 in an older population. Cystic fibrosis, a condition which is non-existent in older populations due to greatly reduced life expectancy (McBennett et al 2021), was replaced with pancreatitis, with one of the original medications (pancreatin) retained; the original variable was strongly associated with health outcomes in previous analyses, and it was suspected that this was as a result of misclassification of pancreatitis as opposed to cystic fibrosis. The other flag used in the old cystic fibrosis coding (mucolytics) was moved to flag for respiratory illness and asthma, for which it is also used (Laforest et al 2007). It was also speculated that psychosis – strongly associated with a number of health outcomes in earlier analyses for this PhD – was a misclassification of dementia, for which antipsychotics are prescribed, though with associated risks, in older people (Ballard et al 2014). The decision was thus taken to replace psychosis in the CDS-H2 with dementia, with new BNF codes of antipsychotic drugs (BNF 4.2.1) and drugs for dementia (4.11). Finally, on recommendation of Prof. Katikireddi, two conditions were redesignated as the BNF codes listed were more appropriate to alternative conditions: end-stage renal disease to renal anaemia/neutropenia, and thyroid disorders to hyperthyroidism. Mindful of the fact that the original weightings derived for the CDS-2 were based on the original conditions rather than the four new ones used here, sensitivity analyses were performed to compare an unweighted to weighted CDS-H2 (Appendix A5). The weighted version performed best, and was used in subsequent analyses.

A full list of the conditions and BNF codes included in the CDS-H1 and CDS-H2 can be found in Appendix A4.

The third medication measure is again a "proxy" by which to compare established scores, in this case a count of unique BNF sub-chapters for which a prescription has been dispensed. This measure has been used in other studies (Brilleman & Salisbury 2012) and again avoids potential issues in similar prescriptions for the same condition being counted more than once. Counts of unique prescriptions have been shown to perform well compared to other measures - the measure performed best at predicting health care uptake in the review by Brilleman & Salisbury (2012) and was only bettered by the CCI in predicting mortality in the same study, and two unique prescription-based measures outperformed the RxRisk prescription score in predicting mortality in Australia in a study by Pratt et al (2018). It should be noted that a refined measure developed by Guthrie et al (2015) specifically for measuring polypharmacy takes into account specific BNF subsections, excluding others, and also counts paragraphs within subsections separately when adjudged to be sufficiently distinct. Whilst this could have been included as an alternative measure, inclusion of all BNF sub-sections would better

suit the purpose of this as a proxy indicator to compare both to the other medication-based measures, and to the studies listed above which have used similar measures.

RxRisk, another medication-based measure used frequently in comparison studies, was not chosen as one of the medication-based scores. Developed by Fishman et al (2003) the RxRisk is a further adaptation of the CDS along similar lines to the CDS-2 (weights derived from regression coefficients) but developed separately for adult and paediatric populations, consisting of 27 conditions for adults. The RxRisk and its companion score, the RxRisk-V (an adaptation for US military veteran populations) have been cited as the best performing medication-based measure. The RxRisk performed best at predicting emergency admissions in the Wallace et al (2016) review in Ireland, and Yurkovich et al (2015) recommends the RxRisk-V over the CDS and CDS-2.

The decision not to adapt the RxRisk-V lies in the supplemental variables in the regression model used to calculate weights. As well as age and sex (as with the CDS-2), the RxRisk also uses weights for if the individual is registered with either of the United States' federal health coverage programs (Medicare or Medicaid). There is no equivalent program in the UK (as all residents receive universal health coverage under the NHS) and as such these weights are incompatible with any potential UK adaptation of the RxRisk. As this would result in a considerably different score to the original RxRisk, it was felt that it would be best to use scores that could be adapted more faithfully to the American versions.

Finally, for analyses using only survey-based data, measures derived from self-reported questionnaires were used.

3.2.4.3. Self-report-based scores

All self-report measures listed here were used in the survey dataset. The methodology used to produce self-report scales are less clear-cut, and generally based on the data available. The first of the measures was a self-report scale based on a list of up to 41 responses for specific complaints (including unclassifiable or "other" complaints). In the SHeS respondents can select up to six complaints from the list – whilst limiting the power of the measure, less than 2% of respondents included in analysis actually registered six complaints.

Two additional self-report measures were derived from these questions. The SHeS provides a "grouped condition" variable which consists of recoding the 41 conditions into 14 "grouped" categories as defined by the ICD-10 classification system. This was again condensed this into a discrete variable measuring the total condition categories for which the respondent has identified

conditions. Whilst similar to the above self-report scale, this was also included given that the diseases correspond to international classification categories and that the avoidance of similar conditions potentially being counted double would lead to greater predictive power for this scale.

An additional weighted self-reported measure was derived from the original list of 41 conditions. Within the SHeS, as well as best asked to list existing conditions, the respondent is asked whether each individual condition "limits activities." This revised score adds an extra point for every condition which "limits activities" to two points per condition (compared to one point if the condition exists, but does not limit activities), to a total of twelve points (assuming six conditions, all of which limit activities). This measure was based on the Self-Administered Comorbidity Measure by Sangha et al (2003) who developed a similar method for weighting self-report answers. This score is slightly different in that only one question was available from which to derive a weighting whilst Sangha's study had two (limiting activities and whether the recipient is receiving treatment for their condition). This was done to investigate whether the addition of additional information on conditions in addition to prevalence would produce a better performing score.

3.3. Conclusion

Multimorbidity is a complex, highly variable concept that cannot be measured or quantified in one single way, due both to the subjective nature of disease and "illness" and how the effectiveness of multimorbidity in predicting an outcome can vary by a number of different factors, and in turn be influenced by the stigma attached to some conditions. To account for this an approach was chosen where number of different multimorbidity measures with different characteristics are used based on data available, conditions (or lack of) and weighting method, in order to compare and contrast their ability to predict different health and care outcomes.

Chapter Four – Methods of analysis

This chapter outlines the methodological approach taken to answer the research questions established in chapter 2, consisting of a discussion regarding the data used, how it was cleaned and prepared, and what analytical methods were used.

4.1. Overview of linked data used in study

This project used two separate datasets to answer three overarching research questions. The first is a linked health and social care dataset encompassing all residents of Scotland aged 65 and up between 2010 and 2017. This dataset consists of linked data on admissions, social care use, demographic data and prescription uptake and is the more comprehensive of the two – as a result, the majority of the output in the project uses this dataset. The second dataset is a pooled cross-sectional linked survey-admission dataset consisting of waves 2008-14 of the SHeS linked to a selection of hospital admission data. This dataset consists of a random sample of Scottish households and contains questions on care provision as well as health, while the admissions data provides information on a list of select health conditions.

The decision was made to use two separate datasets primarily to explore the comparative efficacy of routine data and survey data in predicting similar outcomes. In addition, the survey data provides information on informally provided co-resident care, the effect of which and predictors of were compared with formally provided care in the administrative dataset. Finally, the informal care dataset provides alternative ways of measuring multimorbidity, which was compared with measures available in both datasets.

4.1.1. Linked health and social care dataset

The main dataset used for this study encompassed five separate linked datasets of community health index (CHI) demographics data, SMR 01 & 04 admissions data, SCS information and prescribing information system (PIS) medication data. These datasets are all ID-linked with a unique identifier for individuals. The dataset consists of all people in Scotland aged 65 and above on the 1st April from 2010 to 2016 within the study period (1st April 2010 to 31st March 2017).

The dataset was obtained via Public Benefit and Privacy Panel (PBPP) approval (1617-0012) as part of a wider project examining interactions and pathways between health and social care. Whilst the majority of syntax producing the cohorts used in the thesis was written by the study author over a

period of approximately six months to one year, some cleaning and preparing syntax for data common to both studies, such as converting admissions data to an episode-based format, was also written by other named researchers (Alasdair Rutherford, Feifei Bu, Elizabeth Lemmon). This dataset was an extension of a previously acquired dataset which focused on a smaller subset of the Scottish population in five local authorities from 2010 to 2011 (PBPP 1516-0499). The new dataset differed from the original as it contained prescription data, data on informal carers, additional years of data and included the entire Scottish population over 65 (as social care matching was now based on a probabilistic method, as detailed below). The thesis author adapted some syntax previously written for the old dataset for the new one. This data was accessed in a safe setting via remote access.

The CHI demographic dataset captures each person in Scotland registered with health services. The extract used for this study contains information for each individual at the beginning of the financial year (1st April) from 2010 to 2016. Data contained within this dataset include date of birth, date of death (if applicable), local authority, gender, Scottish health board and data zone in both 2001 and 2011. In addition to the variables already present, this dataset allowed for derivation of age at index date and mortality indicators (death within one year of index date).

The admissions datasets consisted of all admissions to either a general hospital (SMR01) or a psychiatric ward (SMR04) between 2010 and 2017 for all individuals in Scotland. These admissions were divided into component parts or "episodes," with one episode per case. This dataset was used to derive both diagnosis-based multimorbidity scores as well as HCU outcomes, including admission codes for each episode, the admission and discharge dates and the type of admission (i.e. planned and emergency among others).

The SCS consists of cross-sections of all eligible recipients in a census week each year from 2010 to 2016 (though some variables, unused in this study, were longitudinal). Included in this dataset were variables such as a binary indicator of whether the recipient was receiving home care or personal care in a defined census week, a flag as to whether or not the individual has a carer whether resident or non-resident (i.e. an informal care flag), functional forms of the above such as hours of care received, individual care packages such as laundry services or community alarm and an indicator of relative need (IoRN score). The home and personal care indicators (as well as informal care), used in the final cohort for this study, were flagged based on identification of receipt in a census week which always included the date of the 31st of March (Henderson et al 2020). It should be noted that this will therefore not capture differential instances of care use (or non-use) in between these weeks; it is likely that non-permanent instances of social care receipt, increasingly more common in Scotland (Henderson 2019), will not have been captured as a result, and as such the results of these analyses will be more appropriate to long-term permanent receipt of care.

Prior to receipt of the data, the SCS was matched to the population by the Scottish Government via probabilistic matching, a data linkage approach where two records from separate datasets are linked together based on combinations of variables that have identical, or similar, values in each dataset. Probabilistic matching differs from deterministic matching (where records are matched on data which definitively identifies an individual, such as CHI number) in that no linkage ID or other unique identifier is available, and instead matching combinations of variables which are likely to uniquely identify an individual, and are common to each dataset, are evaluated for likelihood of them belonging to the same person (Kamboj 2019). In linking the SCS to CHI, the variables date of birth, sex and postcode were used. The overall match rate of 91%, with variation by local authority from 77% to 99% (bar one local authority with a very low match rate – see below). The majority of individuals (60%) lived in a local authority with a high match rate above 92% (Henderson et al 2019). A number of local authorities had higher-than-expected instances of their day of birth being coded as "1", and it was assumed that this was a default when the day of birth was not known. The only local authority with a very low match rate was Clackmannanshire (1%) and as such it is excluded from any regional analyses (a full list of match rates per local authority can be found in table 4.1). Match rates from the most deprived 10% of datazones (94.4%) were slightly higher than other deciles (93.2 to 93.9%), which may have resulted in a slight overestimation of the effect of deprivation on transition into care in later analyses. The high levels of missing informal care data should also be mentioned; roughly 70-80% per year. Sensitivity checks suggest that this data is not missing at random, and hence will also impact results involving this variable.

Table 4.1. Social Care Survey (SCS) probabilistic match rates to CHI spine, by local authority

Local authority	Match rate
Aberdeen City	82.0
Aberdeenshire	91.5
Angus	98.5
Argyll and Bute	96.9
Clackmannanshire	1.0
Dumfries and Galloway	98.5
Dundee City	90.6
East Ayrshire	96.8
East Dunbartonshire	93.9
East Lothian	86.9
East Renfrewshire	95.7
Edinburgh	94.2
Eilean Siar	95.2
Falkirk	97.9
Fife	94.7
Glasgow City	95.7
Highland	79.3
Inverclyde	97.2
Midlothian	80.1
Moray	91.0
North Ayrshire	96.6
North Lanarkshire	76.7
Orkney Islands	91.4
Perth and Kinross	94.0
Renfrewshire	81.1
Scottish Borders	84.2
Shetland Islands	95.5
South Ayrshire	95.4
South Lanarkshire	96.9
Stirling	96.5
West Dunbartonshire	85.1
West Lothian	83.9

The PIS is a record of all dispensed medications within community pharmacies, and in the context of this study consisted of a longitudinal record of BNF codes for medications dispensed per individual per month. This data was used to derive prescription-based multimorbidity scores including the CDS-H1, CDS-H2 and a proxy count of unique dispensed prescriptions.

Use of this particular linked dataset, which combined admissions, prescribing and care data together, allows for comparison of and contrasting multimorbidity measures in predicting outcomes across a number of data sources. This ensures that an identical methodological approach has been applied to the same population in evaluating these measures in predicting outcomes. Given that the study population comprises all adults aged 65 and above in Scotland, potential results can be generalisable to other countries within the UK, which use similar data, as well as countries within the EU with similar demographic change, i.e. countries that are historically younger on average than the EU as a whole (Ireland, Lithuania, Netherlands, Austria, Belgium) as identified by Kluge et al (2019).

4.1.2. Linked Scottish Health Survey/admissions dataset

In addition to the linked health/social care data, analysis was also performed using the SHeS linked to SMR data. The SHeS is a government-commissioned cross-sectional study taken at private households throughout Scotland (Scottish Government 2021). It was first introduced in 1995 and since 2008 has been conducted on a yearly basis. The study consists of a random selection of private households and asks a wide range of health-related questions to multiple individuals within households such as alcohol/drug use, visits to physicians and self-reported status. Demographic variables such as age, sex, socioeconomic status, and employment are also included. From 2008-11 a nurse visit was also applied to one sixth of the sample which asked further questions such prescription intake. This was subsequently discontinued in favour of a restructuring of the questionnaire. This study used variables such as age, sex, social class (via the National Statistics Socio-economic classification or NS-SEC, a widely used measure of occupational class in the UK) and SIMD. A number of self-reported multimorbidity measures (using semi-free response condition questions) were also derived, as well as education level using the data available.

This study used the SHeS-SMR dataset, which links the SHeS to a limited SMR dataset. This data is similar to the SMR data used in the linked health/social care dataset but only records initial admissions (and accompanying ICD-10 codes) and number of total admissions for a select list of conditions – as a result, this SMR data will underestimate the number and frequency of potential conditions in the multimorbidity indices derived from these data. Date of death and SIMD are also present. The SMR was used to derive a number of multimorbidity scores from ICD-10 codes, as well as SIMD.

The decision to use a survey dataset for informal care analyses in addition to administrative data was taken as informal care is typically measured using survey data. Though a carer variable exists in the SCS, it was considered helpful to compare precision of this common component of both datasets;

however it should be pointed out here that respondents to the SHeS are not asked if they have a carer but rather if they care for someone in the same household. As detailed below, this necessitated derivation of an informal care receipt outcome which was restricted to care provision from another member of the household ("co-resident" care). In addition to this, whilst the linked administrative dataset covers a number of multimorbidity measures, self-reported conditions (which are prominent in a number of studies) were unavailable. This linked survey dataset allowed for comparison of these measures with more commonplace measures found in other data.

4.2. Construction of final datasets and study designs

Prior to conducting any analyses, both the administrative and survey data were cleaned and prepared; primarily for the former as it was initially provided as separate datasets with a linkage ID across each dataset. The cleaning process involved isolating the sample to the study of interest, creating derived variables relative to the study outcomes and explanatory variables, checking for missing data (and unmatched data in the administrative datasets), linking/appending datasets together and labelling final variables correctly. This section is split into three sub-sections, each reflecting on the data cleaning and preparation process for each separate analysis chapter of the thesis. Whilst there is some overlap, each chapter generally required a different set of prepared data, particularly the informal care chapter which uses an entirely separate dataset to the other two. Each sub-section will detail the dataset structure chosen, the reasons for choosing the dataset, a detailed overview of how the dataset was constructed and cleaned and a list and overview of the final variables used in each dataset.

Table 4.2. Overview and description of all health and care outcomes used in study

Outcome	Dataset(s)	Functional form	Description
Mortality	Administrative (ch4)	Binary	Death recorded within one year of index date (1st April)
1+ admissions			One or more admissions of any type recorded in SMR01 within one year of index date
2+ admissions			Two or more admissions of any type recorded in SMR01 within one year of index date
1+ emergency admissions			One or more admissions with emergency code for first stay recorded in SMR01 within one year of index date
2+ emergency admissions			Two or more admissions with emergency code for first stay recorded in SMR01 within one year of index date
7+ hospital days			Cumulative hospital stays of seven days or more recorded in SMR01 within one year of index date
28+ hospital days			Cumulative hospital stays of twenty-eight days or more recorded in SMR01 within one year of index date
Transition into social care	Administrative (ch5 transition)	Binary	Receipt of home or personal care in census year after index date recorded (as transition would have occurred within that year)
Transition into informal care	Administrative (ch6 transition)		Receipt of informal care in census year after index date recorded (as transition would have occurred within that year)
Co-resident care receipt	Survey		Receipt of co-resident care from a member of the same household as identified at interview

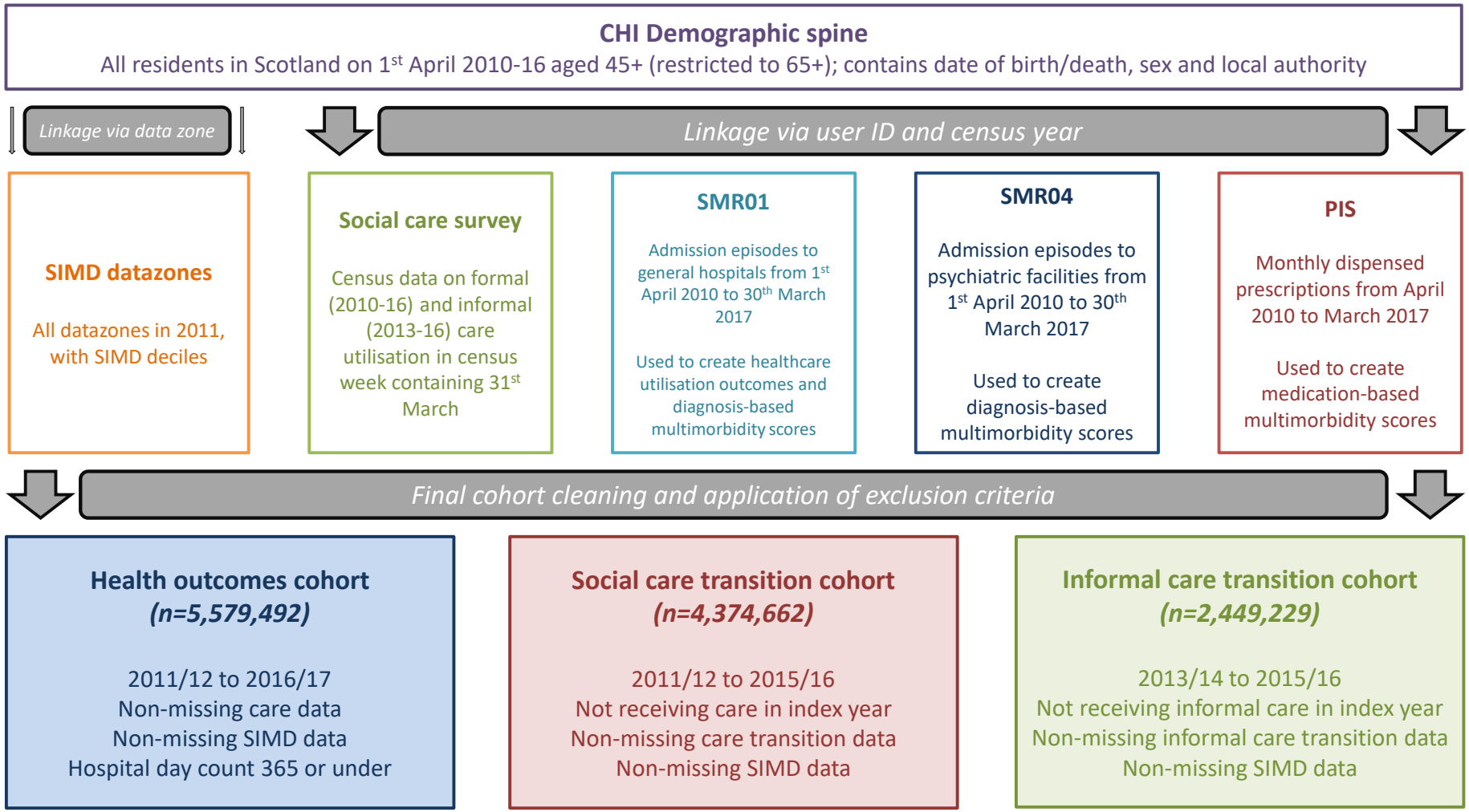

Fig 4.1: Overview of the component administrative datasets and the process used to create the three cohorts used in each chapter

4.2.1. Chapter 5 (mortality and healthcare utilisation) – administrative data only

When evaluating the impact of multimorbidity previous research focuses on an "index" date, prior to which data on multimorbidity is collected and following which the outcome is measured. For this reason, a cohort study design was chosen as opposed to a cross-section, with repeated measures for each individual – this would eliminate the necessity to exclude a large amount of potentially valuable additional data. Given that the census-based datasets (CHI and SCS) had a set date of April 1st regardless of the year, it was decided that the CHI census date would perform best as an index date, with individuals being sampled repeatedly on every CHI census date for which data was available.

Following this, the lookback and outcome "windows" for both the predictor (multimorbidity) and outcome (mortality and HCU) variables were decided. This follows similar designs for cohort studies where the incidence (in this case the health outcome) is measured for a set period of time after the "exposure" (in this case multimorbidity) (Carlson & Morrison 2009). When measuring health outcomes, a number of studies measured the incidence of mortality within 1 year after the index date including the original CCI paper (Charlson et al 1987) and others (Holman et al 2005, Quail et al 2011) as well as healthcare utilization within similar time periods such as 2 years (Wallace et al 2016). Based on the number of years of data available in this study and the apparent diminishing returns in many years of lookback as mentioned in section 3.2.2, it was decided that a one-year lookback period would be used for multimorbidity scores and individual conditions, and a one-year window was used for data on health outcomes following the index date. This would provide a sufficient "window" in which to collect data on recent conditions and would also avoid overlap with repeated measures of the same individual.

Following the decision on data windows, the final cohort was created via linking each dataset together via the unique IDs provided. The data "spine" was the CHI demographics data – this dataset contained what would be the population years for the dataset, and as a result all cases were included. All subsequent data was linked by matching on ID and census year, unless otherwise noted. SIMD 2016 data was linked in via 2011 datazone matching from data publicly available on the Scottish Government website. The 2016 SIMD was chosen across all years of the data to maintain consistency, and also to match up to the more representative 2011 datazones (as the data is from 2010 onwards) as previous years of the SIMD use the older 2001 datazones.

The social care data required extensive cleaning before linking as there were a number of duplicates on ID and year. Duplicates with less missing data by number of variables were initially retained, followed by a seeded random integer to determine removal of cases with identical numbers of missing data. A number of missing values were also checked for or recoded as required. This data was linked

twice, spanning different time points – once to the person-year corresponding to the equivalent person-year in the SC census, and once to the person-year in the previous CHI census year – this was so care could be used both as a predictor and an outcome.

The SMR admissions data was used to develop two separate datasets for health outcomes and diagnosis-based multimorbidity measures. The data was initially separated by financial year (1st April – 31st March), and then reshaped into a wide dataset consisting of person-admissions (i.e. multiple episodes). Via this number of episodes per financial year were derived for each individual, as well as the total hospital days by adding up the length of each admission and rounding to the nearest whole number (admissions which discharged on the same day were recorded as 0.5 hospital days). It was noted that some individuals had hospital day totals which exceeded 365 days due to a small number of admission length with incorrect discharge days – in this case, the hospital days value was recoded as missing. The stay order for each admission was also derived in order to derive the number of emergency admissions per year (emergency admissions were defined as the first "stay" of an admission being coded as an emergency); this cleaning was undertaken independently by another researcher (Feifei Bu) as they were working on a sub-study within the wider project which also required information on stay order. Only SMR01 was used for these outcomes as healthcare utilisation was defined only as admissions to or days spent in a general hospital.

SMR01 and SMR04 were also used to derive diagnosis-based multimorbidity scores in a separate dataset. Code was run which identified ICD-10 flags in any diagnosis code at admission (as opposed to just the main code), and these were aggregated to conditions flags for the individual. The composite flags were then used to sum the total CCI and EI score, providing both scores and condition flags for each case for that year. Finally, code was run to derive the unique ICD-10 condition groups proxy measure. The medication-based multimorbidity conditions and scores were derived similarly using the prescription data; however, the number of records per month meant that the full dataset for the study period was too large for the Safe Haven and thus had to be separated into a number of smaller datasets prior to receipt by the researcher. Due to the large size of each dataset, the component files were initially separated for each financial year and then reshaped so that an individual's unique prescription codes for each year was represented in one row of data. Via this process, flags were derived for individual conditions and composite scores for the CDS-H1, CDS-H2 and unique BNF subchapters.

Seven health outcomes were used in this chapter, and were defined as binary indicators of mortality or HCU in the year following the index date. One-year mortality is a standard measure used in most previous studies and an unambiguous measure of poor health in an individual. The six HCU outcomes were split into three main categories (admissions, emergency admissions and hospital days), all of which were available in and derived from the SMR01 inpatient admissions dataset. HCU outcomes

are also widely used in a number of studies (Lupari et al 2011, Marengoni et al 2011). Whilst the HCU outcomes used in this study were wider reaching than most multimorbidity comparison studies, potential options were limited by the data available; other common HCU outcomes such as GP consultation or accident and emergency attendance were not included for this reason. Each of these were split into levels of "severity" to assess differential predictive ability of multimorbidity measures, and condition and comorbidity risk (2+ compared to 1+ admissions and emergency admissions, 28+ compared to 7+ hospital days).

Number of admissions is the simplest measure and has commonly been used in previous research (Marengoni et al 2011). Emergency admissions is a slightly more refined version of this outcome– an admission was counted as "emergency" if the first episode of the admission was identified as an emergency admission. This outcome was chosen because it is again commonplace in similar literature (Wallace et al 2016, Wodchis et al 2015) and is a more reliable indicator of adverse health in an individual in contrast to a regular or "planned" admission. Multiple admissions are a strong indicator of poor health in long-term care populations (Ouslander & Maslow 2012); similar studies (Quail et al 2011, Wallace et al 2016) have used this in order to examine what contributes to being in this particular high-risk group.

The final indicator, hospital days, was another measure of the severity of an individual's health complaints, given that if someone spent more days in hospital (i.e. had long admissions) they required more treatment than someone who had many episodes but was there for a short duration of each. This also fits the policy narrative in that integration of health and social care is intended to aid older people in spending more days at home as opposed to in hospital. Studies that have used this measure include Elixhauser et al (1998) (as individual length of stay) and Karlsson et al (2008).

The inclusion criteria for this dataset were the following:

- Aged 65 and above
- Complete data present on use of care (i.e. those with missing values for home and/or personal care uptake removed)
- Complete data on deprivation level
- Hospital days value of 365 or under (see above)

4.2.2. Chapter 6 (deprivation and transitions into social care)–- administrative data only

This chapter used a similar version of the dataset from chapter 5, with minor alterations to the study population. The differences between this data and the one in the previous chapter is that it was

restricted to individuals who were currently not receiving care (as the aim was to predict transition into care as opposed to flat uptake), there was no exclusion based on incomplete hospital day data (as this outcome was not used) and exclusion was based on non-missing data on care both that year and the year afterward. The final criteria also meant that all cases in the census period 2016-17 were dropped, as there was no data as to whether care was received in the following year.

The outcome in this scenario was use of social care a year after the index date. Despite the variable indicating social care use within the census week containing the date of March 31st (given it is repeated measures of the same period in time), it is likely that the decision to use social care and/or the transition into social care was not made on that date itself; rather, it was made at some point in the preceding 12 months. It would therefore not make sense to use the social care identifier on the same date as the index date as the transition will have occurred in the preceding 12 months – in this sense, the outcome variable is similar to the other year-based health outcomes in that it is a binary measure of whether or not transition occurred within a year after the index date.

The inclusion criteria for this dataset were the following:

- Aged 65 and above
- Complete data on both care use in the census year and care use the year afterward
- Not receiving care in the census year
- Complete data on deprivation level

4.2.3. Chapter 7 (informal care) – survey and administrative data

Informal care analyses used both survey data and a version of the linked administrative data created above. For the survey data, the seven SHeS waves of 2008 to 2014 were appended into one dataset, with variables of interest harmonised over the waves – this consisted of renaming variables and labels and occasionally converting functional forms of some categorical variables into one consistent form over all waves of data. Some variables were consistent across all datasets – the SIMD in the SHeS consisted of quintiles and was the same throughout the waves. The version of the SIMD released in 2006 was used in all study waves up until 2012, with the 2012 version of the SIMD used thereafter; both were used as one variable for the whole dataset. Three socio-economic variables were retained for use as controls in regression models: education was condensed into a three-class "University degree/high school qualifications/no qualifications" variable, the seven-class National Statistics Socio-economic classification (NS-SEC) was used (recoding those who answered a separate question as to whether they had ever had a job in the negative to the "long term unemployed" class), and

marital status to a four class “never married/married or living with partner/separated or divorced/widowed” variable.

The decision was taken to append all waves for all analysis bar frequencies (where separate weighted datasets for the two survey “cycles” of 2008-11 and 2012-15 were compared to aggregate statistics), and adjust for this in univariate and bivariate analyses, such as reporting separate results for each cycle as well as the full dataset. In addition to this, using a dataset constructed of all seven waves would add further power to analyses. Cases under the age of 65 were excluded, as were cases with no linked SMR data and those who had no data on self-reported conditions (see below) or any of the control socio-economic status variables.

The “index date” in the context of this data was the date of interview for the SHeS. Multimorbidity data was either collected at interview (in the case of the self-report scales) or five years prior to the index date – this extended collection period was due to the limited nature of the SMR data (in that ICD-10 codes and dates are only recorded for the first historical incidence of one of 14 specific conditions). Using a one-year collection period produced very little data on multimorbidity and would have potentially left-out longstanding illnesses that had first been identified more than a year prior.

Receipt of co-resident care was used as an outcome (to assess what the contributors are to use of co-resident care). As only one care identifier was possible for the entire dataset this outcome was taken at interview rather than one year following interview, in contrast to the administrative data. The SHeS does not contain a question assessing receipt of informal care but does ask if any respondents provide informal care to someone else as well as the ID number of the person within the household should they provide care to someone they live with. From this, a “receives informal care from a member of the same household (co-resident care)” variable was derived, in the absence of an informal care question. As studies show that most people in receipt of informal care receive this from a child living outside the family home (Hoffman & Rodrigues 2010) this analysis will largely reflect the impact of care provision from a spouse or other live-in family member, and it was for this reason that this variable is referred to as co-resident, rather than informal care. However, it could also be argued that spousal care covers a wider range of help given that the spouse lives with the care recipient (and therefore cares them more often) and is likely to be closer than a family member. The proportion of cases identifying as receiving co-resident care was again very low, but enough to perform analyses.

The inclusion criteria for this dataset were the following:

- Aged 65 and above
- Linked to SMR data

- No missing data on self-reported conditions, social class, education level or marital status

For informal care analyses using linked data, a "transition into informal care" dataset, similar to the social care dataset in chapter 6, was created. This followed the same procedure as the transition into social care dataset (cases with missing informal care data at either that year's or the next year's census were excluded, and the dataset was restricted to those not receiving informal care that year) but with one difference – the data was restricted to years 13/14 to 15/16, as informal care data was not provided in the SCS until 2013.

The inclusion criteria for this dataset were the following:

- Aged 65 and above
- Complete data on both care use in the census year and care use the year afterward
- Not receiving care in the census year
- Complete data on deprivation (SIMD)

Table 4.3: Overview of all variables in administrative datasets by time period, derived datasets and included cohorts

One-year window prior to index date (1st April 201X-1 to 31st March 201X)	**On index date or census week (1st April 201X or date containing 31st March 201X)**	**One-year window following index date (1st April 201X to 31st March 201X+1)**
		Mortality
CCI/individual conditions		Transition into social care
EI/individual conditions	Age	Transition into informal care
Unique ICD-10 codes	Sex	1+ admissions
CDS-H1/individual conditions	Local authority	2+ admissions
CDS-H2/individual conditions	SIMD decile	1+ emergency admissions
Unique BNF subclasses	In receipt of social care	2+ emergency admissions
		7+ hospital days
		28+ hospital days

Cohort variables are included in are denoted by shading and is as follows: all datasets (white), health outcomes (blue), social care transition (red) or informal care transition (green).
Dataset variable was derived from is denoted by colour of text and is as follows: CHI (purple), SIMD (orange), SCS (green), SMR01/04 (blue), PIS (red)

Table 4.4: Overview of all variables in survey dataset by time period

Five-year window prior to index date	On index date (date of interview)	One-year window following index date
	Age	
	Sex	
	Receipt of co-resident care	
CCI/individual conditions	Self-reported conditions/score	
EI/individual conditions	Weighted self-report score	Mortality
Unique SMR conditions	Grouped SR conditions/score	
	NS-SEC	
	Education level	
	Cycle	
	SIMD	

Dataset variable was derived from is denoted by colour of text and is as follows: survey (red), SMR (blue)

4.3. List of analyses

The majority of analyses performed in each chapter are the same aside from section-specific changes, such as to the outcome variable or some variables included in each model. As such, this section is divided by type of analysis as opposed to chapter. Contained in each analysis sub-section is a description of the analysis itself, and an overview of how the analysis varies between chapters and datasets. In addition, for all analyses bar exploratory univariate and bivariate (sections 4.3.3 onward), a table is included outlining any relevant research questions, and how the analysis contributes to answering these questions. A separate table was included for each analysis subsection (tables 4.6 to 4.12), as opposed to one large table at the end of the chapter, as it was felt this would provide greater emphasis regarding the importance of each set of analyses to the thesis.

It should be noted that given that the study population is a panel dataset, with repeated measures per year, almost all results (bar panel regression which accounts for repeated measures) are represented as the lowest and highest statistic for each individual analysis in any given year; for example, the lowest and highest proportion of people with one or more admissions to hospital, or the lowest and highest mean CCI score. This approach, while unusual, gives a comprehensive account of by-year differences in analyses while omitting redundant data.

A full list of all variables, functional forms and derivation information can be found in Appendix A6. All analyses were run in Stata versions 13 (survey data) and 16 (administrative data).

4.3.1. Univariate analyses

Univariate analyses consisted of either frequency distributions (for categorical variables) or mean and standard deviation (for metric variables) for selected variables in the dataset such as demographics, multimorbidity variables and outcomes. The total number of cases (total and per year) for each dataset was also shown. Histograms were run for continuous variables to test for normal distributions, in order to determine which significance tests should be used later (none were normally distributed).

For multimorbidity, statistics were given for all multimorbidity variables and individual conditions in the chapter 5 dataset but only for the most predictive measures in chapter 6 and 7 (as only one outcome variable was used in subsequent sections).

For univariate results in the survey dataset, separate frequencies/means from each survey cycle and a weighted frequency/mean from the total dataset were presented, weighted using individual non-response found in the SHeS.

4.3.2. Bivariate analyses

Bivariate analyses focused specifically associations between multimorbidity and the outcome variable relevant to each chapter – it was felt that other associations (unless relevant to the research question) were not necessary given that the other variables used in analysis were controls. In addition, only the multimorbidity measure most predictive of each particular outcome (see section 4.3.3) was used. These analyses consisted of the mean multimorbidity score, per year, of those who experienced the respective health outcome compared to those who did not. The results in the survey dataset were not weighted; instead separate results from each cycle were reported as the bivariate interaction between the two variables will have somewhat corrected for any variance.

To test agreement between the multimorbidity measures, all continuous forms of the measures were correlated with each other using a Spearman correlation. This was an exploratory measure and had no bearing on subsequent analyses, as all measures were included regardless.

4.3.3. Nested regression for health and social care outcomes

The main objective of the thesis was to determine which multimorbidity measures were most predictive of each of the health and social care outcomes outlined in section 4.2. For the administrative cohorts, this was done via panel logistic regression modelling. The model was run on the entire cohort, with the panel variable being financial year; in this case, individuals could be

modelled multiple times (if alive), though this was accounted for. The outcome variable was the health or care outcome represented as a binary function (e.g. did or did not transition into social care, was or were not admitted twice as an emergency inpatient), with the outcome window as one year after the index date in each panel year. The main outcome variable of interest was the multimorbidity measure, represented as a composite score derived from individual condition flags in the year preceding the index date. The final model was adjusted for age, sex, deprivation (as SIMD deciles) and social care use (in chapter 5). Further to this, interaction terms were included; specifically, age as a quadratic function (to account for potential non-linear effects of age), age and sex to account for gender differences in age and wellbeing (Arber & Cooper 1999), age and multimorbidity to account for differential impact of multimorbidity by age (Lawson et al 2013) and between multimorbidity and receipt of care (chapter 5 only), to account for any reduction in risk accounted for in those with multimorbidity who are also receiving care.

Initially, nested models were run to account for the impact of step-by-step addition of variables (an overview of variables used at each stage of the nested model is in table 4.5); however, these are not included in the final thesis as the final model (in which all variables were included) was usually the most predictive. For the survey dataset, the design, and functional form of the outcome and main predictor variables were similar, however, logistic regression was used without panel adjustment.

Table 4.5: Variables added in nested models for panel regression by outcome and dataset

Nested model	**Administrative data**		**Survey data**
	Health outcomes	**Care outcomes**	**Care outcomes only**
Null model	No variables		Cycle (binary)
Demographics	Age (count) Sex (binary) SIMD (dummy deciles)		Age (count) Sex (binary) SIMD (dummy quintiles)
Use of care	Social care (binary)	N/A	N/A
Multimorbidity	Multimorbidity score (one-year lookback period)		Multimorbidity score (five-year lookback period for SMR-based, on interview for SHeS-based)
Control variables	N/A		Social class (dummy categories) Education level (dummy categories)
Interactions	Age (quadratic) Age*sex Age*multimorbidity Multimorbidity*care	Age (quadratic) Age*sex Age*multimorbidity	Age (quadratic) Age*sex Age*multimorbidity

The primary difference in model construction between questions is that care-based outcomes did not include a care predictor, and that the survey data used a number of controls for socio-economic status not found in the administrative data. These consisted of dummy variables created from the categorical variables NS-SEC, education status and marital status (the latter not included in the informal care model due to collinearity with the outcome). Prior to running the nested models, potential control variables in the survey data were individually entered into a univariate regression with the outcome. Variables that were significantly associated ($p<0.05$) with this outcome were used in this and the final interaction model. In addition, a binary variable for cycle was included in the survey regression, in every nested model. This was in place of weighting, which could add an extra layer of complexity to the analyses that will be difficult to interpret (Gelman 2007). Using cycle as a control accounted for potential repeated measures of the same population areas (but not the same individuals).

For the administrative data, panel regression was used given the nature of the data (repeated measures of the same people over time); a fixed effects design was used given expected individual variation over time. Repeated measures and a panel regression design provided maximal efficiency with the study population; providing greater predictive power than if individuals were only sampled once. For the survey each individual only took part once, and as such logistic regression was used. A full list of all models and outcome variables is summarised below:

- Panel logistic regression: mortality, 1+ admissions, 2+ admissions, 1+ emergency admissions, 2+ emergency admissions, 7+ hospital days, 28+ hospital days (all chapter 4), transition into informal care (chapter 5), transition into informal care (chapter 6, administrative data)
- Logistic regression: informal care (chapter 6, survey data)

For each outcome, separate regression models were run for each multimorbidity measure. The models were compared by way of the AIC, BIC and AUC. The AIC and BIC are two model selection parameters which compare nested models. Both of these measures are developed according to goodness-of-fit whilst penalising models that add too many unnecessary parameters (i.e. non-significant variables), with the lower score indicating a better model – the difference between the two being that the BIC gives a far lower score than the AIC if unnecessary parameters are added. Some studies that compare multimorbidity indices use this method of comparing models by changing the multimorbidity variable and observing how the AIC and BIC change (Brilleman & Salisbury 2012).

However, for most papers using logistic regression (McGregor et al 2005, Quail et al 2011, Sharabiani et al 2012) the model parameter of choice for is the c-statistic or area under the ROC curve (AUC), a measure which plots sensitivity and specificity in order to determine how predictive the model as a whole is at measuring the outcome. The AUC can range from 0.5 (poor prediction) to 1 (perfect prediction) – however in practice no model can realistically achieve this. A model is considered to

have acceptable prediction at 0.7, good prediction at 0.8 and excellent prediction at 0.9 and above (Mandrekar 2010).

Unlike the AIC and BIC (whose score is in part dependent on the sample size), the AUC can be used as an objective comparator of the predictive ability of any two models, and as such it is generally the preferred postestimation statistic of choice in multimorbidity measure comparison studies, particularly systematic reviews. However, the ROC curve cannot be calculated for models derived from panel data due to the fixed/random effects component of the model. To account for this, separate identical logistic regression models for each year of data were run, with an "AUC" range derived from this (the range of the highest and lowest AUC values from each year). For the survey logistic regression, one AUC was reported.

The best multimorbidity predictor of each outcome was based on the best performing model (either interaction or non-interaction), judged via the lowest AIC or BIC score or highest AUC. If the two parameters disagreed, the AUC was generally deferred to given that it can also be used to cross-compare models from different populations and outcomes.

Table 4.6: Research questions answered in section 4.3.3

Chapter	Research question	How question was answered
5 (health outcomes)	*Which multimorbidity measure(s) best predict mortality & healthcare utilisation outcomes in older people in Scotland using linked administrative data?*	AIC, BIC and AUC range in nested panel regression models determine the most predictive multimorbidity measure for each outcome.
6 (deprivation and transition into social care)	*Which multimorbidity measure(s) best predict transitions into social care in older people in Scotland using linked administrative data?*	AIC, BIC and AUC range in nested panel regression models determine the most predictive multimorbidity measure for transition into social care.
7 (informal care)	*Which multimorbidity measure(s) best predict transition into informal care in older people in Scotland using linked administrative data, and co-resident care using linked survey data?*	AIC, BIC and AUC (range) in nested panel logistic regression models determine the most predictive multimorbidity measure for each outcome.

4.3.4. Nested regression for health and social care outcomes with categorical multimorbidity variable

This analysis intended to explore categorical values of the most predictive multimorbidity variable per outcome and determine whether the effect was exponential, i.e. that individuals with a high multimorbidity score were particularly at risk for any given health outcome. Again, this analysis was performed for all outcomes across all questions, with the same differences between each as in 4.3.3.

This section consisted of two parts: first, the most predictive multimorbidity measure for each outcome was recoded as a categorical variable (based on frequency distributions) and replaced the original metric outcome in an otherwise identical version of the best performing model (interactions involving the multimorbidity variable were also recoded to categorical, should the original have interactions too). The odds ratios/coefficients of these categories were then recorded.

The second stage of this analysis involving recording the summary statistics – AIC, BIC, and AUC (range) – and comparing them to the original models with the metric multimorbidity predictor. This was done in order to see which functional form of the multimorbidity variable best predicted the outcome.

Table 4.7: Research questions answered in section 3.4.4

Chapter	Research question	How question was answered
5 (health outcomes)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?*	Odds ratio of categorical multimorbidity scores identify how strongly these scores are associated with the outcome.
6 (deprivation and transition into social care)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care?*	
7 (informal care)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal/co-resident care?*	

4.3.5. Nested regression for health and social care outcomes with individual conditions

This analysis followed on from the previous nested models in that it substitutes one composite multimorbidity scale with individual conditions from that multimorbidity measure. This was in order to determine from these scales which conditions were particularly associated with each outcome.

The best performing measure from 4.3.3 (or the best performing condition-based measure) corresponding to each health outcome was selected. Prior to running the model, each individual condition was regressed against the outcome in a univariate model. Only conditions that were significantly associated with the outcome ($p<0.05$) were included in the final condition-based model; conditions were also excluded in individual condition models for informal care if they had low overall prevalence (<1%) in administrative data (due to low prevalence of the transition into informal care outcome), or prevalence <10 in survey data. Interactions were still included if the interaction model was the best performing in prior analyses, with individual age (and care) interactions for each condition.

Again, the analysis consisted of two parts – first, the odds ratios of each individual score were recorded to answer the research questions listed below. In addition, the AIC, BIC and AUC (range) were compared to those from the original score-based model to see if the individual conditions produced a better model.

Table 4.8: Research questions answered in section 4.3.5

Chapter	Research question	How question was answered
5 (health outcomes)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?*	Odds ratio of individual conditions identifies which conditions are most strongly associated with the outcome.
6 (deprivation and transition into social care)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care?*	
7 (informal care)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal/co-resident care?*	

4.3.6. Nested regression for health and social care outcomes with condition combinations

This section focused on condition interactions; specifically what particular combinations of conditions were most associated with each outcome. Again, this analysis was performed for every outcome from section 4.3.3. The initial plan was to run a regression with every two-way condition interaction from the best performing condition-based score for each outcome, similar Brilleman et al (2012)'s paper on two-way interactions and healthcare costs – but it was felt that this would be too time consuming, too difficult to interpret and too generalised. Grouping commonly co-occurring conditions together via cluster analysis (Prados-Torres et al 2014) was also considered, but it was felt that the scope of this analysis would likely be beyond that of this PhD due to its complexity and divergence from the methods presented above. Instead, the three most strongly positively associated conditions with each outcome from the regression models in 4.4.5 were interacted with every other condition in their original multimorbidity index. After checking for low frequencies (interactions with cases <100 in any panel year were dropped in regressions derived from administrative data, and cases <30 in regressions from survey data), and excluding any conditions with low (<1% in any year) overall prevalence in the informal care administrative cohort, all remaining interactions were added into three separate models, one for each of the three most strongly associated conditions. All previous control variables were retained in these models.

The odds ratio of the original condition and all condition interactions were recorded, to see if the addition of the interactions changed the effect of the condition itself as well as if any co-morbid risks were observed.

Table 4.9: Research questions answered in section 4.3.6

Chapter	Research question	How question was answered
5 (health outcomes)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?*	Odds ratio of condition combinations identifies any additional co-morbid risk per index condition and the outcome.
6 (deprivation and transition into social care)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care?*	
7 (informal care)	*What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal/co-resident care?*	

4.3.7. Nested panel regression for transition into social care with deprivation interaction

This analysis was run solely for chapter 6 and was a variation of the model run in 4.3.3 for transition into social care to see if the effect of multimorbidity varied by deprivation level.

The previous best performing model from 4.3.3 was used, with the addition of an interaction between each decile of the SIMD and the multimorbidity measure. The odds ratio of the multimorbidity measure and the SIMD deciles as well as the interactions were recorded to determine any impact. The AIC, BIC and AUC range were also compared to the original model.

Table 4.10: Research questions answered in section 4.3.7

Chapter	Research question	How question was answered
6 (deprivation and transition into social care)	*Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?*	Interaction between multimorbidity variable and SIMD will indicate if the effect of multimorbidity varies by inequality.

4.3.8. Nested panel regression for transitions into social care by local authority

This was another analysis performed only for chapter 6, with the aim to see if there was a trend in strength of association between multimorbidity and transition into care by average SIMD of each LA. Clackmannanshire, Eilean Siar, Orkney, and Shetland were excluded due to low numbers.

The average SIMD score of each LA was calculated via an external SIMD datazone list (as not all datazones are included in the cohort) and linked in during the construction of the dataset. Models identical in composition to that in 4.3.3 were then run, but restricted to populations from each local authority, recording the odds ratio of the multimorbidity variable. This was then run again with the sample restricted to the most deprived quintile of the LA – this was to see if the overall deprivation of the LA had an additional effect on the most deprived population.

The odds ratios (with confidence intervals) for both sets of analyses were then arranged in order of average LA deprivation, from most to least deprived in similar style to the paper on child protection plan rates by average LA IMD by Bywaters et al (2015) – this would visually show if there was a trend in the effect of multimorbidity on transition into social care by LA average SIMD.

Table 4.11: Research questions answered in section 4.3.8

Chapter	Research question	How question was answered
6 (deprivation and transition into social care)	*Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?*	Odds ratio of effect of multimorbidity on transition into social care, arranged by local authority SIMD, will indicate any potential local authority effect.

4.3.9. Comparison regression for informal/co-resident care between administrative and survey data

The final analysis performed involved a cross-comparison of regressions in the administrative and survey datasets, in order to see whether the linked health and social care dataset or the linked survey dataset produced a model more predictive of informal/co-resident care, as well as to assess for any data-specific differences in individual predictors (such as demographics or multimorbidity).

Models similar to those from 4.3.3 for informal/co-resident care were used in this section, with variables available to both datasets. To harmonise the models the following changes were made to each:

- For the administrative dataset, SIMD was recoded to quintile
- For the survey dataset, the non-demographic control variables were removed

There were some small differences between the datasets – the multimorbidity measure differed in the informal care model as the administrative data does not have self-report multimorbidity measures (one of which was the best performing in the SHeS for informal care, as per chapter 7) and the survey dataset does not have medication measures (the best performing for informal care in the administrative data, again as per chapter 7). Following this, the full odds ratios and p-values for all variables in the model were shown (to assess variance in strength of association for each informal care outcome) and the AUC range (for the administrative data) and AUC score (for the survey data) was compared.

Table 4.12: Research questions answered in section 4.3.9

Chapter	Research question	How question was answered
7 (informal care)	*Is linked administrative or linked survey data able to better predict informal or co-resident care in older people in Scotland?*	Comparing the AUC of identical models produced in administrative data and survey data will indicate which perform better at predicting informal/co-resident care.

4.4. Ethics

Administrative data were provided following Public Benefit and Privacy Panel for Health and Social Care (PBPP) approval (1617-0012), with ethical approval from the Programme Approval Committee for an earlier PBPP (XRB14001) and the Committee of the School of Applied Social Science within the University of Stirling. Survey data were provided following Caldicott Data Release Form (CDRF) approval (1617-0058 & 1920-0179).

Ethical concerns primarily consisted of use and analysis of sensitive population-wide data and non-consent from study participants. This project used sensitive information including admissions to hospital, care status and prescribing information in older people with dementia and other health conditions, a potentially vulnerable section of the population. This, coupled with demographic data on age, date of (potential) death, location and sex raised the risk of potential identification of vulnerable individuals. To account for this, analysis was performed remotely via the National Safe Haven with the data held centrally within the Electronic Data Research and Innovation Service (eDRIS), of Public Health Scotland. The study author obtained, and was required to regularly renew information governance training prior to being named on the PBPP application authorising access, and any output produced within the Safe Haven was checked and approved via eDRIS disclosure control before release. This reduced the risk of any potentially identifiable output being released or publicly disseminated.

Due to the size and scope of the cohort used in this study (the entire over-65 population in Scotland), obtaining written consent from all study participants was not feasible. In place of this, permission was obtained, via the PBPP and eDRIS, from the data controllers (the organisation responsible for each dataset), all of which have their own information governance and privacy notices for use of individual data. Individuals are typically informed of the use of their own health and personal data via leaflets or posters within health care facilities such as general practices and surgeries, and focus groups are conducted with members of the lay public to solicit views on linking sensitive data and test privacy notices. The data controllers were NHS Scotland (admissions, prescribing, CHI) and the National Records of Scotland (births and deaths); the SCS is held by local authorities but was probabilistically linked and controlled by the Scottish Government, who conducted a Privacy Impact Assessment for this purpose (Scottish Government 2014).

4.5. Conclusion

This chapter outlined the data used in this PhD, the approach taken to cleaning and preparing the separate cohorts and the variables of interest (including outcomes, multimorbidity predictors and covariates), as well as the functional forms. Details of the analyses are outlined, as well as which research question(s) they are answering and why specific approaches were chosen. The following three chapters present results of these analyses and subsequent discussion, stratified by research area.

Chapter Five – Multimorbidity and health outcomes

This chapter focuses on using multimorbidity to predict health outcomes among older people in Scotland; specifically, which particular multimorbidity measures are most predictive and within the best performing measures what particular levels of multimorbidity, individual conditions and condition combinations are associated with greatest risk of each outcome.

It was identified in the literature review that the Scottish Government and local authorities wish to ensure that the needs of people with multimorbidity are met with joined-up, person-centred care, but it is important to identify who with multimorbidity are most susceptible to adverse health outcomes – particularly emergency admission "interventions." This includes which multimorbidity measure performs best at predicting health outcomes using administrative data as well as specific conditions and combinations. Work has been done on this previously, but the predictive ability of many multimorbidity scores differs considerably by the study population, which was frequently identified as the most important factor in determining predictive ability. No studies have been performed on a national population of older people in Scotland.

This chapter consists of four sections, answering two research questions:

- Which multimorbidity measure(s) best predict mortality & healthcare utilisation outcomes in older people in Scotland using linked administrative data?
- What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?

The other two sections consist of descriptive results, and a discussion of the main findings arising from the results.

5.1. Descriptive analyses

This section consists of two subsections: univariate frequency and distribution analyses of key variables, which outline cohort demographics, followed by bivariate analyses of multimorbidity and outcome variables. As mentioned previously in chapter 4, aside from the exact case numbers, all figures presented in this section are ranges from the highest to lowest aggregate value per year.

5.1.1. Univariate analyses

Seven tables are presented in this section – the case numbers by year in the dataset, demographic and care variables, health outcome frequencies, multimorbidity scale scores, and condition prevalence by scale.

For each variable, proportion ranges are presented for categorical variables and mean ranges are presented for metric variables.

Table 5.1: Number of cases in dataset by year

Year	11-12	12-13	13-14	14-15	15-16	16-17	Total
Cases	869,942	900,806	924,846	950,883	958,297	974,718	5,579,492

The number of cases (unique person-years) in each sample rises by around 100,000 over the six years (table 5.1) – this reflects an increasing ageing population in Scotland.

Table 5.2: Demographic and care variable summary ranges

Variable	Category	Proportion range	
		Lower	Upper
Age	**65-74**	54.21%	55.93%
	75-84	32.25%	33.87%
	85+	11.58%	11.92%
Sex	**Male**	43.28%	44.67%
	Female	55.33%	56.72%
SIMD decile	**1st**	7.78%	8.70%
	10th	10.03%	10.63%
Receiving social care		4.86%	5.08%

As clarified in the methods, the demographics in table 5.2, as well as all subsequent univariate analyses involving proportion, are presented as the range of lowest and highest proportions from all panel years of the dataset. As shown in table 5.2 the majority of older people in Scotland in the timeframe are aged 65-74 and female. Slightly more live in more deprived areas compared to less deprived areas. Around 5% of the sample are in receipt of social care in each census year.

Table 5.3: Outcome variable frequency ranges

Outcome	Proportion range	
	Lower	**Upper**
One-year mortality	4.62%	5.02%
1+ admissions	26.47%	27.14%
2+ admissions	10.34%	10.69%
1+ emergency admissions	16.03%	16.25%
2+ emergency admissions	5.06%	5.18%
7+ hospital days	9.63%	10.53%
28+ hospital days	3.46%	3.92%

According to table 5.3, mortality and 28+ hospital days are the least frequent outcomes, with both at or less than 5% prevalence per year. 1+ admissions (26-27%) and 1+ emergency admissions (16%) are the most frequent outcomes.

Table 5.4: Multimorbidity scale mean ranges

Outcome	Mean range	
	Lower	**Upper**
CCI	0.23	0.24
EI	0.25	0.27
Unique ICD-10 codes	0.50	0.53
CDS-H1	3.75	3.89
CDS-H2	4296.26	4321.24
Unique prescriptions	7.06	7.17

The lowest and highest by-year mean scores for each multimorbidity measure (table 5.4) are not intended for direct comparison; as the conditions, weights and frequency of each vary, a higher score relative to another measure is not indicative of higher multimorbidity. However, some inference can be made from the proxy measures as they are both counts of two health behaviours. The medication-based scores are higher than diagnosis-based, with is to be expected given that prescribing generally precedes admission to hospital.

Tables 5.5-7 below outline the frequency of each condition within the CCI, EI and CDS-H2, again as a range of the lowest and highest proportion per year. Conditions with very low frequency (less than 1%) have been suppressed. Prevalence of conditions in the CDS-H1 are not shown, as the CDS-H1

was not the best performing multimorbidity measure for any health outcomes (see section 5.2.1) and is not used in any condition-specific analyses.

Table 5.5: Frequency of individual conditions in the CCI

Condition	Proportion range	
	Lower	Upper
Acute myocardial infraction	1.52%	1.59%
Congestive heart failure	<1.00%	1.25%
Peripheral vascular disease	<1.00%	<1.00%
Cerebrovascular disease	1.28%	1.42%
Dementia	1.20%	1.25%
Chronic obstructive pulmonary disease	2.71%	2.94%
Rheumatoid arthritis	<1.00%	<1.00%
Peptic ulcer	<1.00%	<1.00%
Mild liver disease	<1.00%	<1.00%
Diabetes	2.22%	2.48%
Diabetes & complications	<1.00%	<1.00%
Hemiplegia or paraplegia	<1.00%	<1.00%
Renal disease	1.22%	1.89%
Cancer	2.09%	2.14%
Moderate/severe liver disease	<1.00%	<1.00%
Metastatic cancer	<1.00%	<1.00%
AIDS	<1.00%	<1.00%

Table 5.6: Frequency of individual conditions in the EI

Condition	Proportion range	
	Lower	Upper
Congestive heart failure	<1.00%	1.25%
Cardiac arrythmias	2.86%	3.26%
Valvular disease	<1.00%	<1.00%
Pulmonary circulation disorders	<1.00%	<1.00%
Peripheral vascular disorders	<1.00%	<1.00%
Hypertension, uncomplicated	4.17%	4.73%
Paralysis	<1.00%	<1.00%
Other neurological disorders	<1.00%	<1.00%
Chronic pulmonary disease	2.71%	2.94%
Diabetes, uncomplicated	2.21%	2.47%
Diabetes, complicated	<1.00%	<1.00%
Hypothyroidism	<1.00%	<1.00%
Renal failure	1.22%	1.89%
Liver disease	<1.00%	<1.00%
Peptic ulcer disease (excl. bleeding)	<1.00%	<1.00%
AIDS/HIV	<1.00%	<1.00%
Lymphoma	<1.00%	<1.00%
Metastatic cancer	<1.00%	<1.00%
Solid tumour without metastasis	1.82%	1.86%
Rheumatoid arthritis / collagen vascular	<1.00%	<1.00%
Coagulopathy	<1.00%	<1.00%
Obesity	<1.00%	<1.00%
Weight loss	<1.00%	<1.00%
Fluid and electrolyte disorders	<1.00%	<1.00%
Blood loss anaemia	<1.00%	<1.00%
Deficiency anaemia	<1.00%	<1.00%
Alcohol abuse	<1.00%	<1.00%
Drug abuse	<1.00%	<1.00%
Psychoses	<1.00%	<1.00%
Depression	<1.00%	<1.00%
Hypertension, complicated	<1.00%	<1.00%

Overall prevalence in the CCI (table 5.5) and EI (table 5.6) is considerably lower than in the CDS-H1/2, which is to be expected given that identification of conditions in these indices is conditional on admission to hospital or a psychiatric unit. Hypertension in the EI, with a prevalence of circa 4%, is

the most common condition across both diagnosis-based indices; this reflects overall high prevalence of hypertension in the general population (but considerably higher than reported here). COPD, diabetes (both), cancer (CCI) and cardiac arrythmias (EI) are also relatively common, with prevalence rates of around 2%.

Table 5.7: Frequency of individual conditions in the CDS-H2

Condition	Proportion range	
	Lower	Upper
Coronary and peripheral vascular disease	36.11%	41.68%
Epilepsy	4.79%	7.23%
Hypertension	58.31%	59.86%
Tuberculosis	<1.00%	<1.00%
Rheumatoid arthritis	1.12%	1.54%
HIV	<1.00%	<1.00%
High cholesterol	45.23%	45.85%
Parkinson's disease	5.51%	6.86%
Renal anaemia/neutropenia	<1.00%	<1.00%
Heart disease	47.32%	48.58%
Diabetes	9.98%	10.83%
Glaucoma	4.05%	4.34%
Pancreatitis	<1.00%	<1.00%
Renal failure	<1.00%	<1.00%
Ulcers	38.44%	41.98%
Transplants	<1.00%	<1.00%
Respiratory illness/asthma	15.87%	16.94%
Hyperthyroidism	<1.00%	<1.00%
Gout	3.29%	4.23%
Crohn's disease/inflammation	1.35%	1.43%
Pain/inflammation	12.91%	16.14%
Depression	17.91%	20.44%
Dementia	3.38%	3.91%
Mania	<1.00%	<1.00%
Anxiety/tension	16.52%	16.88%
Pain	11.74%	12.59%

Prevalence of conditions within the CDS-H2 (table 5.7) is closer to national approximations, which again is not unusual given that prescribing will likely capture conditions in an earlier stage. Heart disease, hypertension, ulcers, high cholesterol, and CVD are present in over one in three of the total

population in every year, and respiratory illnesses, pain/inflammation, depression and anxiety are present in one in ten.

When comparing prevalence in the CDS-H2 to that reported elsewhere for older Scottish and UK populations (table 1.1), hypertension (58-60%) was similar, as was depression (18-20%) and respiratory illness (15-17%). Diabetes (10-11%) is slightly underreported, and reported prevalence of dementia (3-4%) is half that of the UK estimate (7%, Kingston et al 2018); these both may reflect underdiagnosis, non-treatment or lack of community prescribing for each condition (besides potential coding problems). Medication is not typically prescribed specifically for dementia, particularly in the latter stages; this will impact the accuracy of medication-derived multimorbidity measures such as the CDS-H2 for dementia and other conditions. In addition to this, dementia in particular is prone to under-detection in older adults (Amjad et al 2018). Pain (12-13%) is underreported compared to national statistics of 30% for 65-74 and 24% for 75+ (McLean et al 2014); this may reflect over-the-counter treatment of pain instead of a formal prescription, widely available in the UK (Hayde-West 2021).

Some condition prevalence in the CDS-H2 diverged greatly compared to reported elsewhere. Prevalence of renal anaemia/neutropenia and renal failure in the CDS-H2 (<1%) is far lower than chronic kidney disease (CKD) estimates of 18.5% in adults aged 75 and above Scotland (McLean et al 2014), though neither of these conditions are directly analogous to CKD. There is no common medicine for CKD, with treatment taking the form of addressing underlying causes and, in more severe cases, dialysis or transplants (NHS 2019). Given this, medication data may not be appropriate for renal conditions. The two BNF paragraphs coding for renal anaemia/neutropenia (9.1.3 and 9.1.6) are primarily used to stimulate red and white blood cell production in bone marrow, and as such this condition was renamed from the original “end-stage renal disease” used in the CDS-2. Only two medications, both polystyrene sulfonates, are listed for renal failure in the CDS-H2. These are both primarily used to treat hyperkalaemia, commonly found in late-stage kidney disease (Georgianos et al 2017). It is therefore possible that the “renal failure” may only capture hyperkalaemia alone, with the apparent low prevalence resulting from in-hospital treatment of hyperkalaemia or renal failure via dialysis in the absence of prescribed medication. Previous research has found that medication data underreports renal diseases relative to other sources of data (Chini et al 2011).

Prevalence of hyperthyroidism (<1%) is low compared to other Scotland-based estimates for thyroid disorders (14.5% in 65-74, 15.9 in 75+, McLean et al 2014), however; hyperthyroidism is considerably less common than hypothyroidism (Barbesino 2019); with prevalence approaching that seen in this study (Patient 2020). It is also noted that the prevalence of mania, which typically occurs as part of bipolar disorder or, in older people, as a side effect of medication or a symptom of infection

(Ljubic et al 2021) is very low (<1%). Neither mania nor bipolar disorder are included in the studies comprising table 1.1; contemporary estimates from other studies place prevalence of bipolar disorder in older people from 0.4% to 1% (Llubic et al 2021). The only drug listed for mania in the original CDS-2 was lithium; in the CDS-H2, this was adapted as lithium carbonate and lithium citrate within BNF section 4.2.3 (drugs used for mania and hypomania), with two other drugs in this section (asenapine and valproic acid) excluded; this may in part explain lower-than-expected prevalence.

It is noted that prevalence of heart disease (47-49%) is much higher than reported elsewhere, the next highest equivalent being 31.2% in over-75s in Scotland (McLean et al 2014). Given that the listed BNF classes for each condition may be used to treat other similar conditions, such as anticoagulants in blood clots unrelated to heart disease (NHS 2021), this is a notable example of one limitation of medication indices in that medications are frequently prescribed for different conditions per individual, and as such may potentially have limited diagnostic ability. In contrast to diagnosis-based indices, in which ICD-10 codes correspond to a specific condition, medication-based indices are only indicative of likely conditions, and as such the likelihood of misidentification is considerably higher. Given this, caution will be used particularly when interpreting condition-specific results using these indices.

5.1.2. Bivariate analyses

Two analyses are shown in this section, both focusing on the relationship between multimorbidity and health outcomes. The first will be the range of the correlation between each multimorbidity index, the second will be the mean multimorbidity score of those who do and do not have each health outcome. For the latter the most strongly associated multimorbidity measure for each outcome (as derived in section 5.2.1) is used.

Table 5.8: Range of correlations between multimorbidity indices

MM measure	CCI	EI	ICD-10	CDS-H1	CDS-H2
EI	0.81 to 0.83				
Unique ICD-10 codes	0.68 to 0.69	0.75 to 0.77			
CDS-H1	0.23 to 0.24	0.25 to 0.25	0.23 to 0.24		
CDS-H2	0.25 to 0.27	0.27 to 0.28	0.28 to 0.29	0.76 to 0.77	
Unique prescriptions	0.28 to 0.29	0.29 to 0.31	0.32 to 0.34	0.74 to 0.74	0.79 to 0.80

Strong associations were observed within the diagnosis-based and medication-based measures, whereas weak associations were found when comparing across the type of measure. The most strongly associated measures were the CCI and EI, whereas the most weakly associated measures were the CCI and CDS-H1.

Table 5.9: Mean multimorbidity score range in those who did and did not experience each health outcome

MM score	Health outcome		Mean score range	
			Lower	Higher
CCI	**Mortality**	**Yes**	1.14	1.23
		No	0.18	0.19
Unique prescriptions	**1+ admissions**	**Yes**	9.03	9.26
		No	6.31	6.40
	2+ admissions	**Yes**	9.85	10.11
		No	6.73	6.82
	1+ emergency admissions	**Yes**	9.62	9.88
		No	6.55	6.65
	2+ emergency admissions	**Yes**	10.76	11.03
		No	6.86	6.96
Unique ICD-10 codes	**7+ hospital days**	**Yes**	1.27	1.45
		No	0.41	0.43
	28+ hospital days	**Yes**	1.46	1.68
		No	0.46	0.49

For all outcomes the multimorbidity score is higher for those who did experience the outcome than those who did not. When comparing outcomes with the same multimorbidity score, similar average numbers of unique prescriptions were found in those who had two or more admissions, or one or more emergency admission, with those with two or more emergency admissions having the highest overall numbers of unique prescriptions. More unique ICD-10 codes are on average observed for those with more time spent in hospital.

5.2. Research question 1: Which multimorbidity measure(s) best predict mortality & healthcare utilisation outcomes in older people in Scotland using linked administrative data?

This question will be answered using the main model parameter comparison for each multimorbidity measure previously mentioned in the methods chapter.

5.2.1. Nested regression for health outcomes

The following presents model parameter results from the nested regression models for each outcome and by each condition. As described in the methods chapter, nested regression models were run for each outcome consisting of demographic variables, a care predictor, the multimorbidity measure and interactions. These models were repeated for each multimorbidity measure, in order to determine which measure is the most predictive for each outcome via the model parameters.

The results presented here are only from the models with all variables (including interactions) – in all models all three model parameters (AIC, BIC and AUC) were optimum for the interaction model. Thus, parameters will be presented for models containing the following variables:

- Age (count)
- Age (quadratic)
- Sex (binary)
- SIMD (dummy decile variables, SIMD 10 excluded as reference)
- Social care use (binary)
- Multimorbidity measure (continuous)
- Age*female interaction
- Age*multimorbidity interaction
- Multimorbidity*care interaction

This section consists of four subsections for each of the four outcomes (mortality, admissions, emergency admissions, hospital days), plus a further subsection comparing measures across all

outcomes. It was noted that for results across all health outcomes, the AIC and BIC ranked the multimorbidity measures in exactly the same order in terms of the best performing model. As such, only one measure of the two (the BIC) is shown here as the results from the AIC would be exactly the same.

These analyses answer the research question outlined earlier as they determine via interpretation of the model parameters which multimorbidity measures perform best at predicting these health outcomes in the older Scottish population. As identified by the literature review and confirmed by the results, focus is on the following four dynamics in particular:

- The best overall measure for each outcome
- Predictive ability of diagnoses-based measures compared to medication-based
- Predictive ability of condition-based indices compared to proxy scores
- Predictive ability of multimorbidity measures overall depending on how severe the outcome is in comparison to others (i.e. emergency admissions compared to admissions, or 28+ hospital days compared to 7+)

5.2.1.1. Nested regression for mortality

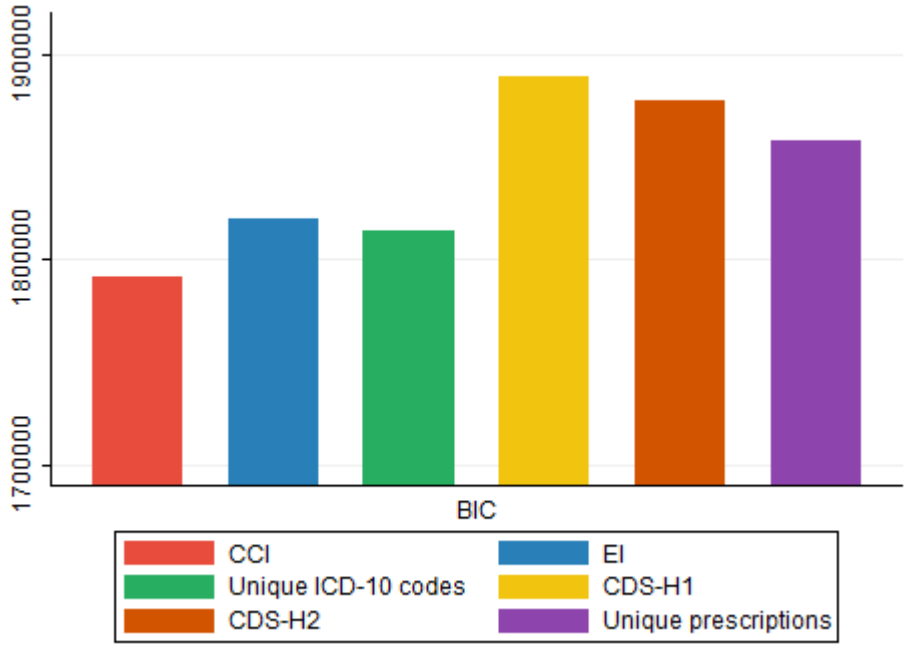

Fig. 5.1: BIC of panel logistic regression models predicting one-year mortality by multimorbidity measure

As shown in fig. 5.1, the CCI outperforms all other measures in predicting one-year mortality across all three parameters. This is consistent with previous literature (Brilleman & Salisbury 2012, Sharabiani et al 2012) which finds that despite its age, the CCI is a consistent predictor of mortality compared to all other measures. It is also notable that diagnosis-based measures universally outperform medication-based measures. This again is consistent with previous research (Yurkovich et al 2015).

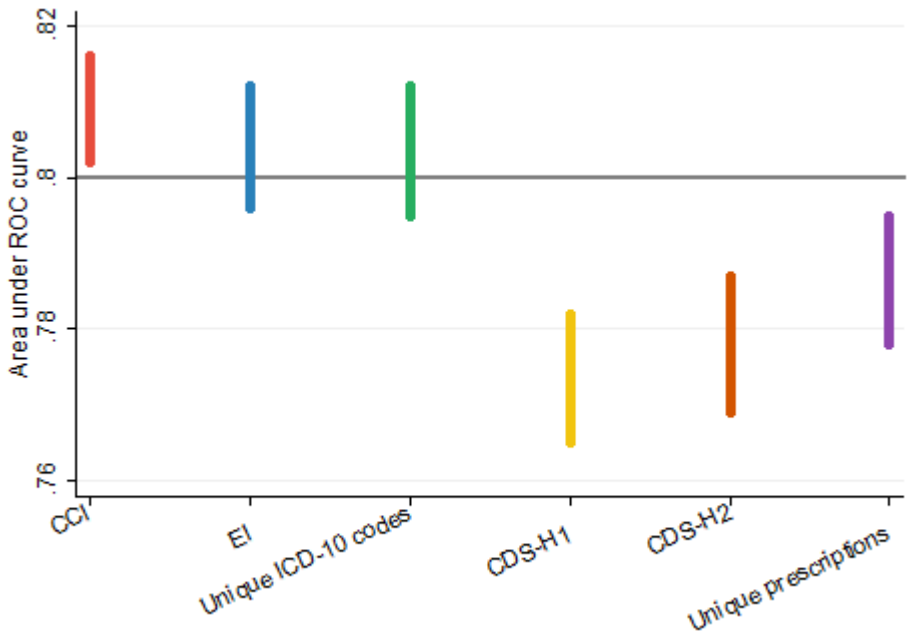

Fig. 5.2: Area under ROC curve (AUC) range of logistic regression models by year predicting one-year mortality by multimorbidity measure

In terms of the AUC, all multimorbidity measures have as least acceptable prediction (0.7) in predicting mortality as shown in fig. 5.2. The CCI is the only measure with good prediction (0.8) across all years, with the remaining diagnosis-based measures ranging between acceptable and good depending on the year.

5.2.1.2. Nested regression for admissions

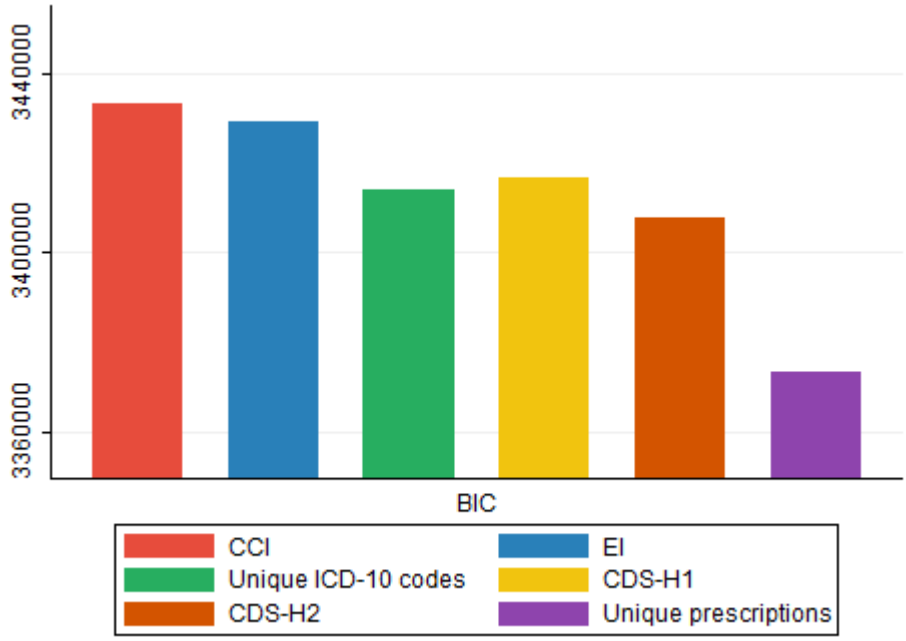

Fig. 5.3: BIC of panel logistic regression models predicting 2+ admissions by multimorbidity measure

The graph for the BIC predicting 1+ admissions is not shown (see Appendix A7) as the results are similar bar that the CDS-H1 is more predictive than the unique ICD-10 codes.

The medication-based measures perform better in predicting both 1+ and 2+ admissions (fig. 5.3), with the proxy unique prescriptions measure performing best overall and the CDS-H2 the best condition-based measure. This reflects previous research which also found that medication-based measures perform better for healthcare utilisation (Yurkovich et al 2015). It is also notable that both proxy measures have the lowest AIC/BIC in both diagnosis-based and medication-based multimorbidity measures.

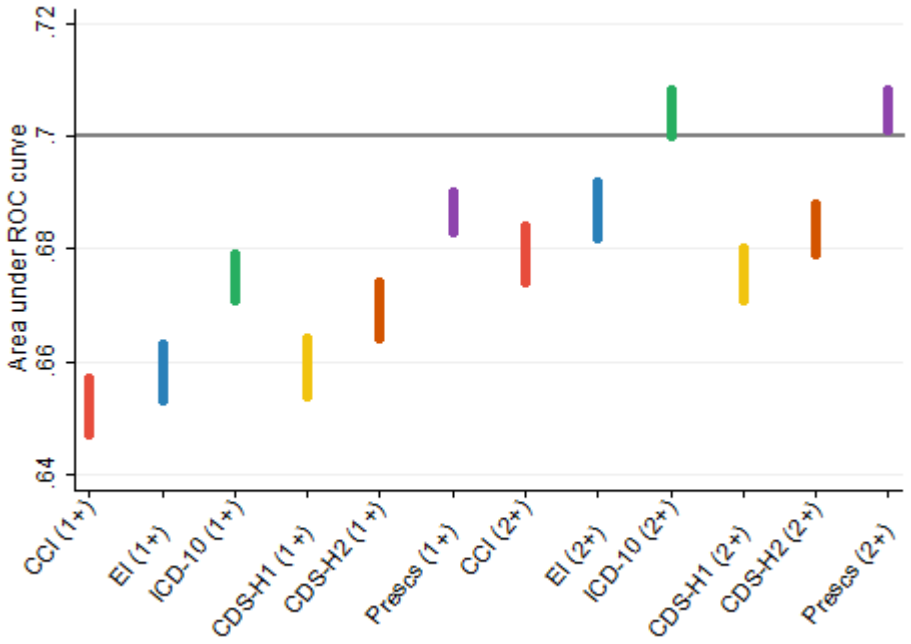

Fig. 5.4. Area under ROC curve (AUC) range of logistic regression models by year predicting 1+ and 2+ admissions by multimorbidity measure

In fig. 5.4 the AUC range of both logistic admissions measures is condensed into one graph to illustrate the overall predictive ability of the measures depending on severity of the outcome (i.e. 2+ compared to 1+ admission). Every measure has poor prediction (0.6) for one or more admissions, but for two or more admissions both proxy measures' prediction ranges from poor to acceptable. Whilst the overall results are the same (prescription count is best performing measure for both outcomes), every measure performs better at predicting the more severe health outcome (i.e. 2+ compared to 1+ admissions), and the differences between the diagnosis-based and medication-based measures almost disappear for 2+ admissions, to the point where the EI marginally outperforms the CDS-H2 as the best performing condition-based measure. This may indicate that the multimorbidity measures appear to perform better as a whole when predicting more severe outcomes, with the diagnosis-based measures in particular performing better relative to their efficacy in predicting the "worse" outcome. It is also notable that for the AUC, in contrast to the AIC/BIC both proxy measures are the best performing overall rather than within their diagnosis-based or medication-based "group."

5.2.1.3. Nested regression for emergency admissions

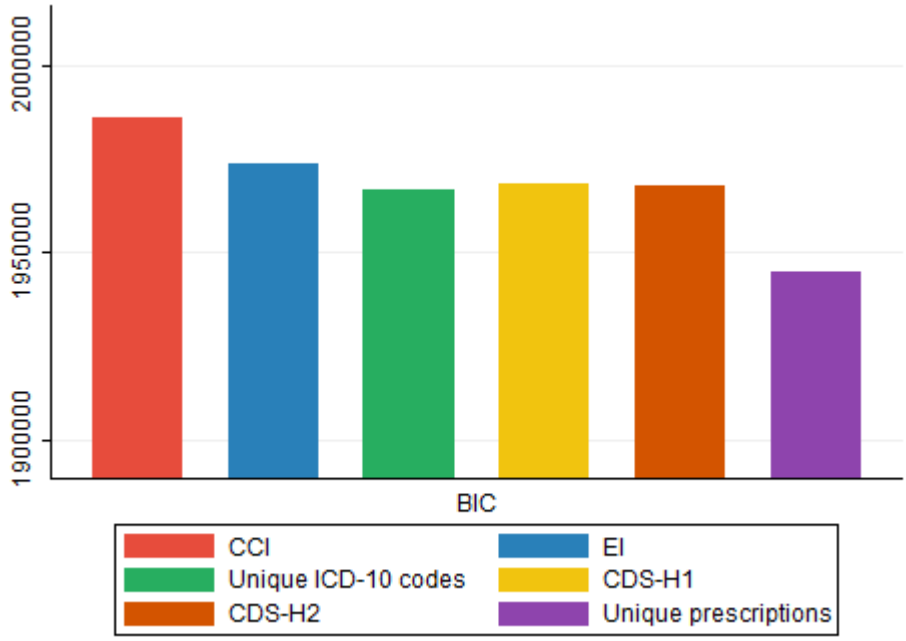

Fig. 5.5: BIC of panel logistic regression models predicting 2+ emergency admissions by multimorbidity measure

Again, only the graph for 2+ emergency admissions is shown (see Appendix A7) as the results are similar save for the CDS-H1 outperforming the ICD-10 and CDS-H2. Much like admissions, medication-based measures produce better parameters for emergency admissions (fig. 5.5), with proxy measures performing best. In particular, the unique prescriptions measure has the lowest AIC and BIC.

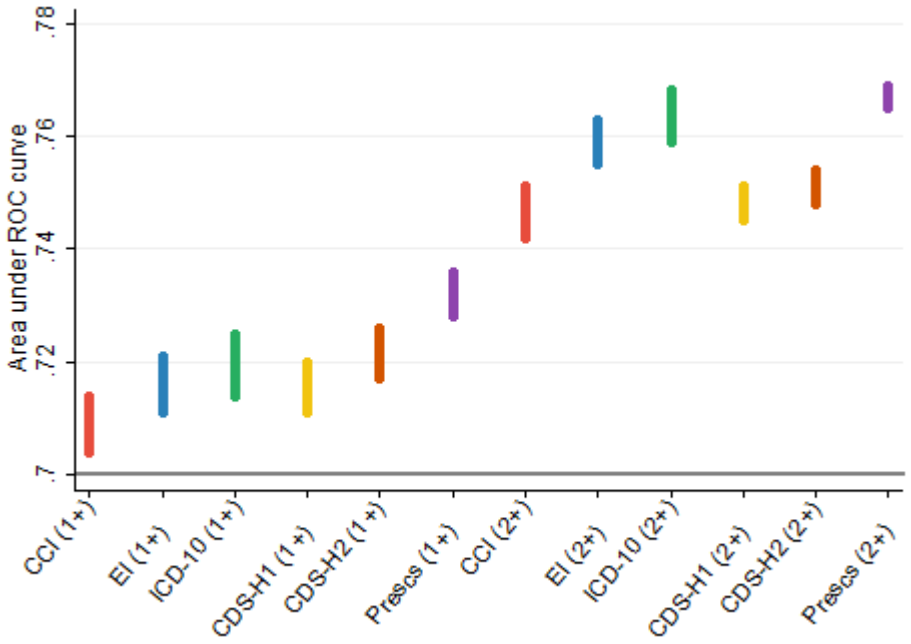

Fig. 5.6. Area under ROC curve (AUC) range of logistic regression models by year predicting 1+ and 2+ emergency admissions by multimorbidity measure

The AUC of each measure in predicting 1+ and 2+ emergency admissions (fig. 5.6) are broadly similar to that seen for elective admissions (fig 5.4), with some discrepancies. The AUC is higher for the more severe outcome (2+ emergency admissions) and the overall results are the same for best performing proxy and condition-based measure (unique prescriptions for both, CDS-H2 and EI for 1+ and 2+ respectively), however, every multimorbidity measure performs better at predicting emergency admissions than for elective admissions, with the AUC range for every measure in the “acceptable” range. The same interpretation used for admissions, that multimorbidity in general has stronger prediction for less severe health outcomes, could also apply here. In addition, the difference between proxy measures and condition indices is not as wide as for elective admissions with the CDS-H2 outperforming unique ICD-10 codes for 1+ emergency admissions. However, for the more severe outcome the diagnosis-based indices perform on par with the medication-based.

5.2.1.4. Nested regression for hospital days

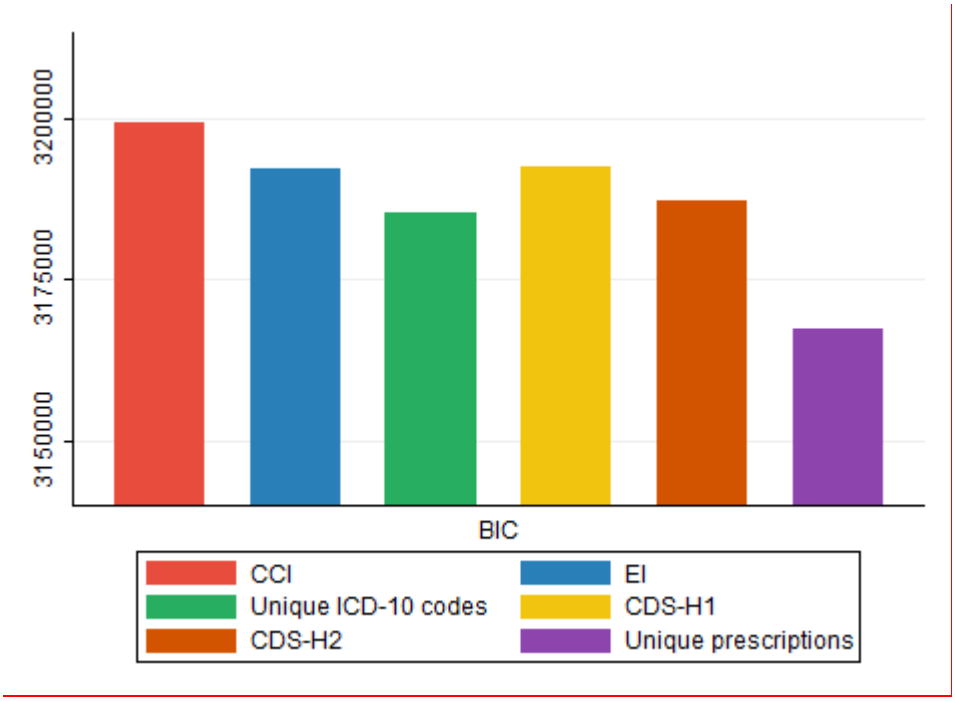

Fig. 5.7. BIC of panel logistic regression models predicting 7+ hospital days by multimorbidity measure

Figures for both 7+ and 28+ hospital days are displayed in this section as variance in predictive ability of multimorbidity measures for each outcome is more pronounced. BIC results for a week or more in hospital (fig. 5.7) reflect previous healthcare utilisation outcomes both in this chapter and earlier studies, with medication-based measures performing better and proxy measures performing best. The CDS-H2 is the best performing condition-based measure.

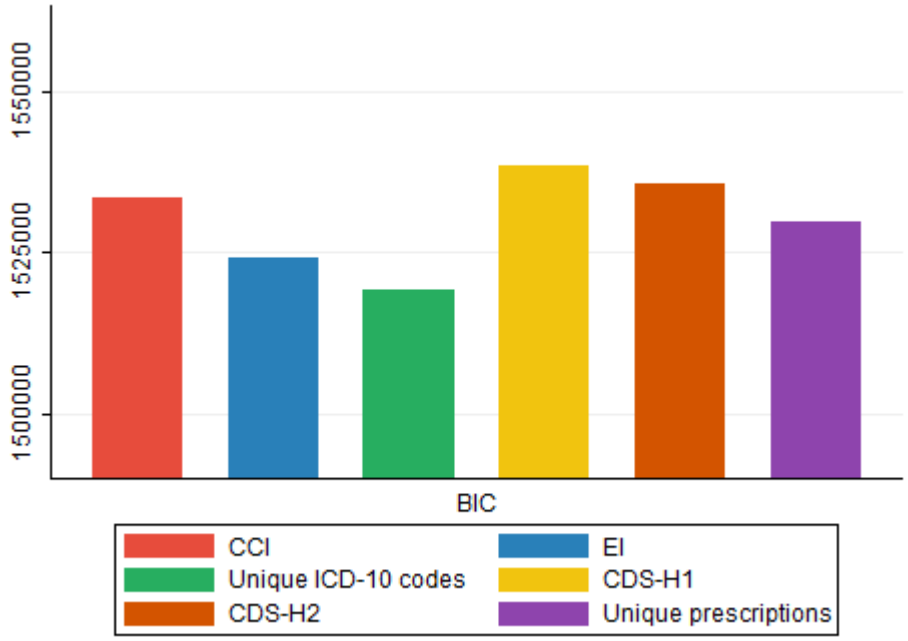

Fig. 5.8. BIC of panel logistic regression models predicting 28+ hospital days by multimorbidity measure

However, for hospital days of a month or more this is reversed (fig. 5.8), with diagnosis-based indices performing better (but still the recurring theme of proxy measures outperforming condition indices). A possible explanation of previous results is that diagnosis-based measures perform better for "worse" measures such as mortality – by the same logic, being in hospital for a month is an indicator of poorer health status than a simple admission. The EI is best-performing in terms of BIC here for a condition-based outcome.

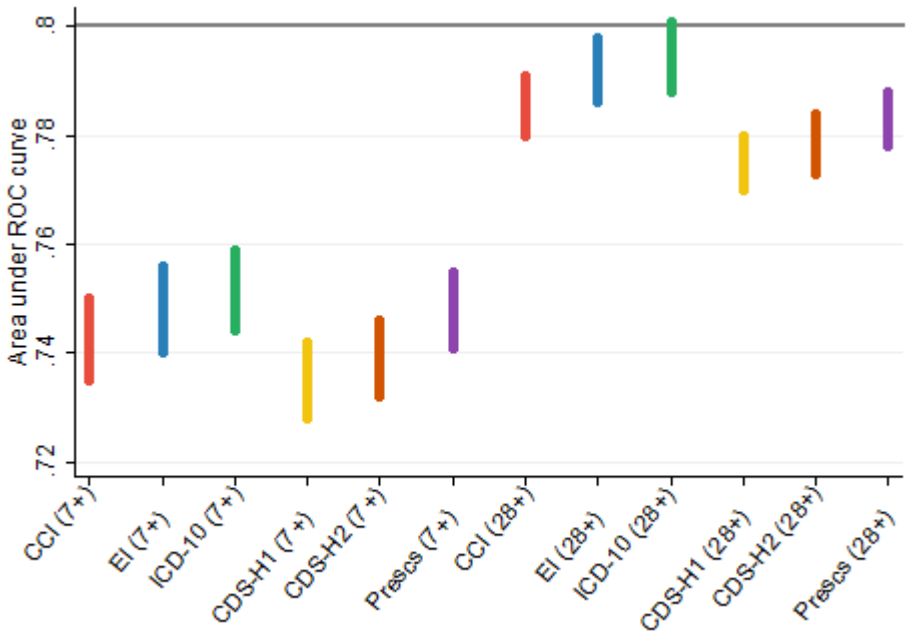

Fig. 5.9. Area under ROC curve (AUC) range of logistic regression models by year predicting 7+ and 28+ hospital days by multimorbidity measure

For the AUC (fig. 5.9) most diagnosis-based measures perform better, suggesting, based on prior results, that lengthy stays in hospital are a “worse” outcome than emergency admissions. All measures predict both outcomes with acceptable prediction, barring ICD-10 codes for 28+ days, in which one year has good predictive ability. The EI outperforms the CDS-H2 in terms of condition-based measures for both outcomes.

5.2.1.5. Cross-outcome comparison of multimorbidity measure performance

Table 5.10: Overview of predictive power, assessed via AUC, of all multimorbidity measures for all health outcomes

	CCI	EI	Unique ICD-10	CDS-H1	CDS-H2	Unique prescs
Mortality	**Good**	Acceptable to good	Acceptable to good	Acceptable	Acceptable	Acceptable
1+ admissions	Poor	Poor	Poor	Poor	***Poor***	**Poor**
2+ admissions	Poor	***Poor***	Acceptable	Poor	Poor	**Acceptable**
1+ emergency admissions	Acceptable	Acceptable	Acceptable	Acceptable	***Acceptable***	**Acceptable**
2+ emergency admissions	Acceptable	***Acceptable***	Acceptable	Acceptable	Acceptable	**Acceptable**
7+ hospital days	Acceptable	***Acceptable***	**Acceptable**	Acceptable	Acceptable	Acceptable
28+ hospital days	Acceptable	***Acceptable***	**Acceptable to good**	Acceptable	Acceptable	Acceptable

Table 5.10 summarises the predictive ability of each multimorbidity measure, by outcome, as represented visually in figures 5.2, 5.4, 5.6 & 5.9. This is to provide cross-comparison of each measure's predictive ability, and overall validity in predicting different health outcomes. For each health outcome and multimorbidity measure, overall performance is described using commonly accepted interpretations of the AUC value, as follows:

- Poor: AUC of 0.6-0.69
- Acceptable: AUC of 0.7 to 0.79
- Good: AUC of 0.8-0.89

If performance across years varied, then both are described (i.e. "acceptable to good" if performance by-year ranged from 0.7-0.89). The best performing measure for each condition is in **bold underline.** If the best performing measure is a proxy, the best-performing condition-based measure is in ***bold italics.*** This was used to determine, for each health outcome, which multimorbidity measure(s) were used in subsequent analyses; this reflects previous research comparing multimorbidity indices, where the AUC is generally preferred to the AIC/BIC to evaluate cross-measure performance (Park 2016, Quail et al 2011).

When the overall model performance is presented in one table (5.10), a number of trends emerge. At least one multimorbidity measure was found to have consistently "acceptable" predictive ability for each health outcome, bar one or more admissions. Overall, the majority of all multimorbidity measures have acceptable predictive ability for all other outcomes bar two or more admissions, where condition-based members have poor predictive ability. In addition, predictive ability of each multimorbidity measure was typically better for "worse" health outcomes, i.e. two or more admissions, or emergency admissions, compared to one, or twenty-eight hospital days compared to seven. Diagnosis-based measures performed better at predicting mortality, which is consistent with previous research; however, they also outperformed medication-based indices in predicting hospital days. This could potentially indicate that diagnosis-based indices, derived from conditions captured in later, more exacerbated stages, also predicts health outcomes that are more severe, or require comparatively high health service use. An extended hospital stay would likely be more resource-intensive than an inpatient admission, and could in this case be considered a "worse" health outcome.

5.3. Research question 2: What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?

This is a three-component question and focuses primarily on examining which aspects of multimorbidity are associated with high risk. This section looks at the best performing multimorbidity scores for each outcome, recoded to categorical, individual conditions, and combinations of conditions.

5.3.1. Nested regression for health outcomes with categorical multimorbidity variable

The following presents the odds ratios of the dummy multimorbidity measure variables when replacing the continuous measure in the models discussed in section 5.2. The models are otherwise identical barring the fact that categorical interactions were also used for any interactions involving the multimorbidity variable. These will be presented in three sections: mortality, admissions (both emergency and all) and hospital days. There will also be a further subsection comparing the BIC and AUC range of these new models with the original models, in order to see which measure best explains the outcome. These analyses examine not just whether there is a flat effect of multimorbid conditions, but also whether those with high multimorbidity scores are exponentially at higher risk of adverse health outcomes.

Table 5.11 presents a list of the categories for each multimorbidity measure and accompanying prevalence. The categories were determined via tabulating the scores and allocating based on

prevalence. Only multimorbidity scores represented in the analyses below are presented. The "zero score" category was used as the reference in all models.

Table 5.11: List of multimorbidity score categories used in categorical models and proportion range of population with each score

CCI			**Unique prescriptions**			**Unique ICD-10 codes**		
Category	***Lower***	***Upper***	***Category***	***Lower***	***Upper***	***Category***	***Lower***	***Upper***
0 (reference)	89.29%	89.59%	0 (reference)	6.69%	7.02%	0 (reference)	76.97%	77.19%
1	4.55%	4.86%	1-4	24.99%	26.15%	1	9.40%	10.18%
2	3.07%	3.16%	5-7	24.64%	25.33%	2-3	8.74%	9.01%
3	1.20%	1.42%	8-10	20.05%	20.82%	4+	3.87%	4.68%
4-6	<1.00%	1.06%	11-14	15.12%	15.58%			
7+	<1.00%	<1.00%	15+	6.72%	7.42%			

5.3.1.1. Categorical CCI model for predicting mortality

Table 5.12: Odds ratios and confidence intervals for categories of the CCI in predicting one-year mortality in panel logistic regression

CCI score	**Odds ratio**	**95% confidence interval**	
0 (reference)	1		N/A
1	***48.47***	***42.18***	***55.69***
2	***397.38***	***343.56***	***459.62***
3	***915.67***	***751.63***	***1115.51***
4-6	***2321.44***	***1881.79***	***2863.80***
7+	***18975.31***	***14431.65***	***24949.48***

Significantly associated categories are in bold italics.

There is a large increase in OR of each CCI category (table 5.12), ranging from those with a score of 1 being almost 50 times as likely to die to a likelihood almost 20,000 times greater than a score of 0 for those who have a score of 7 or more. This suggests a non-linear relationship, and that people with very high scores should be considered a high priority.

5.3.1.2. Categorical unique prescription models for predicting admissions and emergency admissions

Table 5.13 is presented as an aggregate for all four admissions outcomes, and as such the confidence interval is not included.

Table 5.13: Odds ratios for categories of unique prescriptions in predicting 1+ and 2+ admissions and emergency admissions in panel logistic regression

Number of unique prescriptions	OR for 1+ admissions	OR for 2+ admissions	OR for 1+ emerg admissions	OR for 2+ emerg admissions
0 (reference)	1	1	1	1
1-4	***1.25***	***0.77***	***0.46***	***0.28***
5-7	***4.07***	***2.67***	***1.47***	***1.11***
8-10	***11.91***	***8.94***	***5.53***	***5.31***
11-14	***35.50***	***30.74***	***20.15***	***29.82***
15+	***160.97***	***161.36***	***121.15***	***231.81***

Significantly associated categories are in bold italics.

Again, the number of unique prescriptions shows a relatively non-linear effect on admissions, though not as steep as the CCI on mortality (though this may be down to the multimorbidity measure itself, with not as big a difference between the different categories). There is a large increase from 8-10 to 11-14, and those who were dispensed fifteen or more prescriptions in the previous year are between 121-230 times more likely to experience at least one, or two, admissions or emergency admissions.

Is it noted that in the 2+ admissions and emergency admission models there is a significant drop in likelihood for those with 1-4 prescriptions in that they are less likely to undergo emergency admissions than those not taking any; this may be because people who are dispensed prescriptions are aware of and are actively managing their health, therefore decreasing the risk of an "emergency" intervention. The reference group, defined as those with no dispensed prescriptions, may also include those that were prescribed but did not adhere to medication. Whilst the impact of this cannot be fully accounted for, it is possible that this may partly be responsible for the apparent inverse effect of low levels of prescribing compared to none at all.

Additionally, when comparing differences between the more and less severe outcomes there is more of a difference between the emergency admissions models than the admissions models; indeed, prescription uptake as a whole, despite higher overall predictive ability (table 5.10) is not as strongly associated with 1+ emergency admission than either ordinary admission outcome. This may imply underlying dynamics of diagnosis by admission and diagnosis by prescription in that medication is more likely to be taken for managed, early-stage conditions, and therefore be more associated with HCU outcomes of a similar nature (i.e. planned compared to unplanned). The exception to this is the 15+ group, which, as representing the extreme end of multimorbidity is associated with "worse" outcomes i.e. 2+ emergency admissions. However, it should be noted that the differences are comparatively small.

5.3.1.3. Categorical unique ICD-10 code models for predicting hospital days

As with the above, the results from the models with ICD-10 codes as a categorical predictor are presented as an aggregate table for the two hospital days outcomes.

Table 5.14: Odds ratios for categories of unique ICD-10 codes in predicting 7+ and 28+ hospital days in panel logistic regression

Number of unique ICD-10 codes	**OR for 7+ hospital days**	**OR for 28+ hospital days**
0 (reference)	1	1
1	***16.18***	***13.78***
2-3	***104.92***	***189.31***
4+	***1413.93***	***4799.07***

Significantly associated categories are in bold italics.

As with previous health outcomes, in table 5.14 a non-linear effect of the number of unique ICD-10 codes is observed for both hospital day outcomes. Those with 2-3 unique codes are at over 100 times risk of those with no codes in both models, with large differences observed at different levels of outcome severity for those with 4+ codes – over 1000 for 7+ hospital days and approaching 5000 for 28+ days. Given the outcome is admissions-based, and derived from admission-based diagnosis codes, it is to be expected that higher on-admission multimorbidity will be more strongly associated with increased length of stay.

5.3.1.4. Comparison of model parameters for continuous and categorical multimorbidity variable

Table 5.15 presents an overview of the two model parameters, by parameter by model for the seven outcomes. Like in section 5.2, only the BIC is reported as no differences were observed between the AIC as to which was the best performing model.

Table 5.15: Parameters of models with metric and categorical multimorbidity variable by outcome

Param.	MM var.	Mort.	1+ adms	2+ adms	1+ emerg adms	2+ emerg adms	7+ h. days	28+ h. days
BIC	**Metric**	1,791,983	***5,887,349***	***3,373,382***	***4,315,141***	***1,944,924***	3,185,544	1,519,305
	Category	***1,774,848***	5,896,539	3,379,699	4,323,077	1,949,599	***3,182,517***	***1,518,666***
AUC range	**Metric**	0.802 to 0.816	***0.683 to 0.690***	***0.701 to 0.708***	***0.728 to 0.736***	***0.765 to 0.769***	***0.744 to 0.759***	***0.788 to 0.801***
	Category	***0.806 to 0.820***	0.681 to 0.688	0.698 to 0.706	0.726 to 0.734	0.763 to 0.767	***0.744 to 0.759***	0.788 to 0.800

The best performing models are in bold italics.

The majority of the metric models in table 5.15 are best performing across both parameters, with the mortality model the only one where the categorical measure outperformed the metric, though given that the mortality model is the only one in which the CCI was used this is likely measure, rather than outcome specific. For 7+ hospital days the AUCs are identical, and in 28+ hospital days different models were selected by either parameter. Generally speaking, however, these differences are very small. This suggests that either a metric or categorical functional form of mortality can be reliably used in risk prediction dependent on individual circumstances or preferences.

5.3.2. Nested regression for health outcomes with individual conditions

The following presents the odds ratios of component conditions of the most predictive condition-based measure for each outcome; for example, as the CDS-H2 had best predictive ability for one or more admissions (behind the proxy unique prescriptions measure), individual conditions from this measure are used for that outcome. The odds ratios are derived from models that are the same as those in 5.2, with the exception that individual conditions (and interactions for those conditions) replace the multimorbidity scale. Individual conditions were only included in each model if significantly associated in a prior univariate regression with the respective health outcome.

The AUC range, as opposed to the BIC, was used for selection of the best performing condition-based models (in line with previous research) and is presented in seven separate sections, for each health outcome. The predictive ability of these scores is compared to the original metric model via model parameters in an eighth section. These analyses examine which specific conditions people have that are more predictive of particular health outcomes than others, within the multimorbidity scale that previously performed best.

5.3.2.1. Individual CCI conditions for predicting mortality

Table 5.16: Odds ratios and confidence intervals for individual conditions of the CCI in predicting one-year mortality in panel logistic regression

CCI	Odds ratio	95% confidence interval	
Acute myocardial infraction	***1.35***	***1.06***	***1.72***
Congestive heart failure	***7.78***	***6.18***	***9.81***
Peripheral vascular disease	***3.11***	***2.31***	***4.20***
Cerebrovascular disease	***6.70***	***5.28***	***8.49***
Dementia	***174.81***	***138.64***	***220.43***
Chronic obstructive pulmonary disease	***49.00***	***41.40***	***58.00***
Rheumatoid arthritis	***9.13***	***5.90***	***14.14***
Peptic ulcer	***5.13***	***2.78***	***9.47***
Mild liver disease	***10.23***	***5.48***	***19.11***
Diabetes	***3.13***	***2.56***	***3.83***
Diabetes & complications	***3.51***	***1.71***	***7.17***
Hemiplegia or paraplegia	***13.77***	***6.97***	***27.18***
Renal disease	***10.24***	***8.28***	***12.66***
Cancer	***272.06***	***226.15***	***327.30***
Moderate/severe liver disease	***18.99***	***7.25***	***49.75***
Metastatic cancer	***48.71***	***35.28***	***67.26***
AIDS	<0.01	<0.01	101.03

Significantly associated conditions are in bold italics.

All variables included in the model in table 5.16 with the exception of AIDS are significantly associated with increased likelihood of mortality. Cancer is most strongly associated, (OR 272.06 [226.15 – 327.30), followed by dementia (OR 174.81 [138.64 – 220.43]) and COPD (OR 49.00 [41.40 – 58.00]). The relatively weak association of metastatic cancer compared to cancer (OR 48.71 [35.28 – 67.26]), can potentially be explained by non-diagnosis of the former on admission; metastatic cancer will carry an increased risk of death before the ICD-10 code is recorded.

5.3.2.2. Individual CDS-H2 conditions for predicting 1+ admissions

Table 5.17: Odds ratios and confidence intervals for individual conditions of the CDS-H2 in predicting 1+ admissions in panel logistic regression

CDS-H2 condition	Odds ratio	95% confidence interval	
Coronary and peripheral vascular disease	***2.17***	***2.04***	***2.32***
Epilepsy	***2.33***	***2.11***	***2.59***
Hypertension	***0.65***	***0.61***	***0.70***
Tuberculosis	***3.08***	***1.25***	***7.61***
Rheumatoid arthritis	***1.38***	***1.07***	***1.78***
HIV	***145.69***	***3.60***	***5893.32***
High cholesterol	***0.65***	***0.61***	***0.70***
Parkinson's disease	***2.05***	***1.86***	***2.27***
Renal anaemia/neutropenia	***52.48***	***23.54***	***116.99***
Heart disease	***1.44***	***1.34***	***1.54***
Diabetes	***1.20***	***1.09***	***1.32***
Glaucoma	***2.36***	***2.07***	***2.69***
Pancreatitis	***9.23***	***5.27***	***16.17***
Renal failure	***12.36***	***1.56***	***97.82***
Ulcers	***3.27***	***3.10***	***3.46***
Transplants	***4.19***	***2.61***	***6.75***
Respiratory illness/asthma	***1.65***	***1.54***	***1.78***
Hyperthyroidism	***2.43***	***1.53***	***3.83***
Gout	***0.83***	***0.73***	***0.95***
Crohn's disease/inflammation	***2.01***	***1.59***	***2.54***
Pain/inflammation	***1.54***	***1.43***	***1.66***
Depression	***1.72***	***1.60***	***1.85***
Dementia	***4.55***	***3.99***	***5.19***
Mania	0.79	0.44	1.41
Anxiety/tension	***2.12***	***1.97***	***2.28***
Pain	***5.14***	***4.78***	***5.53***

Significantly associated categories are in bold italics.

As per table 5.17, HIV is most strongly associated with one or more admissions, though the estimate is imprecise (OR 145.69 [3.60 – 5893.32]) likely due to low case numbers. Renal anaemia/neutropenia (OR 52.48 [23.54 – 116.99]), renal failure (OR 12.36 [1.56 – 97.82]), pancreatitis (OR 9.23 [5.27-16.17]) and pain (OR 5.14 [4.78-5.53]) are also strongly associated, compared to other conditions. All CDS-H2 conditions are significantly associated with 1+ admissions,

bar mania and hypertension; the former is likely as a result of low case numbers, and the latter is associated with a decreased risk. Taking into account the high overall prevalence of hypertension within the dataset, this may reflect a reduction in risk due to adherence to prescribing, and therefore health-conscious behaviour, rather than from hypertension itself.

5.3.2.3. Individual EI conditions for predicting 2+ admissions

Table 5.18: Odds ratios and confidence intervals for individual conditions of the EI in predicting 2+ admissions in panel logistic regression

EI condition	Odds ratio	95% confidence interval	
Congestive heart failure	***2.82***	***2.22***	***3.59***
Cardiac arrythmias	***2.12***	***1.80***	***2.49***
Valvular disease	***1.42***	***1.06***	***1.89***
Pulmonary circulation disorders	***2.44***	***1.60***	***3.71***
Peripheral vascular disorders	***4.41***	***3.34***	***5.83***
Hypertension, uncomplicated	***1.40***	***1.22***	***1.61***
Paralysis	***4.85***	***2.49***	***9.45***
Other neurological disorders	***14.48***	***10.92***	***19.19***
Chronic pulmonary disease	***10.96***	***9.33***	***12.88***
Diabetes, uncomplicated	***5.01***	***4.16***	***6.03***
Diabetes, complicated	***20.64***	***11.12***	***38.29***
Hypothyroidism	***1.88***	***1.37***	***2.57***
Renal failure	***7.10***	***5.72***	***8.83***
Liver disease	***18.46***	***10.99***	***30.99***
Peptic ulcer disease (excl. bleeding)	***11.18***	***5.89***	***21.21***
AIDS/HIV	0.27	<0.01	45760.94
Lymphoma	***402.63***	***235.86***	***687.31***
Metastatic cancer	***189.19***	***129.19***	***277.05***
Solid tumour without metastasis	***44.25***	***36.17***	***54.14***
Rheumatoid arthritis / collagen vascular	***44.22***	***30.94***	***63.19***
Coagulopathy	***6.17***	***2.92***	***13.06***
Obesity	***4.00***	***2.08***	***7.70***
Weight loss	***4.05***	***2.50***	***6.58***
Fluid and electrolyte disorders	***4.31***	***3.28***	***5.65***
Blood loss anaemia	0.86	0.10	7.50
Deficiency anaemia	***3.21***	***2.35***	***4.40***
Alcohol abuse	***2.44***	***8.13***	***19.03***
Drug abuse	2.09	0.17	26.11
Psychoses	***3.05***	***1.30***	***7.19***
Depression	***5.09***	***3.23***	***8.02***
Hypertension, complicated	1.01	0.58	1.74

Significantly associated categories are in bold italics.

All conditions in the EI (table 5.18) are associated with an increased risk of two or more admissions barring AIDS/HIV, blood loss anaemia, drug abuse and uncomplicated hypertension. Lymphoma is the most strongly associated (OR 402.63 [235.86 – 687.31], followed by metastatic cancer (OR 189.19 [129.19 – 277.05]) and non-metastatic tumour (OR 44.25 [36.17 – 54.14]). All three of these conditions are tumour-related; given the absence of cancer from the CDS-H2 model for 1+ admissions the two cannot be directly compared. It can be inferred that, pooling the two results together, tumour- and kidney-related conditions are most strongly associated with elective admissions.

5.3.2.4. Individual CDS-H2 conditions for predicting 1+ emergency admissions

Table 5.19: Odds ratios and confidence intervals for individual conditions of the CDS-H2 in predicting 1+ emergency admissions in panel logistic regression

CDS-H2 condition	Odds ratio	95% confidence interval	
Coronary and peripheral vascular disease	***3.28***	***3.05***	***3.53***
Epilepsy	***2.97***	***2.65***	***3.33***
Hypertension	***0.46***	***0.42***	***0.50***
Tuberculosis	***8.58***	***3.28***	***22.46***
Rheumatoid arthritis	1.08	0.81	1.44
HIV	7.94	0.15	430.99
High cholesterol	***0.46***	***0.43***	***0.50***
Parkinson's disease	***1.33***	***1.19***	***1.49***
Renal anaemia/neutropenia	***61.17***	***27.43***	***136.39***
Heart disease	***2.04***	***1.88***	***2.21***
Diabetes	***1.60***	***1.44***	***1.78***
Glaucoma	***0.82***	***0.70***	***0.96***
Pancreatitis	***12.41***	***6.87***	***22.42***
Renal failure	***14.22***	***1.78***	***113.73***
Ulcers	***2.58***	***2.42***	***2.76***
Transplants	***2.94***	***1.73***	***4.99***
Respiratory illness/asthma	***3.03***	***2.80***	***3.28***
Hyperthyroidism	***2.23***	***1.32***	***3.76***
Gout	1.16	0.99	1.35
Crohn's disease/inflammation	1.04	0.79	1.37
Pain/inflammation	***0.90***	***0.82***	***0.99***
Depression	***1.54***	***1.41***	***1.67***
Dementia	***15.19***	***13.20***	***17.48***
Mania	0.58	0.30	1.12
Anxiety/tension	***2.82***	***2.59***	***3.06***
Pain	***4.90***	***4.51***	***5.33***

Significantly associated categories are in bold italics.

Most conditions in the CDS-H2 (table 5.19) are associated with increased risk of one or more emergency admissions, though there are some differences between this and the model predicting any admissions (table 5.17). HIV is not significantly associated, though this again is likely as a result of low case numbers, and subsequent volatility in strength of association; this is also observed for mania, another condition with <1% prevalence. Renal anaemia/neutropenia (OR 61.17 [27.43 – 136.39]),

dementia (OR 15.19 [13.20 – 17.48]), renal failure (OR 14.22 [1.78 – 113.73]) and pancreatitis (OR 12.41 [6.87 – 22.42]) are most strongly associated. This is similar too for any admissions, save for dementia which carries a far greater risk than for elective admissions; a possible explanation may be that those with dementia, if alone for long periods of time, are unable to make elective arrangements for admission themselves, leading to a high emergency admission rate to compensate. In addition to hypertension, glaucoma and pain/inflammation are associated with a decreased risk – again, this likely reflects management of common, relatively benign problems compared to those with the conditions who are not receiving treatment.

5.3.2.5. Individual EI conditions for predicting 2+ emergency admissions

Table 5.20: Odds ratios and confidence intervals for individual conditions of the EI in predicting 2+ emergency admissions in panel logistic regression

EI condition	Odds ratio	95% confidence interval	
Congestive heart failure	***4.27***	***3.26***	***5.59***
Cardiac arrythmias	***2.96***	***2.46***	***3.58***
Valvular disease	1.13	0.81	1.58
Pulmonary circulation disorders	***2.41***	***1.50***	***3.85***
Peripheral vascular disorders	***5.18***	***3.75***	***7.16***
Hypertension, uncomplicated	1.09	0.93	1.29
Paralysis	***16.64***	***7.93***	***34.92***
Other neurological disorders	***29.12***	***21.35***	***39.70***
Chronic pulmonary disease	***45.47***	***37.94***	***54.50***
Diabetes, uncomplicated	***7.16***	***5.77***	***8.88***
Diabetes, complicated	***31.42***	***15.61***	***63.25***
Hypothyroidism	***1.82***	***1.25***	***2.63***
Renal failure	***9.33***	***7.31***	***11.92***
Liver disease	***12.31***	***6.80***	***22.31***
Peptic ulcer disease (excl. bleeding)	***4.28***	***1.94***	***9.41***
AIDS/HIV	<0.01	<0.01	1551.71
Lymphoma	***79.84***	***41.19***	***154.76***
Metastatic cancer	***123.98***	***78.75***	***195.18***
Solid tumour without metastasis	***34.96***	***26.99***	***45.28***
Rheumatoid arthritis / collagen vascular	***8.57***	***5.56***	***13.21***
Coagulopathy	***5.96***	***2.51***	***14.14***
Obesity	***6.34***	***2.97***	***13.51***
Weight loss	***4.13***	***2.34***	***7.29***
Fluid and electrolyte disorders	***7.60***	***5.64***	***10.25***
Blood loss anaemia	0.72	0.05	9.61
Deficiency anaemia	***2.35***	***1.62***	***3.39***
Alcohol abuse	***45.42***	***28.26***	***73.01***
Drug abuse	15.61	0.94	259.35
Psychoses	***6.15***	***2.40***	***15.76***
Depression	***11.78***	***7.09***	***19.55***
Hypertension, complicated	1.06	0.57	1.95

Significantly associated categories are in bold italics.

Similarly to that seen for 2+ admissions, most conditions in the EI are associated with an increased risk of 2+ emergency admissions. The overall risk for each condition is slightly smaller, perhaps suggesting that the overall risk is less from any condition in particular but rather from condition complexity. This is backed up by analyses in section 5.2.1 showing improved overall multimorbidity performance in predicting elective compared to emergency admissions. Metastatic cancer (OR 123.98 [78.75 – 195.18]), lymphoma (OR 79.84 [41.19 – 154.76]) and COPD (OR 45.47 [37.94 – 54.50]) carry the greatest risk.

5.3.2.6. Individual EI conditions for predicting 7+ and 28+ hospital days

Table 5.21: Odds ratios and confidence intervals for individual conditions of the EI in predicting 7+ hospital days in panel logistic regression

EI condition	Odds ratio	95% confidence interval	
Congestive heart failure	***3.80***	***3.03***	***4.78***
Cardiac arrythmias	***2.01***	***1.72***	***2.35***
Valvular disease	***3.83***	***2.91***	***5.04***
Pulmonary circulation disorders	***4.13***	***2.78***	***6.15***
Peripheral vascular disorders	***6.46***	***4.94***	***8.46***
Hypertension, uncomplicated	***1.45***	***1.27***	***1.66***
Paralysis	***15.14***	***8.18***	***28.01***
Other neurological disorders	***36.44***	***28.09***	***47.27***
Chronic pulmonary disease	***20.37***	***17.45***	***23.79***
Diabetes, uncomplicated	***6.37***	***5.32***	***7.61***
Diabetes, complicated	***33.74***	***18.61***	***61.15***
Hypothyroidism	***2.15***	***1.58***	***2.92***
Renal failure	***11.02***	***8.97***	***13.54***
Liver disease	***8.63***	***5.23***	***14.25***
Peptic ulcer disease (excl. bleeding)	***4.58***	***2.39***	***8.78***
AIDS/HIV	0.01	<0.01	1854.67
Lymphoma	***479.48***	***284.22***	***808.88***
Metastatic cancer	***162.72***	***113.41***	***233.46***
Solid tumour without metastasis	***71.18***	***58.20***	***87.06***
Rheumatoid arthritis / collagen vascular	***18.91***	***13.34***	***26.81***
Coagulopathy	***10.87***	***5.23***	***22.60***
Obesity	***4.50***	***2.36***	***8.56***
Weight loss	***6.01***	***3.77***	***9.58***
Fluid and electrolyte disorders	***7.82***	***6.07***	***10.06***
Blood loss anaemia	2.14	0.24	19.10
Deficiency anaemia	***3.56***	***2.62***	***4.82***
Alcohol abuse	***28.70***	***19.19***	***42.93***
Drug abuse	3.72	0.34	40.45
Psychoses	***6.98***	***3.21***	***15.19***
Depression	***5.06***	***3.30***	***7.75***
Hypertension, complicated	1.09	0.65	1.83

Significantly associated categories are in bold italics.

Table 5.22: Odds ratios and confidence intervals for individual conditions of the EI in predicting 28+ hospital days in panel logistic regression

EI condition	Odds ratio	95% confidence interval	
Congestive heart failure	***4.76***	***3.55***	***6.38***
Cardiac arrythmias	***2.29***	***1.86***	***2.83***
Valvular disease	***1.75***	***1.21***	***2.53***
Pulmonary circulation disorders	***3.59***	***2.16***	***5.98***
Peripheral vascular disorders	***9.53***	***6.72***	***13.52***
Hypertension, uncomplicated	***1.38***	***1.15***	***1.66***
Paralysis	***28.11***	***12.82***	***61.64***
Other neurological disorders	***68.22***	***49.41***	***94.2***
Chronic pulmonary disease	***24.41***	***19.86***	***30.00***
Diabetes, uncomplicated	***7.71***	***6.09***	***9.77***
Diabetes, complicated	***61.92***	***30.31***	***126.50***
Hypothyroidism	***1.90***	***1.25***	***2.89***
Renal failure	***12.31***	***9.47***	***16.00***
Liver disease	***9.72***	***5.16***	***18.31***
Peptic ulcer disease (excl. bleeding)	***3.93***	***1.62***	***9.51***
AIDS/HIV	0.59	<0.01	526309.90
Lymphoma	***310.68***	***157.44***	***613.08***
Metastatic cancer	***50.47***	***31.32***	***81.31***
Solid tumour without metastasis	***74.63***	***56.48***	***98.60***
Rheumatoid arthritis / collagen vascular	***18.78***	***11.87***	***29.72***
Coagulopathy	***12.50***	***5.06***	***30.91***
Obesity	***4.66***	***1.97***	***10.99***
Weight loss	***10.30***	***5.66***	***18.74***
Fluid and electrolyte disorders	***8.52***	***6.20***	***11.71***
Blood loss anaemia	2.67	0.14	49.53
Deficiency anaemia	***3.20***	***2.15***	***4.77***
Alcohol abuse	***48.10***	***28.82***	***80.27***
Drug abuse	4.27	0.26	69.18
Psychoses	***6.42***	***2.35***	***17.58***
Depression	***6.30***	***3.65***	***10.88***
Hypertension, complicated	1.23	0.64	2.37

Significantly associated categories are in bold italics.

The conditions in the EI associated with the highest risks for both 7+ and 28+ hospital days are consistent (tables 5.21 and 5.22). Lymphoma is associated with the greatest individual risk of both

(OR 479.48 [284.22 – 808.88] in 7+, OR 310.68 [157.44 – 613.08] in 28+), followed by metastatic cancer (OR 162.72 [113.41 – 233.46] in 7+, OR 50.47 [31.32 – 81.31] in 28+) and non-metastatic tumour (OR 71.18 [58.20 – 87.06] in 7+, OR 74.63 [56.48 – 98.60] in 28+). As tumour-related conditions, this is consistent with previous EI models for the other HCU outcomes (tables 5.17, 5.19). Lymphoma and metastatic cancer have higher risk associated with short-term stays in hospital (7+ says) compared to longer-term (28+ days) per year; given that these represent a worse prognosis than a non-metastatic tumour, as both are malignant, this may represent shorter survival time (and therefore being unable to spend up to a month in hospital), compared to the risk associated with a solid tumour where the risk remains relatively similar.

5.3.2.7. Comparison of model parameters for continuous multimorbidity variable and individual conditions

Table 5.23 below presents a comparison of model parameters for the original metric model, and the model with individual conditions (for the same multimorbidity measure). Again, only the BIC is presented as opposed to the AIC and BIC as the results for each outcome were identical for both. In the below table, the best performing measure between each model is shaded in **bold italics.**

Table 5.23: Parameters of models with metric and categorical multimorbidity variable by outcome

Param.	MM var.	Mortality	1+ adms	2+ adms	1+ emerg adms	2+ emerg adms	7+ h. days	28+ h. days
BIC	**Metric**	1,791,983	5,937,567	3,429,171	4,344,371	1,973,535	3,192,377	1,524,141
	Conds	***1,769,759***	***5,910,751***	***3,416,057***	***4,315,182***	***1,966,520***	***3,179,892***	***1,519,095***
AUC range	**Metric**	0.802 to 0.816	0.664 to 0.674	0.682 to 0.692	0.717 to 0.726	0.755 to 0.763	0.740 to 0.756	0.786 to 0.798
	Conds	***0.808 to 0.822***	***0.676 to 0.684***	***0.685 to 0.694***	***0.727 to 0.735***	***0.758 to 0.766***	***0.744 to 0.759***	***0.791 to 0.801***

The best performing models are in bold italics.

Every single individual condition model performs more strongly than its metric counterpart, across both outcomes. This suggests that even though the weighting aspect of a number of these indices is lost, controlling for each individual condition compensates in terms of prediction. Though the differences are again relatively small, and either measure of multimorbidity would be acceptable dependent on circumstances and user preference, this would suggest that individual condition models are preferred when developing or improving risk prediction. However, given that the weights used in the original indices were designed either for specific outcomes (i.e. in-hospital mortality in the CCI) or derived entirely from a separate, potentially demographically different cohort (such as in the CDS-

H2), updated weightings based on or derived from risk to a Scottish older population, with further adjustment to correct discrepancies in prevalence for some conditions, may outperform individual condition models.

5.3.3. Nested regression for health outcomes with condition combinations

The following presents odds for condition combinations from models that take the three most strongly associated conditions per outcome from the models in 5.4.2 and interacts all other conditions (with frequency of 100 or above) with that condition, in one model per main or "index" condition. The models are again identical to those from 5.2.1, save that the multimorbidity score is replaced by the condition and its interactions. Other interactions continue to use the metric multimorbidity score. This is split into seven sections, each by outcome; results for separate models for each of the three conditions will be in one table for all three. These analyses examine "comorbidity" of people with the most strongly associated conditions, and which comorbid conditions in particular have an increasing effect on the likelihood of experiencing health outcomes.

5.3.3.1. Condition combinations and mortality

The three most strongly associated conditions were: cancer, dementia, chronic obstructive pulmonary disease

For this and subsequent subsections, all conditions aside from the "index" condition in the first row present odds ratios from interactions with the index condition.

Table 5.24: Odds ratios for condition combinations predicting mortality

CCI condition		OR for interactions with cancer	OR for interactions with dementia	OR for interactions with COPD
Index condition		***1231.50***	***345.48***	***198.85***
Acute myocardial infraction		1.02	1.05	0.99
Congestive heart failure		***1.58***	***1.54***	***1.93***
Peripheral vascular disease		***1.29***	***1.41***	***1.35***
Cerebrovascular disease		***1.38***	***1.23***	***1.26***
Dementia		***1.90***	*Index condition*	***1.96***
Chronic obstructive pulmonary disease		***1.58***	***1.29***	Index condition
Rheumatoid arthritis		***1.23***	***1.16***	***1.27***
Peptic ulcer		***1.55***	*Excluded*	***1.33***
Mild liver disease		***1.64***	*Excluded*	***1.62***
Diabetes		***1.19***	***1.17***	1.03
Diabetes & complications		*Excluded*	*Excluded*	***1.38***
Hemiplegia or paraplegia		*Excluded*	*Excluded*	***1.32***
Renal disease		***1.35***	***1.25***	***1.31***
Cancer		*Index condition*	***2.52***	***2.85***
Moderate/severe liver disease		*Excluded*	*Excluded*	Excluded
Metastatic cancer		***4.03***	*Excluded*	***4.13***
AIDS		*Excluded*	*Excluded*	Excluded
Comorbid conditions + proportion of total	All	11 91.67%	8 88.89%	12 85.71%
	Increase only	11 91.67%	8 88.89%	12 85.71%

Significantly associated conditions are in bold italics.

Almost all included co-morbid interactions in table 5.24 are associated with an additional risk in addition to the index condition in all three models (92%, 89% and 86% for cancer, dementia and

COPD respectively). Metastatic cancer carries the highest increased risk with cancer and COPD, and cancer carries the highest increased risk for dementia. Both tumour-related conditions (cancer and metastatic cancer) carry the only increasing risk above 2 when included, with metastatic cancer's increased risk above 4; this, in combination with cancer's relatively high odds ratio of independent risk when all comorbidities are accounted for (1231.50) compared to dementia (345.48) and COPD (198.85) suggests that tumour-related conditions are on their own strongly associated with mortality and are generally "dominant" co-morbid conditions. However, it should be noted that the relationship between cancer and metastatic cancer will likely represent occurrence (and flagging) of cancer initially, followed by metastasis later on in the one-year lookback period for which multimorbidity data was collected, rather than a genuine comorbidity. This methodological issue is discussed further in the limitations section in chapter 8 (section 8.2).

5.3.3.2. Condition combinations and 1+ admissions

The three most strongly associated conditions were: HIV, renal anaemia/neutropenia, and renal failure. In prevalence checks, neither HIV nor renal failure were co-morbid with any other condition in over 100 individuals in at least one study year. As a result, pancreatitis and pain, as the next most strongly associated conditions, were used instead.

Table 5.25: Odds ratios for condition combinations predicting 1+ admissions

CDS-H2 condition	**OR for interactions with renal anaemia / neutropenia**	**OR for interactions with pancreatitis**	**OR for interactions with pain**
Index condition	***131.60***	***37.81***	***10.35***
Coronary and peripheral vascular disease	***1.15***	***1.29***	***1.19***
Epilepsy	*Excluded*	***1.25***	***1.34***
Hypertension	0.87	***0.86***	***0.96***
Tuberculosis	*Excluded*	*Excluded*	***1.16***
Rheumatoid arthritis	*Excluded*	*Excluded*	***1.31***
HIV	*Excluded*	*Excluded*	*Excluded*
High cholesterol	***0.83***	***0.86***	***0.92***
Parkinson's disease	*Excluded*	0.92	***1.20***
Renal anaemia/neutropenia	*Index condition*	*Excluded*	***2.15***
Heart disease	***1.35***	***1.22***	***1.20***
Diabetes	***1.22***	***1.14***	***1.18***
Glaucoma	*Excluded*	*Excluded*	***1.10***

Pancreatitis		*Excluded*	*Index condition*	***1.68***
Renal failure		*Excluded*	*Excluded*	*Excluded*
Ulcers		1.03	***1.29***	***1.30***
Transplants		*Excluded*	*Excluded*	***1.48***
Respiratory illness/asthma		***1.45***	***1.25***	***1.34***
Hyperthyroidism		*Excluded*	*Excluded*	1.06
Gout		1.12	*Excluded*	***1.16***
Crohn's disease/inflammation		*Excluded*	*Excluded*	***1.16***
Pain/inflammation		*Excluded*	0.93	***1.03***
Depression		0.91	***1.17***	***1.08***
Dementia		*Excluded*	*Excluded*	***0.75***
Mania		*Excluded*	*Excluded*	1.09
Anxiety/tension		***1.31***	1.01	***1.14***
Pain		1.17	***1.33***	*Index condition*
Comorbid conditions + proportion of total	All	6 54.55%	10 76.92%	21 91.30%
	Increase only	5 45.45%	8 61.54%	18 78.26%

Significantly associated conditions are in bold italics.

The majority of co-morbid conditions included in each model carry an increased risk of one or more admissions (table 5.25), though less so for renal anaemia/neutropenia (55%) and pancreatitis (77%) compared to pain (91%). The increased risk for each condition is generally low compared to mortality (table 5.24); renal anaemia/neutropenia, with pain, carries the only risk with an OR above 2. The large number of interactions with pain, and low baseline risk in comparison to the other two conditions, suggest that pain in itself is not so much an indicator of admission rather than other co-occurring conditions, of which it may be a symptom.

Is it notable that some comorbidities, particularly hypertension and high cholesterol, carry a supposed decreased risk of admission. This is consistent with single condition models and may reflect adherence to prescribing and overall health-conscious behaviour.

5.3.3.3. Condition combinations and 2+ admissions

The three most strongly associated conditions were: lymphoma, metastatic cancer, tumour

Table 5.26: Odds ratios for condition combinations predicting 2+ admissions

EI condition	OR for interactions with lymphoma	OR for interactions with metastatic cancer	OR for interactions with tumour
Index condition	***732.98***	***7075.78***	***206.07***
Congestive heart failure	1.02	0.85	1.03
Cardiac arrythmias	***0.78***	***0.76***	***0.87***
Valvular disease	*Excluded*	*Excluded*	1.24
Pulmonary circulation disorders	*Excluded*	1.05	1.10
Peripheral vascular disorders	*Excluded*	***0.68***	0.96
Hypertension, uncomplicated	1.01	0.92	0.96
Paralysis	*Excluded*	*Excluded*	*Excluded*
Other neurological disorders	*Excluded*	*Excluded*	***0.79***
Chronic pulmonary disease	0.99	***0.75***	0.99
Diabetes, uncomplicated	0.85	***0.87***	1.04
Diabetes, complicated	*Excluded*	*Excluded*	*Excluded*
Hypothyroidism	*Excluded*	*Excluded*	0.97
Renal failure	*Excluded*	0.88	***1.09***
Liver disease	*Excluded*	*Excluded*	***1.16***
Peptic ulcer disease (excl. bleeding)	*Excluded*	*Excluded*	*Excluded*
AIDS/HIV	*Excluded*	*Excluded*	*Excluded*
Lymphoma	*Index condition*	*Excluded*	*Excluded*
Metastatic cancer	*Excluded*	*Index condition*	***1.50***
Solid tumour without metastasis	*Excluded*	0.97	*Index condition*
Rheumatoid arthritis / collagen vascular	*Excluded*	*Excluded*	1.12
Coagulopathy	*Excluded*	*Excluded*	*Excluded*
Obesity	*Excluded*	*Excluded*	*Excluded*
Weight loss	*Excluded*	*Excluded*	0.95
Fluid and electrolyte disorders	*Excluded*	0.87	0.99
Blood loss anaemia	*Excluded*	*Excluded*	*Excluded*
Deficiency anaemia	*Excluded*	*Excluded*	1.04
Alcohol abuse	*Excluded*	*Excluded*	0.93
Drug abuse	*Excluded*	*Excluded*	*Excluded*
Psychoses	*Excluded*	*Excluded*	*Excluded*

Depression		*Excluded*	*Excluded*	0.87
Hypertension, complicated		*Excluded*	*Excluded*	*Excluded*
Comorbid conditions + proportion of total	All	1 20.00%	4 40.00%	5 26.32%
	Increase only	0 0.00%	0 0.00%	3 15.79%

Significantly associated conditions are in bold italics.

There are no comorbidities associated with an increased risk in either lymphoma or metastatic cancer, and one and four associated with a decreased risk respectively. Given that these both have low prevalence (<1% observed on admission to hospital in one year of data), and high severity, prescribing for other conditions may reflect earlier stages of the condition rather than a genuine decreased risk. Only three significant comorbidities (renal failure, liver disease, metastatic cancer) are observed for non-metastatic tumour, though for metastatic cancer this will represent an initial tumour diagnosis and subsequent metastasis during the multimorbidity data window, rather than comorbidity (as in common with similar findings in table 5.24).

5.3.3.4. Condition combinations and 1+ emergency admissions

The three most strongly associated conditions were: renal anaemia/neutropenia, dementia and renal failure. Renal failure was excluded (see 5.3.3.2) and replaced with pancreatitis.

Table 5.27: Odds ratios for condition combinations predicting 1+ emergency admissions

CDS-H2 condition	OR for interactions with renal anaemia / neutropenia	OR for interactions with dementia	OR for interactions with pancreatitis
Index condition	***159.7***	***33.24***	***51.91***
Coronary and peripheral vascular disease	1.12	***1.15***	***1.31***
Epilepsy	*Excluded*	***1.18***	***1.27***
Hypertension	0.87	***1.06***	***0.83***
Tuberculosis	*Excluded*	*Excluded*	*Excluded*
Rheumatoid arthritis	*Excluded*	***1.33***	*Excluded*
HIV	*Excluded*	*Excluded*	*Excluded*
High cholesterol	0.88	1.01	0.92
Parkinson's disease	*Excluded*	***1.28***	0.87
Renal anaemia/neutropenia	*Index condition*	*Excluded*	*Excluded*
Heart disease	***1.38***	***1.10***	***1.29***
Diabetes	***1.36***	***1.23***	***1.19***
Glaucoma	*Excluded*	1.06	*Excluded*
Pancreatitis	*Excluded*	*Excluded*	*Index condition*
Renal failure	*Excluded*	*Excluded*	*Excluded*
Ulcers	0.95	***1.13***	***1.29***
Transplants	*Excluded*	*Excluded*	*Excluded*
Respiratory illness/asthma	***1.49***	***1.38***	***1.35***
Hyperthyroidism	*Excluded*	***1.22***	*Excluded*
Gout	1.12	***1.13***	*Excluded*
Crohn's disease/inflammation	*Excluded*	***1.17***	*Excluded*
Pain/inflammation	*Excluded*	1.02	0.96
Depression	0.92	1.01	***1.19***
Dementia	*Excluded*	*Index condition*	*Excluded*
Mania	*Excluded*	1.04	*Excluded*
Anxiety/tension	***1.30***	1.00	1.04
Pain	1.16	***0.93***	***1.27***
All	4	12	9

Comorbid		36.36%	63.16%	69.23%
conditions + proportion of total	Increase only	4 36.36%	11 57.89%	8 61.54%

Significantly associated conditions are in bold italics.

Most conditions are associated with an increased risk of emergency admissions with dementia (63%) and pancreatitis (69%); just over a third are comorbid with renal anaemia/neutropenia (37%) (table 5.27). The relatively low baseline risk of dementia and large number of comorbidities, all of which are physiological, provide support to previous findings that mental/physiological comorbidities are associated with increased risk, and also suggests, much like pain in table 5.25, that dementia on its own is less responsible for healthcare utilisation than when co-occurring with other conditions.

5.3.3.5. Condition combinations and 2+ emergency admissions

The three most strongly associated conditions were: metastatic cancer, lymphoma, chronic pulmonary disease

Table 5.28: Odds ratios for condition combinations predicting 2+ emergency admissions

EI condition	OR for interactions with metastatic cancer	OR for interactions with lymphoma	OR for interactions with CPD
Index condition	***6222.01***	***207.83***	***246.38***
Congestive heart failure	0.96	*Excluded*	***1.19***
Cardiac arrythmias	***0.80***	0.95	***1.08***
Valvular disease	*Excluded*	*Excluded*	1.02
Pulmonary circulation disorders	1.01	*Excluded*	***1.08***
Peripheral vascular disorders	0.85	*Excluded*	***1.12***
Hypertension, uncomplicated	0.96	0.94	***0.89***
Paralysis	*Excluded*	*Excluded*	0.95
Other neurological disorders	*Excluded*	*Excluded*	***1.11***
Chronic pulmonary disease	0.99	***1.29***	*Index condition*
Diabetes, uncomplicated	0.95	1.08	***1.11***
Diabetes, complicated	*Excluded*	*Excluded*	1.08
Hypothyroidism	*Excluded*	*Excluded*	0.96
Renal failure	0.92	***1.35***	***1.14***
Liver disease	*Excluded*	*Excluded*	***1.14***
Peptic ulcer disease (excl. bleeding)	*Excluded*	*Excluded*	***1.21***
AIDS/HIV	*Excluded*	*Excluded*	*Excluded*
Lymphoma	*Excluded*	*Index condition*	***1.22***
Metastatic cancer	*Index condition*	*Excluded*	***1.19***
Solid tumour without metastasis	0.99	*Excluded*	***1.14***
Rheumatoid arthritis / collagen vascular	*Excluded*	*Excluded*	***1.20***
Coagulopathy	*Excluded*	*Excluded*	1.14
Obesity	*Excluded*	*Excluded*	***1.13***
Weight loss	*Excluded*	*Excluded*	1.05
Fluid and electrolyte disorders	***0.83***	*Excluded*	1.07
Blood loss anaemia	*Excluded*	*Excluded*	*Excluded*
Deficiency anaemia	*Excluded*	*Excluded*	***1.08***
Alcohol abuse	*Excluded*	*Excluded*	***1.12***
Drug abuse	*Excluded*	*Excluded*	*Excluded*

Psychoses		*Excluded*	*Excluded*	*Excluded*
Depression		*Excluded*	*Excluded*	***1.23***
Hypertension, complicated		*Excluded*	*Excluded*	*Excluded*
Comorbid conditions + proportion of total	All	2 20.00%	2 40.00%	18 72.00%
	Increase only	0 0.00%	2 40.00%	17 68.00%

Significantly associated conditions are in bold italics.

Few conditions are comorbid (20%) with metastatic cancer in predicting 2+ emergency admissions (table 5.28); similar to for 2+ admissions (table 5.28); conversely, two of the five conditions in the lymphoma model are associated with an increased risk. The majority of comorbidities in the CPD model (72%) carry an increased risk of two or more emergency admissions, though the increased risks of each were relatively small. The high odds ratio of the baseline CPD risk (246.18) suggests that the risk of the condition on its own is in excess of any potential comorbidities. This is likewise the case for the other two conditions, but the issue still remains of low sample size and subsequent lack of statistical power.

5.3.3.6. Condition combinations and 7+ hospital days

The three most strongly associated conditions were: lymphoma, metastatic cancer and non-metastatic tumour.

Table 5.29: Odds ratios for condition combinations predicting 7+ hospital days

EI condition	OR for interactions with lymphoma	OR for interactions with metastatic cancer	OR for interactions with tumour
Index condition	***1062.18***	***11001.53***	***465.54***
Congestive heart failure	1.04	0.95	***1.18***
Cardiac arrythmias	0.97	***0.83***	0.95
Valvular disease	*Excluded*	*Excluded*	***1.22***
Pulmonary circulation disorders	*Excluded*	***1.19***	***1.20***
Peripheral vascular disorders	*Excluded*	***0.81***	1.03
Hypertension, uncomplicated	1.01	0.93	***0.94***
Paralysis	*Excluded*	*Excluded*	*Excluded*
Other neurological disorders	*Excluded*	*Excluded*	0.98
Chronic pulmonary disease	***1.23***	0.93	***1.12***
Diabetes, uncomplicated	1.09	0.99	***1.07***
Diabetes, complicated	*Excluded*	*Excluded*	*Excluded*
Hypothyroidism	*Excluded*	*Excluded*	0.92
Renal failure	*Excluded*	1.03	***1.17***
Liver disease	*Excluded*	*Excluded*	***1.26***
Peptic ulcer disease (excl. bleeding)	*Excluded*	*Excluded*	*Excluded*
AIDS/HIV	*Excluded*	*Excluded*	*Excluded*
Lymphoma	*Index condition*	*Excluded*	*Excluded*
Metastatic cancer	*Excluded*	*Index condition*	***1.85***
Solid tumour without metastasis	*Excluded*	1.06	*Index condition*
Rheumatoid arthritis / collagen vascular	*Excluded*	*Excluded*	***1.18***
Coagulopathy	*Excluded*	*Excluded*	*Excluded*
Obesity	*Excluded*	*Excluded*	*Excluded*
Weight loss	*Excluded*	*Excluded*	***1.25***
Fluid and electrolyte disorders	*Excluded*	0.96	***1.09***
Blood loss anaemia	*Excluded*	*Excluded*	*Excluded*
Deficiency anaemia	*Excluded*	*Excluded*	1.05
Alcohol abuse	*Excluded*	*Excluded*	***1.26***
Drug abuse	*Excluded*	*Excluded*	*Excluded*

Psychoses		*Excluded*	*Excluded*	*Excluded*
Depression		*Excluded*	*Excluded*	0.96
Hypertension, complicated		*Excluded*	*Excluded*	*Excluded*
Comorbid conditions + proportion of total	All	0 0.00%	3 30.00%	13 68.42%
	Increase only	0 0.00%	1 10.00%	12 63.16%

Significantly associated conditions are in bold italics.

The lack of significant interactions for lymphoma and metastatic cancer (table 5.29) are consistent with previous outcomes (tables 5.26, 5.28) and may reflect lack of prevalence. There are considerably more comorbidities that carry an increased risk of seven or more hospital days with non-metastatic tumour (68%), compared to for 2+ admissions (26%, table 5.27), perhaps reflecting that patients with more complex needs will have an extended length of stay. However, the high baseline risk of having a tumour (465.54) may also suggest that any additional risk is minimal.

5.3.3.7. Condition combinations and 28+ hospital days

The three most strongly associated conditions were: lymphoma, tumour, other neurological conditions

Conditions excluded from model by way of being index condition or having two few occurrences are in *italics.*

Table 5.30: Odds ratios for condition combinations predicting 28+ hospital days

EI condition	OR for interactions with lymphoma	OR for interactions with tumour	OR for interactions with other neurological
Index condition	***1259.03***	***635.28***	***688.52***
Congestive heart failure	*Excluded*	***1.13***	1.08
Cardiac arrythmias	1.14	1.00	1.03
Valvular disease	*Excluded*	***1.25***	1.14
Pulmonary circulation disorders	*Excluded*	1.13	*Excluded*
Peripheral vascular disorders	*Excluded*	0.95	1.04
Hypertension, uncomplicated	1.01	0.98	0.98
Paralysis	*Excluded*	*Excluded*	0.88
Other neurological disorders	*Excluded*	1.08	*Index condition*
Chronic pulmonary disease	1.18	***1.21***	***1.22***
Diabetes, uncomplicated	1.07	***1.12***	***1.10***
Diabetes, complicated	*Excluded*	*Excluded*	*Excluded*
Hypothyroidism	*Excluded*	1.03	0.93
Renal failure	***1.56***	***1.23***	***1.15***
Liver disease	*Excluded*	***1.28***	1.11
Peptic ulcer disease (excl. bleeding)	*Excluded*	*Excluded*	*Excluded*
AIDS/HIV	*Excluded*	*Excluded*	*Excluded*
Lymphoma	*Index condition*	*Excluded*	*Excluded*
Metastatic cancer	*Excluded*	***1.56***	*Excluded*
Solid tumour without metastasis	*Excluded*	*Index condition*	***1.15***
Rheumatoid arthritis / collagen vascular	*Excluded*	1.16	***1.26***
Coagulopathy	*Excluded*	*Excluded*	*Excluded*
Obesity	*Excluded*	*Excluded*	*Excluded*
Weight loss	*Excluded*	1.08	*Excluded*
Fluid and electrolyte disorders	*Excluded*	***1.12***	0.90
Blood loss anaemia	*Excluded*	*Excluded*	*Excluded*

Deficiency anaemia		*Excluded*	1.00	1.10
Alcohol abuse		*Excluded*	***1.43***	***1.31***
Drug abuse		*Excluded*	*Excluded*	*Excluded*
Psychoses		*Excluded*	*Excluded*	*Excluded*
Depression		*Excluded*	1.01	0.94
Hypertension, complicated		*Excluded*	*Excluded*	*Excluded*
Comorbid conditions + proportion of total	All	1 20.00%	9 47.37%	6 35.29%
	Increase only	1 20.00%	9 47.37%	6 35.29%

Significantly associated conditions are in bold italics.

The lack of significant comorbid interactions with lymphoma for 28+ hospital days (table 5.30) is consistent with previous outcomes, and the proportion associated with non-metastatic tumour (47%) is similar to that for 7+ days (68%, table 5.29). Other neurological conditions have six conditions (35%) that carry an increased risk of over twenty-right hospital days, similar to solid tumours. All of these conditions have a high individual risk after adjustment for comorbidities, again suggesting that the added risk from other comorbidities is low in comparison.

5.4. Discussion

Following analysis in the sections above, six key findings were identified. These are summarised in table 5.31, and elaborated on further in the below sub-sections.

Table 5.31: Research questions from chapter 5 and key findings

Research questions	Key findings
• Which multimorbidity measure(s) best predict mortality & healthcare utilisation outcomes in older people in Scotland using linked administrative data?	• All multimorbidity measures generally perform well at predicting mortality, admissions and healthcare utilisation, particularly outcomes indicating poorer health • The CCI performs best at predicting mortality, and proxy measures perform best at predicting all other outcomes • Diagnosis-based measures predict mortality best, medication-based measures predict admissions best, and there are mixed performances for predicting hospital days
• What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?	• The effect of multimorbidity on health outcomes is consistently non-linear for all measures and outcomes when recoding the multimorbidity measure to categorical • Individual condition models outperformed metric models, with differing impacts of conditions by multimorbidity measure • COPD, pain and dementia have most comorbid interactions with health outcomes

5.4.1. Most multimorbidity measures perform adequately at predicting most health outcomes

In the older Scottish population, diagnosis-based and medication-based indices predicted most mortality and HCU outcomes with at least acceptable prediction. For each of the seven health outcomes (table 5.10), at least one measure had acceptable prediction for each outcome barring 1+ admissions, with consistently "acceptable" prediction of all measures for every outcome barring 1+ and 2+ admissions. In addition, consistently "good" by year prediction was found for CCI and mortality, and "acceptable to good" prediction was found for the other diagnosis-based measures and mortality, as well as unique ICD-10 codes and 28+ hospital days.

Previous performance of multimorbidity scores in other studies has varied. The systematic review by Yurkovich et al (2015) observed widely varying results in prediction from 0.5 to above 0.8, whilst Quail et al (2011) found similar results to this study in predicting mortality and 1+ admissions, with the exception that all measures (the same as this study bar CDS-H2) performed poorly at predicting

2+ admissions. Wallace et al (2016) found that both diagnosis-based and medication-based measures had poor prediction in predicting 1+ admissions, but this was a small (<1000), older sample, which may have impacted overall prediction.

All multimorbidity measures in this study performed better when predicting the "worse" outcome of a pair of similar health outcomes, i.e. 2+ admissions/emergency admissions compared to 1+ and 28+ hospital days compared to 7+. This is not restricted to particular measures, or indeed the data derived from each – all measures perform better when the outcome is more severe. Whilst the overall predictive range by outcome was relatively similar (i.e. for emergency admissions all measures have "acceptable" prediction for both outcomes) larger differences were observed for some outcomes. In 28+ hospital days, for example, one measure (unique ICD-10 conditions) had acceptable-to-good prediction whilst all measures in 7+ were acceptable. In addition, the worst performing measure for the more severe outcome in emergency admissions (2+) and hospital days (28+) still outperforms the best performing for the less severe outcome (1+ and 7+ respectively). The results for mortality reinforce this – whilst there is no direct comparator, mortality in itself is unarguably the "worst" adverse health outcome, and the by-measure AUCs for mortality are on average the highest out of all seven outcomes.

These results suggest that when using multimorbidity to predict health outcomes in older populations, one will achieve greater predictive ability with outcomes indicating poorer health. What constitutes how "bad" an outcome is in itself ambiguous – generally speaking more severe outcomes are less prevalent in the population, but 2+ emergency admissions are only marginally less prevalent in the dataset than mortality and 28+ hospital days (table 5.3) and the predictive ability of multimorbidity measures in predicting it is far lower than the other measures. The most prevalent outcome is 1+ admissions and the lowest overall predictive ability is observed for this outcome, so this may be an indicative factor.

Few studies have examined differences in predictive ability at levels of severity in the same outcome – Quail et al (2011) found that a number of similar multimorbidity measures predicted both 1+ and 2+ admissions poorly, but predictive ability was slightly greater overall for 2+. This study has found that this effect extends to a number of other paired types of outcomes, such as emergency admissions and hospital days. Possible explanations for this could be that both diagnosis-based and medication-based measures are derived from data which represents a previous health outcome, such as an admission (in the case of diagnosis) or consultation for a health problem and subsequent prescribing from a GP (in the case of medication). These healthcare utilisation-derived scores would therefore be more predictive of increased likelihood of these happening again, particularly if more than once (such as admissions) or for longer (such as hospital days). The results from this study give an indication as to

which types of data perform best at predicting different types of health outcomes, with variation observed by type of health-care utilisation. Regardless of the interpretation of the results, the scores from the best performing indices can be used to improve existing HCU prediction algorithms in Scotland, such as SPARRA (ISD 2011) or pHHG (Public Health Scotland 2020).

5.4.2. The CCI performs best at predicting mortality, and proxy measures perform best at predicting all other outcomes

In terms of the performance of individual measures, disparity was found between outcomes for mortality compared to HCU (table 5.10). The CCI, a measure developed in 1987 and only modified slightly since, outperformed all other measures and proxy counts in predicting mortality and was the only measure to achieve "good" prediction across all years for a specific outcome. This suggests that the CCI is still sufficient for future studies investigating mortality in older people in Scotland as well as countries with similar demographics.

Previous research has generally found, with occasional divergence, that the EI generally outperforms the CCI when predicting mortality. Systematic reviews by Yurkovich et al (2015), Sharabiani et al (2012) and Fernando et al (2019) found the EI performs best for mortality, long-term mortality (the closest outcome to this study) and one-year mortality respectively and Quail et al (2011)'s comorbidity study found that the EI had good predictive ability whilst the CCI only had acceptable-to-good. However, the three studies mentioned focus on comorbidity as opposed to multimorbidity, and the systematic reviews do not restrict the population to older people. It could be that the CCI performs better in studies where there is no index condition being measured; in studies looking at comorbidity the condition of interest (whether the main reason for admission or the condition under study) is omitted as part of the score, which may diminish the CCI's predictive ability compared to other indices. The EI in turn performs better in studies looking at comorbidity, perhaps due to the fact that it is an unweighted index and the removal of one condition may not make as big differences to the score. The divergence in results is part of a wider commentary, referenced previously in this thesis, that the study population can impact variance in multimorbidity measure prediction.

For all HCU outcomes a proxy measure was the best predictor, whether it be the unique BNF subclasses measure (as was most common) or unique ICD-10 codes. This was also the case within each multimorbidity measure sub-class – the proxy measure was the best diagnosis- or medication-based performing for every single outcome bar mortality. Whilst the difference was not especially large between the measures (greater differences were observed between diagnosis- and medication-based measures, as discussed in the following section), this was nevertheless a consistent observation

across all outcomes and types of measures. The most likely interpretation, based on similar results in previous literature (Brilleman & Salisbury 2012, Pratt et al 2018) is that proxy measures are more adaptable to heterogeneous populations given their simplicity and generally perform well as a baseline count of medical complexity be it different diagnosis codes or medications. Condition indices are often initially derived from a specific population, or with a specific outcome measure in mind (i.e. in-hospital mortality as per the CCI) and whilst performing well in their initial cohort (or populations with similar characteristics) they do not translate as well to other populations for or other outcomes, as the composite conditions in each index or weightings used may not be as appropriate in other settings.

Some studies have found evidence of the above – Brilleman & Salisbury (2012) found that a count of drugs was best for consultation rates, Quail et al (2011) found that number of ICD-9/10 codes was most predictive of admissions (more so than prescribed drugs, in contrast to that observed in this thesis) and Perkins et al (2004) found that a simple medication count outperformed all other measures (including the CCI, CDS and medication subclasses) in predicting ambulatory visits.

The findings from this study suggest that in a national population proxy measures are consistently better performing than more complex weighted condition indices. One conclusion would be to advise that when using multimorbidity to predict healthcare utilisation outcomes, proxy counts will suffice. However, this would preclude investigating the impact of specific conditions or comorbidities. In addition, there is again the issue that multimorbidity measure performance varies by population. As mentioned earlier, the systematic review of systematic reviews by Johnston et al (2018) states that an appropriate condition index is the most informative way of predicting health outcomes – it may be that none of the measures used in this study are particularly "informative" because they are not derived from to the Scottish older population (or demographically similar populations). There is prior evidence for this – the original CDS-2 (Clark et al 1995) outperformed all other measures compared with it using the population it was derived from, and the Multipurpose Australian Comorbidity Scoring System (Holman et al 2005), a comprehensive admissions-based score designed for an Australian population outperformed the CCI in its initial study.

It may be that in order to achieve optimum predictive ability for healthcare utilisation outcomes in Scotland measures should be derived from and specifically for an older Scottish population – one each for diagnosis and medication codes. The Barnett count (Barnett et al 2012), which derives conditions via established general practice Read codes and prescribing data, is the closest approximation to this at present; subsequent research with this score has found links between physical and mental health condition counts and emergency or unplanned admissions to hospital (Payne et al 2013), though the study cohort included those aged 20 and above. It would be worth comparing its predictive power with that of the CCI, EI and proxy measures in this population; however, given that the Barnett count

is part-derived from Read codes, and that general practice data did not exist nationally at the time of study, comparing predictive ability to the same depth as scores derived from admissions or prescribing data may be difficult. The count of self-reported conditions available in the SHeS (which is used in chapter 7 to predict informal care) predicts poorer health-related quality of life (Lawson et al 2013) and, if linked to administrative data, can be compared to other measures for all the health outcomes included in this study. Again, however, this could not be done with a national population.

5.4.3. Differences observed across all outcomes when comparing diagnosis-based and medication-based measures overall

For mortality, all three diagnosis-based indices reported acceptable-to-good or good predictive ability whilst all three medication-based measures were acceptable. That diagnosis-based measures outperformed medication-based is consistent with previous studies.

Overall performance of multimorbidity measures varied with HCU outcomes by both type and severity. Medication-based measures, specifically unique prescriptions, performed best for all four admissions-based outcomes, but diagnosis-based measures, specifically the ICD-10 codes measure, performed best for hospital days, with the measure for 28+ hospital days producing the best individual measure of a non-mortality outcome (acceptable-to-good). Prior literature has generally found that medication-based measures perform better for HCU outcomes, but to the author's knowledge none have compared diagnosis-based to medication-based measures in predicting hospital days, which may explain why the general consensus is that medication-measures should be preferred. The systematic reviews by Sharabiani et al (2012) and Yurkovich et al (2014)'s identified a number of papers that use hospital days (or "length of stay") as an outcome, but all of these only compare measures derived from diagnosis data.

A potential explanation for the above, similar to that discussed in 5.4.1, is that severity of each outcome impacts predictive ability of diagnosis-based and medication-based scores differentially. The difference in predictive ability between measures derived from separate data sources narrowed with severity for admissions and emergency admissions, and widened for hospital days (where diagnosis-based indices already performed better on the whole). As discussed in chapter 3, the diagnosis-based measures used in this study were derived from prior admission data, and will only capture conditions in a later stage where hospital-provided health care is required. Medication-based scores will capture conditions in earlier stages when treatment is being prescribed but no inpatient interventions are necessarily required; in addition, in very sick patients, preventative medication is rarely prescribed (Schneeweiss et al 2004). They may also, as alluded to in some of the individual condition analyses, indicate proactive health-conscious behaviour (i.e. attending GP appointments for and adhering to

treatment for potentially minor ailments). As a result, diagnosis-based scores will perform more strongly at predicting prolonged or debilitating health outcomes indicative of worse functional status (i.e. death, or prolonged stays in hospital) whilst medication-based ones perform better at predicting outcomes which are either relatively less severe, or outcomes which encompass initial health-care utilisation preceding an extended stay in hospital or death, such as admissions irrespective of length.

Few studies have investigated predictive ability of multiple multimorbidity measures for many different health outcomes in the same population, and as such these findings have not been replicated elsewhere.

5.4.4. Non-linear effect of multimorbidity observed on all health outcomes

When recoding the multimorbidity scores to categorical in order to examine the effect on health outcomes at specific values, it was found that those in the highest category (representing the top <1% of the population to the top 7%, depending on the measure, as per table 5.11) were invariably many more times at risk of any given health outcome than the rest of the population. The exponential risk was higher in the diagnosis-based indices with the top-most categories representing very high multimorbidity – resulting, for example, in an odds ratio of almost 20,000 for mortality for those with the highest multimorbidity scores (table 5.12). Similar scores (though lower) were observed for admissions and hospital days, with those in the highest category being many magnitudes more likely to experience the outcome than those with no score at all – around 120-200 for admissions, and 1500-5000 for hospital days. However, it should be noted that cross-comparison, given the varying prevalence of each score, is difficult.

The results suggest an exponential risk of multiple conditions on health in excess of the individual risk of each condition on their own. Similar results, though in a general Scottish population (Payne et al 2013) found that those with 4+ physical conditions, identified using the Barnett count (Barnett et al 2012), comprised one third of emergency admissions to hospital, despite making up less than one tenth of the total population. The majority of studies looking at multimorbidity use metric measures instead of categorical (Perkins et al 2004, Quail et al 2011, Badia et al 2013) without particularly focusing on people with specific magnitudes of scores. The study by Kasteridis et al (2015) which identified the "3+ group" is one example of a study that does focus on one particular demographic within multimorbidity.

The results suggest greater efficiency and reduced costs to health services if preventative care were focused on people at the extreme ends of scales as identified using multimorbidity measures, given far greater risk of mortality or health care use by these groups. However, the scales used for this study

vary due to the differing prevalence of conditions identified by diagnosis and by medication, making definitive identification of a particular proportion of the population difficult. It may be worth standardising all multimorbidity scores into “deciles” or “quintiles” to create the same proportion for each score per the Scottish population, but this already presents challenges as the majority of the population (between 77-89%, as per table 5.11) have no score for the diagnosis-based indices. However, the medication-based scores are far more evenly distributed. The latest iteration of SPARRA (ISD 2011) and pHHG (Public Health Scotland 2020) do account for particular conditions whether identified through medication or diagnosis codes, but limited in number. The inclusion of a composite multimorbidity score derived from admissions, medication, or both, has the potential to improve predictive ability in future iterations.

5.4.5. Individual condition models outperformed metric models, with differing impacts of conditions by multimorbidity measure

Individual condition models had consistently greater prediction of health outcomes when compared to metric models (table 5.15); for some health outcomes, such as 28+ hospital days, replacement of a multimorbidity score with individual conditions improved predictive ability greatly (from acceptable to acceptable-to-good). This would suggest that individual conditions are preferred over condition weighting, in the case of the CCI & CDS-H2. Individual condition-based CCI variables have outperformed score-based measures in predicting mortality before, though in hospital discharge, and younger patients (Sundararajan et al 2007). It may again be that because the weightings were developed using a population other than that used for this study, a hypothetical index with weightings derived from the Scottish population may outperform an individual condition measure.

In the individual condition models (tables 5.16-22), conditions with the strongest risk of each health outcome generally remained consistent for each index, reflecting a number of common risk factors for mortality (cancer, dementia, COPD in the CCI), admission to hospital (lymphoma and metastatic cancer in the EI, renal anaemia/neutropenia in the CDS-H2) and length of stay (lymphoma and metastatic cancer in the EI). In diagnosis-based indices, cancer or cancer-related conditions are predominantly associated with the highest risk, particularly lymphoma in the EI, with an OR in excess of 300 for 2+ admissions and both 7+ and 28+ hospital days. Previous literature has identified cancer, dementia, and COPD as strong predictors of mortality over other conditions (Ferrer et al 2017), and renal disease and cancer with inpatient and outpatient costs (Kasteridis et al 2015).

The results for the medication-based CDS-H2 for 1+ admissions and emergency admissions (tables 5.17 & 19) are somewhat hindered by the fact that cancer-related conditions have been excluded as a consequence of no dispensation of cancer-related drugs in the UK, and that a number of additional

conditions such as dementia and kidney-related conditions have lower-than-expected prevalence, likely due to lack of community prescribing. In addition, as the CDS-H2 identifies drugs that may be used to treat a condition rather than the condition itself, apparent risk of health outcomes on a by-condition basis are likely to be less accurate than that seen for the CCI or EI. Given this, and the "work-in-progress" nature of the adapted CDS-H2, these results should be treated with more caution. Aside from HIV, which is strongly associated with 1+ admissions and nonsignificant with 1+ emergency admissions, likely due to low case numbers, the most strongly associated condition was renal anaemia/neutropenia (OR 52.48 [23.54 – 116.99] 1+ admissions, 61.17 [27.43 – 136.39]) followed by renal failure for 1+ admissions and dementia/pancreatitis for 1+ emergency admissions. The discrepancies in prevalence for renal conditions in the CDS-H2 compared to national statistics have already been discussed (section 5.1.1) but it is notable that the odds ratios for renal failure (12.36 [1.56 – 97.82] 1+ admissions, 14.22 [1.78 – 113.73] 1+ emergency admissions) are similar to that observed for the equivalent condition in EI models (7.10 2+ admissions, 9.33 2+ emergency admissions, 11.02 7+ hospital days, 12.31 28+ hospital days); this, however, is following adjustment for cancer-related conditions. Whilst it is likely given prevalence that the renal conditions in the CDS-H2 are identifying later, more severe stages of CKD, kidney-related conditions are associated with primary care costs particularly when co-morbid with other conditions (Kasteridis et al 2015).

Cross-comparison of differential risk of each condition across each health outcome is difficult given that different indices were used for each outcome; however, odds ratios were overall lower for 28+ hospital days compared to 7+, and for emergency admissions compared to admissions (in both EI and CDS-H2), and whilst there was consistent risk associated with some conditions (primarily cancer-related), some variation was observed (such as dementia for emergency admissions compared to admissions in the CDS-H2). A combined index, drawing from both admissions and medication-based data, would create a more accurate picture of relative risk per condition. In addition, backed up by the overall acceptable-to-good prediction of the models as shown by this study (table 5.15), this could potentially aid SPARRA (ISD 2011), pHHG (Public Health Scotland 2020), or a new risk prediction tool by either identifying potential additional conditions to code for (as well as the respective codes), informing a rudimentary weighting system derived from the odds ratios identified here, and expand the algorithm to health outcomes other than admissions such as mortality, or multiple admissions (which may be better indicators of poor health as per Ouslander & Maslow 2012).

5.4.6. COPD, pain and dementia have most comorbid interactions with health outcomes

The number of comorbid condition interactions with health outcomes was primarily resultant from the nature of the condition itself than the outcome (specifically prevalence), with the proportion of significant comorbid conditions remaining consistent across outcomes for the majority of conditions

used more than once. Regardless, that a large number of comorbid interactions were found – the majority being positively associated – demonstrates, as for similar analyses discussed in section 5.4.4, that there is an increased risk for adverse health outcomes for those with multimorbidity in particular conditions.

Chronic obstructive pulmonary disease (COPD) was included in two interaction models and had a range of 68-86% comorbidities carrying increased risk, suggesting that for those with COPD having more conditions has a high chance of an increased impact on health. COPD is a disease that is heavily linked to smoking (Fabbri et al 2007) and results in inflammation and restriction of airways, causing breathing problems. Barnes & Celli (2009) have suggested that this inflammation can spread to other parts of the body (in what they term "systemic inflammation"), exacerbating other comorbid conditions such as heart problems, diabetes, and depression. In both outcomes in which COPD is one of the index conditions (table 5.24 and 5.28) it is significantly comorbid with a number of heart problems, diabetes, and depression (when included). This suggests that systemic inflammation may result in a number of visible comorbid interactions which increase the individual's risk of adverse health outcomes.

In table 5.25, eighteen conditions (78% of the total) were associated with an added risk for one or more admissions when co-morbid with pain, the strongest being renal anaemia/neutropenia (OR 2.15), pancreatitis (OR 1.68) and transplants. The overall OR of pain in the comorbidity model was 10.35, much lower than odds ratios for index conditions in the other comorbidity models; this hints at pain being a symptom of underlying conditions, all of which will have varying impacts on health status, rather than a consistent risk from pain itself on healthcare utilisation. For dementia, eight conditions (89%, table 5.24) were associated with an increased risk for mortality and eleven (58%, table 5.27) for one or more emergency admissions. The difference in proportion co-morbid can partly be explained by the fact that different indices were used for each outcome (CCI for mortality and CDS-H2 for 1+ emergency admissions), though some conditions were commonly co-morbid with dementia across both outcomes (heart disease, arthritis, and diabetes).

A number of conditions had few, or no comorbid interactions, specifically lymphoma, renal anaemia/neutropenia, and metastatic cancer. All of these conditions have very low (<1%) prevalence in the CDS-H2 (table 5.7), which may partly explain the paucity of interactions given that there are very few observations. HIV and renal failure were excluded entirely from analyses for the same reason: there were no consistent interactions >100 with any of the other CDS-H2 conditions. Whilst low prevalence is not explicitly synonymous with lack of interactions (dementia and COPD have a prevalence across all datasets of <5%), there may be a threshold at which prevalence is so low that no viable information can be obtained from models with many interaction terms. Previous research (Ogle

et al 2000) has suggested that comorbidity is common with those in cancer, for example, and is associated with worse prognosis. Metastasis, a late-stage form of cancer where the cancer cells spread throughout the body (NHS 2018), was generally more strongly associated with poor health than cancer/tumour in section 5.3.2, and may have many co-morbid interactions with health outcomes if a larger population is used.

However, it should also be noted that most conditions with low numbers of comorbidity had very high baseline risk after adjustment for other conditions, well in excess of the equivalent risk in the individual condition model. This may suggest that, regardless of prevalence, the individual risk of these particular conditions is far greater than any potential comorbidities to the point at which they are of diminished relevance to the health status of the patient, or that the impact on health was terminal and the individual died before any comorbidities could occur. It is known that some conditions, such as dementia (Scottish Government 2015) are the "dominant" condition in patients with complex needs, and all decisions regarding treatment, such as prescribing, are with the dominant condition at the forefront. Given that the majority of the conditions with low comorbidities and high after-adjustment risk are late-stage or terminal conditions (renal failure, metastatic cancer), the impact of any other conditions is very small in comparison.

Whilst the threshold for inclusion of comorbidities (at least >100 cases across all study years) was based on previous literature (Brilleman et al 2012), a larger threshold, based on proportion rather than frequency, may have led to more meaningful results. Alternatively, cluster analyses, where patterns of commonly occurring conditions are identified and modelled, may have produced more meaningful findings, and will have excluded conditions with low prevalence. Despite this, results even with relatively uncommon (<5%) conditions have shown that specific conditions have comorbidities that are particularly debilitating to the individual's overall health, are not associated at all, or in fact are associated with better prognosis (possibly due to earlier detection and treatment) – something that previous research has not examined in detail. Whilst further research may be required, perhaps with a different approach, the results have identified comorbid interactions that can potentially be added to risk prediction models.

5.4.7. Conclusion

Depending on the type of outcome, multimorbidity measures derived from different sources of data and using different scoring systems vary in predictive ability, principally by severity of the outcome i.e. two or more admissions compared to one or more, or 28+ hospital days compared to 7+. Diagnosis-based measures typically perform better for more severe outcomes, though medication-based measures (in particular proxy measures) perform well overall for healthcare utilisation whilst

diagnosis-based measures (in particular the CCI) perform best for mortality. Varying results were found for individual condition and condition combination analyses, though most were consistent for each health outcome and varied more by source of multimorbidity data. Findings from this chapter can inform and improve existing risk prediction algorithms in Scotland such as SPARRA and pHHG to take account of strongly associated conditions and condition combinations, high-risk multimorbidity groups, and expand prediction algorithms to account for long length of stay in addition to admissions.

Chapter Six – Multimorbidity, deprivation and transition into social care

This chapter focuses on how best to predict social care using a number of different multimorbidity methods and which performs best, within that measure which particular level, individual conditions and condition combinations are most predictive, and how these effects vary by micro and macro levels of deprivation.

As identified in the literature review, people with multimorbidity are considered one of the target groups in terms of benefitting from integrated care, as they are a largely heterogeneous population to which the traditional specialist treatment focus may not work as effectively. However, it is not known how best to identify those with multimorbidity in most need of social care whether that be which data should be used to derive multimorbidity scores, specific levels of multimorbidity, individual conditions or combinations of conditions. Comparing multimorbidity measures in predicting outcomes is typically restricted to medically focused papers predicting health outcomes, and to date no study has compared multiple multimorbidity measures in predicting transition into social care.

This chapter consists of five sections, answering three research questions:

- Which multimorbidity measure(s) best predict transitions into social care in older people in Scotland using linked administrative data?
- What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care?
- Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?

The other two sections consist of descriptive results, and a discussion of the main findings arising from the results.

It should be noted that this chapter uses a slightly different cohort to that in chapter 5 (as outlined previously in section 4.2.2), in that at baseline (i.e. the index date) any cases identified as receiving social care (i.e. recorded as "Yes" for a home care or personal care flag in the SCS census week for that year) have been excluded. This approach was taken as the outcome is transition into social care, defined as being identified as receiving social care in the SCS census week one year from the index date, conditional on not receiving care in the prior year (i.e. no care flag in 2012, care flag in 2013).

6.1. Descriptive analyses

This section consists of two subsections. The first is univariate frequency and distribution analyses of key variables, which will outline the composition of the sample. The second is bivariate analyses of multimorbidity and the outcome variables – this section examined trends which may be replicated by the more detailed analyses in further sections.

The only multimorbidity measure used in this section is the CDS-H2 – this is because it was found to be the best performing measure in section 6.2.

6.1.1. Univariate analyses

Three tables are presented in this section – the case numbers by year in the dataset, demographic, and care variables, and CDS-H2 prevalence.

For each variable, proportion ranges are presented for categorical variables and mean ranges are presented for metric variables.

Table 6.1: Number of cases in dataset by year

Year	11-12	12-13	13-14	14-15	15-16	Total
Cases	826,376	854,453	879,274	904,790	909,769	4,374,662

Table 6.1 presents the number of cases in two separate datasets used for analyses in this chapter – as in chapter 5, increases are observed by year.

Table 6.2: Non-individual condition variable summary ranges

Variable	Category	Statistic range	
		Lower	Upper
Age	**65-74**	56.11%	57.67%
	75-84	32.26%	33.51%
	85+	10.00%	10.38%
Sex	**Male**	43.99%	45.14%
	Female	54.86%	56.01%
SIMD decile	**1st**	7.69%	8.52%
	10th	10.19%	10.70%
Transitioning into social care		1.64%	1.66%
CDS-H2 score		4215.35	4221.64

Over half of cases in the dataset are in the youngest age band and are female. More live in the most deprived data zones than the most affluent. Around 1.6% of the sample in each year transition into social care.

Table 6.3: Frequency of individual conditions in the CDS-H2

Condition	Proportion range	
	Lower	Upper
Coronary and peripheral vascular disease	35.74%	40.63%
Epilepsy	4.48%	6.36%
Hypertension	58.43%	59.59%
Tuberculosis	<1.00%	<1.00%
Rheumatoid arthritis	1.11%	1.46%
HIV	<1.00%	<1.00%
High cholesterol	45.00%	45.55%
Parkinson's disease	5.12%	6.33%
Renal anaemia/neutropenia	<1.00%	<1.00%
Heart disease	46.71%	47.79%
Diabetes	9.79%	10.45%
Glaucoma	3.93%	4.13%
Pancreatitis	<1.00%	<1.00%
Renal failure	<1.00%	<1.00%
Ulcers	37.69%	40.68%
Transplants	<1.00%	<1.00%
Respiratory illness/asthma	15.68%	16.57%
Hyperthyroidism	<1.00%	<1.00%
Gout	3.24%	4.03%
Crohn's disease/inflammation	1.33%	1.41%
Pain/inflammation	13.80%	16.44%
Depression	17.09%	19.23%
Dementia	2.87%	3.09%
Mania	<1.00%	<1.00%
Anxiety/tension	15.76%	16.08%
Pain	11.20%	11.97%

Prevalence of conditions in this cohort are functionally identical to that seen in the cohort used in chapter 5 (see table 8). Previous considerations regarding comparison to national statistics (see section 5.1.1), as well as explanations for potential discrepancies, apply here also.

6.1.2. Bivariate analyses

Two analyses are shown in this section; the mean CDS-H2 score range of those who did and did not transition into social care, and the proportion of those who transitioned into social care by SIMD decile. A separate table for correlation between multimorbidity measures is not included in this chapter, as the results for this and all other linked administrative cohorts in the thesis are virtually identical to those in chapter 5 (table 5.8).

Table 6.4: Mean multimorbidity score range in those who did and did not transition into social care

Multimorbidity score	Health outcome		Mean score range	
			Lower	Higher
CDS-H2	**Transition into social care**	**Yes**	5311.33	5531.70
		No	4196.67	4215.48

Table 6.5: Proportion of those in SIMD deciles 1-10 who transitioned into social care

SIMD decile	Proportion range	
	Lower	Upper
1st (most deprived)	2.17%	3.16%
2nd	2.01%	2.66%
3rd	1.81%	2.45%
4th	1.86%	2.17%
5th	1.70%	1.96%
6th	1.53%	1.86%
7th	1.36%	1.73%
8th	1.42%	1.82%
9th	1.27%	1.72%
10th (least deprived)	1.33%	1.56%

As shown in table 6.4, those who transitioned into social care have a higher average CDS-H2 score and are more likely to live in deprived areas, compared to those who did not (table 6.5).

6.2. Research question 1: Which multimorbidity measure(s) best predict transitions into social care in older people in Scotland using linked administrative data?

As in chapter 5, this question will be answered by comparing the main model parameter for each multimorbidity measure previously mentioned in the methods.

6.2.1. Nested logistic regression for transition into social care

The following presents model parameter results from the nested regression models for transition into social care. Nested regression models were run, consisting of demographic variables, the multimorbidity measure and interactions. These models were repeated for each multimorbidity measure, in order to determine which is the most predictive via the model parameters.

As in common with the health outcome-based models, the results presented here are from the models with all variables (including interactions) only – this is because in all models all three model parameters were optimum for the interaction model. Thus, parameters will be presented for models containing the following variables:

- Age (count)
- Sex (binary)
- SIMD (dummy decile variables, SIMD 10 excluded as reference)
- Multimorbidity measure (continuous)
- Age (quadratic)
- Age*female interaction
- Age*multimorbidity interaction

Unlike the equivalent section in chapter 5 there is only one outcome. Graphs will only contain the BIC (and not the AIC), as in common with previous results the rank of multimorbidity measures in terms of performance was exactly the same for both.

These analyses answer the research question as they determine via interpretation of the model parameters which multimorbidity measures perform best at predicting transition into social care in a population-wide Scottish sample of older people, specifically:

- The best overall measure for transition into social care
- Predictive ability of diagnoses-based measures compared to medication-based
- Predictive ability of condition-based indices compared to proxy scores
- How the measures perform overall

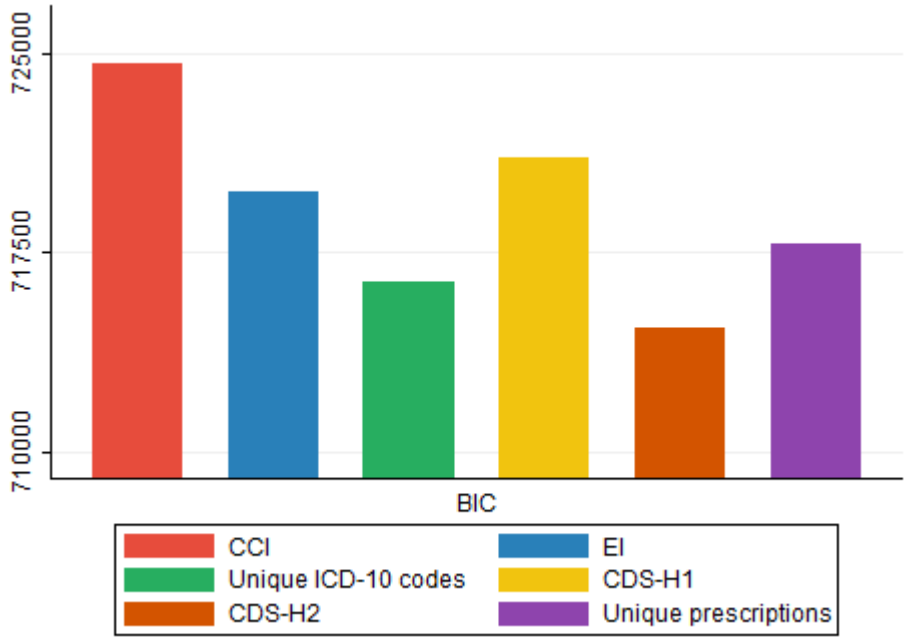

Fig. 6.1: BIC of panel logistic regression models predicting transition into social care by multimorbidity measure

The CDS-H2 performs best at predicting transition into social care (fig. 6.1), with the proxy unique ICD-10 count the next best performing. Compared to chapter 5, this is the only instance in which the unique prescriptions measure is not the best performing medication-based score and only the second instance in which a proxy measure is not the best predictor of a binary outcome. Aside from the CCI, diagnosis-based and medication-based measures perform equally well in predicting the outcome.

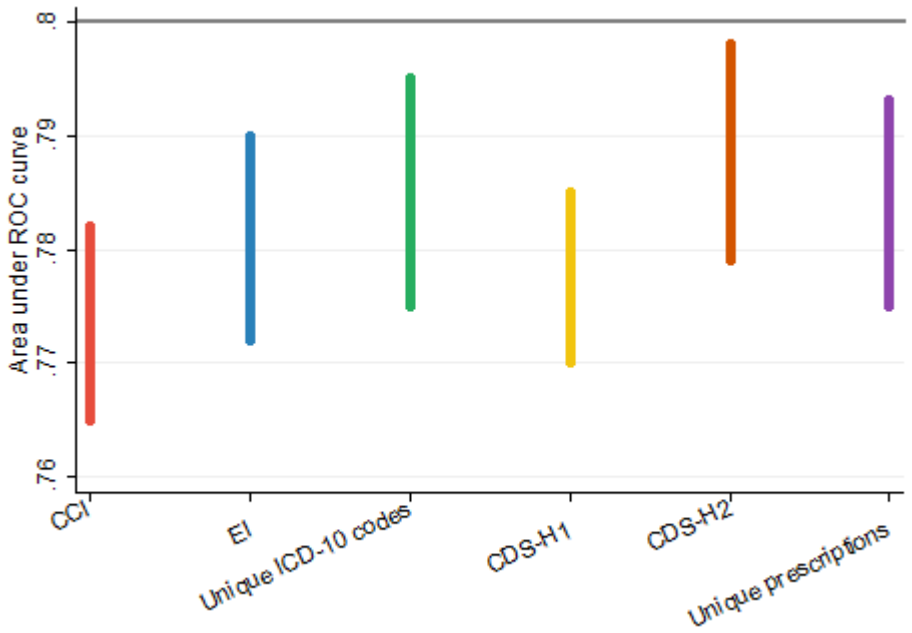

Fig. 6.2: Area under ROC curve (AUC) range of logistic regression models by year predicting transition into social care by multimorbidity measure

All multimorbidity measures have acceptable prediction of transition into social care according to fig. 6.2. The CDS-H2 is again the best performing (almost reaching 0.8 in one year), followed by the ICD-10 count.

It is notable that little difference is observed between diagnosis-based and medication-based measures in predicting the transition into social care outcome. For health outcomes in chapter 5, predictive ability was typically greater overall for multimorbidity measures derived from one particular data source.

6.3. Research question 2: What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care?

As in chapter 5, this focuses primarily on finding a way to determine which aspects of the CDS-H2 are particularly predictive of specific health outcomes. This section will contain three analysis subsections – an overview of the CDS-H2 in predicting transition into social care recoded to categorical, individual conditions, and combinations of conditions.

6.3.1. Nested panel logistic regression for transition into social care with categorical CDS-H2

The following presents the odds ratios of the dummy CDS-H2 categories when replacing the continuous outcome in the model discussed in section 6.2. The model is otherwise identical other than the fact that categorical interactions were also used for any interactions involving the CDS-H2. There will also be a further subsection comparing the BIC and AUC range of this new model with the original model, in order to see which measure best explains the outcome.

The analyses below answer the research question because they will examine whether there is an exponential risk of high multimorbidity, in excess of individual conditions, on transition into social care.

Prior to presenting the analyses, the prevalence of those in each category of the CDS-H2 is shown (table 6.7). The "zero score" category was used as the reference in all models.

Table 6.6: List of CDS-H2 categories used in categorical models and number/proportion of population with these scores

CDS-H2 score	**Proportion range**	
	Lower	***Upper***
0 (reference)	7.00%	7.34%
0.1-3000	24.62%	25.04%
3000.1-4500	22.46%	23.94%
4500.1-5500	14.95%	16.17%
5500.1-6500	14.39%	15.34%
6500.1-8000	10.14%	10.34%
8000+	3.86%	4.46%

Table 6.7: Odds ratios and confidence intervals for categories of the CDS-H2 in predicting transition into social care in panel logistic regression

CDS-H2 score	Odds ratio		95% confidence interval
0 (reference)	1		N/A
0.1-3000	***0.05***	***0.03***	***0.08***
3000.1-4500	1.07	0.65	1.77
4500.1-5500	***3.54***	***2.13***	***5.89***
5500.1-6500	***7.22***	***4.36***	***11.98***
6500.1-8000	***62.22***	***37.46***	***103.33***
8000+	***778.14***	***454.79***	***1331.37***

Significantly associated categories are in bold italics.

In table 6.7 an exponential effect of increasing multimorbidity, measured via CDS-H2, is evident, in common with similar analyses for health outcomes in section 5.3.1. A score above 0 but less than 3000 carried a much lower risk than a score of 0; this is similar to results for medication-based measures for health outcomes (table 5.13), but the odds ratio (0.05) is extremely low, indicating that those with low medication are around twenty times less likely to transition. Whilst it is reasonable that adherence to prescribing medication for relatively low-risk conditions may result in better health, compared to non-adherence (which may be present in some cases in those with no score), this also may be an indicator of unobserved missing medication data for some in the zero-score group, as the comparative risk is likely not this low.

The model parameters are compared in the table below (table 6.8) – again, the AIC and BIC are similar, so only the BIC is shown. The best performing measure for each is rendered in ***bold italics.*** The categorical model outperforms the metric model in the BIC, and the upper AUC range is identical for both models.

Table 6.8: Model parameters for both panel logistic regression models for the CDS-H2 in predicting transition into social care, metric and categorical

Model	BIC	AUC range
Metric	714669	***0.779 to 0.798***
Categorical	***714359***	***0.779 to 0.798***

6.3.2. Nested panel logistic regression for transition into social care with individual conditions from CDS-H2

The following presents the odds ratios of component conditions of the CDS-H2 (the best performing measure) in predicting social care transition. Like chapter 5, the odds ratios are derived from models that are the same as those in 5.2, with the exception that individual conditions (and interactions for those conditions) replace the multimorbidity scale. All CDS-H2 conditions bar HIV were included in the final model as per significance testing in univariate models.

Two separate analyses are presented – the table described above, and a cross-model comparison of the parameters from the original model, the categorical model, and the condition model. In this case the AIC, BIC and AUC are shown.

The analyses below answer the research question because they will examine which CDS-H2 conditions are associated with greatest risk of transition into social care.

Table 6.9: Odds ratios and confidence intervals for individual conditions of the CDS-H2 in predicting transition into social care in panel logistic regression

CDS-H2 condition	Odds ratio	95% confidence interval	
Coronary and peripheral vascular disease	***5.94***	***4.87***	***7.25***
Epilepsy	***11.29***	***8.44***	***15.11***
Hypertension	***0.08***	***0.07***	***0.10***
Tuberculosis	7.08	0.65	77.01
Rheumatoid arthritis	1.90	0.90	4.00
High cholesterol	***0.37***	***0.30***	***0.45***
Parkinson's disease	***7.85***	***6.04***	***10.20***
Renal anaemia/neutropenia	5.71	0.82	39.84
Heart disease	***4.18***	***3.34***	***5.23***
Diabetes	***5.21***	***3.98***	***6.83***
Glaucoma	0.97	0.66	1.43
Pancreatitis	***4.54***	***1.05***	***19.55***
Renal failure	121.29	0.43	34464.44
Ulcers	***1.27***	***1.07***	***1.52***
Transplants	2.89	0.75	11.13
Respiratory illness/asthma	***3.03***	***2.44***	***3.75***
Hyperthyroidism	***12.04***	***3.40***	***42.64***
Gout	0.91	0.59	1.41
Crohn's disease/inflammation	0.62	0.30	1.28
Pain/inflammation	***0.18***	***0.14***	***0.24***
Depression	***7.70***	***6.16***	***9.62***
Dementia	***6902.14***	***5167.48***	***9219.11***
Mania	0.72	0.21	2.50
Anxiety/tension	***6.00***	***4.81***	***7.50***
Pain	***4.55***	***3.64***	***5.70***

Significantly associated conditions are in bold italics.

Sixteen of the twenty-five CDS-H2 conditions are associated with increased risk of transition into social care (table 6.9). Of these, dementia is by some distance the strongest (OR 6902.14 [5167.48 – 9219.11]). Whilst this is not completely unprecedented, as dementia is associated with a loss of independence and reliance on others due to diminished cognitive function and decision making (Alzheimer's Society 2021), the magnitude of association is considerably higher than for other conditions, both here and in the individual condition models for health outcomes (section 5.3.2).

Beyond dementia, the most strongly associated conditions are hyperthyroidism (OR 12.04 [3.40 – 42.64]), epilepsy (OR 11.29 [8.44 – 15.11]), Parkinson's disease (OR 7.85 [6.04 – 10.20]), depression (OR 7.70 [6.16 – 9.62]) and anxiety (OR 6.00 [4.81 – 7.50]). It is notable, particularly in comparison to for health outcomes, that many of these conditions have a strong mental health or neurological component, and highlight the importance of cognitive impairment in addition to physical in determining need for care. Thyroid disorders including hyperthyroidism are associated with impaired cognitive function in adults (Ritchie & Yeap 2015), which may explain the high level of risk shown. Three conditions (hypertension, high cholesterol, and pain/inflammation) are associated with a decreased risk – as speculated in chapter 5, this may reflect health-aware behaviour and management of relatively common conditions rather than an inherent decreased risk from the condition itself.

The parameters of this model were then compared with the parameters of the previous two models, in this case including the AIC as well (given the increasing number of models being compared). The best performing model for each is rendered in ***bold italics.***

Table 6.10: Model parameters for both panel logistic regression models for the CDS-H2 predicting transition into social care, score and individual conditions

Model	AIC	BIC	AUC range
Metric	714,443	714,669	0.779 to 0.798
Categorical	714,000	714,359	0.779 to 0.798
Individual conditions	***704,466***	***704,330***	***0.792 to 0.814***

In table 6.10 the individual conditions model outperforms the other two across all parameters, to the extent where the range is improved from acceptable to acceptable-to-good. This is consistent with that observed for similar health outcome models in chapter 5.

6.3.3. Nested panel logistic regression for transition into social care with condition combinations from CDSH-2

The following presents odds for condition combinations from models that take the three most strongly associated conditions with transition into social care from the models in 6.3.2 and interacts all other conditions (with frequency of 100 or above) with that condition, in one model per main or "index" condition. The models are again identical to those from 6.2, except that the multimorbidity score is

replaced by the condition and its interactions. Other interactions continue to use the metric multimorbidity score.

The analyses below answer the research question because they examine “comorbidity” of people with the most strongly associated conditions, and which comorbid conditions in particular have additional effects on the likelihood of transitioning into social care.

As determined via the regression model in section 6.3.2, table 6.9, the three most strongly associated conditions with transition into social care are dementia, hyperthyroidism, and epilepsy. These are the three conditions that will be interacted with all others in the table below (table 6.11). Conditions excluded from model by way of being index condition or having two few occurrences are in *italics.*

Table 6.11: Odds ratios for condition combinations predicting transition into social care

CDS-H2 condition		OR for interactions with dementia	OR for interactions with hyper-thyroidism	OR for interactions with epilepsy
Index condition		***72690.59***	***21.08***	***140.15***
Coronary and peripheral vascular disease		***0.91***	***1.40***	***1.26***
Epilepsy		*Excluded*	*Excluded*	*Index condition*
Hypertension		***1.39***	1.18	***0.82***
Tuberculosis		*Excluded*	*Excluded*	*Excluded*
Rheumatoid arthritis		***1.38***	*Excluded*	***1.30***
HIV		*Excluded*	*Excluded*	*Excluded*
High cholesterol		***1.20***	0.89	***0.94***
Parkinson's disease		***1.46***	***1.85***	***1.68***
Renal anaemia/neutropenia		*Excluded*	*Excluded*	*Excluded*
Heart disease		***0.88***	0.94	***1.30***
Diabetes		1.01	1.30	***1.33***
Glaucoma		1.03	*Excluded*	1.02
Pancreatitis		***2.23***	*Excluded*	0.99
Renal failure		*Excluded*	*Excluded*	*Excluded*
Ulcers		0.97	1.08	1.04
Transplants		0.98	*Excluded*	1.28
Respiratory illness/asthma		***1.08***	1.28	***1.10***
Hyperthyroidism		0.91	*Index condition*	1.25
Gout		0.99	*Excluded*	***1.12***
Crohn's disease/inflammation		0.86	*Excluded*	0.98
Pain/inflammation		***1.11***	0.85	***0.79***
Depression		***0.93***	1.22	***1.11***
Dementia		*Index condition*	*Excluded*	1.55
Mania		0.89	*Excluded*	***1.83***
Anxiety/tension		***0.70***	1.11	***1.23***
Pain		***0.88***	1.20	***1.30***
Comorbid conditions + proportion of total	All	12 60.00%	2 16.67%	14 66.67%
	Increase only	7 35.00%	2 16.67%	11 52.38%

Significantly associated conditions are in bold italics.

The majority of comorbidities are associated with an increased risk of transition into social care with epilepsy (67%), and whilst many comorbid interactions are found with dementia (60%), with pancreatitis carrying the strongest increased risk (2.23) five of these are associated with a decreased risk. Given that, after adjustment for comorbidities the individual risk of dementia is exponentially higher (72690.59), these risk-increasing effects, although significant, may be very small. Only two conditions (17%) are associated with an increased risk of transition into social care for those with hyperthyroidism.

6.4. Research question 3: Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?

This section presents an additional exploratory analysis into the effect of micro (data zone) and macro (local authority) level deprivation on the effect of multimorbidity on transition into social care, in two parts: an analysis of the original model from 6.2 but with a deprivation/multimorbidity interaction, and the 6.2 model restricted to individuals from all LAs.

6.4.1. Nested logistic panel regression for transition into social care with deprivation interaction

Addition of a deprivation/multimorbidity interaction effect to the best performing model from 6.2 (the CDS-H2 interaction model) was performed by interacting the CDS-H2 score with all deciles of the SIMD bar the reference category (SIMD 10). The impact of adding the interaction will be discussed, followed by comparison of the model parameters with the three other model variants discussed earlier (metric, categorical and individual conditions). The below answers the research question for micro-level deprivation (data zone) as it shows that the effect of multimorbidity is augmented by the SIMD of the individual.

The full model results when interacting the CDS-H2 with the SIMD deciles (Appendix A8) found that whilst SIMD and the CDS-H2 are still significantly associated with the outcome, the interaction was associated with a slightly decreased risk of transition into social care, with a lower OR with decreasing deprivation. This suggests that the impact of multimorbidity is greater in more deprived areas, which has been suggested previously (O'Brien et al 2011).

The parameters of the model were then compared with previous models (table 6.12). The best performing model for each is rendered in ***bold italics.***

Table 6.12: Model parameters for panel logistic regression models for CDS-H2 predicting transition into social care, score, interaction, categories and individual conditions

Model	AIC	BIC	AUC range
Metric	714,443	714,669	0.779 to 0.798
Metric, MM*SIMD interaction	714,208	714,554	0.779 to 0.799
Categorical	714,000	714,359	0.779 to 0.798
Individual conditions	***704,466***	***704,330***	***0.792 to 0.814***

The individual conditions model still performs best across all parameters. The deprivation interaction model outperforms the original model but not the categorical model, suggesting that splitting the multimorbidity variable into categories explains more regarding transition into social care than adding a deprivation interaction. However, these differences are very small.

6.4.2. Nested panel logistic regression for transitions into social care by local authority

In this section the model from 6.2 is run separately for each local authority, with the odds ratio of multimorbidity and transition to social care presented for each. As described in the methods, local authorities in Scotland have differing overall levels of deprivation, as measured via averaging all data zones in these LAs (see table 6.13). To example whether this impacted the strength of association between multimorbidity and transition into social care, models were run, as described above, consisting of the whole sample of the LA, followed by running these models again but restricting the sample to those who are in the most deprived 20% nationally (in order to control for the differing datazones in the LA but seeing if there was an overall "macro" effect of wider local authority deprivation). Orkney, Shetland, Eilean Saar, and Clackmannanshire were excluded due to either low numbers or poor linking to social care data.

Table 6.13: Local authorities in Scotland ordered by average data zone deprivation level in 2016

Local authority	Average data zone SIMD
Glasgow City	3.74
West Dunbartonshire	3.83
North Lanarkshire	4.21
Inverclyde	4.22
North Ayrshire	4.23
East Ayrshire	4.45
Dundee City	4.51
South Lanarkshire	5.06
Renfrewshire	5.10
West Lothian	5.37
Falkirk	5.38
Midlothian	5.39
South Ayrshire	5.39
Dumfries and Galloway	5.42
Fife	5.52
Argyll and Bute	5.62
Highland	5.86
Scottish Borders	5.97
Angus	6.19
East Lothian	6.22
Stirling	6.45
Moray	6.48
Perth and Kinross	6.64
City of Edinburgh	6.77
Aberdeen City	6.81
Aberdeenshire	7.47
East Dunbartonshire	7.55
East Renfrewshire	7.87

Results are presented in three graphs, one for the results from regression by each LA (fig 6.3), represented in the form of a scatterplot which plots the average data zone SIMD per LA (see table 6.13) with the OR of multimorbidity in predicting transition into social care from each LA-specific model. Two graphs are presented for analyses representing the most deprived 20%: a scatterplot the same as the above, and an error bar plot showing 95% confidence intervals of the OR of multimorbidity with transition into social care.

The analyses below answer the research question as they demonstrate how the effect of multimorbidity on transitions into social care can vary by macro-level (local authority) deprivation.

6.4.2.1. Nested panel logistic regression for transitions into social care by local authority, full sample

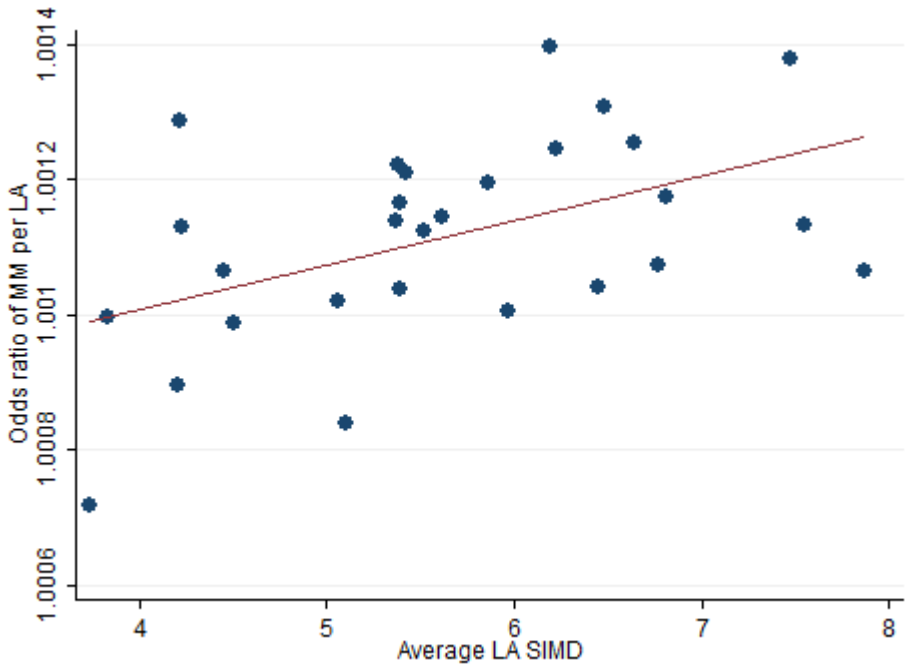

Fig. 6.3: Odds ratio of CDS-H2 with transitions into social care by average SIMD of local authority

Before discussing the results in fig 6.3 in depth, it should be noted that the reason why the OR of multimorbidity is very small is not because the relationship is weak, but the baseline CDS-H2 score is very large (typically in the thousands) and there is therefore a very small by-unit effect.

As shown in fig. 6.3, there is a gradual increase in the strength of the relationship between increasing multimorbidity and transitions into social care in each LA-specific model as the average SIMD of the local authority increases – i.e. whilst earlier results have shown that transition into social care is higher in more deprived areas (as is increasing multimorbidity), in local authorities that are overall less deprived the strength of association between multimorbidity and transition into social care is higher.

In more deprived local authorities, prevalence of multimorbidity may be higher at younger ages; increase in condition count, and concurrently multimorbidity score, will not have as great an impact on healthy life expectancy, whereas in less deprived areas it is likely an increase in multimorbidities will occur near the end of one's healthy life expectancy, coinciding with when the individual becomes

frail; in this case, onset of multiple conditions may be seen as clinically significant in determining a transfer into social care. There are also parallels with some of the points put forward in Bywaters et al (2015)'s paper on inverse interventions, applied to social care: as multimorbidity is more common in deprived local authorities, multimorbidity scores will be more common and therefore less visible to care providers; alternatively, one's circumstances may not be considered out of the ordinary compared to someone who has multiple conditions in more affluent areas. The inverse care effect may also apply here, in that given higher overall multimorbidity it may take longer for people to be seen by a GP or assessed for care unless their multimorbidity is higher than in less deprived areas. In addition, there may be greater "community support" for people with multiple conditions in more deprived LAs as a result of increased prevalence, as theorised by Bywaters et al (2015) in reference to child welfare – this could take the form of informally provided care.

6.4.2.2. Nested panel logistic regression for transitions into social care by local authority, most deprived 20% of national population

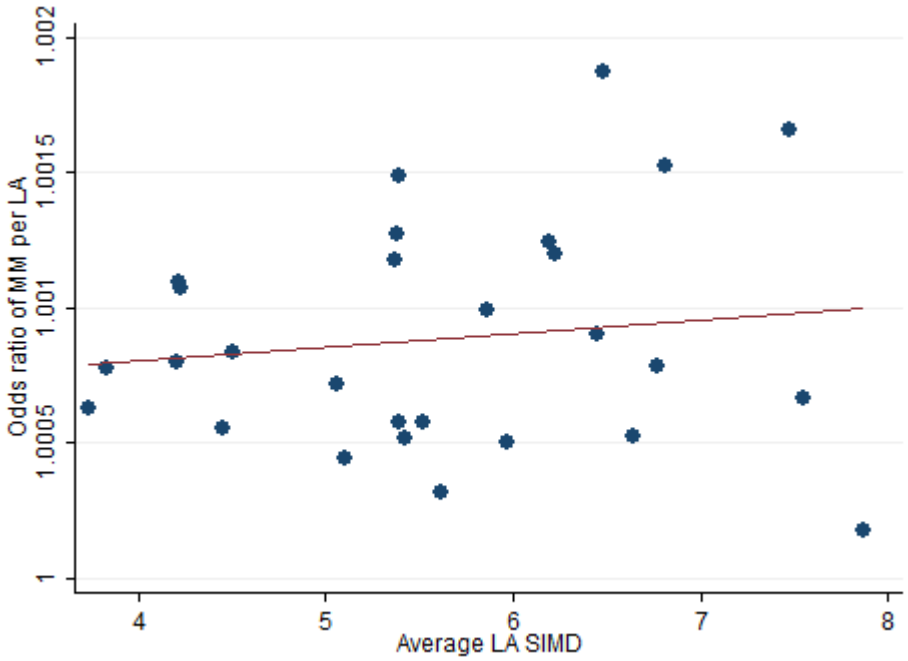

Fig. 6.4: Odds ratio of CDS-H2 with transitions into social care by average SIMD of local authority, SIMD quintile 1

The scatterplot (fig. 6.4) appears to show an equivalent trend to the one in the previous section (increasing strength of association in less deprived LAs), albeit less strong than when applied to the full population. Within the graph itself, the association between local authority SIMD and OR of multimorbidity on transition into social care is stronger in more deprived areas, with less correlation

to the right of the scale. To investigate this, the same graph is presented below but with confidence intervals added. (fig. 6.5).

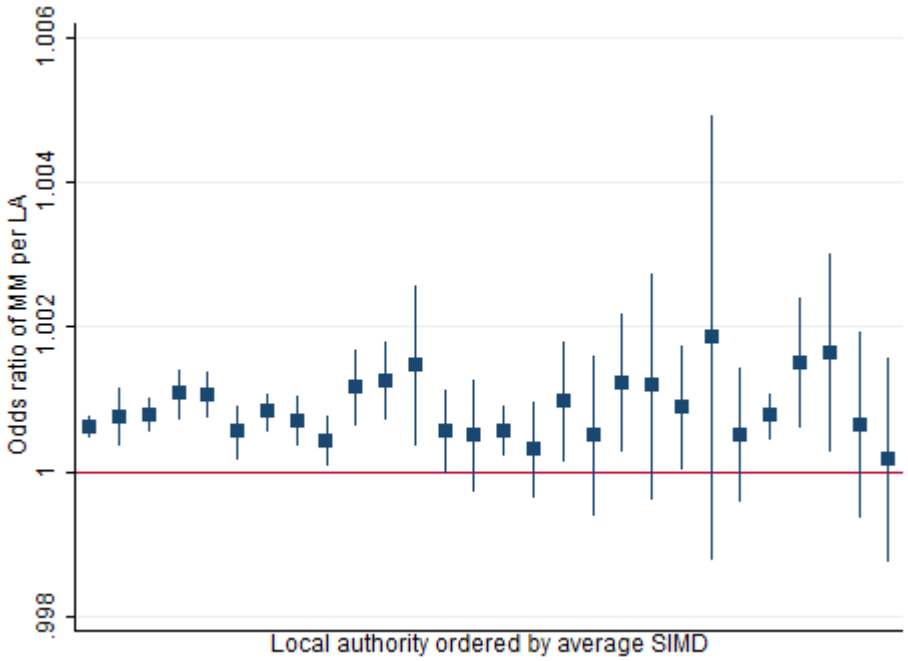

Fig. 6.5: Odds ratio of CDS-H2 with transitions into social care by local authority ordered from least to most deprived, SIMD quintile 1 (with 95% confidence intervals)

As per fig. 6.5, whilst all the ORs of multimorbidity in the full models are significantly associated, a number of them are not when restricted to SIMD quintile 1 – particularly the less deprived local authorities. This may suggest that when there is little relative inequality the effect disappears, though it is more likely that reliable effect sizes cannot be estimated due to low sample sizes, particularly in the more affluent LAs.

6.5. Discussion

Following analysis in the sections above, six key findings were identified. These are summarised in table 6.14, and elaborated on further in the below sub-sections.

Table 6.14: Research questions from chapter 6 and key findings that answered questions

Research questions	Key findings
• Which multimorbidity measure(s) best predict transitions into social care in older people in Scotland using linked administrative data?	• All multimorbidity measures generally perform well at predicting transition into social care, with the CDS-H2 performing best • Medication-based measures perform slightly better at predicting transition overall
• What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care?	• The effect of multimorbidity on transition into social care is non-linear, with those in the most extreme groups more at risk • Dementia is strongly associated with transition into social care, far in excess of other conditions • Epilepsy and dementia have many comorbid interactions with transition into social care
• Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?	• The impact of multimorbidity on care transition varies by LA even when controlling for deprivation

6.5.1. All multimorbidity measures generally perform well at predicting transition into social care, with the CDS-H2 performing best

All multimorbidity measures had acceptable predictive ability for transition into social care, with the AUC range within 0.75-0.8 by year. When compared to equivalent analyses elsewhere, overall performance is behind only mortality, 28+ hospital days and informal care (equivalent analysis for informal care is in the following chapter, section 7.2.1). This suggests that administrative data-based multimorbidity scores can be reliably used in predicting transition into social care in Scotland and in countries with similar demographics (Kluge et al 2019).

The CDS-H2 – an adaptation of an American score by the author of this study, previously not used on a UK-based population – outperformed all other scores, with an AUC approaching 0.8. It is the only medication-based score to outperform the proxy prescription count for any outcome and the only condition-based measure to be the best performing measure for any outcome bar the CCI and

mortality, and itself and informal care. As discussed in chapter 5, it is likely that proxy measures typically performed best as the original measures were developed from a specific population and may not adapt well to others. Taking this into account, the CDS-H2, though flawed, can be adapted with minimal change to derive a Scottish-specific multimorbidity index, particularly when predicting transition into social care.

The CDS-H2 also performed well regarding predicting less severe healthcare utilisation outcomes in chapter 5, which may suggest that transition into social care is an indicator of functional status similar to that which would result in admission to hospital. The proportion of those transitioning into social care (table 6.2, around 1.5%) is lower than any of the health outcomes in chapter 5 (table 5.3, minimum 3% for 28+ hospital days), though it should be noted that the sample parameters were very different, with inclusion in the cohort conditional on not receiving care the prior year – the actual social care uptake rate per year in the data, when all older adults are included, is around 5%. Regardless, this is a comparatively infrequent outcome, yet the most predictive measures are the CDS-H2 (which performs better for less severe outcomes) and unique ICD-10 codes (which generally performs better for more severe outcomes) – both measures also performing better for healthcare utilisation outcomes than mortality. These results highlight that multimorbidity in general, however derived, can be reliably used to predict those about to transition into social care, and a number of different data sources can be considered when developing risk prediction models.

6.5.2. Medication-based measures perform slightly better at predicting transition overall

In chapter 5 it was found that diagnosis-based indices generally perform better at predicting mortality and hospital days, whilst medication-based indices perform best for both admissions-based outcomes. The "worse" or more severe an outcome was, the better diagnosis-based indices performed at predicting the outcome. Transition into social care, while in some respects related to health-care utilisation in that the recipient is using a service to improve their health, is otherwise very different to the outcomes in chapter 5, and is also conditional on not receiving care initially; therefore, it would be unwise to interpret this outcome as "better" or "worse" than health outcomes regardless of the results.

Comparatively speaking, for transition into social care the difference between the two measures is small (fig 6.2). The CCI and CDS-H1 are the least predictive measures, but among the other four the overall range is marginally higher for the CDS-H2, and unique ICD-10 codes compared to the EI and unique prescriptions. This is in contrast to the outcomes in chapter 5, in which measures derived from either diagnosis-based or medication-based data were typically dominant. An interpretation of this could be that diagnosis-based and medication-based outcomes can be used equally well to predict transition into social care, which is helpful if only one type of data is readily available. Given that the

individual measures that best predict transition differ from that observed for health outcomes, social care transition is a distinct indicator of functional status, separate from more direct measures of health, though this may (as mentioned previously) be at least partly impacted by the conditional nature of the outcome and subsequent restriction of the cohort in this chapter.

The results may suggest that transition into social care is distinct from other health outcomes and in this regard is predicted by a very different set of parameters, as outlined by the individual condition and comorbidity findings in later sections (6.5.3, 6.5.4). Given this, a similar approach to that used to develop SPARRA (ISD 2011) – but taking into account the variance in prediction of social care as opposed to health care utilisation – may be a useful tool for pre-emptive targeting of assessment for social care. Given the inherent differences between diagnosis-based and medication-based indices, particularly in regard to prediction of severe or end-of-life conditions (Schneeweiss et al 2004), and the aforementioned similar predictive ability of the measures outlined in this study, policymakers have greater flexibility in deciding which index to choose based on individual circumstances. A number of characteristics derived from the most predictive multimorbidity index (CDS-H2), discussed below, can be considered when developing this.

6.5.3. The effect of multimorbidity on transition into social care is non-linear

In common with the health outcomes in chapter 5, when recoding the CDS-H2 to categorical there is an exponential impact of increasing multimorbidity. This effect becomes particularly large for those in the most extreme two categories (a score of 6500-8000 and 8000+), representing around 10% and 4% of the population respectively (table 6.6). Those with a score between 6500 and 8000 are 62 times as likely, and those with a score of 8000+ are almost 800 times as likely (table 6.7) to transition into social care compared to those who have no score; this represents 14% of the population with a very high need for social care. In addition to this, there is a large decreased risk (0.05) of transition into social care in those with present, but low medication use (a score of 3000 and less, but above zero). Whilst this may indicate health-conscious behaviour, or alternatively, more pro-active prescribing from general practices, this score is considerably smaller than that observed for health outcomes and may indicate missing prescribing data for some individuals.

The fact that almost one fifth of the population are far more likely to use care suggests that it is this particular level of multimorbidity to whom integrated care should be targeted. Provision of better quality, person-focused care to this group in particular may alleviate considerable pressure on health services, and weighting of this group in potential risk prediction models may improve predictive ability. Another potential application of the findings from this study is that policymakers can predict future care demand by analysing whether the proportion of older people with this particular

multimorbidity score is set to increase (as well as other groups of multimorbidity scores). This could be done by modelling increases in the proportion of the population with these scores with the same health data used in this project, whilst also accounting for changes in sex, age, and deprivation. Projections of the future multimorbidity of the population can potentially inform demand for and costs of integrated care, though this may be limited by unforeseeable changes in potential aspects such as drug costs, or inherent heterogeneity of multimorbidity beyond a simple score. However, the fact that the odds ratios are significantly associated, with little variance, suggest this could still be an effective strategy.

6.5.4. Individual conditions outperform metric measures in predicting transition into social care, dementia the most strongly associated

In section 5.4.5, all individual condition models for health outcomes performed better than the metric models, improving model performance. The same was observed for transition into social care, with the individual condition model improving to the extent that overall prediction was acceptable-to-good as opposed to acceptable. Dementia, a condition added to the CDS-H2 in place of the original psychotic illness to due concerns regarding misdiagnosis, is strongly associated with transition into social care (OR 6902.14 [5167.48 – 9219.11]) many times in excess of the next most strongly associated (hyperthyroidism, OR 12.04 [3.40 – 42.64]). This is consistent with previous research into dementia and social care: it is repeatedly cited in previous literature as being strongly associated with care placement, and is a "dominant" condition when considering health care requirements such as prescribing; decisions around prescribing for comorbidities must be made with dementia at the forefront (Scottish Government 2015). Kuzuya et al (2012) found that dementia was most strongly associated with long-term care placement among a list, and Kasteridis et al (2015) found that it was associated with long-term care costs.

That dementia is the strongest predictor is not an unusual finding, but the strength of association compared to other CDS-H2 conditions, and indeed all other conditions in any of the individual condition models in chapter 5, is somewhat unexpected. Given concerns regarding the low prevalence of dementia in the CDS-H2 (table 6.3) compared to national statistics (table 1.1), and that dementia is generally under-reported and underdiagnosed (ISD 2008), the high strength of association seen in table 6.9 may reflect latter stages of dementia when cognitive decline is more apparent and independent function is severely inhibited; however, this may be mediated somewhat by the fact that earlier stages of dementia are more heavily medicated. Despite this, however, it is apparent that dementia is by far the strongest predictor of transition into social care above all other conditions, and this should be taken into account when developing risk prediction for social care uptake.

Four further conditions (hyperthyroidism, epilepsy, Parkinson's disease, depression) had an odds ratio of seven or above. Whilst the strength of association is considerably smaller when compared to dementia, it is notable that of the five most strongly associated, two (dementia, depression) are mental health or neurological conditions compared to physiological. This emphasises the importance of providing care for people with mental health comorbidities, which is more common in deprived areas (Barnett et al 2012). The fact that the majority of mental health conditions included in the model are more predictive of transition into social care than others reinforce this need to focus on people with mental health conditions.

As discussed in section 6.5.3, policymakers could use the results of this analysis to derive projections for future costs of care to particular groups in supplemental analyses. The prevalence of particular conditions is projected to change at different rates in the older population (Kingston et al 2018); demand can be more reliably estimated by modelling rate of increase of these conditions with their strength of association with transition into social care. The conditions most strongly associated with transition into social care diverge somewhat from those for the health outcomes seen in chapter 5; an adapted version of SPARRA, developed specifically for predicting those who will be most in need of social care, may also prove to be useful. However, it must also be noted that the results observed for the CDS-H2 carry a greater risk of misidentification of conditions than diagnosis-based measures due to flagging for medication rather than a condition itself; given this, combining medication-based identification with diagnosis-based may be helpful.

6.5.5. Epilepsy has many risk-increasing, and dementia risk-increasing and risk-decreasing, comorbid interactions with transition into social care

The results in table 6.11 looking at comorbid conditions with the most predictive conditions of transition into social care was consistent with similar analyses done in chapter 5, in that small significant comorbid effects were found with the outcome, whilst the overall predictive power of the index condition increased considerably when controlling for all comorbid interactions. This suggests that there is an additional effect of multimorbidity on transition into social care as well as health outcomes.

The three most strongly associated conditions, and consequently index conditions for the comorbidity models, were dementia, hyperthyroidism, and epilepsy. Parkinson's disease was universally associated with an increased risk for all three conditions, and pancreatitis was most strongly associated with an increased risk with dementia (2.23) and mania for epilepsy (1.83). A number of these conditions, whether the index condition (dementia, epilepsy) or a comorbidity (Parkinson's disease, mania) are associated with impaired cognition or barriers to independent function. Many

interactions associated with an increased risk (dementia and hypertension/arthritis/high cholesterol/Parkinson's/pancreatitis/pain, epilepsy, and depression/mania/anxiety) are mental/physiological comorbidities, further highlighting those individuals with these multimorbidities are greatly in need of integrated care (Mercer et al 2012).

Whilst the majority of the conditions included in the dementia and epilepsy models were significantly comorbid (60% and 67% respectively), several carried a decreased risk of transition into social care (five for dementia and three for epilepsy). The three comorbidities carrying a decreased risk of epilepsy (hypertension, high cholesterol, pain/inflammation) are consistent with results in chapter 5, and, as discussed there, may account for health-conscious management of minor ailments. In contrast, the decreased risk comorbidities with dementia are primarily cardiovascular (coronary and peripheral vascular disease, heart disease) or mental health (depression, anxiety/tension). As discussed earlier, the odds ratio for dementia when adjusted for comorbidities (72690.59) is exponentially higher even than the already large risk in the individual condition model, and it is likely that these impacts on risk, whilst significant, are very small.

Few comorbidities (2, 16.67%) were associated with an increased risk of transition into social care with hyperthyroidism. As speculated in prior sections, it is likely that this is as a result of low prevalence (<1%, table 6.3) and may not reflect underlying trends. The potential weaknesses of the approach chosen, and implications, has been discussed earlier (section 5.4.6); however, a number of comorbid impacts on risk of transition into social care have still been identified, which can be used to inform risk prediction and proactive targeting of social care, or further study.

6.5.6. The impact of multimorbidity on care transition varies by LA even when controlling for deprivation

The results observed in section 6.4 show the impact of multimorbidity on transition into care is stronger in areas with lower overall deprivation. In the models that included all cases the results were significant for every model, whilst in the models restricted only to the most deprived quintile the scale of the effect was lower and many of the results in the less deprived LAs were not significantly associated, though it is suspected this was as a result of low case numbers reducing statistical power. A possible explanation for this is that many people in more deprived areas have already transitioned into social care prior to turning 65, reducing the number of people who have transitioned later. In this respect it may be worth running the same analyses on a population encompassing older age groups – it has been established in previous literature (Barnett et al 2012) that in more deprived areas multimorbidity is more common at younger ages. An explanation for the difference in strength of association could be that in less deprived areas, multimorbidity is the primary reason for greater

dependence and therefore use of social care. In comparison, in less deprived areas multimorbidity is only one of a number of factors that influences use of care. It also may be the case that in more deprived LAs, individuals are not getting the care they need despite high levels of multimorbidity. The paper by Lemmon & Bell (2019) investigating care uptake by LA in Scotland found that uptake was low if the deprivation rate was high. It is well documented that people in deprived areas have more health problems and are more dependent, so the fact that there is a baseline lack of care provision (not just associated with multimorbidity) suggests that people who require care and live in more deprived local authorities are less likely to receive it.

The fact that there is a macro-level effect of multimorbidity independent of deprivation may possibly be explained along the same lines as the "inverse intervention" effect outlined by Bywaters et al (2015) in their paper examining child protection plan (CPP) rates, and how they are more prevalent in deprived areas of more affluent LAs in England. The first is that of those requiring CPP being more "visible" due to the LA being more affluent as a whole. This may also be the case for those with high multimorbidity in affluent LAs in Scotland – they are less common and therefore more visible to the authorities and are more likely to receive help, whilst in more deprived LAs there are many more people in the same situation. The Bywaters et al (2015) paper also suggests that there is a greater community support in more deprived LAs and therefore people are less reliant on authority-provided help.

It may also be that the inverse care law, which stems from general practitioners being evenly distributed by population in Scotland rather than by need (Blane et al 2012), extends to assessment for social care, with more opportunities for assessment and provision in less deprived areas as a result of less overwhelmed health services. This would result in a higher multimorbidity threshold for assessment for care in more deprived areas compared to less deprived. Regardless of potential implications, these findings reinforce the importance of taking into account both local authority deprivation and data zone deprivation in developing risk prediction for social care need, and may reflect a need for separate models, or weightings, by local authority.

6.5.7. Conclusion

In this chapter it is demonstrated that admission-based and mediation-based multimorbidity scores derived from Scottish routine data can be used to adequately predict transition into social care. An author-adapted medication measure, the CDS-H2, is the best performing, and indicates applicability of using medication data to identify specific multimorbid conditions (though some work is needed to address discrepancies in prevalence). Dementia is by far the strongest predictor of transition into social care, well in excess of other conditions, though many risk-decreasing comorbidities were found

likely due to the strong individual risk. It was also found that stronger associations between multimorbidity and transition into social care exist in less overall deprived local authorities. Findings from this chapter can aid in development of risk prediction models to identify those who may require social care, or pre-emptive targeting of social care provision on order to reduce emergency interventions.

Chapter Seven – Multimorbidity and informal care

This chapter examines how informal/co-resident care can be best predicted based on a number of multimorbidity measures spanning different kinds of data, what particular level of multimorbidity, conditions and condition combinations are most predictive, and whether administrative or survey data best predicts informal care.

The analyses presented here are partly derived from a number of arguments put forward in chapter 5 and 6, in that people with multimorbidity will particularly benefit from provision of care as they have complex needs. Informally provided care is an important part of the overall care package and that as the demographics of people who receive formal or informal care are likely different, it may be that different multimorbidity measures or conditions are most predictive of informal care uptake.

This chapter consists of six sections, answering three research questions:

- Which multimorbidity measure(s) best predict transition into informal care in older people in Scotland using linked administrative data, and co-resident care in linked survey data?
- What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal and co-resident care?
- Is linked administrative or linked survey data able to better predict informal or co-resident care in older people in Scotland?

The other two sections consist of descriptive results, and a discussion of the main findings arising from the results.

As in chapter 6, and mentioned in methods section 4.2.2, the administrative cohort used in this chapter uses inclusion criteria dependent on non-receipt of informal care at baseline (i.e. the index date). Any cases identified as having an informal carer in the SCS have been excluded. This approach was taken as the outcome is transition into informal care, defined as being identified as having a carer in the SCS census week one year from the index date, conditional on having one in the prior year (i.e. no carer flag in 2014, carer in 2015).

7.1. Descriptive analyses

This section consists of two subsections–- univariate frequency and distribution analyses of key variables, and bivariate analyses of multimorbidity and outcome variables.

Analyses are presented in one table for each dataset, with statistics from both the linked transition into informal care administrative dataset (as a yearly range as in previous chapters) and the survey dataset (with figures presented from both "cycles" of years of data) for the same outcomes, allowing for comparison of demographics across each dataset. For the administrative dataset, the only multimorbidity scale reported is the CDS-H2 as it was the best performing at predicting informal care transition. Statistics are presented from all of the multimorbidity measures in the survey dataset for univariate analyses, and the best performing for each outcome for bivariate analyses as these have not previously been used in this thesis.

7.1.1. Univariate analyses

Seven tables are presented in this section: cases in each dataset, demographic variable ranges, and individual condition frequencies. Statistics are presented by year for administrative data and by weighted cycle for survey data.

Table 7.1: Number of cases in administrative dataset by year

Year	**13-14**	**14-15**	**15-16**	**Total**
Cases	814,409	816,524	818,296	2,449,229

As in chapters 5 & 6, increases in the number of cases in the administrative dataset are observed by year. The overall size of the dataset is smaller due to informal care uptake being recorded in fewer years (table 7.1); less years of data will impact adjustment for repeated measures in panel regression; however, given the overall high case numbers the impact is likely minimal.

Table 7.2: Number of cases in survey dataset by cycle

Cycle	**08-11**	**12-14**	**Total**
Cases	5,434	2,900	8,334

There are more cases in the 2008-11 cycle than 2012-14. This is to be expected given the former spans more years than the latter. This dataset is considerably smaller than the administrative cohorts used elsewhere in this thesis, and will impact strength of association of findings and generalisability to a wider population compared to the larger cohorts in the study; however, the sample size is large enough to produce meaningful results.

Table 7.3: Non-individual condition variable summary ranges

Variable	Category	Statistic range			
		Administrative data		Survey data	
		Lower	Upper	Lower	Upper
Age	**65-74**	60.08%	61.54%	56.40%	57.61%
	75-84	30.98%	31.52%	33.97%	35.65%
	85+	7.48%	8.40%	7.95%	8.42%
Sex	**Male**	45.69%	46.35%	44.03%	44.27%
	Female	53.65%	54.31%	55.73%	55.97%
SIMD decile*	**1st**	7.68%	7.87%	16.21%	16.83%
	2nd	8.72%	8.86%		
	9th	10.48%	10.70%	20.92%	21.19%
	10th	10.76%	10.91%		
NS-SEC	**Higher managerial**			6.59%	8.64%
	Lower managerial			19.52%	20.55%
	Intermediate			12.97%	15.42%
	Small employers/own account			7.34%	8.27%
	Lower supervisory/technical		N/A	8.12%	10.70%
	Semi-routine			18.21%	18.62%
	Routine			19.60%	20.22%
	Long-term unemployed			1.60%	3.62%
Education level	**No high school qualifications**			41.77%	45.53%
	High school qualifications		N/A	44.79%	46.17%
	Higher education qualification			9.68%	12.07%
Informal/co-resident care**		<1.00%	<1.00%	6.59%	6.98%

* Quintiles in survey data.

** Transition into informal care in administrative data, in receipt of co-resident care as of date of interview in survey data.

According to table 7.3, the administrative sample is slightly older than the survey sample, which may be selection bias on account of very old people being unable to take part. Sex is similar, with slightly more in both datasets being female. More cases in both datasets are in the more affluent deciles/quintiles. More people are identified as being in receipt of co-resident care in the survey than transition into informal care in the administrative data – this could potentially be as a result of the informal care variable in the administrative data being poorly recorded. In terms of the survey-specific variables, the majority worked in either professional or routine occupations, and very few have degree-level qualifications.

Table 7.4: Multimorbidity scale mean ranges

Dataset	Multimorbidity measure	Mean range	
		Lower	Upper
Administrative	**CDS-H2**	4098.14	4125.7
Survey	**CCI-7**	0.19	0.20
	EI-8	0.09	0.09
	Unique SMR episodes	0.24	0.25
	Self-reported	1.40	1.67
	Self-reported weighted	2.27	2.79
	Self-reported ICD-10	1.24	1.46

As shown in table 7.4, the CDS-H2 score is slightly lower in the informal care data than the data in chapters 5 and 6, primarily as a result of the sample being younger. In the survey data, the self-reported scores are all higher than the diagnosis-based scores. This is because the diagnosis-based scores have limited data.

Table 7.5: Frequency of individual conditions in the CDS-H2

Condition	Proportion range	
	Lower	Upper
Coronary and peripheral vascular disease	33.80%	36.02%
Epilepsy	5.06%	5.80%
Hypertension	57.33%	57.93%
Tuberculosis	<1.00%	<1.00%
Rheumatoid arthritis	1.25%	1.43%
HIV	<1.00%	<1.00%
High cholesterol	44.44%	44.70%
Parkinson's disease	5.39%	5.68%
Renal anaemia/neutropenia	<1.00%	<1.00%
Heart disease	45.13%	45.81%
Diabetes	9.90%	10.07%
Glaucoma	3.83%	3.91%
Pancreatitis	<1.00%	<1.00%
Renal failure	<1.00%	<1.00%
Ulcers	38.45%	39.42%
Transplants	<1.00%	<1.00%
Respiratory illness/asthma	15.69%	16.09%
Hyperthyroidism	<1.00%	<1.00%
Gout	3.52%	3.91%
Crohn's disease/inflammation	1.33%	1.39%
Pain/inflammation	14.22%	15.76%
Depression	17.42%	17.95%
Dementia	2.30%	2.67%
Mania	<1.00%	<1.00%
Anxiety/tension	14.56%	15.07%
Pain	10.88%	11.09%

Prevalence of conditions in this cohort (table 7.5) are similar to those found in previous chapters (tables 5.7, 6.3). Interpretations, and speculation on discrepancies between frequency of these conditions and prevalence in other studies, apply here also.

Table 7.6: Frequency of individual conditions in the self-reported condition list

Condition	Proportion range*	
	Lower	Upper
Cancer (neoplasm)	4.93%	5.22%
Diabetes	8.43%	9.36%
Other endocrine / metabolic	6.42%	7.50%
Mental illness / anxiety / depression	2.67%	3.12%
Learning disability	<1.00%	<1.00%
Epilepsy / fits / convulsions	<1.00%	<1.00%
Migraine / headaches	<1.00%	<1.00%
Other nervous system	3.88%	4.08%
Cataracts / blindness	3.04%	2.93%
Other eye problems	2.25%	2.39%
Poor hearing / deafness	3.46%	3.46%
Tinnitus	<1.00%	<1.00%
Meniere's disease	<1.00%	<1.00%
Other ear problems	<1.00%	<1.00%
Stroke	3.04%	3.05%
Heart disease / heart attack / angina	6.85%	6.88%
Hypertension / high blood pressure	12.46%	13.75%
Other heart problems	9.02%	9.77%
Piles	<1.00%	<1.00%
Varicose veins excluding anus	<1.00%	<1.00%
Other blood vessels	2.57%	2.61%
COPD / bronchitis	1.58%	2.64%
Asthma	4.67%	4.68%
Hay fever	<1.00%	<1.00%
Other respiratory	3.82%	4.32%
Ulcers	2.21%	2.24%
Other digestive	1.80%	2.29%
Bowel complaints	2.76%	3.40%
Teeth / mouth / tongue complaints	<1.00%	<1.00%
Kidney complaints	1.20%	1.44%
Urinary tract infection	<1.00%	<1.00%
Other bladder problems	<1.00%	<1.00%
Reproductive system disorders	1.69%	1.87%
Arthritis	19.75%	19.88%
Back problems	5.48%	6.08%
Other bones problems	14.08%	14.39%

Infection / parasitic	<1.00%	<1.00%
Blood disorders	1.40%	1.57%
Skin complaints	1.01%	1.18%
Other complaints	<1.00%	<1.00%
Unclassifiable	<1.00%	<1.00%

Table 7.7: Frequency of individual conditions in the self-reported ICD-10 condition list

Condition	**Weighted proportion range**	
	Lower	**Upper**
I: Infectious disease	<1.00%	<1.00%
II: Neoplasms	4.93%	5.22%
III: Blood / immune system	1.40%	1.57%
IV: Endocrine / metabolic	14.10%	15.90%
V: Mental / behavioural	2.71%	3.16%
VI: Nervous system	4.64%	4.98%
VII: Eye diseases	5.17%	5.17%
VIII: Ear diseases	4.40%	4.53%
IX: Circulatory system	29.48%	31.11%
X: Respiratory system	9.94%	10.43%
XI: Digestive system	6.35%	7.44%
XII: Skin diseases	1.01%	1.18%
XIII: Musculoskeletal system	34.10%	34.87%
XIV: Genitourinary system	3.63%	4.02%

Comparison of the prevalence in tables 7.6 and 7.7 to national statistics (table 1.1) is difficult, as the unweighted frequencies are derived from the same dataset (SHeS) as that used in the Bromley et al (2013) report, though the prevalence in the Bromley report is weighted, and in-part based on doctor diagnosis as opposed to self-report. When compared to UK estimates, a number of conditions in this cohort are underreported: cancer (5% compared to 13%), diabetes (9% compared to 15%), heart disease (7% compared to 18%), hypertension (13-14% compared to 49%), stroke (3% compared to 8%) and arthritis (20% compared to 49%). This may reflect general underreporting tendencies in data derived from self-report (Frost et al 2011) perhaps due to reluctance, recall or lack of knowledge regarding disease.

Note that CCI and EI conditions are not included here as very small case numbers were observed.

7.1.2. Bivariate analyses

Two analyses are shown in this section: the range of the correlation of each multimorbidity index in the survey data (the correlation for the administrative survey multimorbidity indices is not shown, as scores are similar to table 5.8 in chapter 5), and the mean multimorbidity score (range) of those who did and did not use informal/co-resident care.

Table 7.8: Range of correlations between multimorbidity indices in survey dataset

Multimorbidity measure	SR	SR (weighted)	SR (ICD-10)	Unique SMR	CCI-7
Self-reported (weighted)	0.96				
Self-reported (ICD-10)	0.95	0.90			
Unique SMR episodes	0.11 to 0.12	0.11	0.11 to 0.13		
CCI-7	0.10 to 0.11	0.09 to 0.11	0.11	0.86 to 0.87	
EI-8	0.12	0.11	0.12 to 0.13	0.72 to 0.75	0.86 to 0.87

All outcomes are highly significantly associated ($p<0.001$).

Strong associations were observed within the self-report-based and diagnosis-based measures, whereas weak associations were found when comparing across the type of measure. The most strongly associated measures were the self-reported and weighted self-reported, whereas the most weakly associated measures were the weighted self-reported and CCI-7. The weak association between the two different types of measure is likely explained by the fact that the SMR-based measures are derived from a very small data pool (first admission for a select list of conditions, with subsequent admissions for the same condition excluded); this will omit conditions normally included in the CCI/EI in larger datasets, as well as conditions which were first identified prior to the five-year lookback period.

Table 7.9: Mean multimorbidity score range in those who did and did not transition into informal care, or use co-resident care

Dataset	Multimorbidity score	Group	Mean score range	
			Lower	Higher
Administrative	**CDS-H2**	**Yes**	5579.13	5704.13
		No	4093.25	4123.11
Survey	**Self-reported weighted**	**Yes**	4.20	5.21
		No	2.09	2.57

As table 7.9 shows, for both datasets the multimorbidity score is higher for those in receipt of/transitioning into co-resident/informal care than for those who are not.

7.2. Research question 1: Which multimorbidity measure(s) best predict informal/co-resident care uptake in older people in Scotland using linked administrative data and linked survey data?

As in chapters 5 & 6, this question will be answered, this time for both datasets, via comparison of model parameters, by each multimorbidity measure.

7.2.1. Nested regression for informal care using administrative and survey data

The following, as in previous chapters, is model parameter results from nested regression for either transition into informal care (in administrative data) or co-resident care uptake (in survey data), consisting of demographic variables, the multimorbidity measure, covariates determined via univariate regression prior (in survey data only) and interactions. These models were repeated for each multimorbidity measure.

As models were run for two separate cohorts, the variables included, and selection criteria for preferred nested model, differed. For the administrative data, model parameters from the models with all variables (including interactions) only are presented as in chapters 5 and 6, containing the following variables:

- Age (count)
- Sex (binary)
- SIMD (dummy decile variables, SIMD 10 excluded as reference)
- Multimorbidity measure (continuous)
- Age (quadratic)
- Age*female interaction
- Age*multimorbidity interaction

For the survey data, no model type was universally the most predictive across all three parameters. As such, best performing parameters for each step of the model are summarised in table 7.10. This also lists the variables added in each step. Variables in all models are as follows:

- Age (count)
- Sex (binary)
- Data cycle (binary)
- SIMD (dummy quintile variables, SIMD 5 excluded as reference)

Table 7.10: List of variables in each nested model and best performing parameter in each, by multimorbidity measure

	Multimorbidity measure	**Control variables**	**Interactions**
Multimorbidity measures and best performing parameters	**Multimorbidity measure (metric)**	**Social class (dummy categories)** **Education level (dummy categories)**	**Age (quadratic)** **Age*sex** **Age*multimorbidity**
CCI-7	BIC	AIC	AUC
EI-8	BIC	AIC	AUC
Unique SMR episodes	BIC	AIC	AUC
Self-reported	BIC	AIC, AUC	
Self-reported weighted	AIC, BIC	AUC	
Self-reported ICD-10	BIC	AIC, AUC	

The small models always have the lowest BIC (the control and interaction effects in each model were usually not significantly associated, and the BIC penalises more harshly for redundant parameters) whilst the control models usually have the lowest AIC, whilst the highest AUC is split between the control models (for self-report measures) and interaction models (for diagnosis measures).

Separate output will be presented for each cohort. When presenting graphs only the BIC will be presented, as in common with previous results the rank of multimorbidity measures in terms of performance was exactly the same for both.

These analyses answer the research question as they determine via interpretation of the model parameters which multimorbidity measures perform best at predicting informal/co-resident care in both a population-wide Scottish sample of older people and in survey data, via four areas:

- The best overall measure for informal/co-resident care

- Predictive ability of diagnosis-based measures compared to medication-based (for administrative data) and diagnosis-based compared to self-report-based (for survey data)
- Predictive ability of condition-based indices compared to proxy scores
- How the measures perform overall

7.2.1.1. Transition into informal care (administrative data)

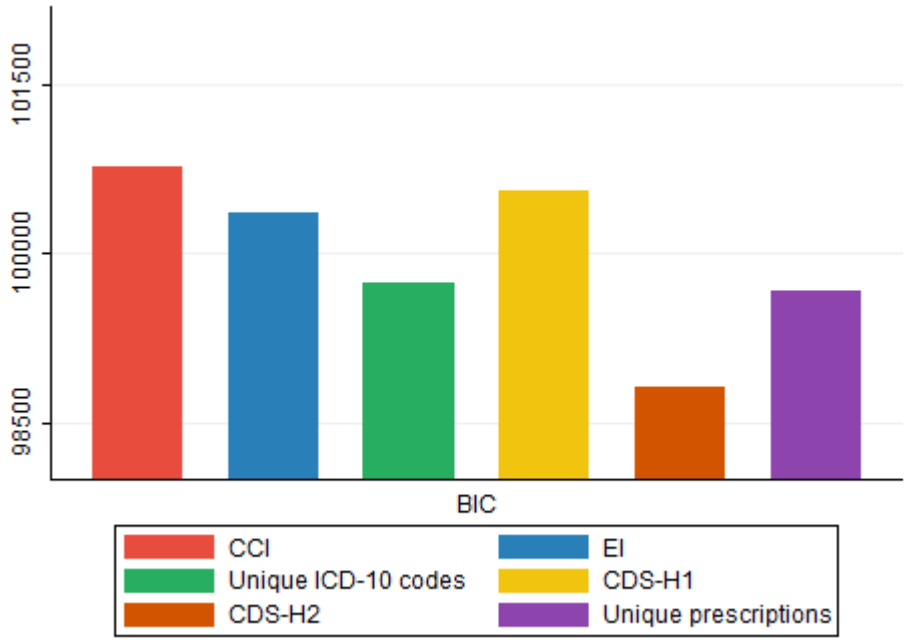

Fig 7.1: BIC of panel logistic regression models predicting transition into informal care in administrative data by multimorbidity measure

The CDS-H2 is the best performing measure in predicting transition into informal care, followed by unique prescriptions. This result (and the relative performance of each index) is similar to that observed for transition into social care (fig. 6.1); this suggests that – at least at index level – the parameters indicative of both need of social and informal care are similar. This is likely given that both indicate diminished functional capacity and loss of independence.

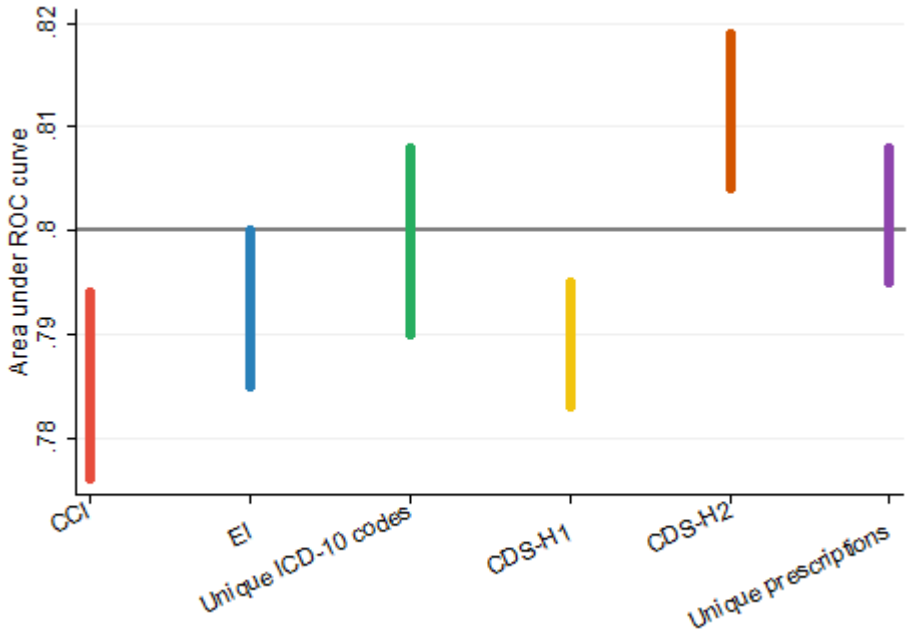

Fig. 7.2: Area under ROC curve (AUC) range of logistic regression models by year predicting transition into informal care in administrative data by multimorbidity measure

The CDS-H2's predictive ability for transition into informal care (fig. 7.2) is universally "good" – i.e. AUC of 0.8-0.9 – for all survey years, similar to the CCI for mortality in chapter 5 (fig. 5.2). Three other measures (EI, ICD-10 codes, unique prescription) all have acceptable-to-good prediction, suggesting that of all health and care outcomes in this study, the overall performance of all measures used in this study is highest in predicting transition into informal care. This however should be interpreted cautiously due to the smaller dataset and high levels of missingness for the informal care outcome.

7.2.1.2. Informal care uptake (survey data)

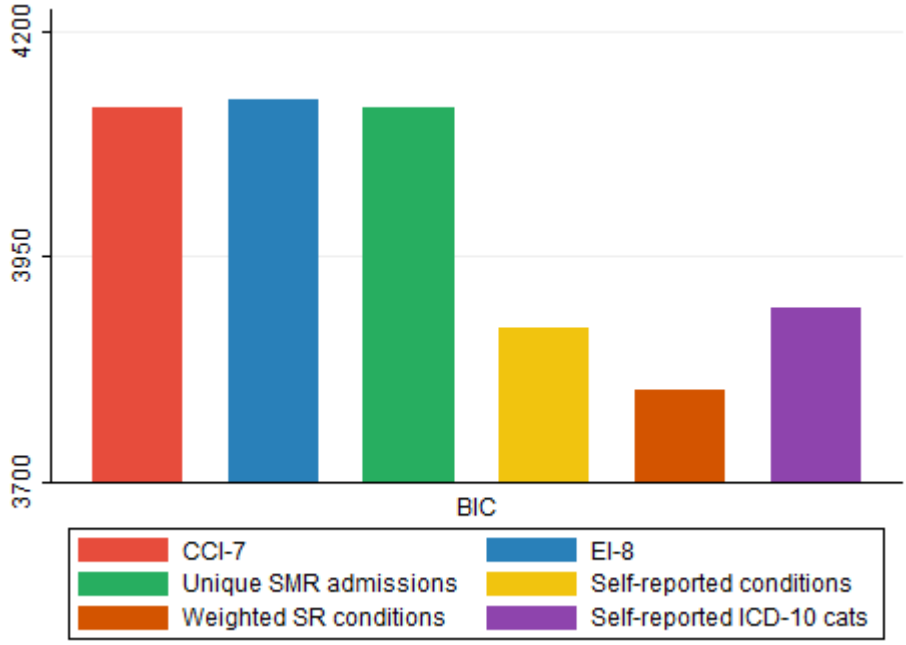

Fig. 7.3: BIC of logistic regression models predicting co-resident care receipt in survey data by multimorbidity measure

In predicting co-resident care uptake using the survey data (fig. 7.3), the self-report measures were the best performing, with the only weighted measure performing best. There was little difference between each of the diagnosis-based measures, with the CCI performing marginally better than the other two condition-based measures.

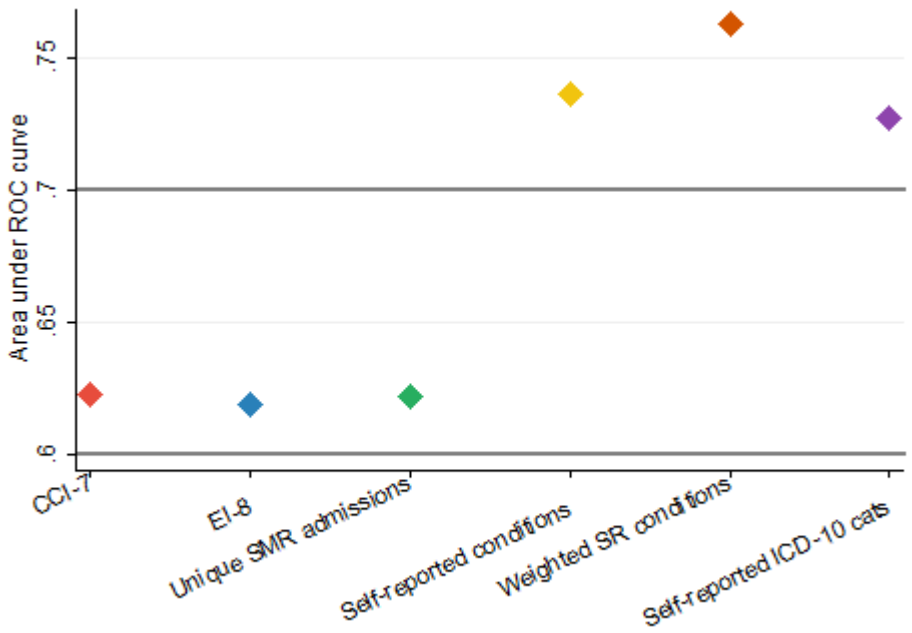

Fig. 7.4: Area under ROC curve (AUC) of logistic regression models predicting co-resident care receipt in survey data by multimorbidity measure

Unlike in section 7.2.1.1, the AUC value for co-resident care in the survey data by multimorbidity measure is presented as a scatter graph; only one AUC value is reported given that this is a logistic, and not panel logistic, model. As shown in fig. 7.4, the results are much the same as for the BIC – the self-report-based measures all have acceptable prediction, with the weighted score the best overall, whilst the diagnosis-based measures have poor prediction. In comparison to the administrative data, the overall prediction was much lower, and the diagnosis-based measures were considerably weaker than the equivalent measures, though this is probably explained by the limited nature of the SHeS SMR data.

7.3. Research question 2: What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal/co-resident care?

As in chapters 5 and 6, this question is answered with three separate types of analyses, all focusing on which CDS-H2 & weighted self-report score aspects (for administrative and survey data respectively) are associated with greatest risk of either informal care transition or co-resident care receipt: analyses of categorical recoding of the multimorbidity measure, individual conditions within the measure and condition interactions of those conditions.

7.3.1. Nested logistic regression for informal care with categorical multimorbidity variable

The following presents the odds ratios of the dummy multimorbidity categories when replacing the continuous outcome in the models discussed in section 7.2. The models are otherwise identical other than the fact that categorical interactions were also used for any interactions involving the multimorbidity measure (when applicable). This will be presented in two subsections, one for each dataset. There will also be a further subsection comparing the AIC, BIC, and AUC range of these new models with the original models by dataset, in order to see which functional forms best explain the outcome. All three parameters (AIC, BIC, AUC) are used in this chapter as the most predictive measure is not consistent across different nested models in the survey dataset. The analyses below answer the research question because they will examine whether there is an exponential effect of multimorbidity on informal/co-resident care.

Prior to presenting the analyses, the prevalence of those in each category of the CDS-H2 and weighted self-report score is shown (table 7.11). The "zero score" category was used as the reference in all models.

Table 7.11: List of multimorbidity score categories used in categorical models and proportion of population with each score

CDS-H2			**Weighted self-reported conditions**		
Category	***Lower***	***Higher***	***Category***	***Lower***	***Higher***
0 (reference)	7.59%	7.65%	0 (reference)	26.58%	31.48%
0.1-3000	26.10%	26.45%	1-2	30.13%	32.89%
3000.1-4500	23.71%	24.39%	3-4	20.37%	21.87%
4500.1-5500	14.69%	15.10%	5+	15.26%	21.42%
5500.1-6500	13.73%	14.22%			
6500.1-8000	9.31%	9.55%			
8000.1+	3.71%	3.78%			

7.3.1.1. Categorical CDS-H2 model for predicting transition into informal care using administrative data

Table 7.12: Odds ratios for categorical functional forms of the CDS-H2 in predicting transition into informal care in panel logistic regression

CDS-H2 score	Odds ratio		95% confidence interval
0 (reference)	1		N/A
0.1-3000	***0.09***	***0.02***	***0.48***
3000.1-4500	1.59	0.31	8.03
4500.1-5500	***6.51***	***1.27***	***33.37***
5500.1-6500	***12.26***	***2.41***	***62.39***
6500.1-8000	***39.01***	***7.67***	***198.38***
8000+	***1275.63***	***234.65***	***6934.68***

As with all previous outcomes, a non-linear relationship is observed (table 7.12) between increasing multimorbidity and transition into informal care. It should be noted that the strength of association is far higher than for transition into social care at similar levels – 1275.63 compared to 778.14 (table 6.7) at 8000+ and above. In addition, a large decreased risk (0.09) of non-zero medication use compared to none is observed, though less than that for social care (0.05 – table 6.7).

7.3.1.2. Categorical weighted self-report model for predicting co-resident care receipt using survey data

Table 7.13: Odds ratios for categorical functional forms of the weighted self-report score in predicting co-resident care receipt in logistic regression

Weighted SR score	Odds ratio		95% confidence interval
0 (reference)	1		N/A
1-2	***7.54***	***4.65***	***12.20***
3-4	***13.04***	***8.06***	***21.11***
5+	***26.79***	***16.66***	***43.07***

It should be noted that the results from the categorical self-report model for co-resident care receipt (table 7.13) are not as extreme as those in section 6.3.1.1 as the model used does not incorporate interactions; the control model was used as the AUC was highest for that model in section 7.2.1.2. However, there is still an exponential increase from a score of 0 to a score of 5+, with those with a score of five or over being over 20 times as likely to be in receipt of co-resident care.

7.3.1.3. Comparison of model parameters for continuous and categorical multimorbidity variable

The below presents an overview of the three model parameters, by parameter by model for the two different datasets. In table 7.14, the best performing measure between each model is shaded in **bold italics.** Note that in the above table parameters are presented for the equivalent nested model to the one with the best performing AUC measure; hence, the parameters presented here for the survey-based model may differ from those in section 7.2.1.2 as different parameters were presented based on the best performing across all nested models.

Table 7.14: Parameters of models with metric and categorical multimorbidity variable by outcome

Parameter	MM variable	Transition into informal care (administrative)	Co-resident care receipt (survey)
AIC	**Metric**	98602	3,739
	Category	***98504***	***3,686***
BIC	**Metric**	***98818***	3,838
	Category	98847	***3,799***
AUC (range)	**Metric**	0.804 to 0.819	***0.764***
	Category	***0.804 to 0.820***	0.756

Table 7.14 shows that for the administrative-based models the AIC and AUC perform best for the categorical model, with the BIC performing best for the metric model. The AUC range is similar. This little difference in overall predictive ability – the difference in BIC may be explained by the fact that the lowest two categories of the CDS-H2 were not significantly predictive of transition into social care.

For the survey-based models the AUC is best for the original metric model, but the categorical AIC and BIC perform best. This suggests that while the metric model is more precise, the categorical model's inclusion of addition parameters is justified. Given that the effect is exponential, the categorical model would probably see better use in a policy setting.

7.3.2. Nested regression for informal/co-resident care using administrative and survey data with individual conditions

As in chapters 5 & 6, the following presents the odds ratios of component conditions of the most predictive condition-based measure for analyses in each dataset. The odds ratios are derived from

models that are the same as those in 7.2, with the exception that individual conditions (and interactions for those conditions) replace the multimorbidity scale. Two separate analyses are presented – the table described above, and a cross-model comparison of the parameters from the original model, the categorical model, and the condition model. In this case the AIC, BIC and AUC will all be included. There will be two sub-sections, one for each dataset. The analyses below answer the research question because they will examine which specific conditions people have that are more predictive of informal/co-resident care than others, within the pre-determined best performing multimorbidity measure.

7.3.2.1. Individual CDS-H2 conditions for predicting transition into informal care in administrative data

Nine conditions (tuberculosis, HIV, renal anaemia/neutropenia, pancreatitis, renal failure, transplants, hyperthyroidism, Crohn's disease, mania) were not significantly associated with transition into informal care in univariate regression, or had an overall prevalence of <1%, and were thus not included in the final model.

Table 7.15: Odds ratios and confidence intervals for individual conditions of the CDS-H2 in predicting transition into informal care in panel logistic regression

CDS-H2 condition	Odds ratio	95% confidence interval	
Coronary and peripheral vascular disease	***6.86***	***3.71***	***12.70***
Epilepsy	***9.59***	***4.05***	***22.72***
Hypertension	***0.17***	***0.08***	***0.35***
Rheumatoid arthritis	***0.34***	***0.18***	***0.64***
High cholesterol	***2.53***	***1.26***	***5.07***
Parkinson's disease	***4.71***	***2.06***	***10.78***
Heart disease	0.90	0.52	1.56
Diabetes	1.45	0.73	2.86
Glaucoma	1.69	0.52	5.57
Ulcers	0.90	0.52	1.56
Respiratory illness/asthma	1.45	0.73	2.86
Gout	1.76	0.45	6.83
Pain/inflammation	***0.11***	***0.05***	***0.28***
Depression	***12.20***	***6.19***	***24.05***
Dementia	***8313.18***	***4030.07***	***17148.33***
Anxiety/tension	***3.48***	***1.78***	***6.81***
Pain	***5.48***	***2.75***	***10.89***

Significantly associated conditions are in bold italics.

Eleven of the seventeen conditions in table 7.15 are associated with transition into informal care. Dementia (OR 8313.18 [4030.07 – 17148.33]), depression (OR 12.20 [6.19 – 24.05]), epilepsy (OR 9.59 [4.05 – 22.72]), coronary and peripheral vascular disease (OR 6.86 [3.71 – 12.70]) and pain (OR 5.48 [2.75 – 10.89] are the most strongly associated; the relatively high risk associated with dementia, and overall greater risk from mental health conditions, reflects that found for social care (table 6.9). One difference is that the risk of depression is notably higher than for epilepsy, suggesting that provision of informal care may be slightly more dependent on day-to-day difficulty observed by the carer (such as a noticeable reduction in self-support or self-management, or increase in risk-increasing

behaviour such as drinking or poor dietary choices in the potential care recipient) rather than objectively limiting physiological conditions, such as epilepsy. However, these differences are very small.

7.3.2.2. Individual self-reported conditions for predicting co-resident care in survey data

Table 7.16: Odds ratios for individual self-reported conditions in predicting co-resident care in logistic regression

Self-reported condition	Odds ratio	95% confidence interval	
Cancer (neoplasm)	***2.11***	***1.54***	***2.89***
Diabetes	***1.67***	***1.29***	***2.15***
Mental illness/anxiety/depression	***2.78***	***1.91***	***4.03***
Other nervous system	***5.40***	***4.06***	***7.18***
Cataracts/blindness	***2.01***	***1.36***	***2.97***
Poor hearing / deafness	1.11	0.73	1.70
Heart disease/heart attack/angina	***1.36***	***1.01***	***1.83***
Other heart problems	***1.95***	***1.54***	***2.49***
Other blood vessels	***1.66***	***1.08***	***2.55***
COPD/bronchitis	***3.27***	***2.24***	***4.78***
Other respiratory	***1.88***	***1.33***	***2.66***
Ulcers	1.43	0.87	2.33
Bowel complaints	1.37	0.91	2.07
Kidney complaints	***2.62***	***1.58***	***4.37***
Arthritis	***1.64***	***1.33***	***2.01***
Back problems	***1.78***	***1.32***	***2.41***
Other bones problems	***2.17***	***1.76***	***2.68***
Unclassifiable	***9.89***	***4.17***	***23.48***

Significantly associated categories are in bold italics.

In table 7.16, 15 of the 18 conditions in the final model are significantly associated with co-resident care. The most strongly associated by a distance is “unclassifiable” conditions, which are essentially conditions which did not fit into any other self-report category. Aside from this, other nervous system problems were the most strongly associated, followed by COPD. Few of the conditions in the administrative model are included in the survey model, though mental illness/depression is strongly associated in both models.

7.3.2.3. Comparison of model parameters for continuous multimorbidity variable and individual conditions

The below presents a comparison of model parameters of the original two models and the model with individual conditions (for the same multimorbidity measure). Again, for survey data the metric model may not necessarily be the best performing for each parameter, as the only model being compared is the one with the best AUC. In the below table, the best performing measure between each model is shaded in **bold underline.**

Table 7.17: Model parameters for logistic regression models for best performing models predicting informal care outcomes, score and individual conditions

Parameter	MM variable	Transition into informal care (administrative)	Co-resident care receipt (survey)
AIC	**Metric**	98,602	3,807
	Conditions	***96,075***	***3,714***
BIC	**Metric**	98,818	***3,905***
	Conditions	***96,698***	3,931
AUC (range)	**Metric**	0.804 to 0.819	0.736
	Conditions	***0.829 to 0.847***	***0.778***

For the administrative data, the individual conditions model outperforms the metric models for all observed parameters, suggesting that the individual condition breakdown of the CDS-H2 performs well at predicting informal care transition outcomes. For the survey data, the same is observed in that the individual condition model is the best performing for two of three parameters (with the BIC difference being considerably smaller), and that it also outperforms the metric weighted condition model (table 7.17). This suggests that individual self-reported conditions in survey data perform well, and almost to the standard of a clinically developed medication index.

7.3.3. Nested regression for transition into informal care using administrative data with condition combinations

The following presents odds for condition combinations from models in 7.3.2 that take the three most strongly associated conditions from the model in the administrative data with transition into informal care and interacts all other conditions (with co-morbid frequency of 100 or above and with conditions with a prevalence of >1%) with that condition, in one model per main or "index" condition. The

models are again identical to those from 7.2, except that the multimorbidity score is replaced by the condition and its interactions. Other interactions continue to use the metric multimorbidity score. Whilst it was initially planned to have two sections (one for each dataset), no conditions were comorbid with the three conditions used from the survey data. Therefore, these results are omitted.

The analyses below answer the research question because they examine "comorbidity" of people with the most strongly associated conditions, and which comorbid conditions in particular have an additional effect on the likelihood of transitioning into informal care.

As shown in table 7.15, the three most strongly associated conditions with transition into informal care are dementia, depression, and epilepsy.

Conditions excluded from model by way of being index condition or having two few occurrences are in *italics.*

Table 7.18: Odds ratios for condition combinations predicting transition into informal care using administrative data

CDS-H2 condition		OR for interactions with dementia	OR for interactions with depression	OR for interactions with epilepsy
Index condition		***27718.57***	***194.06***	***253.56***
Coronary and peripheral vascular disease		1.09	***1.44***	***1.44***
Epilepsy		0.92	***1.38***	Index condition
Hypertension		***1.34***	0.99	0.83
Tuberculosis		Excluded	Excluded	Excluded
Rheumatoid arthritis		1.27	***1.36***	0.91
HIV		Excluded	Excluded	Excluded
High cholesterol		1.13	1.05	0.88
Parkinson's disease		***1.38***	***1.48***	***1.65***
Renal anaemia/neutropenia		Excluded	Excluded	Excluded
Heart disease		***0.78***	1.04	***1.25***
Diabetes		0.85	***1.24***	***1.27***
Glaucoma		1.09	1.10	1.22
Pancreatitis		Excluded	Excluded	Excluded
Renal failure		Excluded	Excluded	Excluded
Ulcers		1.03	1.01	***1.32***
Transplants		Excluded	Excluded	Excluded
Respiratory illness/asthma		0.93	0.98	0.87
Hyperthyroidism		Excluded	Excluded	Excluded
Gout		0.92	0.93	0.86
Crohn's disease/inflammation		1.16	1.14	0.93
Pain/inflammation		***1.25***	***0.81***	***0.67***
Depression		***0.86***	Index condition	***1.24***
Dementia		Index condition	***3.19***	***2.91***
Mania		Excluded	Excluded	Excluded
Anxiety/tension		1.02	***1.45***	***1.23***
Pain		***0.81***	***1.20***	***1.20***
Comorbid conditions + proportion of total	All	6 35.29%	9 52.94%	10 58.82%
	Increase only	3 17.65%	8 47.06%	9 52.94%

Significantly associated categories are in bold italics.

For dementia and depression, few comorbid interactions are observed (table 7.18), and less carrying an increased risk of transition into social care (16% and 47% for dementia and depression respectively). As speculated for social care (table 6.11), the greatly enhanced individual risk of dementia, when all other comorbidities are accounted for (combined with the smaller size of dataset and less reliable outcome measure) may mean that any observed interaction effects are not meaningful. Dementia is also associated with a high increased risk when comorbid with depression (3.19) and epilepsy (2.91). Epilepsy has a number of risk-increasing conditions, similar to that observed for transition into social care.

7.4. Research question 3: Is linked administrative or linked survey data able to better predict informal/co-resident care of older people in Scotland?

This analysis is again unique to chapter 6 and focuses on cross-comparison of models focusing on comparing the ability of administrative or survey data to predict informal, or co-resident care use.

7.4.1. Comparison regression for informal care between administrative and survey data

The following presents a further model comparison between the ability of administrative and survey data to predict informal care. In order to do this, two models containing equivalent variables for each (or as close approximations as possible), for the most predictive model from each outcome. The administrative data models do not contain a "control variables" model (which was the most predictive in the survey data), so the interaction model was used, which was the most predictive in the administrative data and the second most predictive in the survey data.

The SIMD in the administrative model was changed from deciles to quintiles (as this is what is available in the survey data), and removed the "control" variables from the survey model (as there is no equivalent in the administrative data). Therefore, both models contain the following:

- Age (count)
- Sex (binary)
- SIMD (dummy quintile variables, SIMD 5 excluded as reference)
- Multimorbidity measure (continuous)
- Age (quadratic)
- Age*female interaction
- Age*multimorbidity interaction

The only differences between the models are that the survey model still contains the survey cycle, the administrative model is panel data (to control for repeated measures) and that the multimorbidity variable is different for each (CDS-H2 in the administrative data, weighted self-report in the survey data), as these were the two most predictive measures. In addition, the outcome is slightly different: receipt of informal care in the year following the index date (administrative data), receipt of informal care from a member of the same household at the interview date (survey data).

The odds ratios from the full models (bar constant) are presented in table 7.19, as well as the AUC (range) for each to evaluate model prediction. Models with and without interactions are presented; this is because in the original models the non-interaction model performed best for the survey data, whilst the opposite was observed for the administrative data.

These analyses answer the research question as they examine differences in how individual characteristics predict informal/co-resident care outcomes (via the odds ratios of each variable) as well as whether administrative or survey data is better at predicting the outcome in similar models (via the AUC).

Table 7.19: Model results from identical models in predicting transition into/receipt of informal/co-resident care in administrative and survey data

Variable	Non-interaction models		Interaction models	
	Receipt (survey)	**Transition (admin)**	**Receipt (survey)**	**Transition (admin)**
Age in years	***1.02***	***1.14***	1.16	***1.54***
Age (quadratic)	*Excluded*		<1.00	***<1.00***
Female	***0.71***	***1.18***	1.87	1.64
SIMD 1	1.11	***1.42***	1.09	***1.38***
SIMD 2	0.96	***1.48***	0.95	***1.44***
SIMD 3	1.16	***1.32***	1.15	***1.30***
SIMD 4	<1.00	***1.24***	<1.00	***1.23***
Multimorbidity score	***1.33***	***>1.00***	***1.67***	***>1.00***
Age*female interaction	*Excluded*		0.99	<1.00
Age*multimorbidity interaction	*Excluded*		<1.00	***<1.00***
2012-14 cycle	0.85	*N/A*	0.85	*N/A*
AUC (range)	**0.761**	**0.803 to 0.818**	**0.760**	**0.803 to 0.819**

Significantly associated categories are in bold italics.

Reference categories: male, SIMD 5, 2008-11 cycle

As observed in table 7.19, the administrative models have superior predictive ability than the survey models, with good prediction (0.8-0.9) compared to acceptable (0.7-0.8) observed for non-interaction and interaction models. However, this distance is relatively small given the size of the administrative dataset compared to the survey, and suggests that survey data can be adequately used to predict care receipt outcomes if administrative data is unavailable.

In the survey models the only variable significantly associated with the outcome in both is the multimorbidity score. Age and female are predictive in the non-interaction model but this affect disappears in non-interaction models (notably, the effect of being female is the inverse of in the administrative model, but this is likely down to the outcome itself – men are more likely to be cared for by female spouses as they will reach the end of their healthy life expectancy earlier) whilst all variables are significantly associated in the administrative model (bar gender when interactions are again controlled for).

The likely explanation for the differences observed in the models is as much the differences between the two outcomes measures and the smaller survey dataset as coding accuracy in the data. Inclusion in the administrative cohort was dependent on non-receipt of care in the prior year, which will have excluded long-term informal care recipients prior to the beginning of the data window; there is no such restriction in the survey window, and as such the overall health of the survey cohort may be worse as the administrative data will typically capture people who are either healthy or close to requiring care. In addition, the informal care variable in the administrative data captures care receipt from people both in and outside the recipient's residence, whilst the survey data only captures co-resident care. Older people in more deprived areas are also more likely to live alone, and the construction of the variable used in the survey eliminates this as a predictor when it may have likely played a part. The small size of the survey dataset in comparison to the administrative data may also be responsible for a number of non-generalisable results, predictive power of which could be improved using a larger dataset. Future research would benefit from using an informal care outcome in survey data that is derived from the care recipient rather than a member of the same household, and from survey analysis with a greater sample size.

7.5. Discussion

Following analysis in the sections above, six key findings were identified. These are summarised in table 7.20, and elaborated on further in the below sub-sections.

Table 7.20: Research questions from chapter 5 and key findings

Research questions	Key findings
• Which multimorbidity measure(s) best predict informal/co-resident care uptake in older people in Scotland using linked administrative data and linked survey data?	• The overall predictive ability of multimorbidity for informal care in administrative data is the highest in the study, with similar between-measure performances to social care • The self-response measures predict co-resident care uptake to an acceptable standard in survey data, whilst diagnosis-based measures perform poorly
• What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal/co-resident care?	• A non-linear effect of multimorbidity on informal/co-resident care was found in both datasets when recoding the variable to categorical • Individual condition models outperform metric models, but the most predictive conditions differ between datasets • Few comorbidities were found in predicting transition into informal care in the administrative data except epilepsy; no interactions were found in the survey data
• Is linked administrative or linked survey data able to better predict informal/co-resident care in older people in Scotland?	• Far more variables were predictive of transition into informal care in admin data than receipt of co-resident care in survey data

7.5.1. The overall predictive ability of multimorbidity for informal care in administrative data is the highest in the study, with similar between-measure performances to social care

The CDS-H2 was the best performing measure in predicting transition into informal care in administrative data, followed by both proxy measures, with similar performance between diagnosis-based and medication-based indices. Three of the six multimorbidity measures had acceptable-to-good prediction, whilst in all years the prediction of the CDS-H2 was good (>0.8), the highest overall performance of the multimorbidity scores for any outcome in the study. These results were similar to that for transition into social care as shown in chapter 6; given that many underlying characteristics will be associated with risk of both types of care, it is not unsurprising that the results are similar. However informal care prediction was overall greater than social care, which only produced results at the high end of the "acceptable" scale. This would suggest informal care can be predicted most

effectively and consistently by a wide range of multimorbidity outcomes, more so that mortality, healthcare utilisation, or other care transition outcomes. Multimorbidity would appear to explain a large proportion of variance in transition into informal care, however measured.

However, it is possible that the improved performance of the multimorbidity measures in predicting informal care may be more closely attributed to the high levels of outcome missingness in the cohort; given the wide spectrum of what is considered informal care, alluded to by the wide inclusion criteria for the "carer" variable within the SCS (Scottish Government 2015) and that many carers, particularly women, or those who care for longer or for particularly dependent recipients are likely to under-report care provision (Rutherford & Bu 2017), those flagged as receiving informal care may primarily correspond to situations when unambiguous care is provided, providing an inaccurate depiction of the outcome as represented within the cohort. It is likely that social construction of what is considered care, similar to discussions regarding disease and multimorbidity in chapter 3, also apply here. It is conceivable that for many informal carers, the definition of care only extends to services solicited from an agency or local authority with no personal involvement in the care recipient's life, and does not apply when the same service is voluntarily provided by a family member or friend, with different terminology used such as "looking after" someone (Rutherford & Bu 2017). Given this, these and subsequent results should be treated with caution; ambiguity over what is considered "care", as outlined in the numerous potential scenarios above, may have led to significant underreporting.

If it were to be assumed that data for informal care are missing at random, one potential interpretation of these findings, when compared to similar results for the health care utilisation outcomes in section 5.3.1, would be that informal care is a "worse" or more severe counterpart to social care and reflects worse health status or dependence. However, this assumption is problematic; given that informal care provision is dependent both on situation as well as need. Informal carers are typically female and either a spouse or child of the care recipient (Scottish Government 2015); this will potentially exclude single older people, older women, or those without children, from receiving informal care irrespective of health status. As a result, comparison with formal care as an indicator of poor health, which is provided on a means-tested basis, may not be possible given the demographic differences. Given that increase in informal care provision is typically in response to reduced formal care provision due to lack of services, as has occurred in England (Zigante et al 2021), apparent poorer health status of informal care recipients may instead reflect lack of social care provision in more deprived areas either via lack of resources or decreased visibility of those in poorer health in more deprived areas, with informal care substituted for social care on this basis.

Previous research has compared (either directly or indirectly) whether one variant of care is associated with more adverse health outcomes – Hellstrom et al (2004) found that people receiving home

informal and formal care had lower health-related quality of life (HRQoL) but there was no difference for people only receiving formal care, but Badia et al (2013) found no difference in mortality between a sample of home care participants and only those receiving informal care whilst Asmus-Szepesi et al (2014) found that among hospitalised patients, formal care costs may be slightly higher than informal care costs.

Whilst these findings should be treated with caution, given the issues raised above, they can still potentially inform differences between recipients of informal care and social care beyond demographic characteristics.

7.5.2. The self-response measures predict co-resident care uptake to an acceptable standard in survey data, whilst diagnosis-based measures perform poorly

In the survey data, medication data was not available; instead, self-report and limited diagnosis-based scores were used instead. As the diagnosis-based measures were derived from only the initial admission for a select list of conditions, it is not unexpected that the survey-based measures performed better. Overall prediction of the self-report measures was mid-acceptable (around 0.75), with the weighted non-grouped measure performing above 0.75 – this was comparable to the predictive ability of multimorbidity measures in the admin data for 2+ emergency admissions or 7+ hospital days, and outperformed prediction for measures such as admissions and 1+ emergency admissions. Whilst not as high as in the administrative data, this suggests that in the absence of comprehensive population data surveys and self-reported multimorbidity measures can be used to accurately predict co-resident care outcomes.

The lower sample size, the fact that this was not a whole population sample, and difference in outcome (co-resident as opposed to informal care as a whole) may have impacted overall predictive ability of the survey-based measures in comparison to that observed for transition into informal care in the administrative data. However, it could also be possible that as there is less missing data in the survey, compared to high missingness in the administrative data, means that the severity of the informal care outcome is not artificially inflated, and that a value approaching 0.75 is more reflective of the actual impact on health of informal care receipt.

The finding that the weighted version of the self-report score in the SHeS is the best performing is consistent with previous observations in this study, in that the weighted multimorbidity indices usually outperformed the non-weighted ones (though weighted and non-weighted versions of the same score were not compared in administrative data). The application of part of Sangha et al

(2003)'s self-administered comorbidity questionnaire adds value to the score and improves its predictive ability, to the point where it outperformed both the original and grouped condition counts. Additional weighting of the question in the survey as in Sangha's paper, if the respondent is receiving treatment for their condition, may further improve the predictive ability of the measure, should it be included in future iterations of the SHeS.

Diagnosis-based measures did not perform to the same standard as in the administrative data, with prediction averaging around low 0.6 (poor) with the CCI-7 marginally the best performing. The overall performance of the diagnosis-based measures was the lowest in the whole study; this is highly likely to be the result of that a very limited set of indicators were used, with only the first incidence of an admission for a list of particular conditions recorded. Unrecorded conditions could have first occurred in the SMR prior to the five-year window, and conditions that did not appear in the list but were in the full CCI/EI will have been ignored altogether. It is surprising that, given these limitations, prediction was not nearer to 0.5 (indicating no discrimination ability). Future research could re-examine these outcomes and link the SHeS to full SMR data, or alternatively expand the lookback period for the limited SMR dataset to all historical admissions.

7.5.3. A non-linear effect of multimorbidity on informal/co-resident care was found in both datasets when recoding the variable to categorical

As with all outcomes in this study, the effect of multimorbidity on transition into and receipt of informal care was non-linear in both datasets. In the administrative model those with a CDS-H2 score of 6500-8000 (around 9% of the population) were 40 times more likely to transition than those with a score of 0, and those with 8000 or more (approximately 4% of the population) were over a thousand times more likely to transition (table 7.12). The score for 6500-8000 is similar to that observed in the social care model, but the score for 8000+ is much larger. This suggests that those at the extreme end of the multimorbidity score are far more likely to transition into informal care use than social care, though as mentioned above high levels of missingness may have impacted the result.

In the survey dataset (table 7.13) a non-linear effect was again observed to an extent, though due to the fact that interaction terms were not used (as the model performed more poorly if they were added) the difference between the reference and most extreme category is not as large. Those with a weighted self-report score of five or more are 27 times as likely to be in receipt of care in this model as those with a score of zero. As the models are not identical, cross-comparison between this and the administrative dataset is not possible; a larger effect may be observed in models with interactions – something that future research could look at in survey data.

7.5.4. Individual condition models outperform metric models, but the most predictive conditions differ between datasets

Informal care models using individual conditions performed more strongly than those with scores in both administrative and survey data (table 7.17). In the administrative data, the AUC range of the individual condition model (0.829 – 0.847) improved on the metric model (0.804 – 0.819), with similar results for the survey models (0.778 for individual conditions compared to 0.736 for score). This suggests that the information lost via weighting individual conditions is compensated for by including them as dummy variables in both types of data.

In the administrative data, similar results were found for which conditions are strongly associated with transition into informal care (table 7.15) compared to for social care. A very large risk is found for dementia (OR 8313.18 [4030.07 – 17148.33]), larger than the strength of association found for the same condition with social care. Whilst risk associated with other conditions is somewhat overshadowed by the importance (and dominance) of dementia, it is still of note that depression (OR 12.20 [6.19 – 24.05]), is associated with an elevated risk compared to that for social care. Symptoms of depression may be more visible to potential informal caregivers, who will typically have a close relationship with care recipients as family members or spouses, whilst in a formal setting the individual may not seek out formal care provision as they do not believe they have mental illness, or feel ashamed of admitting to depression (Murray et al 2006). Alternatively, increased depressive symptoms may reflect difficulties with co-ordination arising from overly large care networks (Andersson & Monin 2018); given that informal carers are less likely to be trained professionals, situations where many carers are involved with one person may present a greater chance of poor co-ordination and more conflicting approaches toward caring for the recipient, increasing the risk of poor psychosocial well-being. This may explain why the strength of association between depression and informal care is stronger than that for social care.

In the survey model (table 7.16) COPD, “other” nervous system problems and mental illness/depression were the strongest predictors (bar “unclassifiable” conditions). COPD, a respiratory condition, is not included in the CDS-H2; “other” nervous system problems are likely to include dementia-related conditions (despite the fact that it is primarily neurological). This reflects both the administrative data results and previous literature which strongly associates dementia with need for care (Kasteridis et al 2015).

Mental health or neurological conditions such as dementia and depression are strongly associated in both indices, which is expected – the strong link between mental health conditions and uptake of care has been established here and throughout. There are few conditions which are common to both

models, however, making cross-comparison difficult. Future research would benefit not just from making an index developed from a Scottish population for use with both diagnosis and medication data, but also from a variant which uses similar conditions from self-report surveys. A harmonised national set of multimorbid conditions would be a useful addition to future national surveys, and may provide a less resource-intensive alternative to individual risk prediction than SPARRA/pHHG when required.

7.5.5. Few co-morbid interactions were found for administrative data except epilepsy, and none in survey data

The three most strongly associated conditions with transition into informal care as per table 7.15 were dementia, depression, and epilepsy. Of the comorbid interactions included in each model, relatively few were significantly associated with transition into informal care (36%, 53% and 59% for dementia, depression, and epilepsy respectively) and less were associated with an increased risk (18%, 47% and 53% for dementia, depression and epilepsy respectively). Compared to the equivalent results for transition into social care (table 6.11), there are less comorbid interactions with dementia. Risk-limiting comorbidities (heart disease, depression, pain) are still observed for dementia, and the same interpretation (of this being a reflection of a less dominant/severe state of dementia) still applies. Of the eight conditions carrying an increased risk of transition into informal care for those with depression, six (vascular disease, epilepsy, rheumatoid arthritis, Parkinson's disease, diabetes, pain) are physiological, emphasising the dual physical/mental nature of comorbidity in older people at risk of care, as in previous chapters. Depression will make it more difficult to manage other comorbid conditions such as pain (Turner et al 2005), increasing the cumulative likelihood of receiving informal care the following year. The proportion of comorbidities with epilepsy are similar to that observed for social care in chapter six, most of which are risk-increasing. This, combined with the low individual risk of epilepsy (253.36) compared to dementia suggests that comorbid conditions may have a greater impact on functional status of the individual compared to more "dominant" conditions.

The smaller size of the cohort in general compared to chapter 5 and 6, and high levels of missing data for the transition into informal care outcome, may also impact whether these results can be generalised. It is unlikely that less comorbidities are found in people transitioning into informal care compared to social, and further research using a more robust measure of informal care may produce more fruitful findings.

All interaction models for receipt of co-resident care in the survey data produced no significantly associated comorbid interactions. As established, interaction terms in survey models were generally nonsignificant throughout, likely due to the low size of the dataset. A large number of the two-way

interactions in the dataset had very low cell counts and were therefore excluded, and the conditions that were included in the models still had cell counts of generally below 100. As shown with the administrative data interactions were found for almost all conditions, so it is unlikely that there are none when using a different type of data. Grouping similar conditions together, or a larger sample size, may produce significant interactions in future research.

7.5.6. Far more variables were predictive of transition into informal care in admin data than receipt of co-resident care in survey data

When comparing predictive ability of the survey and administrative models side-by-side, the administrative model had acceptable-to-good prediction compared to the survey model which had acceptable prediction. Whilst this would suggest that survey data despite limited coverage of the population and a low sample size performs on the whole at a comparable level to large-scale administrative population data, the individual variables within the survey model explain little variance. Whilst all variables in the administrative data were significantly associated with the outcome bar sex and the age-sex interaction in the interaction model (albeit probably because of the large population size, with very small effects for some) only the multimorbidity score, and no other variables, were significantly associated with co-resident care in the interaction model (age and sex are associated in the non-interaction model). This suggests that multimorbidity is a strong predictor of receipt of informal care by a member of the same household, to the point where it controls entirely for the effect of all other circumstances, at least in the small sample used. If a larger sample size was available, significant (but small) associations for some other variables may have been shown.

Deprivation, ordinarily a strong predictor of adverse health outcomes, as noted throughout this study both in previous literature and in analyses, is not associated with co-resident care use in the survey data. This may have been as a result of the outcome measure rather than an absence of inequality in informal care provision. As mentioned previously, the variable measures receipt of informal care from a member of the same household, thereby excluding care received from people who do not live with potential recipients such as relatives. The outcome is therefore conditional on whether or not someone lives with the recipient and whether they too are able to provide care. In Scotland women, older people, and those in more in deprived areas are more likely to live alone (NRS Scotland 2019), and informal care providers are typically female relatives (Scottish Government 2015) and as such the outcome itself may already be controlling for the effect of these variables. However, living alone is also associated with multimorbidity, so it is likely that the effect of multimorbidity is still stronger than all these other variables.

Future research in this area would benefit from using survey data with access to an informal care variable that is asked of the potential care recipient, rather than one derived from respondents in the same household who provide care. The inclusion of these questions in future waves of the SHeS would be helpful in this regard.

7.5.7. Conclusion

In this chapter it is demonstrated that admission-based and mediation-based multimorbidity scores derived from Scottish routine data may be used to predict transition into informal care, though these results should be verified in other samples due to less-than-satisfactory data quality. Survey-based measures of multimorbidity perform adequately at predicting co-resident care in older people, demonstrating a viable alternative if administrative data is not available. There is again an exponentially strong risk of dementia for transition into informal care, though less comorbid risk-increasing conditions were observed, and strong associations between COPD and other nervous system conditions with co-resident care. Though methodological issues are apparent, the findings presented here can be used to inform future research regarding development of risk prediction algorithms for informal or co-resident care.

Chapter Eight–- Conclusion

Over the course of thesis it has been established using multimorbidity to predict health and social care is a complex and multifaceted process, and provided some answers to the main gaps in previous literature. This chapter sums up the main conclusions discussed in the previous chapter, by way of a "key findings" section which also gives an overview of implications and next steps for policy and research. This chapter will also discuss the limitations of the study, and sum up the study in a "concluding remarks" section.

8.1. Key findings and implications for policy/research

In chapter 2, eight research questions for this study were identified based on gaps in the literature, and were subsequently answered, and discussed, in chapters 5-7. This section – via table 8.1 below and accompanying text – will summarise the key findings pertaining to each research question and the implications for policy narratives and future research.

Table 8.1: Research questions and key findings across study

Research questions	Key findings
Which multimorbidity measure(s) best predict mortality & healthcare utilisation outcomes in older people in Scotland using linked administrative data?	• All multimorbidity measures generally perform well • Proxy outcomes perform best for healthcare utilisation, whilst the CCI performs best for mortality • All measures, but particularly diagnosis-based, have greater predictive ability when the outcome is more severe
What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with mortality & healthcare utilisation outcomes?	• People at the extreme end of multimorbidity scores are disproportionately more at risk for all health outcomes • It is difficult to determine which conditions are most strongly associated overall as conditions in indices vary • COPD, pain, and dementia have most comorbid interactions with health outcomes
Which multimorbidity measure(s) best predict transitions into social care in older people in Scotland using linked administrative data?	• Prediction for social care is high across all multimorbidity measures, but CDS-H2 performs best
What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with transition into social care?	• People at the extreme end of multimorbidity scores are disproportionately more at risk for transition into social care • Dementia is strongly associated with transition into social care, far more so than other conditions

	• Epilepsy and dementia have the most comorbid interactions with transition into social care
Does the effect of multimorbidity on transitions into social care differ by deprivation at data zone and/or local authority level?	• When controlling for data zone deprivation, there is an inverse effect of multimorbidity on transition into social care by overall deprivation level of local authority
Which multimorbidity measure(s) best predict informal/co-resident care uptake in older people in Scotland using linked administrative data and linked survey data?	• In administrative data prediction for social care is higher across all multimorbidity measures than all other outcomes in study, but CDS-H2 performs best • In survey data weighted self-report score performs best, and limited diagnosis-based measures perform poorly
What multimorbidity scores and/or conditions/combinations of conditions are most strongly associated with informal care?	• People at the extreme end of multimorbidity scores are disproportionately more likely to receive informal care, though this is less pronounced in survey data • Mental illness/nervous system conditions are generally the most strongly associated across both datasets, but few comorbid interactions were observed
Is linked administrative or linked survey data able to better predict informal/co-resident in older people in Scotland?	• Administrative data produces model with best predictive ability, but both perform at least moderately • No variables are significantly associated with co-resident across both models in survey data bar multimorbidity, whilst almost all variables are significantly associated in administrative data

When predicting health outcomes, all multimorbidity measures used performed well overall, and that there was usually at least one measure with at least acceptable prediction (AUC of 0.7-0.8). Whilst the Charlson Comorbidity Index (CCI) outperformed all other measures for mortality, proxy measures, whether diagnosis-based or medication-based, performed best for all healthcare utilisation outcomes. The more "severe" a health outcome (such as two or more admissions compared to one or more), the greater overall predictive ability of the multimorbidity measures, particularly in diagnosis-based measures, which performed more poorly than medication-based healthcare utilisation outcomes with lower severity but vice versa for outcomes with higher severity. Whilst the CCI is generally a good fit for predicting mortality, it would be preferable for a measure to be constructed which was derived from a Scottish population using both diagnosis-based and medication-based flags, in order for consistent use for all health outcomes. The differences, however small, will impact predictive ability and improve efficiency of services (Schneeweiss et al 2004). However, when healthcare officials are not concerned with specific conditions proxy counts of medications will suffice. Policymakers should consider these findings when identifying multimorbidity within the population; the health targets they are looking to meet should inform their method for identifying multimorbidity. The discussion of the

literature regarding policy in chapter 2 notes that those with multimorbid conditions were identified as most benefitting from integrated care, but that there was no strategy for systematically identifying this group. The population-level associations of multimorbidity scores and conditions with health and care outcomes found within this study will allow policymakers and health/social care workers to assess and predict demand for care, and imminent health risk, based on a relatively short window of health care utilisation data.

There was a non-linear effect of multimorbidity for all health outcomes, with people at the extreme end of the multimorbidity scale disproportionately more at risk; care providers should prioritise provision of integrated care to those at this end of the scale, as they are most at risk for all outcomes. In terms of specific conditions, a number of different associations were found but it was difficult to cross-compare across outcomes (even varying levels of severity) if the same index was not used, given the variation in conditions. Similar results were observed with comorbid interactions, but generally speaking COPD, pain and dementia had the most significant comorbid interactions with health outcomes. These findings lend further weight for a need to develop a national multimorbidity index with harmonised conditions of interest.

It has been mentioned throughout this thesis that risk prediction for a number of healthcare utilisation outcomes such as emergency admission and bed days exists in Scotland in the form of SPARRA, and within this a "frail elderly" cohort of those aged 75 and above. Whilst evaluations of SPARRA show acceptable specificity and sensitivity, and more so in older cohorts (Liley et al 2021), the algorithm has not been updated in over ten years, with the latest version (SPARRA v3) developed in 2011 (ISD 2011). Whilst efforts to incorporate machine learning into the risk factors for hospital admission within SPARRA are ongoing (Liley et al 2021) this approach, considerably more complex than its predecessor, only shows small improvements in performance.

SPARRA v3 uses admissions, prescribing, emergency department and outpatient data to develop risk of a number of HCU outcomes for three cohorts, one of which is the "frail elderly" cohort described above and another is a "long-term conditions" cohort, consisting of all those aged 56-74 and those 16-55 with at least one emergency department attendance. Inclusion criteria when deriving the risk prediction algorithm was anyone in Scotland who appears at least once in any of these datasets par psychiatric admissions (SMR04), totalling 3.5 million people. Whilst there are identifiers in SPARRA for specific BNF medication chapters as well as a count of unique medications per chapter, and both admission and medication identifiers for conditions including dementia, there are no weighted composite multimorbidity scores, nor condition combinations. As this thesis has demonstrated, multimorbidity scores whether condition counts or proxy measures perform universally well in predicting a number of different health outcomes, including those used in SPARRA. Whilst for HCU

proxy measures generally performed best (and indeed a form of this is included in SPARRA version 3 in BNF chapters) it is likely that this is as a result, as discussed, of weightings for condition-based indices having less-than-good adaptation outside of their native population. An adapted version of the CDS-H2 in particular may outperform a proxy count, and the addition of this, or specific conditions, to a new version of SPARRA may improve predictive ability. In addition, the algorithm could be expanded to encompass multiple admissions or emergency admissions, where multimorbidity performs with universally better predictive ability as shown by this study. Multiple admissions are a better indicator of poor health among populations with complex combinations of conditions (Ouslander & Maslow 2012), and may be a more effective method of identifying those who will use an exponentially large number of resources. The main aim of the similar and more recent pHHG tool (Public Health Scotland 2020) – identifying those in the population who are in need of anticipatory care – align with the aims of this PhD; however pHHG also uses counts of unique BNF chapters rather than any medication-based index. Despite the established limitations of medication-based condition identification, a refined CDS-H2 or select derived conditions may improve predictive ability of both SPARRA and pHHG.

In terms of multimorbidity and social care, the predictive ability of multimorbidity indices was acceptable in general for social care, but it was the author's adaptation of the CDS-2 (CDS-H2) which performed best. This finding was particularly notable as condition-based medication-based measures have not previously been evaluated in the UK. This suggests that when predicting transition into social care the CDS-H2 is a viable multimorbidity measurement, and one that providers could theoretically use immediately. However, the absence of cancer and liver failure due to logistical reasons and inaccurate estimates of prevalence of conditions such as renal failure suggest that this index should be refined by medical practitioners before being used in a policy setting. A refined CDS-H2 could form the spine of a risk prediction algorithm, similar to SPARRA, for identifying those in the general population who have high care requirements.

As with health outcomes, there was again a non-linear effect of multimorbidity on transition into social care, with the same recommendations as before (focusing on this particular group). In terms of specific conditions, a very large risk from dementia was found, exponentially more so than other conditions, for transition into social care. In addition, dementia and epilepsy had a number of comorbid interactions with transition. Health and social care providers should particularly focus on people with dementia, as they are at high risk of requiring social care. It would also be wise for policymakers to draw up guidelines or action plans for people with dementia or other strongly associated conditions.

Macro- and micro-level effects of deprivation on transition into social care were also found. Increasing deprivation at data zone level is associated with increased likelihood of transitioning, but when controlling for this at LA level an inverse trend of the strength of association of multimorbidity with transitioning was observed, by the overall deprivation of each LA. This suggests an "inverse intervention" effect, with future research advised to examine why in particular this is the case. Local authorities with higher overall deprivation should be identified for better provision of integrated care, as the lower strength of association of the multimorbidity variable suggests that people who require care are being missed for potential assessment in deprived areas.

When looking at multimorbidity and informal or co-resident care, it was found that in the administrative data overall prediction was higher than for any other outcome in the study and between-measure trends were identical to social care, with the CDS-H2 performing best (though this may have been confounded by a high proportion of missing informal care data, giving an underestimation of the proportion of people receiving informal care). In the survey data, the weighted self-reported measure performed better than other non-weighted self-reported measures, with the limited diagnosis-based measures performing poorly. This suggests that health and social care providers can adequately use self-report data in the absence of more complex administrative tools. Policymakers should consider utilising self-report methods such as questionnaires in order to identify need for care in, for example, high deprivation areas, when administrative data is not available, or the processes involved in obtaining such data would be lengthy.

As with health and social care outcomes a non-linear effect of multimorbidity was found on informal and co-resident care, though this was weaker in the survey dataset (though likely as a result of exclusion of interaction effects in the model). As with the health outcomes, it was difficult to determine conditions associated with increased risk of informal/co-resident care over both datasets, as the conditions used in each cohort differed, though mental health or nervous system conditions were common in both. This and other results highlight the importance of providing care to those with mental health or neurological conditions, particularly dementia, as they are highly predictive on their own and can exponentially increase the effect of other conditions. In order to cross-compare it would be helpful to apply a standardised Scottish population index to survey designs as well, reporting the same conditions.

When comparing administrative-based and survey-based models in their predictive ability of informal or co-resident care and performances of individual characteristics, the only variable significantly predictive of receipt of co-resident care across survey models was the multimorbidity variable itself, in contrast to the administrative model where almost all variables were significantly predictive. The composition of the survey outcome (receipt from a member of the same household) is likely to have

compounded the impact of all other variables; future research should either use a survey which has questions regarding receipt of care, or use a future version of the SHeS which has been updated to contain these variables.

8.2. Limitations and next steps

A number of limitations may have impacted both the results of the thesis and potential interpretation. It has been noted already that the adaptations of the CDS and CDS-2 (CDS-H1 and CDS-H2) showed inconsistencies in prevalence estimates with national statistics, in particular renal failure (which is less than 1% compared to 18.5% in McLean et al). In addition, prevalence of dementia (3-4%) is around half of other estimates. Whilst some of these incorrect estimates may reflect genuine coding error, the source of the data and, within that, social construction of disease must be considered. In the context of dementia, specifically, this may reflect lack of diagnosis or adherence to prescribing from perceived stigma or refusal of family members to seek a diagnosis. Conversely, pain may be underreported in the CDS-H2 due to ambiguity as to what "pain" is. It could be argued that pain is a by-product or poor health or a symptom of another condition, rather than a condition in itself; over-the-counter prescribing for pain is common (Hayde-West 2021) and this may reflect extreme rather than typical pain. Some conditions may be primarily treated in-hospital or via management of underlying causes, with no regular community prescribing; examples include cancer (which was excluded from the CDS-H2) or CKD (NHS 2019). Finally, the inherent nature of a medication-derived index (in that it flags medication, not conditions) will greatly impact accuracy and risks misidentification. The absence or unsuitability of certain conditions from medication-based indices in this regard is a major limitation; potential solutions for this are detailed below.

Whilst the principal aim of this thesis (as mentioned in chapter 1) was improving estimation of care and health risk for people with multimorbidity, rather than developing a finished index, the anomalies between some of these conditions in the cohort and in other studies should be noted. Renal failure and renal anaemia/neutropenia as flagged in the CDS-H2 are strongly associated with a number of health outcomes in chapter 5, but in chapter 6, renal failure is not significantly associated with transition into social care (though presenting a very high odds ratio). It may be that either a particularly severe terminal stage of each condition is being reported, hence high odds ratios, or that given the small numbers of cases the results cannot be generalisable due to high variance. Given this, results for these conditions, and CDS-H2 in general, should be interpreted with caution. It is recommended throughout that the CDS-H2 be further refined by a team of clinicians or public health researchers before it is used in further contexts, and possibly updated on a regular basis given frequently changing prescribed medications (Schneeweiss et al 2004). In addition, conditions which are primarily treated

in hospital (such as CKD) or for which medication is not usually prescribed (such as dementia) may have to be excluded. This will impact the relevance of the index, but this can potentially be compensated for with a dual diagnosis and medication-based index. Preliminary findings, and estimates of its predictive ability for outcomes such as social care in this thesis, are promising; in addition, modified CDS scores have been shown to outperform the CCI even for mortality (Iommi et al 2020).

It should also be noted that due to the nature of prescribing in the UK cancer was omitted from the CDS-H2, as well as liver failure due to the drugs included in the original American CDS-2 not being used in the UK. Equivalent condition-specific analyses in chapter 5 have shown that both of these conditions are strongly associated with mortality and healthcare utilisation, and this would also be the case were they included in the CDS-H2, potentially impacting the risk associated with other conditions. Chronic liver disease death rates in Scotland, primarily as a result of alcohol (ScotPHO 2019) are in excess of most other countries in Europe (ScotPHO 2020); whilst alcohol abuse is included within the CDS-H2 it would also be helpful to include liver failure as well. Revisions of this index can include prescribed drugs for liver failure in the UK, incorporate hospital prescribing data if available (such as the hospital electronic prescribing and medications administration system or HEPMA) to account for cancer, or combine medication with diagnosis-based flags such as those used in the CCI or EI. New weightings will greatly improve performance compared to counts, especially in combined indices (Sinvani et al 2018). In general, population-specific weightings would improve performance, more so if derived separately by outcome; attempts to weight the EI have found, whilst overall performance was improved, negative weights were found for some conditions (van Walraven et al 2009). It should also be mentioned that hospital prescribing or diagnosis-only flags for these conditions may only capture late-stage disease and therefore artificially inflate the associated risk.

Frailty or "functional status", mentioned earlier in chapter 2, was not available as a control variable. Frailty is a measure of resilience or ability to recover from a period of ill health or injury, which is gradually depleted through ageing. Functional form is a measure of the individual's ability to carry out certain tasks, and is commonly measured as either personal or instrumental "activities of daily living" (ADLs), such as in the study by Condelius et al (2010) which looked at predictors of healthcare utilisation. ADLs are frequently cited as one of the strongest predictors of health (Condelius et al 2010) and care outcomes (Hellstrom et al 2004), can improve prediction of multimorbidity for mortality (Harvey et al 2020) and may be a bigger predictor of outcomes such as functional decline than multimorbidity (Marengoni et al 2009), though its impact in conjunction with multimorbidity on health care utilisation is minimal in other studies (Harvey et al 2020, Gips et al 2018). Neither the administrative nor the survey datasets contained any way of reliably measuring ADL – the administrative dataset has the indicator of relative need (IoRN) score, but this had high

levels of missing data and would not be effectively used without imputation or reducing the data to a far smaller dataset. Had this study access to a reliably collected measure of frailty, it would have been included in all models as a control variable, allowing for estimation of average risk per condition or condition combination independent of functional status.

The concept of frailty itself, from a social constructivist perspective, could be misconstrued as a disease given that it impacts one's overall long-term health. However, it is accepted that frailty is not disease itself but rather a syndrome which presents decreased resilience to disease or injury and increased likelihood of permanent physiological decline as a result (Fried et al 2001). Frailty is separate from multimorbidity (Fried et al 2001); whilst the majority of frail adults have multiple conditions, most multimorbid adults are not frail (Vetrano et al 2018). Some conditions will be more closely associated with, and exacerbated by, frailty than other conditions, and their presence may be diagnosed as progression of frailty and interpreted in these analyses as such. The absence of frailty in this study may artificially inflate the independent risk in conditions in which high levels of frailty are present such as diabetes or cardiovascular disease (Chen et al 2014), and vice versa.

Absence of similar markers of poor health, such as disability (Academy of Medical Sciences 2018) are also important confounders of the impact on multimorbidity, and specific conditions, on health, and could be considered a further limitation of the data. The impact of disability in turn may be impacted by extraneous factors such as accommodation for the disabled person as discussed by Scully (2004); those in deprived areas, impacted by the inverse care law, may not experience as readily available help. Future research using Scottish would greatly benefit from a reliable measure of frailty or other measures of poor health; frailty (as the eFrailty Index) is present in primary care data in Scotland (Henderson et al 2020), but this data is difficult to obtain.

It is noted in chapter 2 that the approach taken to synthesising evidence in literature was atypical in respects to similar studies. The scope of the review was very wide to begin with using broad keywords for multimorbidity, health and social care, narrowing when the main focus of the PhD was decided until key themes and relationships were apparent. This approach may have initially missed key literature, and led to incorrect assumptions regarding multimorbidity predictive ability and health outcomes. This is why a second, more thorough review was undertaken later on when weaknesses were identified, including searching three literature aggregators (PubMed, Web of Science, Medline) and using keywords and search terms sourced from previous reviews and literature. Regardless, the approach taken to summarise literature and identify gaps is consistent with what is expected in the social sciences.

As the administrative data was a panel dataset with repeated measures, an overall AUC measure for direct comparison with other studies was not possible; instead, a range of values for each year was derived. It was felt the strengths of using this study design would allow for greater statistical power given the overall higher case numbers, and the one-year lookback period whilst lowering the overall predictive ability of the multimorbidity measures would not have been overly impacted. Future studies could instead use a much larger lookback period of 5-6 years, which may potentially provide a better approximation of the impact of complex disease (Fortin et al 2012), but this would allow less methodological manoeuvrability for longitudinal analyses – as discussed earlier, previous research has demonstrated that a one-year lookback period allows for an optimum trade-off between predictive power and data used.

Different condition-based indices performed better at predicting different outcomes. As the most predictive index per condition only was used in individual condition and comorbid condition analyses, cross-comparison proved difficult as the number of conditions unique to specific indices was high resulting in potential confounding from conditions absent to these indices. Care has been taken not to cross-compare differential risk of outcomes if the index used (but not the condition) was different; however, some interpretation, such as that comorbidities were common in some conditions, but not others, may not be accurate if comorbid models were run for every health outcome, for example, using the same index. Future research could alleviate this by using a homogenised index detailed above, using multiple indices per outcome (perhaps one diagnosis-based or one medication-based), or persisting with one index rather than many.

Further to this, the potential impact of conditions excluded from indices must also be taken into account. The omission of cancer and liver disease from the CDS-H2 has been discussed, but a number of common conditions were also missing from some or all indices including obesity (CCI), thyroid disorders (CCI, EI), depression (CCI, EI), cardiac arrythmia (CCI, CDS-H2), hypertension (CCI), stroke (all), COPD (CDS-H2), constipation (all), dyspepsia (all), inflammation (CCI, EI) and pain (CCI, EI). Reasons for omission include that some conditions (such as depression) will not have been relevant to the outcome the index was developed before (such as in-hospital mortality in the CCI), whilst other conditions may be difficult to code for with the data available (cancer in the CDS-H2 is the best example of this). It is also important to note that some of the indices, whilst recently adapted, are based on older conceptions of disease, and some such as obesity or drug abuse may not have necessarily be interpreted as a “condition”. This relates back to the earlier discussion of the social construction of disease; symptoms that may be apparent on attendance at a GP clinic, where medication is prescribed, may not be as noticeable (or considered important) to code for on admission to hospital. Pain and inflammation may have been excluded from the CCI/EI as ambiguous terms

which may refer to symptoms rather than a disease, but their inclusion (and association with HCU and social care) in the CDS-H2 suggest otherwise.

Whilst a cumulative impact of omission of all of these conditions on the overall results is difficult, a notable omission from the diagnosis-based indices in particular is mental health conditions such as depression (which was prevalent in the EI, but at a very low rate). The CDS-H2 contains a number of mental health conditions, all with higher prevalence. The first point-of-contact for mental health conditions is a GP, as opposed to hospital (Fleury et al 2012), which may explain higher overall performance of these indices for most HCU and care outcomes. Mental health conditions are generally underrepresented in diagnosis-based multimorbidity indices (Ho et al 2021), which potentially indicates an implicit preference for physiological conditions with unambiguous symptoms, this is problematic especially given high prevalence of physical and mental health comorbidities in deprived populations (NICE 2016) which will be ignored in these indices. Absence of mental health conditions in diagnosis-based models may have missed a number of people with underlying mental health conditions who were admitted as inpatients. A harmonised, cross-data index can potentially alleviate some of these problems, as will an index developed from and including conditions common to a Scottish older population.

The study author considered, but ultimately elected to exclude, separate analyses with a mental/physical multimorbidity split, primarily due to space constraints. As mentioned in the literature review, it has been previously mentioned that mental health and physical multimorbidities should be treated as separate concepts, particularly because the effect of mental health multimorbid conditions is greater in more deprived areas. This could have been investigated further by splitting each condition-based index into separate scores for mental health and physical conditions, but it was decided that composite scores should take priority. As a result, independent risk of physical and mental health conditions could not be estimated in models that only used scores, though some could be done in individual models. This is a potential research design for future studies, particularly if the effect of a physical or mental health multimorbidity score varies both overall and by deprivation.

The sections in this PhD which focused on combinations of conditions only used two-condition combinations rather than cluster approaches, the closest approximation to investigating multi-condition multimorbidity specifically being investigating risk associated with high multimorbidity scores, which are likely to include multiple conditions (i.e. sections 5.3.1, 6.3.1 and 7.3.1). Whilst the benefits of a more complex cluster approach are acknowledged and have been discussed (Prados-Torres et al 2014), it is a very complex analytical procedure, far removed from the other analyses done here, and would have likely required its own chapter on methods, results, and interpretation. Given that investigation of comorbid conditions was not the main focus of this thesis, it was decided

that a simpler two-condition approach be taken along the lines of Brilleman et al (2012), in which strongly associated individual conditions were paired with commonly occurring comorbidities to investigate additional risk. Whilst this helped inform recommendations for inclusion of specific comorbidities in risk prediction models, it is acknowledged that the full scope of multimorbidity was not covered, and many common multimorbidity profiles in excess of two conditions will not have been considered. Some recent reports (NIHR 2021, Whitty et al 2020) focus primarily on multimorbidity clusters; it is acknowledged that the omission of cluster analyses within this thesis is a significant limitation going forward. Future research should build on the findings here regarding new medication-based indices, and once a refined CDS-H2 has been developed (as outlined above) cluster analyses can be run on the same population to investigate this particular avenue further.

It was also noted that in some of the two-condition comorbidity analyses (e.g. mortality in table 5.24 and 2+ admissions in table 5.26), apparent comorbidity was observed between cancer and metastatic cancer, when these two conditions would ordinarily be mutually exclusive. The explanation behind this is that a tumour would have been identified initially in the one-year lookback period for which multimorbidity data is recorded, followed by recording of metastasis later on. This underlines a limitation of the one-year lookback window in which the definition of comorbid conditions is not limited to direct co-occurrence, i.e. in the case of admissions, ICD-10 codes do not have to be recorded at the same admission, but at any point in a twelve-month period. The decision to use a one-year lookback period for multimorbidity was taken based on careful synthesis of previous literature and methodological considerations, and has many inherent advantages to other approaches (see section 3.2.2). There are instances when comorbid conditions may not be simultaneously identified (such as symptoms from a "dominant" condition masking the other, or ICD-10 codes for secondary conditions simply not being recorded by health professionals), but in the case of mutually exclusive conditions this interpretation is wrong and is clarified when necessary.

A minor issue was observed in the hospital days outcome as a result of some incorrect values for length of stay. Whilst syntax was written to fix some incorrect length of stay times in the hospital data, some discharge dates had incorrect years of discharge, creating incorrect length of stay dates that spanned many years. Whilst this was obviously incorrect there was no systematic way of fixing this problem, and as a result a very small number of yearly length of stay values for person-years were recoded as missing if they exceeded 365. Given the low incidence it is expected the impact on results was minimal.

A number of limitations were noted in the SCS. As each local authority would have had to provide data separately (which was not logistically possible in the time frame), probabilistic matching was used with varying rates of success. Some local authorities had incomplete data on day of birth, with

abnormally high instances of the first day of the month being recorded (and hence only month and year could be used). There was a consistent match rate between 92-93% if the year of birth was from 1930-60, with match rates only low if the if the birth year was in the late 1800s/early 1900s. There was typically a high match rate by local authority (barring Clackmannanshire), but some cases failed to match, non-randomly, and will have incorrectly recorded non-use of care. The effect this will have on the results is a slight underestimation of the likelihood of receiving care; this is an unavoidable consequence of electing to use almost-complete care data from the majority of local authorities instead of complete care data from a select group of local authorities. Future research could use samples consisting exclusively of complete care data (i.e. provided on a LA-by-LA basis) from some local authorities, or from one local authority that closely reflects the Scottish population in demographics.

The design of the SCS also presented problems in interpretation. It has been noted previously that the census only captures care receipt in one week of every year (the "census" week). This would therefore not capture dynamic instances of social care use in which the recipient was provided care in between census weeks. This type of care package is becoming more common in Scotland, and estimates by Henderson (2019) for one local authority (Renfrewshire) place this population at 39-43% during the years for which data was used for this study. Henderson goes on to state that care recipients not captured in the census week have, on average, less hours of care provided (24-29 hours per financial year, compared to 71-78 hours in those who were captured in the census week) and are more likely to be older, and male. The potential impact on this study's findings is difficult to quantify, though the duration of care and demographics of missed care recipients suggests an absence of both those who do not require long-term care services (and will therefore be in better overall health), and those who cease to receive home care altogether prior to the census window due to death. Given how social care was measured in this study (social care receipt in one census week if not receiving social care in the previous census week), most uncaptured instances of transition into social care will be short-term care packages, as the cases who died before the census week will likely have been consistently receiving care up until the first instance of non-capture. As a result, the recommendations made by this study (and analyses using the SCS in general) are appropriate for predicting long-term, generally permanent onset of care, as these are usually captured by the census, but will be less suitable for predicting instances of short-term instances of care, for which alternative data should be used.

In addition to this, there was a high amount of informal care data missing per year, at around 70-80%. This likely has resulted in a large underestimation of the number of people receiving informal care, unless "missing" in this case meant "is not receiving informal care"; this cannot be proven either way. Sensitivity checks suggest that this data is not missing at random – the majority of those receiving social care had missing informal care data, whilst only a very small number of those not receiving

social care had missing informal care data. This was a problem that could not be addressed given the volume of missing data, and hence despite the informal care models producing high prediction it may be that these results are not transferrable to the general population. Future research could compare the overall prevalence of informal care to national estimations, or run sensitivity analyses to see whether multimorbidity is predictive of having a "missing" value for informal care. It could be that recording missing as simply not receiving informal care may be a viable option, but this would have required large-scale checks.

An issue with the survey data mentioned previously was that the outcome measure is not a true reflection of receipt of informal care as no such question exists in the SHeS. Rather, this variable was derived from if someone from the same household had identified themselves as providing informal care to the individual, and as such is referred to as "co-resident" informal care. As a result, informal care provided by someone who did not live in the same household was excluded, restricting the measure almost solely to spousal care. The study author recommends that future iterations of the SHeS contain questions directly asking the individual if they receive informal care.

Finally, it should be mentioned that the limited SMR data linked to the SHeS produced largely incomplete diagnosis-based measures, due to ICD-10 codes only being recorded for the first admission to hospital for a list of select conditions. As a result, there was no equal comparison to the self-report measures in terms of the diagnosis data, though they did perform well (AUC of 0.6-0.7) given the circumstances. Future research should consider linking full admissions (and possibly medication) data to the SHeS in order to provide equivalent comparison to the self-report measures when looking at informal/co-resident care (and other) outcomes; however, for this to be meaningful the high missingness of the informal care variable in the SCS would also need to be addressed.

8.3. Concluding remarks

In developing this PhD the study author undertook a thorough review of the challenges facing provision of integrated care to people with multimorbid conditions in Scotland, and found a considerable gap in identifying those with multimorbidities and within that group who was most at risk for adverse health outcomes. With the data available, multiple different measurements of multimorbidities were compared, identifying which had greatest predictive ability for varying health and care outcomes. Different functional forms of these measurements were then observed, such as categorical scales, individual conditions, and comorbid condition interactions, to investigate within the best performing measure which aspects of that measure were most predictive of health and care outcomes.

The resulting thesis provides an overview of which multimorbidity measures (by data source, type of measure and operationalisation of measure) best predict a health and care outcomes, and within those measures which individual conditions, condition combinations and scores are most strongly associated with these outcomes. Patterns were observed in which measures performed best according to type of outcome, type of condition data and severity of outcome, as well as that the impact of multimorbidity on transition into social care varies at macro- and micro-deprivation level. In addition, the predictive ability of models derived from administrative or survey data for informal/co-resident care outcomes were compared. These findings can potentially inform on how best to use available data to provide better care, and who with multimorbidities provision of care should be focused, as well as improving existing risk prediction models for health (and potentially care) in Scotland.

This PhD contributes to the already established literature on multimorbidity and health/care. No study has previously compared predictive ability of multimorbidity measures on a national older population dataset in Scotland, and no studies to date have compared the predictive ability of multiple measures for either social or informal care. In addition, this study is the first in the UK to adapt BNF prescribing data for condition-based medication measures (the CDS-H1 and CDS-H2), finding that the CDS-H2 more strongly predicts transition into both social and informal care than other measures used, though the index needs further refinement to accurately estimate prevalence of some conditions, including renal failure.

This PhD has potential to contribute to policy. Policymakers should, in addition to prioritising provision of care for older people with multimorbidity, determine how they are going to measure multimorbidities and within people with multimorbidities who is most at risk for the health outcome of interest, as this varies depending on what outcome as used. The study findings demonstrate which method of measuring multimorbidities should be used when identifying who in this demographic is most at risk, and within that measure what conditions and combinations of conditions are most predictive of health outcomes. Adequately identifying distinct groups of multimorbidity should be used in future guidelines and protocols on provision of person-centred care.

The primary recommendations for future research are as follows: considering the difficulties in applying one index to an outcome and cross-comparing indices, as well as the overall performance of condition-based indices a national index should be derived from Scottish data, containing conditions relevant to a Scottish population, and containing flags derived from both diagnosis-based and medication-based data. In addition, specifically for transition into social care, that a modified version of the CDS-H2 be considered as part of a prediction algorithm for those in need of care within the Scottish older population.

Appendices

Appendix A1: Summary of literature review, phases 1 & 2

Table A1.1: Terms used in previous searches, categorised

1. Health	2. Social care	3. Multimorbidity	4. Older people	5. Pathways	6. Scotland	7. Deprivation	8. Informal care	9. Comparison
health	"social care"	multimorbid*	elderly	pathway*	Scotland	SIMD	"informal care*"	comparison
"health outcome*"	"home care"	comorbid*	aged		Scottish	"deprived areas"	"unpaid care*"	"systematic review"
wellbeing	"care at home"	"multiple condition*"	"older people"		"NHS Scotland"	depriv*	"family care*"	
admission*	telecare	"multiple medication*"	pensioner			disadvantaged	"volunteer care*"	
"health service*"	"self-directed support"	"multiple ailment*"	ageing				carer	
"health cost*"	"home support"	"multiple disease*"	age*				"young care*"	
hospitalisation	"health care"	"multiple prescription*"	"old* people"					
"clinical care"	"care home"	"long term conditions"	geriatric*					
"hospital care"	caregiver	multimorbidities	"over 65*"					

“hospital admission*”	“care nurse*”	diabetes	OAP*					
“general practice”		hypertension	“old* person”					
clinician		stroke	pensioner*					
“emergency admission*”		cardiovascular						
hospitali*ation		CCI						
“urgent admission*”		“chronic conditions”						
“unplanned admission*”		“multiple illness*”						
“emergency department”		polypharmacy						
“emergency *admission*”		“condition ind*”						
“urgent *admission*”		“Charlson comorbidity index”						
“emergency appointment*”		“Elixhauser index”						
“hospital appointment*”		“chronic disease score”						

“urgent appointment*”		multimorbidity identification bnf codes						
“quality of life”								
wellbeing								
“unplanned *admission*”								
mortality								
death								
surviv*								
admissions								

Table A1.2: Search strings used in previous searches

#	**Search strings**
1a	health
1b	(“health outcome*” OR wellbeing OR admission*)
1c	(“health outcome*” OR wellbeing OR admission* OR “health service*” OR “health cost*”)
1d	hospitalisation
1e	(“clinical care” OR “hospital care” OR “hospital admission*” OR “general practice” OR clinician)
1f	(“health outcome*” OR admission*)
1g	(“emergency admission*” OR hospitali*ation)
1h	(“emergency *admission*” OR “urgent *admission*” OR “unplanned *admission*”)
1i	(“emergency *admission*” OR “urgent *admission*” OR “unplanned *admission*” OR “emergency department”)
1j	(“emergency *admission*” OR “hospital admission*” OR “health outcome*” OR “urgent *admission*” OR “emergency appointment* OR “hospital appointment*” OR “urgent appointment*” OR “quality of life” OR wellbeing OR “unplanned *admission*” OR “emergency department” OR mortality OR death OR surviv*)
1k	((mortality OR admissions))
2a	(“social care” OR “home care”)
2b	(“home care” OR “social care” OR “care at home” OR “telecare” OR “self-directed support” OR “home support”)
2c	“home care”
2d	(“health care” OR “social care” OR “care home” OR “self-directed support” OR “care at home” OR “home care” OR telecare OR caregiver* OR “care nurse*”)
2e	telecare
2f	(“social care” OR “care at home” OR “home care”)
3a	(multimorbid* OR comorbid*)
3b	(multimorbid* OR comorbid* OR “multiple condition*” OR “multiple medication*” OR “multiple ailment*” OR “multiple disease*” OR “multiple prescription*” OR “long term conditions”)

3c	multimorbidities
3d	(diabetes OR hypertension OR stroke OR cardiovascular)
3e	(multimorbid* OR comorbid* OR “multiple * condition*” OR “multiple medication*” OR “multiple ailment*” OR “multiple disease*” OR “multiple prescription*” OR “long term conditions”)
3f	multimorbidity
3g	(multimorbid* OR comorbid* OR “multiple * condition*” OR “multiple medication*” OR “multiple ailment*” OR “multiple disease*” OR “multiple prescription*” OR “long term conditions” OR CCI OR “chronic conditions” or “multiple illness*” or polypharmacy or “condition ind*”)
3h	((multimorbid* OR “elixhauser comorbidity index” OR “elixhauser index” OR “chronic disease score”)))
3i	(multimorbid* OR comorbid* OR “multiple * condition*” OR “multiple disease*”)
3j	multimorbidity identification bnf codes
4a	(elderly OR aged OR “older people” OR pensioner OR ageing)
4b	(elderly OR aged)
4c	(elderly OR age* OR “older people”)
4d	(elderly OR “old* people” OR geriatric* OR “over 65*” OR OAP* OR “old* person” OR pensioner*)
5a	pathway*
6a	(Scotland OR Scottish OR “NHS Scotland”)
7a	SIMD
7b	“deprived areas”
7c	depriv*
7d	(depriv* OR SIMD OR disadvantaged)
7e	deprivation
7f	(depriv* OR SIMD)
8a	(“informal care*” OR “unpaid care*” OR “family care*” OR “volunteer care*” OR carer OR “young care*”)
9a	((comparison OR “systematic review”)))

Table A1.3: Overview of literature searches and papers extracted

Search terms	Approximate date of search*	Papers extracted**
1a, 2a, 3a in Google Scholar	19/02/2015	Mathers & Thomas 2012: Integration of care: a bridge too far?
1a, 2a, 3a in PsycINFO	19/02/2015	**Lupari et al 2011: 'We're just not getting it right' – how should we provide care to the older person with multi-morbid chronic conditions?**
1a, 2a, 3a in Social Care Online	19/02/2015	**Department of Health 2014: Comorbidities: a framework of principles for system-wide action** Kasterdis et al 2014: The importance of multimorbidity in explaining utilisation and costs across health and social care settings: evidence from South Somerset's Symphony Project
1a, 2a, 3a in Social Services Abstracts	19/02/2015	**Hoeck et al 2011: Health-care and home-care utilization among frail elderly persons in Belgium**
1a, 2a, 3a in Sociological Abstracts	19/02/2015	**Gott et al 2007: Patient views of social service provision for older people with advanced heart failure**
1b, 2b, 3a in ProQuest	19/02/2015	**Badia et al 2013: Predictors of mortality among elderly dependent home care patients**
1c, 2b, 3a, 4a in ProQuest	19/02/2015	**Bradshaw et al 2013: Six-month outcomes following an emergency hospital admission for older adults with co-morbid mental health problems indicate complexity of care needs** **Kuzuya et al 2012: Day-care service use is a risk factor for long-term care placement in community-dwelling dependent elderly** **Rosstad et al 2013: Development of a patient-centred care pathway across healthcare providers: a qualitative study** Ruggiano et al 2013: Person-centeredness in home- and community-based long-term care: current challenges and new directions Scalmana et al 2013: Use of health and social care services in a cohort of Italian dementia patients

1d, 2b, 3a, 4a in ProQuest	19/02/2015	Landi et al 2004: Comorbidity and social factors predicted hospitalization in frail elderly patients Levine et al 2012: Home care program for patients at high risk of hospitalization
1e, 2b, 3a, 5a in ProQuest	27/02/2015	Randall et al 2014: Case management of individuals with long-term conditions by community matrons: report of qualitative findings of a mixed method evaluation
1c, 2b, 3a, 4b in Google Scholar	27/02/2015	Onder et al 2007: Case management and risk of nursing home admission for older adults in home care: results of the AgeD in Home Care study
1f, 2b, 3a, 4c, 6a on Google Scholar	27/02/2015	Themessl-Huber et al 2007: Frail older people's experiences and use of health and social care services
1g, 2b, 3a, 4a in Google Scholar	27/02/2015	Koehler et al 2009: Reduction of 30-day postdischarge hospital readmission or Emergency Department (ED) visit rates in high-risk elderly medical patients through delivery of a targeted care bundle Monsen et al 2011: Linking home care interventions and hospitalization outcomes for frail and non-frail elderly patients
3b, 7a in Google Scholar	24/03/2015	**Blane et al 2012: Distribution of GPs in Scotland by age, gender and deprivation** Blane et al 2013: Attitudes towards health inequalities amongst GP trainers in Glasgow, and their ideas for changes in training NHS Highland Board 2015: NHS Highlands 10 year operational implementation plan **Lawson et al 2013: Double trouble: the impact of multimorbidity and deprivation on preference-weighted health related quality of life a cross sectional analysis of the Scottish Health Survey**
2c, 3c, 7b in Google Scholar	03/04/2015	**Orueta et al 2014: Prevalence and costs of multimorbidity by deprivation levels in the Basque Country: a population based study using health administrative datasets** Power et al 2013: An evidence-based assessment of primary care needs in an economically deprived urban community

		Rijken et al 2015: Caring for people with multiple chronic conditions in the Netherlands: policy and practices
2a, 3d, 7c in Google Scholar	07/04/2015	Sidhu & Rao 2010: Variations in admissions for heart attacks and cardiac procedures by ethnicity and deprivation Soljak et al 2011: Does higher quality primary health care reduce stroke admissions?
1h, 2a, 3a in Google Scholar	11/05/2015	Oliver 2012: 21st century health services for an ageing population: 10 challenges for general practice Panagioti et al 2014: Self-management support interventions to reduce health care utilisation without compromising outcomes: a systematic review and meta-analysis Simmonds et al 2012: Factors influencing professional decision making on unplanned hospital admission: a qualitative study
1i, 2d, 3e, 4d in ProQuest	11/05/2015	**Deschodt et al 2015: Characteristics of older adults admitted to the emergency department (ED) and their risk factors for ED readmission based on comprehensive geriatric assessment: a prospective cohort study** Kennelly et al 2014: Characteristics and outcomes of older persons attending the emergency department: a retrospective cohort study **Ouslander & Maslow 2012: Geriatrics and the triple aim: defining preventable hospitalizations in the long-term care population** Teruel et al 2014: Home care programme for patients with advanced chronic kidney disease. A two year experience
1i, 2d, 3e, 4d, 7d in ProQuest	11/05/2015	Bierman & Clancy 2001: Health disparities among older women: identifying opportunities to improve quality of care and functional health outcomes Hung et al 2015: A qualitative study on why did the poorly-educated Chinese elderly fail to attend nurse-led case manager clinic and how to facilitate their attendance

		Pears et al 2003: Gender, age and deprivation differences in the primary care management of hypertension in Scotland: a cross-sectional database study
2c, 3f, 7e in StirGate	24/05/2015	Moran et al 2014: The relationship between activities of daily living and multimorbidity. A view from telecare
2e, 7f on StirGate	24/05/2015	Buckner et al 2013: The impact of demographic change on the infrastructure for housing, health and social care in the north of England Poder et al 2015: Social acceptance and population confidence in telehealth in Quebec
3g on Google Scholar	05/06/2015	**Barnett et al 2012: Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study**
1j, 3g, 8a; search engine not recorded	17/03/2016	**Diederichs et al 2011: The measurement of multiple chronic diseases: a systematic review on existing multimorbidity indices** **Kasteridis et al 2015: Who would most benefit from improved integrated care? Implementing an analytical strategy in South Somerset**
1k, 3h, 9a in PubMed	Date not recorded	**Boyd & Lucas 2014: Patient-centered care for people living with multimorbidity** **Ferrer et al 2017: Multimorbidity as specific disease combinations, an important predictor factor for mortality in octogenarians: the Octabaix study** Fraccaro et al 2017: Predicting mortality from change-over-time in the Charlson Comorbidity Index **France et al 2012: Multimorbidity in primary care: a systematic review of prospective cohort studies** Kirchberger et al 2012: Patterns of multimorbidity in the aged population: results from KORA-age study **Ou et al 2012: Comparative performance of comorbidity indices in predicting health care-related behaviors and outcomes among 243 medicaid enrollees with type 2 diabetes**

		Pratt et al 2018: The validity of the Rx-Risk comorbidity index using medicines mapped to the Anatomical Therapeutic Chemical (ATC) classification system **Willadsen et al 2016: The role of diseases, risk factors and symptoms in the definition of multimorbidity: a systematic review**
2f, 3i in ProQuest	Date not recorded	Collerton et al 2015: Deconstruction complex multimorbidity in the very old: findings from the Newcastle 85+ Study Grundberg et al 2016: Home care assistants' perspectives on detecting mental health problems and promotion mental health among community-dwelling seniors with multimorbidity Lo et al 2016: The perspectives of patients on health-care for co-morbid diabetes and chronic kidney disease: a qualitative study
3j in Google Scholar	Date not recorded	Walker et al 2015: Socioeconomic status, comorbidity and mortality in patients with type 2 diabetes mellitus in Scotland 2004-2011: a cohort study

* Derived from "content created" date of file containing search terms and results

** **Bold**: Included in thesis

Table A1.4: Overview of papers found in reference list of other papers

Source paper	Papers extracted*
Original PhD proposal	**Scottish Government 2014: A route map to the 2020 vision for health and social care**
Blane et al 2013: Attitudes towards health inequalities amongst GP trainers n Glasgow, and their ideas for changes in training	**Mercer & Watt 2007: The inverse care law: clinical primary care encounters in deprived and affluent areas of Scotland**
Bradshaw et al 2013: Six-month outcomes following an emergency hospital admission for older adults with co-morbid mental health problems indicate complexity of care needs	Gladman et al 2010: Days at home: an outcome measure in studies of specialist services providing care for older people Goldberg et al 2011: The prevalence of mental health problems among older adults admitted as an emergency to a general hospital
Brilleman & Salisbury 2012: Comparing measures of multimorbidity to predict outcomes in primary care: a cross sectional study	**Perkins et al 2004: Common comorbidity scales were similar in their ability to predict health care costs and mortality** Reeve & Bancroft 2014: Generalist solutions to overprescribing: a joint challenge for clinical and academic primary care
Diederichs et al 2011: The measurement of multiple chronic diseases: a systematic review on existing multimorbidity indices	**Holman et al 2005: A multipurpose scoring system performed better than the Charlson index** Incalzi et al 1997: The interaction between age and comorbidity contributes to predicting the mortality of geriatric patients in the acute-care hospital **Marengoni et al 2011: Aging with multimorbidity: a systematic review of the literature**
Innes et al 2006: Service provision for people with dementia in rural Scotland: difficulties and innovations	Nemet & Bailey 2000: Distance and health care utilization among the rural elderly
Landi et al 2004: Comorbidity and social factors predicted hospitalization in frail elderly patients	**Landi et al 2001: A new model of integrated care for the elderly: impact on hospital use** **Marcantonio et al 1999: Factors associated with unplanned hospital readmission among patients 65 years of age and older in a Medicare managed care plan** Williams & Fitton 1988: Factors affecting early unplanned readmission of elderly patients to hospital

Lawson et al 2013: Double trouble: the impact of multimorbidity and deprivation on preference-weighted health related quality of life a cross sectional analysis of the Scottish Health Survey	**O'Brien et al 2010: An 'endless struggle': a qualitative study of general practitioners' and practice nurses' experiences of managing multimorbidity in socio-economically deprived areas of Scotland**
Rosstad et al 2013: Development of a patient-centred care pathway across healthcare providers: a qualitative study	Tinetti et al 2004: Potential pitfalls of disease-specific guidelines for patients with multiple conditions

* **Bold**: Included in thesis

The following papers were recommended by colleagues (included in thesis in **bold**):

Bottle et al 2014: Can valid and practical risk-prediction or casemix adjustment models, including adjustment for Fquail, be generated from English hospital administrative data (Hospital Episode Statistics)? A national observational study

Brilleman & Salisbury 2012: Comparing measures of multimorbidity to predict outcomes in primary care: a cross sectional study

Bunn et al 2014: Comorbidity and dementia: a scoping review of the literature

Bywaters et al 2014: Inequalities in child welfare intervention rates: the intersection of deprivation and identity

Bywaters et al 2015: Exploring inequalities in child welfare: the inverse intervention paradox

Bywaters et al 2016: Child welfare inequalities: new evidence, further questions

Chini et al 2011: Can we use the pharmacy data to estimate the prevalence of chronic conditions? A comparison of multiple data sources

Guthrie et al 2015: The rising tide of polypharmacy and drug-drug interactions: population database analysis 1995-2010

Health and Social Care Alliance Scotland 2014: Many conditions, one life: living well with multiple conditions

Huber et al 2013: Identifying patients with chronic conditions using pharmacy data in Switzerland: an updated mapping approach to the classification of medications

Lamers & van Vilet 2003: The Pharmacy-based Cost Group model: validating and adjusting the classification of medications for chronic conditions to the Dutch variation

Salisbury et al 2011: Epidemiology and impact of multimorbidity in primary care: a retrospective cohort study

Scottish Government 2014: My health, my care, my outcomes: multimorbidity action plan

Scottish Government 2014: Social care services, Scotland, 2014

Tonelli et al 2015: Methods for identifying 30 chronic conditions: application to administrative data

Wallace et al 2016: Comparison of count-based multimorbidity measures in predicting emergency admission and functional decline in older community-dwelling adults: a prospective cohort study

Appendix A2: Summary of literature review, phase 3

Table A2.1: Terms used in searches, categorised

1. Multimorbidity indices	1a. Stirland multimorbidity terms	1b. Stirland index terms	2. Health/care outcomes	3. Older people*	4. Predictive ability
"multimorbidity index"	polypatholog*	index	mortality	elderly	precision
"comorbidity index"	poly-patholog*	indices	admission*	"old* people"	"predictive ability"
"multimorbidity indices"	polymorbidit*	measure*	"social care"	"over 65*"	"area under the curve"
"comorbidity indices"	poly-morbidit*	score*	"informal care"	"old* population"	"c-statistic"
"measure* of *morbidity"	multipatholog*		"health*care utilisation"	"age* population"	AIC
"multimorbid* measure*"	multi-patholog*		"social care uptake"	"65 year*"	BIC
"comorbid* measure*"	multicondition*		"informal care uptake"	"age* 65"	"information criteri*"
"multimorbidity score*"	multi-condition*		"hospital days"	"old* adult*"	"ability to predict"
"comorbidity score*"	pluripatholog*		"bed days"		performance
"Charlson Index"	pluri-patholog*		"length of stay"		"comparison of measures"
"Chronic Disease Score"	multiple chronic condition		"health outcome*"		"comparison of indices"
"Elixhauser Index"	"morbidity burden"		"care outcome*"		"predictive validity"
RxRisk			"outcome assessment"		"ROC curve"
"unique prescri*"			"hospital visit*"		"receiver operating characteristic"
"number of medication*"			"emergency visit*"		"reliability of measure*"
"count of medication*"			"health*care utilization"		"validity of measure*"

“Charlson Comorbidity Index”					
“Charlson measure”					
“Elixhauser measure”					

* Not used due to relevant papers being excluded.

Table A2.2: List of search strings used

#	Strings
1	(“multimorbidity index” OR “comorbidity index” OR “multimorbidity indices” OR “comorbidity indices” OR “measure* of *morbidity” OR “multimorbid* measure*” OR “comorbid* measure*” OR “multimorbidity score*” OR “comorbidity score*” OR “Charlson Index” OR “Chronic Disease Score” OR “Elixhauser Index” OR RxRisk OR “unique prescri*” OR “number of medication*” OR “count of medication*” OR “Charlson Comorbidity Index” OR “Charlson measure” OR “Elixhauser measure”)
1a	(polypatholog* OR poly-patholog* OR polymorbidit* OR poly-morbidit* OR multipatholog* OR multi-patholog* OR multicondition* OR multi-condition* OR pluripatholog* OR pluri-patholog* OR "multiple chronic condition" OR "morbidity burden")
1b	(index OR indices OR measure* OR score*)
2	(mortality OR admission* OR “social care” OR “informal care” OR “health*care utilisation” OR “social care uptake” OR “informal care uptake” OR “hospital days” OR “bed days” OR “length of stay” OR “health outcome*” OR “care outcome*” OR “outcome assessment” OR “hospital visit*” OR “emergency visit*” OR “health*care utilisation”)
3	(elderly OR “old* people” OR “over 65*” OR “old* population” OR “age* population” OR “65 year*” OR “age* 65” OR “old* adult*”)
4	(precision OR “predictive ability” OR “area under the curve” OR “c-statistic” OR AIC OR BIC OR “information criteri*” OR “ability to predict” OR performance OR “comparison of measures” OR “comparison of indices” OR “predictive validity” OR “ROC curve” OR “receiver operating characteristic” OR “reliability of measure*” OR “validity of measure*”)

Table A2.3: Conversion of terms in Table 1 to MeSH terms/abstract and title terms for Medline search, and summary of search

#	Original format	Medline format	Hits (11/01/21)
1a. Multimorbidity indices			
1	"multimorbidity index"	exp Comorbidity/	104,842
	"comorbidity index"		
	"multimorbidity indices"		
	"comorbidity indices"		
	"measure* of *morbidity"		
	"multimorbid* measure*"		
	"comorbid* measure*"		
	"multimorbidity score*"		
	"comorbidity score*"		
2	"Charlson Index"	Charlson Index	1,030
3	"Chronic Disease Score"	Chronic Disease Score	123
4	"Elixhauser Index"	Elixhauser Index	50
5	RxRisk	RxRisk	28
6	"unique prescri*"	unique prescri*	30
7	"number of medication*"	number of medication*	2,247
8	"count of medication*"	count of medication*	44
9	"Charlson Comorbidity Index"	Charlson Comorbidity Index	4,451
10	"Charlson measure"	Charlson measure	4
11	"Elixhauser measure"	Elixhauser measure	6
12	1 OR 2 OR 3 OR 4 OR 5 OR 6 OR 7 OR 8 OR 9 OR 10 OR 11		110,504
2a. Health/care outcomes			
13	mortality	Mortality/	25,923
14	admission*	Hospitalization/ or Length of Stay/	144,568
	"hospital days"		
	"bed days"		
	"length of stay"		
	"hospital visit*"		
15	"social care"	Social Support/	60,223
	"informal care"		
16	"social care uptake"	Patient Care/	8,027
	"informal care uptake"		
17	"health*care utilisation"	health*care utilisation	649
18	"health*care utilization"	health*care utilization	3,074
19	"care outcome*"	care outcome*	2,852
20	"outcome assessment"	Outcome Assessment, Health Care/	68,186

21	“emergency visit*”	emergency visit*	1,031
22	“health outcome*”	health outcome*	40,059
23	13 OR 14 OR 15 OR 16 OR 17 OR 18 OR 19 OR 20 OR 21 OR 22		336,982
4a. Predictive ability			
24	precision “predictive ability” “ability to predict” performance	Predictive Value of Tests/	183,730
25	“area under the curve” “c-statistic” “predictive validity” “ROC curve” “receiver operating characteristic”	ROC Curve/	55,443
26	AIC	AIC	1,705
27	BIC	BIC	1,922
28	“information criteri*”	information criteri*	3,281
29	“comparison of measures”	comparison of measures	239
30	“comparison of indices”	comparison of indices	61
31	“reliability of measure*”	reliability of measure*	2,034
32	“validity of measure*”	validity of measure*	1,399
33	24 OR 25 OR 26 OR 27 OR 28 OR 29 OR 30 OR 31 OR 32		235,861
34	12 AND 23 AND 33		549

Table A2.4: Details, dates and summaries of searches performed

Search terms	Date	Results*
1, 2, 4 in PubMed (titles / abstracts only)	12/10/2020	1,164 search results 116 abstracts screened 44 full texts checked further: 11 papers reviewed: Aubert et al 2020: Best definitions of multimorbidity to identify patients with high health care resource utilization **Austin et al 2011: Using the Johns Hopkins Aggregated Diagnosis Groups (ADGs) to predict mortality in a general adult population cohort in Ontario, Canada** **Fernando et al 2019: Effect of comorbidity on injury outcomes: a review of existing indices** Hsu et al 2020: Administrative and claims data help predict patient mortality in intensive care units by logistic regression: a nationwide database study **Huang et al 2020: Predicting the cost of health care services: a comparison of case-mix systems and comorbidity indices that use administrative data** Liu et al 2019: Comparison of measures to predict mortality and length of stay in hospitalized patients **Lu et al 2010: Charlson and Rx-Risk comorbidity indices were predictive of mortality in the Australian health care setting** Schneeweiss et al 2003: Improved comorbidity adjustment for predicting mortality in Medicare populations **Schneeweiss et al 2004: Consistency of performance ranking of comorbidity adjustment scores in Canadian and U.S. utilization data** **Stanley & Sarfati 2017: The new Measuring Multimorbidity index predicted mortality better than Charlson and Elixhauser indices amongst the general population** Zekry et al 2012: Prospective comparison of 6 comorbidity indices as predictors of 1-year post-hospital discharge institutionalization, readmission, and mortality in elderly individuals 8 additional papers unrelated to review retained for thesis: **Chaudhry et al 2005: Use of a self-report-generated Charlson Comorbidity Index for predicting mortality** **Gips et al 2018: Do frailty and comorbidity indices improve risk prediction of 28-day ED reattendance? Reanalysis of an ED discharge nomogram for older people**

		Olomu et al 2012: Do self-report and medical record comorbidity data predict longitudinal functional capacity and quality of life health outcomes similarly? Simard et al 2018: Validation of the combined comorbidity index of Charlson and Elixhauser to predict 30-day mortality across ICD-9 and ICD-10 **Sinvani et al 2018: Using Charlson Comorbidity Index to predict short-term clinical outcomes in hospitalized older adults** **Sundararajan et al 2007: Cross-national comparative performance of three versions of the ICD-10 Charlson Index** Wimmer et al 2015: Medication regimen complexity and number of medications as factors associated with unplanned hospitalizations in older people: a population-based cohort study Yusof et al 2009: Developing a self-reported comorbidity index to predict mortality of community dwelling older adults
1, 2, 4 in Web of Science (titles / abstracts / keywords only)	09/11/2020	1,833 search results 52 abstracts screened 16 full texts checked further 3 papers reviewed: Bari et al 2006: Predictive validity of measures of comorbidity in older community dwellers: The Insufficienza Cardiaca negli Anziani Residenti a Dicomano study **Snow et al 2020: Comparative evaluation of the clinical laboratory-based Intermountain risk score with the Charlson and Elixhauser comorbidity indices for mortality prediction** **Susser et al 2008: Comorbidity information in older patients at an emergency visit: self-report vs. administrative data had poor agreement but similar predictive validity** 2 additional papers unrelated to review retained for thesis: **Harvey et al 2020: Does identifying frailty from ICD-10 coded data on hospital admission improve prediction of adverse outcomes in older surgical patients? A population-based study** **van Walraven et al 2009: A Modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data**
Ovid MEDLINE® without Revisions, 1996 to December Week 5 2020 (see table 2)	11/01/2021	549 search results 33 abstracts screened 5 full texts checked further 3 papers reviewed:

		Corrao et al 2017: Developing and validating a novel multisource comorbidity score from administrative data: a large population based cohort study from Italy **Mnatzaganian et al 2012: Accuracy of hospital morbidity data and the performance of comorbidity scores as predictors of mortality** Yang et al 2014: Which risk-adjustment index performs better in predicting 30-day mortality? A systematic review and meta-analysis 1 additional paper unrelated to review retained for thesis: **Iommi et al 2020: Modified-Chronic Disease Score (M-CDS): Predicting the individual risk of death using drug prescriptions**
1a, 1b, 2, 4 in PubMed (titles / abstracts only)	17/05/2021	30 search results 9 abstracts screened 3 full texts checked further 1 paper reviewed: **Shadmi et al 2011: Assessing socioeconomic health care utilization inequity in Israel: impact of alternative approaches to morbidity adjustment**
1a, 1b, 2, 4 in Web of Science (titles / abstracts / keywords only)	17/05/2021	37 search results 5 abstracts screened No papers reviewed
(1 or 1a, 1b), 2, 4 in PubMed (titles / abstracts only, 12/10/2020 – present)	20/02/2021	232 search results 10 abstracts screened 2 full texts checked further 3 papers reviewed: Girwar et al 2021: A systematic review of risk stratification tools internationally used in primary care settings Novella et al 2022: Relation between drug therapy-based comorbidity indices, Charlson's comorbidity index, polypharmacy and mortality in three samples of older adults Vela et al 2021: Performance of quantitative measures of multimorbidity: a population-based retrospective analysis
(1 or 1a, 1b), 2, 4 in Web of Science (titles / abstracts only, 09/11/2020 – present)	20/02/2021	237 search results 1 abstract screened No papers reviewed

* Papers in **bold** were included in the thesis. Papers were also retained if potentially useful for thesis, but unrelated to specific literature search.

Appendix A3: Sample evaluation and grading of ten papers in literature review

Table A3.1: Data extraction table

Title, author	Categor (ies)*	How study was found**	Aim of study	Cohort, data	Key variables of interest***	Methods ***	Health variable type	Social care type	Multimorbidity type and conditions	Key findings	Relevance to thesis
Brilleman & Salisbury 2012 Comparing measures of multimorbidity to predict outcomes in primary care: a cross sectional study	Measuring multimorbidity	Recommended by colleague	Compare a number of multimorbidity measures in their ability to predict health outcomes using primary care data	Sample of 95,372 patients at English GPs within the General Practice Research Database followed from 2005-08 Primary care data including record of death	Outcomes: Mortality, GP consultations Predictors: Multimorbidity, age, sex, deprivation, general practice	GLM (consultations), logistic regression (mortality), separate models run for each multimorbidity measure and AIC, BIC and deviance based R^2 used to compare performance	Mortality and GP consultations, both measured within three years of baseline.	N/A	Six measures, all historic diagnoses until baseline: Chronic QOF disease count CCI, adapted for Read codes Count of Expanded Diagnosis codes (EDCs) Aggregated Diagnosis Groups (ADGs) Count of unique BNF sub-headings	R^2 ranges from ~20-40 for all measures for both outcomes Prescribed drugs performs best at predicting consultations. CCI performs best at predicting mortality, followed by prescribed drugs.	One of few UK-based studies to use a prescribing measure as well as a HCU outcome. Good reference for evidence that proxy counts perform well. Not age-restricted, and uses GP data as opposed to admissions,

											but still highly relevant.
Bywaters et al 2015 Exploring inequalities in child welfare: the inverse intervention paradox	Deprivation	Recommended by colleague	Explore the "inverse intervention" rule in child protection rates in England	All 4,546 children on a child protection plan (CAP) and 7,210 in out-of-home local authority care (LAC) in 13 local authorities in the midlands of England in 2012 Data structured as 3252 lower super output areas (LSOA), roughly analogous to	Outcome: CAP and LAC rates Predictors: Local authority Deprivation decile and quintile (index of multiple deprivation, IMD) of LSOA/MSOA, average IMD of local authority	Aggregate bivariate analysis of CAP/LAC rates by local authority, within most deprived IMD decile/quintile	N/A	N/A	N/A	Intervention rates increase with overall LA deprivation; however, the inverse is found when restricting to the most deprived quintile or decile of each LA. This does not change when controlling for ethnicity. Suggested that people in more affluent LAs are more	Despite not having much in common with the majority of the thesis, this is a key methodological reference as the results and discussion, inform similar analyses in the social care chapter

				datazones. Also represented as middle SOAs, which are around five times as bigger as LSOAs						visible or feel more shamed into intervening, or that there is greater community support or a higher threshold for intervening in more deprived LAs.	
Deschodt et al 2015 Characteristics of older adults admitted to the emergency department (ED) and their risk factors for ED readmission	General Integrated care	1i, 2d, 3e, 4d in ProQuest (phase 1 & 2)	Determine risk factors for readmission to hospital in an older cohort	Sample of 442 emergency inpatients at a Belgian hospital, aged 75 and above and Dutch speaking. Data based on patient records or	Outcome: 1-month and 3-month emergency readmission Predictors: Multimorbidity, frailty, age, sex, living arrangements, care requirements	Bivariate comparisons of predictor variables in those who were and were not readmitted Logistic regression on one- and three-month readmission; backwards	One-month and three-month readmission to emergency department following index date	A number of care requirements included as predictors, including nursing care, home care, meals on wheels, cleaning help, shopping assistance.	Modified Cumulative Illness Rating Scale (CIRS); rates 14 body systems on severity scale of 0 to 4 with a maximum score of 56. Calculated on nurse assessment Number of medications	In bivariate analyses a number of care variables (but not home care) are significantly associated with one- and three-month readmission.	Whilst this study includes examples of all three areas of interest in the initial literature review (health, social care, multimorbidity), the small

based on comprehensive geriatric assessment: a prospective cohort study				proxy interview. Cohort study; patients followed up at one and three months, 2011-12		selection used to choose model variables. Complete-case sample.			taken at home; data recorded via records or interview	A higher CIRS is significantly associated with one-month readmission; medication count does not. In the regression models only some care, mental health and health status variables are retained, all of which are associated with increased risk. Both multimorbidity measures are excluded.	sample size and restriction to inpatient data limits the generalisability of the conclusions.

Ho et al 2021 Examining variation in the measurement of multimorbidity in research: a systematic review of 566 studies	Measuring multimorbidity	Recommended by colleague	Examine scope of multimorbidity measurement in previous literature, as well as definition	566 studies measuring multimorbidity, primarily in community, primary care, care home or hospital settings	Multimorbidity measurement (primary objective) Number of conditions, and study parameters (secondary objective)	Descriptive analyses of study characteristics, including setting, population, data source, definition and type of multimorbidity, as well as conditions included. Negative binomial GLM used to ascertain relationship between study characteristics and number of conditions included in measure	N/A	N/A	Any and all definitions, grouped by definition, type of measure and number of conditions included. Grouped by ICD-10 classification when reporting prevalence.	Collection method split evenly between self-report and administrative data; counts of conditions more common in the former and weighted measures in the latter. Almost all indices were disease-based. Six medication-based measures, two of which were the CDS Only eight conditions	Provides comprehensive account of research to date on multimorbidity to date, as well as recommended conditions and direction of future research.

										were common to over half of the studies, suggesting wide variation. Authors recommend that mental health conditions be included as standard; over half of the studies reviewed did not contain any. List of twenty recommended conditions to include in future measures (and additional situation-	

										dependent conditions)	
Huang et al 2020: Predicting the cost of health care services: a comparison of case-mix systems and comorbidity indices that use administrative data	Measuring multimorbidity	1, 2, 4 in PubMed (phase 3)	Compare predictive ability of multimorbidity and case-mix measures in predicting HCU	3,478,091 adults in British Columbia, Canada, 19+ whole adult population from 2012-2014 Linked hospital, admissions, demographic and payment data	Outcome: Yearly medical costs Predictors: Multimorbidity, case-mix measure, age, sex	Logistic regression, then GLM, for healthcare costs. R^2 used to compare multimorbidity measures, as well as RMSE and MAE	Total, pharmaceutical, physician and acute care costs in second year of cohort, as well as individual costs	Care costs one of the outcomes, though acute care rather than social care	Measures are multimorbidity despite being labelled as comorbidity. CCI, EI and two case-mix measures: Adjusted Clinical Groups (ACG) and CIHI Population Grouper, data calculated in year prior to outcome window. CCI and EI represented as index score and individual conditions as separate models	EI outperforms CCI for all four outcomes, though R^2 is similar for both. Bar acute care, where all measures perform poorly, index score outperforms binary variables.	Novel study, with large representative population (though not just restricted to older people) and different functional forms of CCI and EI Uses metric health outcome which differs from this study (and also notable that metric measure performs far better)
ISD 2011 Scottish patients at	Policy	Search on Scottish Governmen	Report on updates to the	Whole Scottish population	Outcome: emergency admission	Logistic regression. Individual	Emergency readmission and	N/A	No standardised multimorbidity measures used;	Actual vs expected predictive	Importance of study to thesis is less

risk of readmission and admission (SPARRA): a report on the development of SPARRA version 3	Measuring multimorbidity Deprivation	t website for SPARRA reports	SPARRA risk prediction algorithm	aged 16 and above, who have data in at least one dataset (bar SMR04), alive September 2009 and in areas with acceptable data completeness Split into three cohorts (75+, 16-55 with an ED attendance, 56-75 AND 16-55 without ED attendance) Prescribing, emergency and admissions	Predictors: prior health outcomes, prescribing for specific conditions, prior HCU, age, SIMD	analyses carried out to determine inclusion of variables in each regression, split by cohort. PPV, sensitivity and specificity of new model evaluated.	emergency bed days, within one year		individual condition markers derived from admissions (three-year lookback) and prescribing data (one-year lookback) included in models	ability improved on previous version of SPARRA, as does sensitivity and specificity. AUC of models not stated.	in the results (which are to be expected) and more the derivation of the cohort; this study should inform development of future versions of SPARRA. Included in thesis prediction which isn't in SPARRA include: weighted risk, whole population (for quantifying risk of particular conditions and therefore importance

				data from 2006-2010							for inclusion), whole older cohort, and inclusion of more health outcomes other than emergency admissions. Thesis may be able to provide guidance on what could be included in SPARRA next time around, and expand the algorithm to other outcomes such as social care.
Kuzuya et al 2012	General Integrated care	1c, 2b, 3a, 4a in ProQuest	Determine principally the	1,582 community dwelling	Outcome: Moving from home	Hazard ratios via Cox	Relationship between informal	Long-term care placement	CCI, and individual conditions,	In bivariate analyses, higher CCI	Small, restricted sample, but

Day-care service use is a risk factor for long-term care placement in community-dwelling dependent elderly	Informal care Measuring multimorbidity	(phases 1 & 2)	relationship between informal care provision and placement in long-term care, but other factors too.	disabled older people. Nagoya Study of Longitudinal Ageing (Japan) linked to admission and mortality data, plus three years of follow-up. Recruited 2003-04.	to long-term care (and insufficient informal care) Predictors: Age, sex, multimorbidity, frailty, HCU, SEC, health status, informal care	regression for placement in long-term care, bivariate and logistic regression for informal care	care and service use examined in bivariate analyses	and informal care (from family members and evaluated by trained nurses into sufficient, moderate and insufficient)	derived from patient records. Data collection method and lookback period not stated	score corresponded with insufficient IC; not included in either regression analysis. Cancer associated with higher likelihood of placement in long-term care Insufficient care linked with mortality and admission.	shows some associations between multimorbidity, care and health outcomes.
Landi et al 2001 A new model of integrated care for the	Integrated care General	Referenced in Landi et al (2004)	Examine impact of home care and case management on HCU	1,204 people eligible for integrated care as defined by	Outcome: Admission to hospital, hospital days	Bivariate analysis between home care intervention and two	Admission to hospital, and total hospital days. Measured in	Integrated care program delivered by multidisciplinary team, based on	Average no. of conditions and no. of medications reported, but not	Proportion of people admitted and total hospital days reduced after care	Provides a reference linking integrated care interventions

elderly: impact on hospital use			in older people	Minimum Data Set for Home Care (MDSHC) in four Italian health care agencies Survey-based screening linked to 12-month admissions data (1998-99). Minimum age not stated, but heavily implied to be older people. Mean age is 77	Predictor: Home care intervention	HCU outcomes. Univariate distributions and frequencies also reported.	12 months preceding and after intervention.	case management	included in main analysis.	implementation.	with improved health outcomes, though this is a very small study with unadjusted analyses.
Marengoni et al 2011	General Measuring multimorbi	Referenced in	Examine what research	41 articles examining clinically	N/A; prevalence and impact	Summary of literature via	Disability, mortality, quality of	Quality of care and relationship	Main focus of study. Clinical diagnoses only;	All studies show multimorbid	Provides a comprehensive summary

Aging with multimorbidity: a systematic review of the literature	dity Integrated care Deprivation	Diederichs et al (2011)	says regarding likelihood, causes of and impact of multimorbidity in conjunction with ageing	diagnosed multimorbidity, published 1990-2010	of multimorbidity on health outcomes discussed	systematic review; some aggregate statistics reported	life, healthcare utilization all discussed with regard to multimorbidity in separate sections	with multimorbidity discussed	no specific measure.	ity in >50% of population when restricted to older people, and also people from lower social classes (not necessarily >50%). Mortality results conflicting – increased risk in most, but not all. MMs associated with higher risk of admissions. Very little focus on specific combinations of conditions –	of the risk of numerous health outcomes with multimorbidity, negating the need for this to be investigated further, as well as emphasising the need for a holistic approach. Key reference.

										some conditions may not be as debilitating as others. No basis for evidence-based care as not enough research has been done. People from deprived backgrounds may not know how to manage their health well. Very little focus on quality of care found. Specific guidelines should be developed for	

										multimorbidity, moving away from single-disease approach.	
Rosstad et al 2013 Development of a patient-centred care pathway across healthcare providers: a qualitative study	Integrated care General	1c, 2b, 3a, 4a in ProQuest (phases 1 & 2)	Examine how best to develop care pathways for people with complex needs across multiple divisions	27 people in two hospitals within Norway (hospital and care nurses, administrators, occupational therapists) trained in developing care pathways, 23 people (including some those trained, as well as additional	Qualitative study	Qualitative study	Health service provision, outcomes not stated	Focus of paper is developing patient centred care pathway	People with complex needs/multimorbidity are target of care	Hospital nurses focused on diagnoses and not the patient themselves, despite most patients having more than one condition. Care nurses given insufficient information, and clinical GPs felt care services were too slow	Provides good examples of difficulties in integrated care, especially between clinical and care professionals. Qualitative study, so conceptually very different to thesis, but provides useful underlying explanation.

				people) later interviewed						Consensus reached on disease-based approach in hospital, and common approach in transition to and during primary care	

* Seven categories used for indexing of studies: general, measuring multimorbidity, deprivation, integrated care, informal care, policy, and other. Main category is listed first

** See Appendices 1 & 2 for list of search strings

*** Quantitative papers only

Table A3.2: Sample paper evaluation table

Title, author	Multimorbidity relevance	Social/informal care relevance	Health outcome relevance	Focus on older people (65+)	Quantitative methodology	Key reference	Grade
Brilleman & Salisbury 2012 Comparing measures of multimorbidity to predict outcomes in primary care: a cross sectional study	Relevant	None	Relevant	No	Yes	Yes	A
Bywaters et al 2015 Exploring inequalities in child welfare: the inverse intervention paradox	None	None	None	No	Yes	Yes	A
Deschodt et al 2015 Characteristics of older adults admitted to the emergency department (ED) and their risk factors for ED readmission based on comprehensive geriatric assessment: a prospective cohort study	Relevant	Relevant	Partially relevant	Partially	Yes	No	B
Ho et al 2021 Examining variation in the measurement of multimorbidity in research: a systematic review of 566 studies	Relevant	None	None	Partially	Yes	Yes	A
Huang et al 2020: Predicting the cost of health care services: a comparison of case-mix systems and comorbidity indices that use administrative data	Relevant	Partially relevant	Partially relevant	No	Yes	No	C
ISD 2011	Partially relevant	None	Relevant	Partially	Yes	Yes	A

Scottish patients at risk of readmission and admission (SPARRA): a report on the development of SPARRA version 3							
Kuzuya et al 2012 Day-care service use is a risk factor for long-term care placement in community-dwelling dependent elderly	Partially relevant	Relevant	Partially relevant	Yes	Yes	No	D
Landi et al 2001 A new model of integrated care for the elderly: impact on hospital use	Partially relevant	Relevant	Relevant	Yes	Yes	No	C
Marengoni et al 2011 Aging with multimorbidity: a systematic review of the literature	Relevant	Partially relevant	Relevant	Yes	Yes	Yes	A
Rosstad et al 2013 Development of a patient-centred care pathway across healthcare providers: a qualitative study	Partially relevant	Relevant	None	Partially	No	No	C

Appendix A4: List of each condition (and codes used) in multimorbidity measures

Table A4.1: Conditions, scores and scores in the Charlson Comorbidity Index, Quan adaptation (Quan CCI)

Condition	Code(s)	Score
Myocardial infarction*	I21.x, I22.x, I25.2	1
Congestive heart failure	I09.9, I11.0, I13.0, I13.2, I25.5, I42.0, I42.5–I42.9, I43.x, I50.x, P29.0	1
Peripheral vascular disease	I70.x, I71.x, I73.1, I73.8, I73.9, I77.1, I79.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9	1
Cerebrovascular disease*	G45.x, G46.x, H34.0, I60.x–I69.x	1
Dementia*	F00.x–F03.x, F05.1, G30.x, G31.1	1
Chronic pulmonary disease	I27.8, I27.9, J40.x–J47.x, J60.x–J67.x, J68.4, J70.1, J70.3	1
Rheumatic disease	M05.x, M06.x, M31.5, M32.x–M34.x, M35.1, M35.3, M36.0	1
Peptic ulcer disease	K25.x–K28.x	1
Mild liver disease	B18.x, K70.0–K70.3, K70.9, K71.3–K71.5, K71.7, K73.x, K74.x, K76.0, K76.2–K76.4, K76.8, K76.9, Z94.4	1
Diabetes without chronic complication*	E10.0, E10.1, E10.6, E10.8, E10.9, E11.0, E11.1, E11.6, E11.8, E11.9, E12.0, E12.1, E12.6, E12.8, E12.9, E13.0, E13.1, E13.6, E13.8, E13.9, E14.0, E14.1, E14.6, E14.8, E14.9	1
Diabetes with chronic complication*	E10.2–E10.5, E10.7, E11.2–E11.5, E11.7, E12.2–E12.5, E12.7, E13.2–E13.5, E13.7, E14.2–E14.5, E14.7	2
Hemiplegia or paraplegia	G04.1, G11.4, G80.1, G80.2, G81.x, G82.x, G83.0–G83.4, G83.9	2

Renal disease	I12.0, I13.1, N03.2–N03.7, N05.2–N05.7, N18.x, N19.x, N25.0, Z49.0–Z49.2, Z94.0, Z99.2	2
Any malignancy, including lymphoma and leukaemia, except malignant neoplasm of skin*	C00.x–C26.x, C30.x–C34.x, C37.x–C41.x, C43.x, C45.x–C58.x, C60.x–C76.x, C81.x–C85.x, C88.x, C90.x–C97.x	2
Moderate or severe liver disease	I85.0, I85.9, I86.4, I98.2, K70.4, K71.1, K72.1, K72.9, K76.5, K76.6, K76.7	3
Metastatic solid tumour*	C77.x–C80.x	6
AIDS/HIV	B20.x–B22.x, B24.x	6

* In CCI in survey data

Table A4.2: Conditions in the Elixhauser Index, Quan adaption (Quan EI)*

Condition	Code(s)
Congestive heart failure	I09.9, I11.0, I13.0, I13.2, I25.5, I42.0, I42.5–I42.9, I43.x, I50.x, P29.0
Cardiac arrythmias	I44.1–I44.3, I45.6, I45.9, I47.x–I49.x, R00.0, R00.1, R00.8, T82.1, Z45.0, Z95.0
Valvular disease	A52.0, I05.x–I08.x, I09.1, I09.8, I34.x–I39.x, Q23.0–Q23.3, Z95.2–Z95.4
Pulmonary circulation disorders	I26.x, I27.x, I28.0, I28.8, I28.9
Peripheral vascular disorders	I70.x, I71.x, I73.1, I73.8, I73.9, I77.1, I79.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9
Hypertension, uncomplicated	I10.x
Paralysis	G04.1, G11.4, G80.1, G80.2, G81.x, G82.x, G83.0–G83.4, G83.9
Other neurological disorders	G10.x–G13.x, G20.x–G22.x, G25.4, G25.5, G31.2, G31.8, G31.9, G32.x, G35.x–G37.x, G40.x, G41.x, G93.1, G93.4, R47.0, R56.x
Chronic pulmonary disease	I27.8, I27.9, J40.x–J47.x, J60.x–J67.x, J68.4, J70.1, J70.3
Diabetes, uncomplicated**	E10.0, E10.1, E10.9, E11.0, E11.1, E11.9, E12.0, E12.1, E12.9, E13.0, E13.1, E13.9, E14.0, E14.1, E14.9
Diabetes, complicated**	E10.2–E10.8, E11.2–E11.8, E12.2–E12.8, E13.2–E13.8, E14.2–E14.8
Hypothyroidism	E00.x–E03.x, E89.0
Renal failure	I12.0, I13.1, N18.x, N19.x, N25.0, Z49.0–Z49.2, Z94.0, Z99.2
Liver disease	B18.x, I85.x, I86.4, I98.2, K70.x, K71.1, K71.3–K71.5,

	K71.7, K72.x–K74.x, K76.0, K76.2–K76.9, Z94.4
Peptic ulcer disease excluding bleeding	K25.7, K25.9, K26.7, K26.9, K27.7, K27.9, K28.7, K28.9
AIDS/HIV	B20.x–B22.x, B24.x
Lymphoma**	C81.x–C85.x, C88.x, C96.x, C90.0, C90.2
Metastatic cancer**	C77.x–C80.x
Solid tumour without metastasis**	C00.x–C26.x, C30.x–C34.x, C37.x–C41.x, C43.x, C45.x–C58.x, C60.x–C76.x, C97.x
Rheumatoid arthritis/collagen vascular disease	L94.0, L94.1, L94.3, M05.x, M06.x, M08.x, M12.0, M12.3, M30.x, M31.0–M31.3, M32.x–M35.x, M45.x, M46.1, M46.8, M46.9
Coagulopathy	D65–D68.x, D69.1, D69.3–D69.6
Obesity	E66.x
Weight loss	E40.x–E46.x, R63.4, R64
Fluid and electrolyte disorders	E22.2, E86.x, E87.x
Blood loss anaemia	D50.0
Deficiency anaemia	D50.8, D50.9, D51.x–D53.x
Alcohol abuse**	F10, E52, G62.1, I42.6, K29.2, K70.0, K70.3, K70.9, T51.x, Z50.2, Z71.4, Z72.1
Drug abuse	F11.x–F16.x, F18.x, F19.x, Z71.5, Z72.2
Psychoses**	F20.x, F22.x–F25.x, F28.x, F29.x, F30.2, F31.2, F31.5
Depression**	F20.4, F31.3–F31.5, F32.x, F33.x, F34.1, F41.2, F43.2
Hypertension, complicated	I11.x–I13.x, I15.x

* The EI is a non-weighted index and as such all conditions have a score of 1

** In EI in survey data

Table A4.3: Conditions in the Chronic Disease Score, Henery adaptation (CDS-H1)*

Condition	Medication class**	Code(s)	Score
Heart disease	Anticoagulants, haemostatics	2.8 (excluding 2.8.2.X0, 2.8.2.Z0, 2.8.2.Y0), 2.11	1 medication class = 3 2 medication classes = 4 3 medication classes = 5
	Cardiac agents, ACE inhibitors (ACEI)	2.5.5.1, 2.5.5.2	
	Diuretic loop	2.2.2, 2.2.3, 2.2.4	
Respiratory illness	Beta-adrenergic, miscellaneous	3.1.1	1 medication class = 2 2+ medication classes = 3
	Xanthine products	3.1.3	
	Respiratory products including bronchodilators and mucolytics but excluding cromolyn	3.1.2, 3.1.4, 3.7	
	Epinephrine	3.4.3	
Asthma, rheumatism	N/A	6.3.1, 6.3.2	3
Rheumatoid arthritis	N/A	10.1.3	3
Parkinson's	N/A	4.9.1, 7.4.2	3
Hypertension	Antihypertensives (except ACE inhibitors and angiotensin-II receptor antagonists)	2.5.5.3	Medication 1 = 2 Medication 2 and not 1 = 1
	Beta blockers, diuretics	2.2.1, 2.4	
Diabetes	N/A	6.1.1, 6.1.2	2
Epilepsy	N/A	4.8	2
Asthma, rhinitis	N/A	3.3.2, 3.3.3	2
Acne	N/A	13.6.1	1
Ulcers	N/A	1.3	1
Glaucoma	N/A	11.6.X0, 11.6.Y0	1
Gout, hyperuricemia	N/A	10.1.4	1
High cholesterol	N/A	2.12	1
Migraines	N/A	4.7.4.1.D0, 4.7.4.1.F0	1
Tuberculosis	N/A	5.1.9	1

* Cancer excluded from original CDS-1.

** Only included if scoring depends on types of medication classes flagged

Table A4.4: Conditions in the Chronic Disease Score 2, Henery adaptation (Henery CDS-2)*

Condition	Code(s)	Score
Coronary and peripheral vascular disease	2.6.4.AG, 2.6.4.AE, 2.8, 2.9	1932.3
Epilepsy	4.8	771.5
Hypertension (HBP)	2.2.1, 2.4, 2.5.1, 2.5.2.E0, 2.5.2.H0, 2.5.2.I0, 2.5.2.J0, 2.5.3, 2.5.4, 2.5.5.1, 2.5.5.2, 2.6.2	64.3
Tuberculosis	5.1.9	5109.8
Rheumatoid arthritis	10.1.2.1, 10.1.3	1199.6
HIV	5.1.9.Q0, 5.3.1, 5.4.8.P0, 5.4.8.A0	4853.2
High cholesterol	2.12 (excluding 2.12.U0, 2.12.A0, 2.12.AE, 2.12.AB, 2.12.V0)	293.4
Parkinson's disease	4.9.1, 7.4.2	2114.4
Renal anaemia/neutropenia	9.1.3, 9.1.6	2192.8
Heart disease	2.2.2, 2.3, 2.4, 2.6.1, 2.6.2	789.1
Diabetes	6.1.1, 6.1.2	1108.4
Glaucoma	2.2.7, 11.6	351.7
Pancreatitis	1.9.4	2341.6
Renal failure	9.2.1.1.L0, 9.2.1.1.P0	16579.0
Ulcers	1.3 (excluding 1.3.4.M0)	797.1
Transplants	8.2.1.G0, 8.2.2.G0	3411.6
Respiratory illness, asthma	3.1.1.1, 3.1.3, 3.2, 3.3, 3.7	561.2
Hyperthyroidism	6.2.2	282.8
Gout	10.1.4.C0, 10.1.4.G0	833.8
Crohn's disease & inflammation of bowel	1.5.1	614.7
Pain and inflammation	10.1.1	137.6
Depression	4.3	545.4
Dementia	4.2.1, 4.11	1438.7
Mania	4.2.3.K0, 4.2.3.P0	260.1
Anxiety, tension	4.1.1, 4.1.2, 4.3.3	480.0
Pain	4.7.2	633.2

* Malignancies, liver failure, cystic fibrosis and psychotic illness excluded from original CDS-2; pancreatitis and dementia added

Table A4.5: Conditions in self-reported measure, uncategorised*

Condition
Cancer (neoplasm)
Diabetes
Other endocrine / metabolic
Mental illness / anxiety / depression
Learning disability
Epilepsy / fits / convulsions
Migraine / headaches
Other nervous system
Cataracts / blindness
Other eye problems
Poor hearing / deafness
Tinnitus
Meniere's disease
Other ear problems
Stroke
Heart disease / heart attack / angina
Hypertension / high blood pressure
Other heart problems
Piles
Varicose veins excluding anus
Other blood vessels
COPD / bronchitis
Asthma
Hay fever
Other respiratory
Ulcers
Other digestive
Bowel complaints
Teeth / mouth / tongue complaints
Kidney complaints
Urinary tract infection
Other bladder problems
Reproductive system disorders
Arthritis
Back problems
Other bones problems

Infection / parasitic
Blood disorders
Skin complaints
Other complaints
Unclassifiable

* Conditions are unweighted and self-reported, and have no code(s).

Table A4.6: Conditions in self-reported measure, categorised by ICD-10 codes*

Condition
I: Infectious disease
II: Neoplasms
III: Blood / immune system
IV: Endocrine / metabolic
V: Mental / behavioural
VI: Nervous system
VII: Eye diseases
VIII: Ear diseases
IX: Circulatory system
X: Respiratory system
XI: Digestive system
XII: Skin diseases
XIII: Musculoskeletal system
XIV: Genitourinary system

* Conditions are unweighted and self-reported, and have no code(s).

Appendix A5: Comparison of predictive ability of weighted and unweighted CDS-H2

Table A5.1: AIC, BIC and AUC of weighted and unweighted CDS-H2 in models predicting all health and care outcomes

Outcome	AIC		BIC		AUC range	
	Weighted	**Unweighted**	**Weighted**	**Unweighted**	**Weighted**	**Unweighted**
Mortality	***1877931***	1884890	***1878188***	1885147	***0.769 to 0.787***	0.766 to 0.784
1+ admissions	***5937310***	5942829	***5937567***	5943086	***0.664 to 0.674***	0.663 to 0.672
2+ admissions	***3407364***	3409672	***3407621***	3409929	***0.679 to 0.688***	0.677 to 0.686
1+ emergency admissions	***4344113***	4351097	***4344371***	4351354	***0.717 to 0.726***	0.714 to 0.722
2+ emergency admissions	***1967472***	1970119	***1967729***	1970376	***0.748 to 0.754***	0.745 to 0.750
7+ hospital days	***3187037***	3191288	***3187294***	3191546	***0.732 to 0.746***	0.729 to 0.743
28+ hospital days	***1535609***	1539206	***1535866***	1539464	***0.773 to 0.784***	0.770 to 0.780
Transition into social care	***714443***	716994	***714669***	717220	***0.779 to 0.798***	0.776 to 0.793
Transition into informal care	***98602***	99182	***98818***	99398	***0.804 to 0.819***	0.797 to 0.810

The best performing measure, by outcome and parameter, is in **bold italics**.

Appendix A6: Overview of all variables used in thesis

Table A6.1: Overview of variables in administrative datasets

Variable	Used as	Functional form	Categories	How derived
1-year mortality	Outcome	Binary	N/A	Mortality recorded within one year of index date
1+ admissions	Outcome	Binary	N/A	One or more admissions recorded within one year of index date
2+ admissions	Outcome	Binary	N/A	Two or more admissions recorded within one year of index date
1+ emergency admissions	Outcome	Binary	N/A	One or more emergency admissions recorded within one year of index date
2+ emergency admissions	Outcome	Binary	N/A	Two or more emergency admissions recorded within one year of index date
7+ hospital days	Outcome	Binary	N/A	Cumulative length of stay of seven days or more recorded within one year of index date
28+ hospital days	Outcome	Binary	N/A	Cumulative length of stay of 28 days or more recorded within one year of index date
Receipt of social care	Outcome	Binary	N/A	Recorded as receiving social care in SCS
Transition into social care	Outcome	Binary	N/A	Recorded as receiving social care in following year's SCS, and not receiving social care in index date SCS
Transition into informal care	Outcome	Binary	N/A	Recorded as receiving informal care in following year's SCS, and not

				receiving informal care in index date SCS
Age	Covariate	Metric	N/A	Age last birthday at index date
		Ordinal	65-74	
			75-84	
			85+	
Sex	Covariate	Nominal	Male	Sex at index date
			Female	
SIMD decile	Covariate Predictor	Ordinal	1st	SIMD rank at data zone recorded at index date, converted into deciles
			2nd	
			3rd	
			4th	
			5th	
			6th	
			7th	
			8th	
			9th	
			10th	
Local authority	Predictor	Nominal	All Scottish LAs excluding Eilean Siar, Orkney and Shetland	LA derived from data zone recorded at index date
Charlson Comorbidity Index	Predictor	Metric	N/A	Individual conditions recorded one year prior to index date, weighted and scored
		Categorical	0	
			1	
			2	
			3	
			4-6	
			7+	
		Individual conditions	See appendix A4.1	
Elixhauser Index	Predictor	Metric	N/A	Individual conditions recorded one year prior to index date, scored
		Categorical	0	
			1	
			2	
			3	
			4	
			5+	

		Individual conditions	See appendix A4.2	
Unique ICD-10 codes	Predictor	Metric	N/A	Unique codes counted from one year prior to index date
		Categorical	0	
			1	
			2-3	
			4+	
Henery Chronic Disease Score 1	Predictor	Metric	N/A	Individual conditions recorded one year prior to index date, weighted and scored
		Categorical	0	
			1-2	
			3-4	
			5-6	
			7-9	
			10+	
		Individual conditions	See appendix A4.3	
Henery Chronic Disease Score 2	Predictor	Metric	N/A	Individual conditions recorded one year prior to index date, weighted and scored
		Categorical	0	
			0.1-3000	
			3000.1-4500	
			4500.1-5500	
			5500.1-6500	
			6500.1-8000	
			8000+	
		Individual conditions	See appendix A4.4	
Unique BNF prescription sub-classes	Predictor	Metric	N/A	Unique codes counted from one year prior to index date
		Categorical	0	
			1-4	
			5-7	
			8-10	
			11-14	
			15+	

Table A6.2: Overview of variables in survey datasets

Variable	Used as	Functional form	Categories	How derived
Receipt of informal co-resident care	Outcome	Binary	N/A	Member of household responding to survey identifies that they provide informal care to respondent
Age	Covariate	Metric	N/A	Self-reported
		Ordinal	65-74	
			75-84	
			85+	
Sex	Covariate	Nominal	Male	Self-reported
			Female	
SIMD quintile	Covariate	Ordinal	1st	
			2nd	
			3rd	
			4th	
			5th	
NS-SEC 7	Covariate	Nominal	Higher managerial / professional	Derived from generic question regarding most recent work, coded by interviewer
			Lower managerial / professional	
			Intermediate	
			Small employer / own account worker	
			Lower supervisory / technical	
			Semi-routine	
			Routine	
			Never worked / long term unemployed	
Education level	Covariate	Ordinal	No high school qualifications	Self-reported
			High school qualifications	

			Higher education qualification	
Charlson Comorbidity Index	Predictor	Metric	N/A	Individual conditions recorded five years prior to index date, weighted and scored
		Categorical	0	
			1	
			2+	
		Individual conditions	See appendix A4.1	
Elixhauser Index	Predictor	Metric	N/A	Individual conditions recorded five years prior to index date, weighted and scored
		Categorical	0	
			1+	
		Individual conditions	See appendix A4.2	
Unique SMR admissions	Predictor	Metric	N/A	Unique admissions counted five years prior to index date
		Categorical	0	
			1	
			2+	
Self-reported conditions	Predictor	Metric	N/A	Self-reported conditions coded by interviewer, scored
		Categorical	0	
			1	
			2	
			3+	
		Individual conditions	See appendix A4.5	
Self-reported conditions (weighted)	Predictor	Metric	N/A	Self-reported conditions coded by interviewer, weighted and scored
		Categorical	0	
			1-2	
			3-4	
			5+	
Self-reported conditions (ICD-10)	Predictor	Metric	N/A	Self-reported conditions coded by interviewer, scored
		Categorical	0	
			1	
			2	
			3+	
		Individual conditions	See appendix A4.6	

Appendix A7: BIC of multimorbidity measures for 1+ admissions and emergency admissions

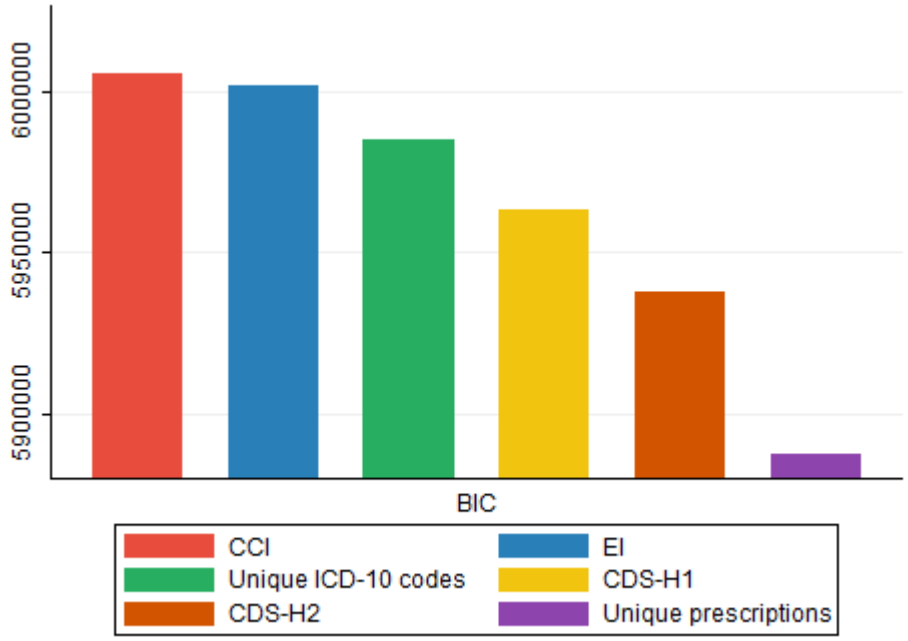

Fig. A7.1: BIC of panel logistic regression models predicting 1+ admissions by multimorbidity measure

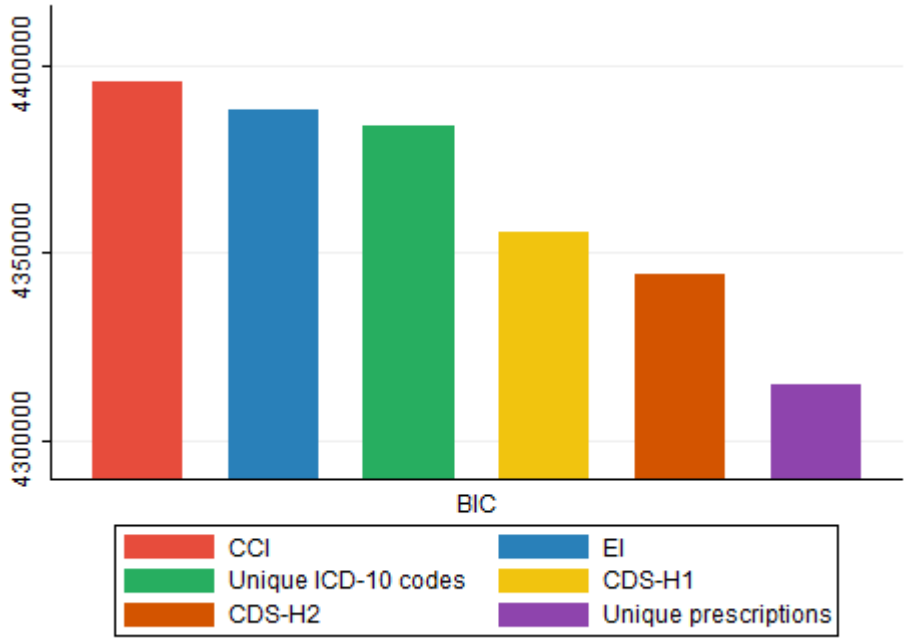

Fig. A7.2: BIC of panel logistic regression models predicting 1+ emergency admissions by multimorbidity measure

Appendix A8: Full model results for transition to informal care using multimorbidity and deprivation interaction

Table A8.1: SIMD, CDS-H2 & SIMD/CDS-H2 interaction* odds ratios from transition into social care model with multimorbidity/deprivation interaction

Variable	OR	C.I. lower	C.I. upper
SIMD1	***2.93***	***2.67***	***3.21***
SIMD2	***2.23***	***2.04***	***2.45***
SIMD3	***1.98***	***1.81***	***2.17***
SIMD4	***1.74***	***1.58***	***1.9***
SIMD5	***1.53***	***1.39***	***1.68***
SIMD6	***1.37***	***1.24***	***1.5***
SIMD7	***1.27***	***1.16***	***1.4***
SIMD8	***1.30***	***1.18***	***1.43***
SIMD9	***1.11***	***1.00***	***1.22***
CDS-H2	***>1.00***	***>1.00***	***>1.00***
CDS-H2*SIMD1	***0.999903***	***<1.00***	***<1.00***
CDS-H2*SIMD2	***0.999926***	***<1.00***	***<1.00***
CDS-H2*SIMD3	***0.999936***	***<1.00***	***<1.00***
CDS-H2*SIMD4	***0.999954***	***<1.00***	***<1.00***
CDS-H2*SIMD5	***0.999958***	***<1.00***	***<1.00***
CDS-H2*SIMD6	***0.999971***	***<1.00***	***<1.00***
CDS-H2*SIMD7	***0.999973***	***<1.00***	***<1.00***
CDS-H2*SIMD8	***0.999974***	***<1.00***	***<1.00***
CDS-H2*SIMD9	0.999992	<1.00	>1.00

* Significant figures increased to six to highlight changes

Significantly associated variables are in bold italics.

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