SoPI 2018-19

Supplementary Paper 111:

Multimorbidity Methodology Paper

Version 1.0

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System Purchasing and Performance
Department of Health and Human Services

Tasmanian Government

Contents

1 Executive Summary

1.1 Background

The ongoing evolution of our population demographic, driven in part by increasing life expectancy and in part declining fertility rates, has resulted in the proportion of older people in our population increasing. This trend is common across most developed countries.

Developed countries have high prevalence rates of multimorbidity. Multimorbid patients have high rates of service utilisation, complications, longer hospital stays and higher cost to the health system.

In order to develop an adequate policy framework for multimorbid patients, a robust methodology is required to describe and compare multimorbidity either between geographical regions or longitudinally over time. Part of this methodology is the development of a chronic disease listing and associated ICD10 map that allows for standardised data extraction and subsequent comparison.

1.2 Methodology

An initial literature scan was undertaken searching for multimorbidity studies which contained listings of chronic conditions and ICD10 codes. Fourteen published journal articles were identified and included as an initial chronic condition listing.

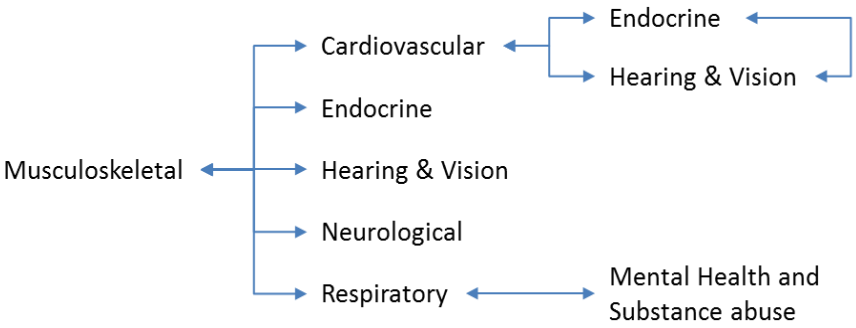
Data was extracted from the acute inpatient coded data for two years with a number of filters applied post extraction. A novel mix of standard statistical methods and social network analysis is proposed as a means to create and compare morbidity profiles. Odds Ratios are calculated between shared conditions to ascertain the strength of effect. These are subsequently translated into a network graph in order to visualise the network. Linear regression using the odds ratios is utilised to determine the degree of similarity between morbidity profiles.

1.3 Results

Linear regression indicated that there is no significant difference between the Tasmanian regions: North and South, and Statewide morbidity profiles. Thus the Statewide profile was used for further analysis and conclusions.

1.4 Conclusions

The following conditions were identified as benefiting from increased collaboration:



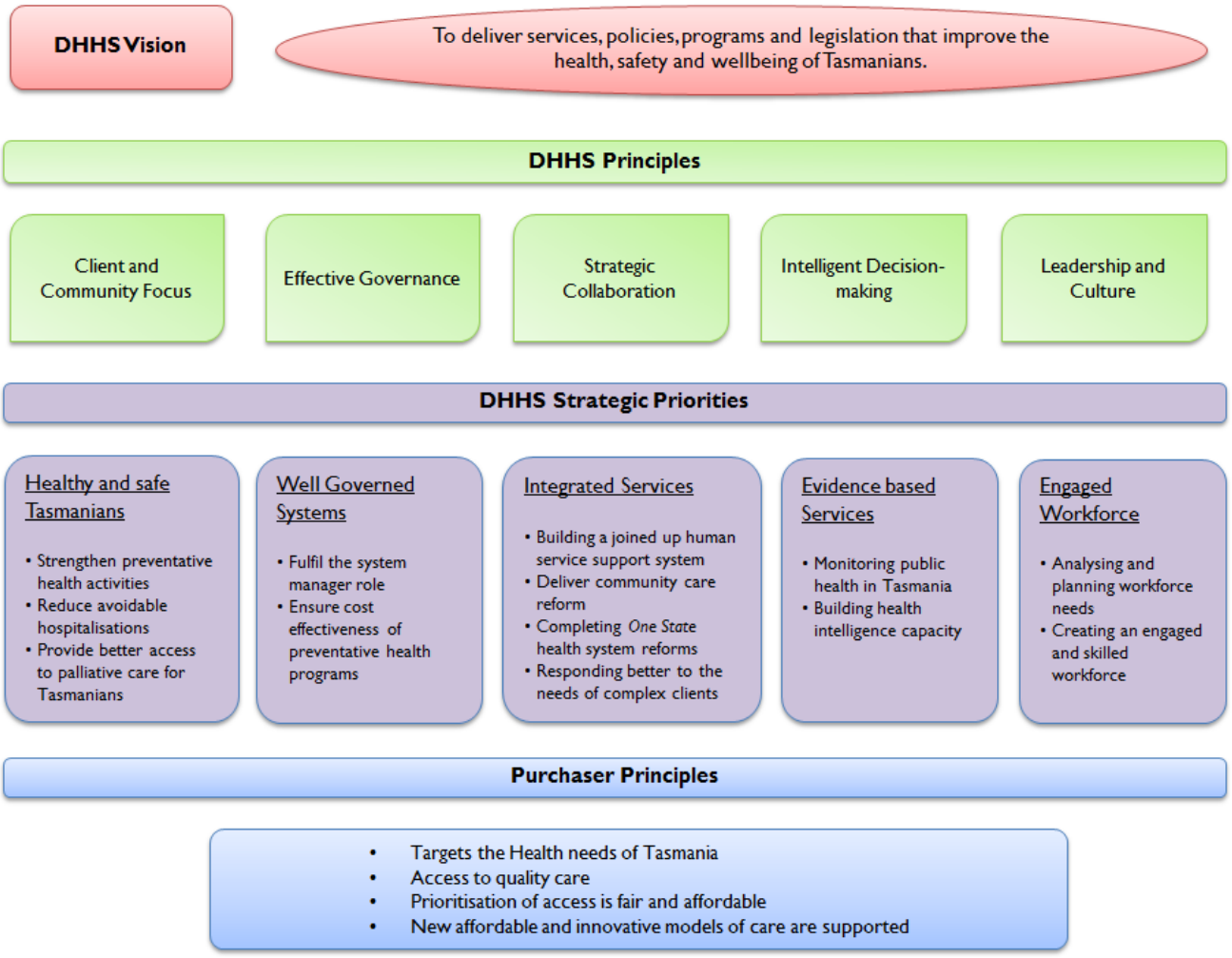
These combinations of conditions represent those that provide the greatest burden for Tasmanians and have the strongest associations with each other across the state.

2 Principles and Strategic Priorities

The DHHS will work in accordance with the vision, principles and strategic priorities outlined in the *'DHHS Corporate Plan 2016-18'* to keep Tasmanians safe, healthy and well.

The Tasmanian Health System Purchasing Framework figure below outlines the Purchaser Principles to support the DHHS to guide health service planning and delivery in Tasmania:

Figure 1: Tasmanian Health System Purchasing Framework



3 Multimorbidity

A chronic condition is a condition that is present, usually for twelve months or more and requires ongoing medical attention and/or limits activities of daily living (Warshaw 2006 in Goodman et al. 2013).

The ongoing evolution of our population demographic, driven in part by increasing life expectancy and in part declining fertility rates, has resulted in the proportion of older people in our population increasing. This trend is common across most developed countries. Australia, and more specifically Tasmania, is experiencing the same trend resulting in the population profile of Tasmania changing considerably by 2050 (Figure1).

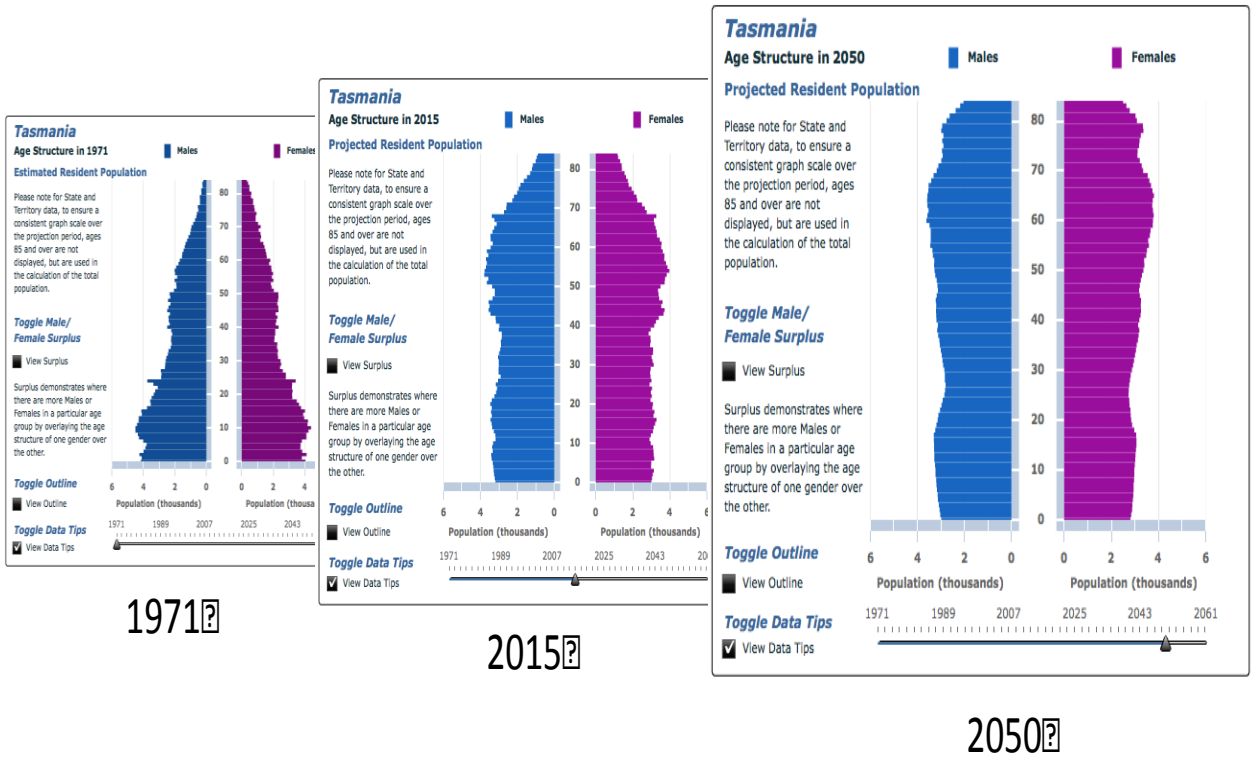
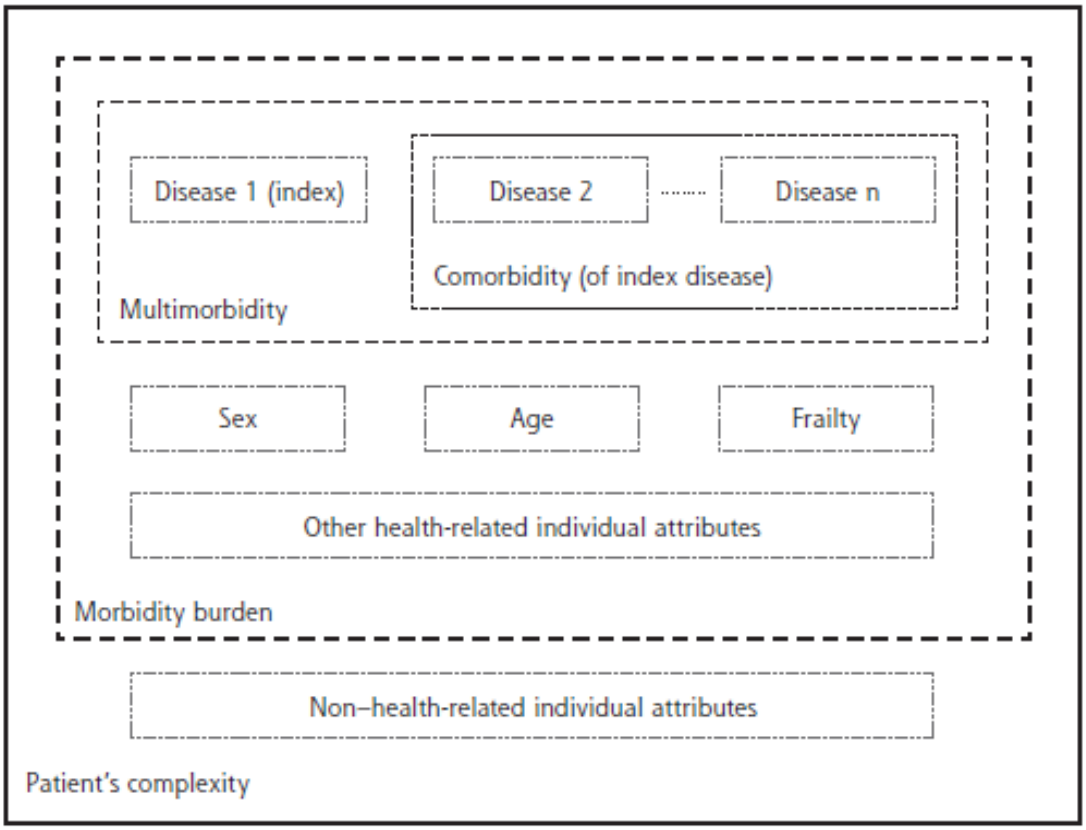


Figure 1: The changing population profile for Tasmania from 1971 to 2050 (Australian Bureau of Statistics data)

Concomitant with this trend have been improvements in the treatment regimens and management of individual chronic conditions.

This demographic evolution combined with advances in medical management has resulted in a high prevalence of people living with multiple chronic conditions (multimorbidity). There is no agreed standard definition of multimorbidity, but the most common definition is the presence of two or more chronic conditions (Marengoni et al. 2009).

It should be noted at this point, the difference between comorbidity and multimorbidity. Comorbidity refers to those conditions that "co-occur" with a reference or index disease (van den Akker, Buntinx & Knottnerus 1996). For example, conditions that commonly occur with respiratory disease or conditions that occur with cardiovascular disease. Multimorbidity on the other hand has no central reference disease. Valderas (2009) put forward this useful construct (Figure 2) to explain comorbidity, multimorbidity and patient complexity:



Comorbidity: presence of additional diseases in relation to an index disease in one individual.

Multimorbidity: presence of multiple diseases in one individual.

Morbidity burden: overall impact of the different diseases in an individual taking into account their severity.

Patient's complexity: overall impact of the different diseases in an individual taking into account their severity and other health-related attributes.

Figure 2: Comorbidity and multimorbidity constructs (Valderas et al. 2009)

The number of life years spent in multimorbidity is increasing (Tetzlaff et al. 2017). This trend is occurring in many countries across the world and introduces increasing complexity (as opposed to acuity) into the treatment and management of patients.

Australian multimorbidity prevalence estimates in the primary care sector are reported between 25% (Britt et al. 2008) and 32.6% (Harrison et al. 2016). Multimorbidity increases with age with prevalence rates exceeding 60% for those over the age of sixty five (Eckardt et al. 2017).

Multimorbid patients have higher rates of health care utilisation (Wang et al. 2017), are at greater risk for further complications (Weir et al. 2015) and mortality (Le Corvoisier et al. 2015; Prior et al. 2016). Furthermore, the cost of care required by multimorbid patients is also higher (Navickas et al. 2016; Picco et al. 2016; Specogna et al. 2017). Anecdotally, complexity introduces "inefficiency" in a system that is designed around single disease care and has a multiplier effect on the care requirements of multimorbid patients. For example, in surgery, they take longer to anaesthetise, longer to operate on with a higher risk of complications and take longer to recover.

Similar findings are evident in the Tasmanian acute admitted data (DHHS-PPP-MRA, 2015) as illustrated in the below Figure 3.

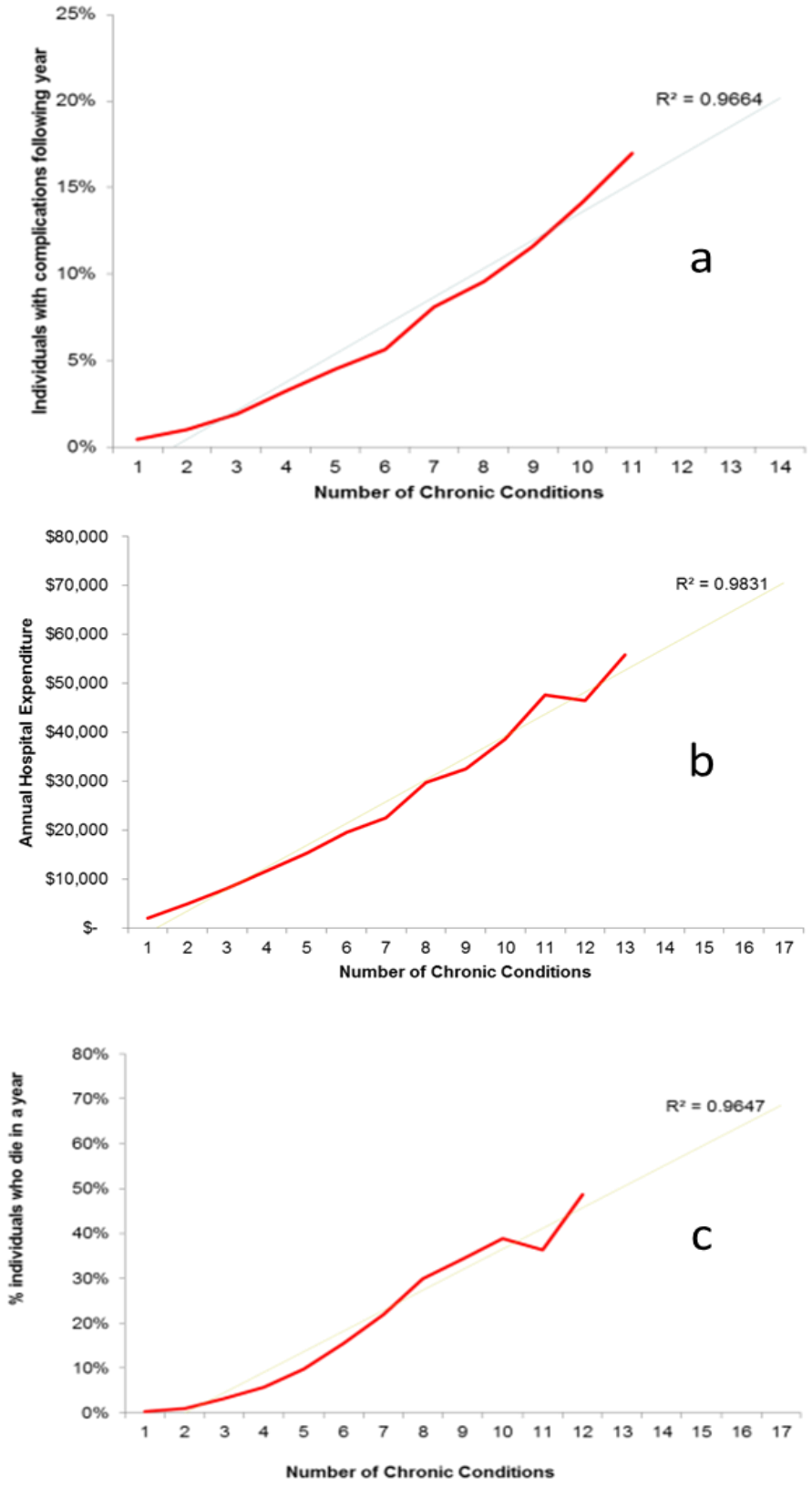


Figure 3: The relationship between the number of chronic conditions in the acute sector and (a) individuals experiencing complications, (b) annual hospital expenditure and (c) mortality (DHHS-PPP-MRA, 2015)

There are significant health care burdens (Table 1) for those that are grossly multimorbid (those identified as having six or more chronic conditions). This group of patients have more than twice as many hospital episodes as other patients, stay in hospital for longer, and are more likely to experience hospital acquired complications (HACs).

Table 1: 2015 Multimorbid vs non-multimorbid acute episodes in Tasmanian Major Hospitals (Internal DHHS analysis).

	<6 chronic conditions	**6+ chronic conditions**
Total Persons	50,608	3,904
Total Episodes	93,603	18,096
Total Episode days	238,512	61,100
Episodes Average Length of Stay (days)	2.5	3.4
Episodes per person per annum	1.8	4.6
Days per person	4.7	15.7
Hospital Acquired Complication rate per Episode	2.60%	5.00%
Hospital Acquired Complication rate per Person	4.80%	23.20%

This presents a challenge for health care systems which are designed and funded for single conditions (Harrison et al. 2016). It is more difficult for patients to navigate the system and it is more difficult for clinicians to treat and manage these patients. Across developed country health systems we are seeing a rise in health care roles that "coordinate" and "navigate" with the need for "command centres", and also calls for Information and Communications Technology (ICT) solutions with complex workflows capabilities.

These initiatives are symptomatic of the increasing complexity in our patient population and reflect that system design, commissioning, policy and funding models have not kept pace with the evolving morbidity profile of the community. Background inefficiencies that have crept in place the delivery of health care under chronic and systemic stress.

The DHHS, as System Manager, is undertaking a body of work to address multimorbidity. The issue of multimorbidity was identified in the Statement of Purchaser Intent 2017_18 (SoPI) with the intent of expanding on this work for SoPI 18_19.

Tasmania's high rates of lifestyle-related risk factors (refer to SoPI 2018-19 Supplementary Paper 11: *Chronic Disease Risk Factors – Research and Discussion Paper*) have contributed to Tasmania having higher rates of multimorbidity (three or more self-reported chronic conditions) than any other jurisdiction. In 2014–15, 50.3% of Tasmanians had three or more chronic conditions, increasing from 41.8% in 2011–12 (DHHS 2016).

Since then, significant work has been undertaken to progress this work to identify strategic purchasing priorities and directions for SoPI 18_19. This includes a literature scan in order to provide a standardised list of chronic conditions and ICD10 codes that can be used to identify chronic conditions within data sets. The work will identify the chronic conditions that are shared the most among multimorbid patients in Tasmania (see Section 4 - Methodology below).

It is further envisaged that the multimorbidity profiles for the Tasmanian regions will also be compiled and compared. One of the benefit of comparing such profiles is that it will guide policy, funding, governance and purchasing decisions and if necessary, regional differences. It will assist in guiding which services to connect. Further consultation and engagement with service providers will help guide how these services can be connected.

To enable this work, the DHHS has secured some Commonwealth funding via the National Partnership Agreement (NPA) "Improving Health Services in Tasmania" initiative. This funding will be used to refine the chronic conditions listing and code mapping as well as fund the development of a Complex Patients Framework.

4 Methodology

The data used in this methodology paper is acute data. Hence the output is an acute view of the system. Further work will be undertaken to obtain primary care data in order to gain a more accurate view of the complexity along the full continuum of care within the health system.

4.1 Data Specification

The following data specifications were applied for this study:

- Inclusions
    - Period – 2015/16 and 2016/17 financial years
    - Acute admissions
- Exclusions
    - Age range – under eighteen years old on 1 July 2015 (start of study period)
    - Non Tasmanian postcode
    - No chronic condition ICD10 code

4.2 Chronic Conditions List

In order to standardise data extraction and analysis, it is necessary to have a standardised listing of chronic conditions. Many lists have been published in the literature. These are summarised in Appendix 1. In addition to a standardised listing of chronic conditions, a map of associated ICD10 codes that clearly identifies chronic conditions coded is required.

Further work will be done to not validate, with clinical experts, the chronic condition list and the ICD10 mapping.

4.3 Data extraction and exclusions

Applying the data specifications n115 643 individual patients being extracted from the original data extract, leaving 66 208 patients. This constituted 57% of the initial data extract (Figure 4).

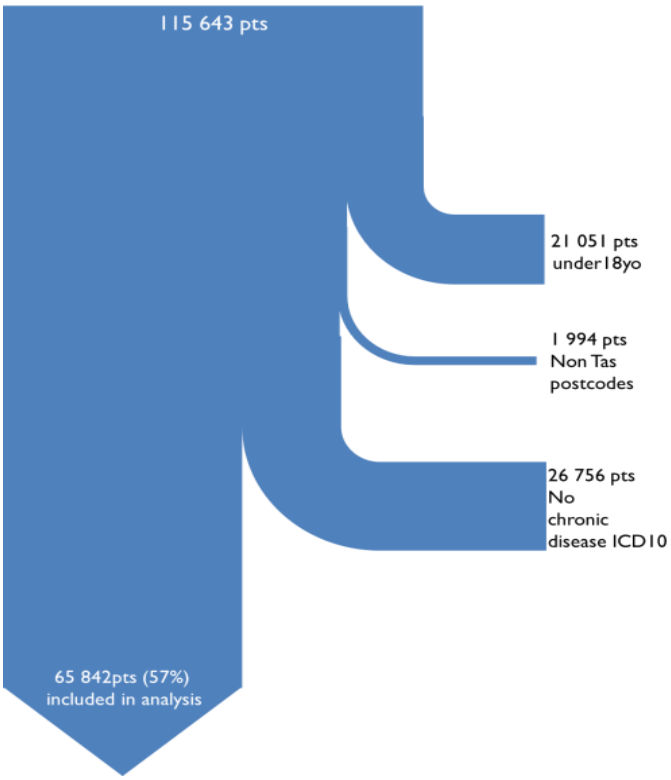


Figure 4 Summary of exclusions from analysis.

4.4 Data Analysis

The analysis of the data occurred in multiple stages:

4.4.1 Stage 1 – extraction and cleaning

Data extraction

Data for all hospitals was extracted using the following fields:

- URN | Date of Birth | Postcode | multiple individual ICD10 codes
- All acute episodes for the financial years 2015/16 and 2016/17

First round data cleansing

- Age
  - Exclude anyone under the age of 18 years old during the period of study.
  - Chronic conditions in children require further work and clinical input.
- Residence
  - Exclude all non-Tasmanian postcodes (NOT 7xxx)
  - There were some postcodes that were 7xxx postcodes but not valid postcodes, these were excluded as the patients residential addresses could not be verified.
- Diagnosis codes
  - The maximum diagnosis codes for anyone person was 156. In order to rationalise the data set, the frequency distribution of diagnosis codes was analysed (Figure 5).

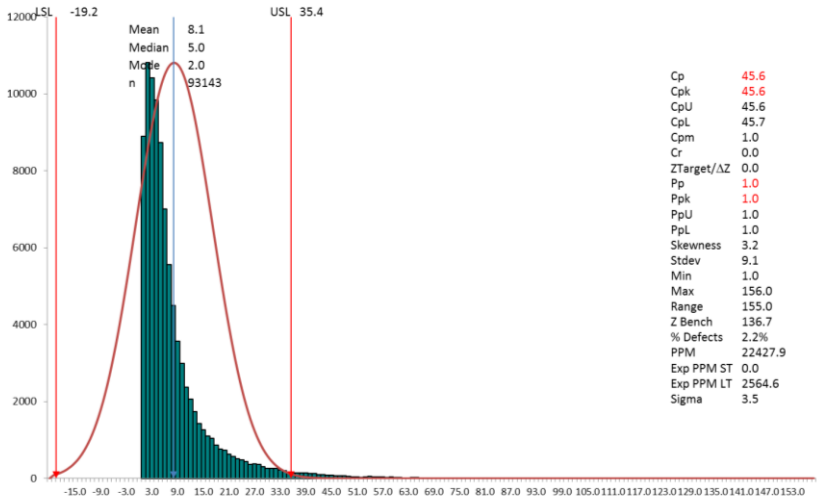


Figure 5 Frequency analysis showing cut off of diagnostic code count.

The upper control limit was determined to be 36 codes (Figure 5). All diagnosis codes beyond 36 were removed from the data.

4.4.2 Stage 2 – mapping and cleaning

Mapping of ICD10 to AIHW Groupers

This entails the mapping of Australian Institute of Health and Welfare (AIHW) Burden of Disease categories from the master mapping file to the ICD10 codes in the data. Note that extra spaces were evident in the extracted data causing errors. This was overcome by utilising the TRIM function embedded in the lookup function:

=Vlookup(TRIM(ref.cell),range, return, FALSE))

IMPORTANT *It should be noted that at the time of writing, there were some limitations in the mapping file. Extensive work has been undertaken identifying ICD10 codes from the literature that pertain to chronic conditions. However, more work needs to be undertaken by an expert clinical panel to refine this initial work and ensure its accuracy.*

AIHW categories (groupers) were chosen for two reasons. Firstly, these align with the SoPI burden of chronic disease priorities and secondly to group the diagnosis codes into more manageable numbers for analysis purposes. In the future, it may be beneficial from a service planning perspective to utilise Service Related Groups (SRGs) as these often mirror clinical governance structures within health systems.

Mapping the ICD10 codes and an episode's final Diagnostic Related Group (DRG) first need to be resolved. This could be overcome by using an expert panel to assign/map chronic conditions to SRGs.

Mapping Local Government Areas and Tasmanian Regions to postcodes

Patient postcodes are mapped to Local Government Areas (LGAs) and Tasmania Health Service regions (North and South).

Second round data cleansing

Further postcode errors were identified as the LGA to postcode mapping process returns any errors in Tasmanian postcodes. These patients were excluded.

4.4.3 Stage 3 – Generate columns for edge calculation

This is a key data transformation stage. One column per AIHW grouper is created. The header is cross matched by each patient to determine whether that grouper is present for that patient:

=MATCH(lookup grouper, in array,0)

For example =MATCH(AO$1,$E2:$AN2,0)

Note:

- Fixed row (AO$1) and fixed columns ($E2:$AN2)
- 0 means find the first value that matches the lookup grouper
- The function returns the position in the array of the lookup grouper

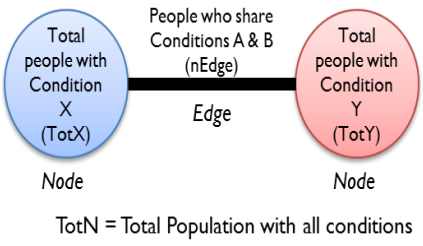
4.4.4 Stage 4 – Further data cleansing and calculation of 2x2 table values for Odds Ratio calculations

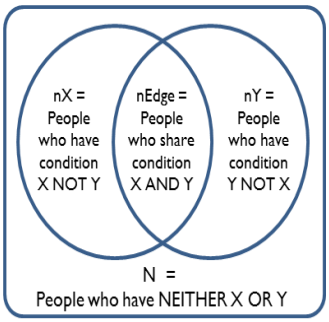
Third round data cleansing

- The MATCH function produces numerous #NA results where an ICD10 code in the raw data is not referenced in the mapping file i.e. that code is not listed as a chronic condition. These were removed with the FIND and REPLACE function.
- The output from the MATCH function returns a value that corresponds to the position of the lookup grouper. In order to standardise the data, these values are replaced with simple 1,0 flags:
  - =IF(cell>0,1,0)
- At this point those patients who have no chronic conditions coded can be identified by summing all rows (patients). Those patients who have a total of 0 have no chronic condition coded and are excluded from the analysis.

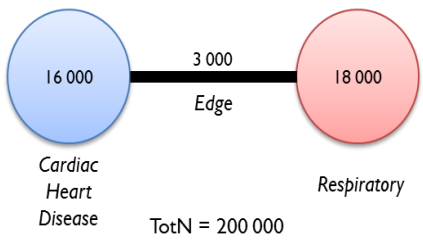
Construction of 2x2 tables

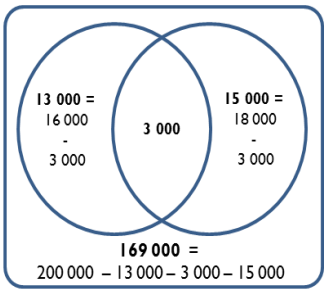
The following logic is applied in the calculation of the 2x2 table values. The creation of sets for each of the relationships between conditions within each profile occurred as follows:





For example





Data from each of the sets are used to populate a two by two table and calculate OR and p values (see Stage 5).

		Condition X: Yes	Condition X: No
Condition Y	Yes	nEdge	nY
	No	nX	N

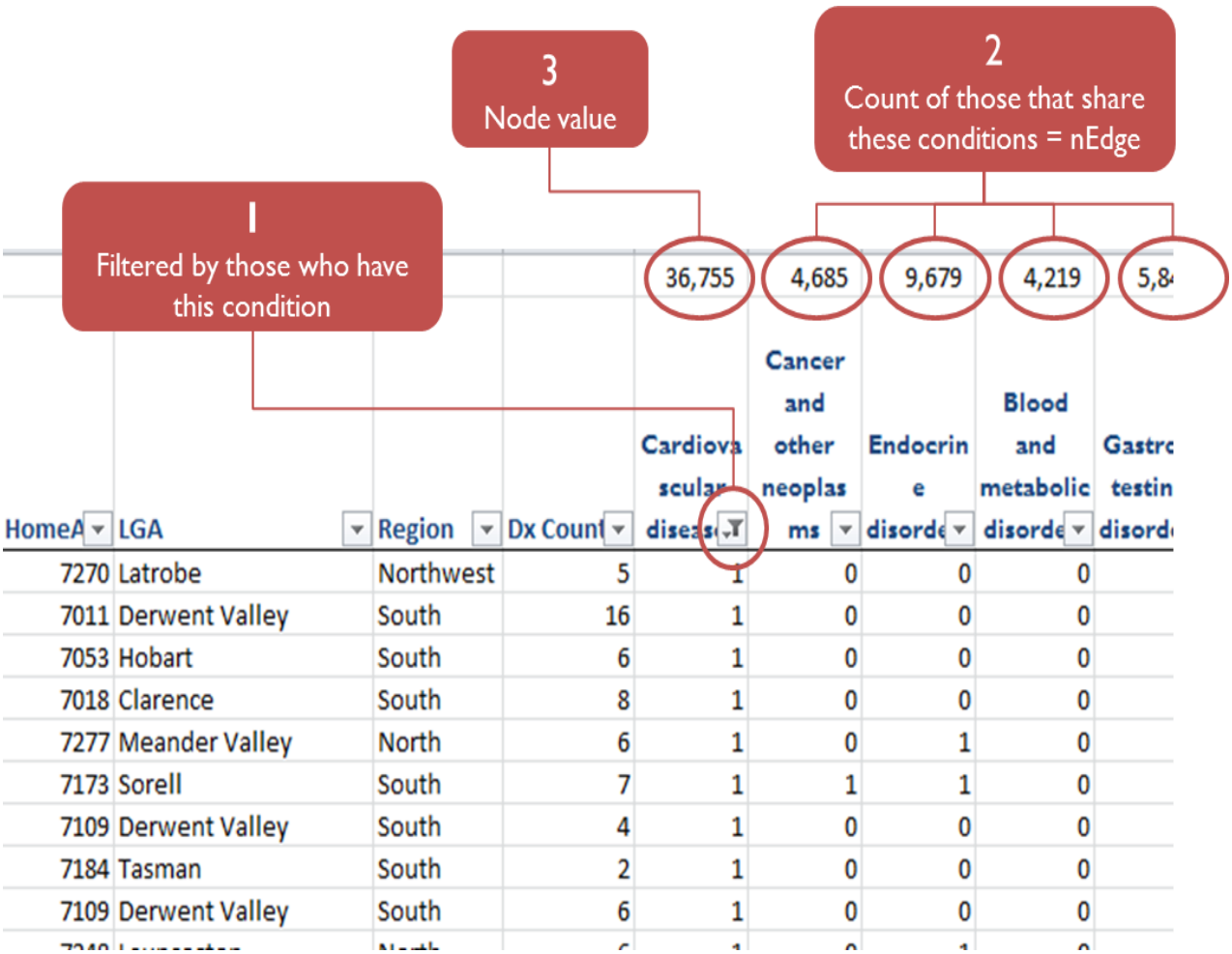
For example:

		Cardiac Disease (CHD): Yes	Cardiac Disease (CHD): No
Respiratory (Resp)	Yes	3 000	15 000
	No	13 000	169 000

Calculation of nEdge, nX, nY and N values

nEdge

This value is systematically calculated and noted for each combination of condition using the method outlined below. For the 15 AIHW groupers, this results in 104 edges (different combinations).



HomeA	LGA	Region	Dx Count	Cardiovascular disease	Cancer and other neoplasms	Endocrine disorde	Blood and metabolic disorde	Gastro testin disord
7270	Latrobe	Northwest	5	1	0	0	0	
7011	Derwent Valley	South	16	1	0	0	0	
7053	Hobart	South	6	1	0	0	0	
7018	Clarence	South	8	1	0	0	0	
7277	Meander Valley	North	6	1	0	1	0	
7173	Sorell	South	7	1	1	1	0	
7109	Derwent Valley	South	4	1	0	0	0	
7184	Tasman	South	2	1	0	0	0	
7109	Derwent Valley	South	6	1	0	0	0	

nX

nX = Node value (X) – nEdge i.e. those with only condition X and not condition Y

nY

nY = Node value (Y) – nEdge i.e. those with only condition Y and not condition X

N

N = Total sample – nEdge – nX – nY i.e. those with neither condition X nor condition Y

4.4.5 Stage 5 – Calculation of Odds Ratios, 95% Confidence Intervals and Chi Squared p values

In order to understand the size of the effect of shared conditions and whether that effect is significant or not, OR and Chi Squared p values are calculated. The data from Stage 5 was exported to R Statistical package. The code used to perform the calculations is shown below.

R code to compute edge Odds Ratios and Chi Squared p values

```
#Calculate Odds Ratios for each edge
    edges$OR<-round((edges$nEdge*edges$N)/(edges$nX*edges$nY),2)

#Calculate 95%CI interval for Odds Ratio
  #Calculate Log of the Odds Ratio
    edges$log.OR<-log(edges$OR)

  #Calculate the Standard Error
    edges$se<-log(sqrt((1/edges$nEdge)+(1/edges$nX)+(1/edges$nY)+(1/edges$N)))

  #Calculate log Confidence intervals
    edges$CI.Lo.log<-edges$log.OR-1.96*exp(edges$se)
    edges$CI.Hi.log<-edges$log.OR+1.96*exp(edges$se)

  #Convert log CIs
    edges$CI.Lo<-round(exp(edges$CI.Lo.log),2)
    edges$CI.Hi<-round(exp(edges$CI.Hi.log),2)

#Calculate Chi Squared p values for each edge
    library(dplyr)
    edges<-edges %>%
      rowwise() %>%
      mutate(p_value = chisq.test(matrix(c(nEdge, nX, nY, N), nrow = 2))$p.value)

  #Round edge p values to 4 decimal points
    edges$p_value<-round(edges$p_value,4)

  #Flag significant edges
    edges$Significance = if_else(edges$p_value<0.05,1,0)

  #Recode significance as factor
    edges$Significance_f = recode_factor(edges$Significance, "0"="Not Significant", "1"="Signficant")

#Export Edges Table
```

Figure 6: R code for calculating OR, p values and flagging those Odds Ratios that are significant (p<0.05).

The full output table is available in Appendix 2.

The output from this analysis is utilised in two parts in Stage 6:

a. Regression analysis is undertaken to analyse how the regions in Tasmania differ from the State profile.
b. Utilised to create a visual representation of the data in the form of a network graph.

4.4.6 Stage 6a – Regression analysis

Note that Odds Ratio for these relationships will be symmetrical. Thus when applied to the edges within a social network are therefore bi directional (or non-directional).

Odds Ratios are calculated for each of the relationships (Edges) within each profile. The R statistical package was used to generate the linear models using the following code:

```
State.South<-(lm(combined$All_OR~combined$S_OR))
summary(State.South)

State.North<-(lm(combined$All_OR~combined$N_OR))
summary(State.North)

South.North<-(lm(combined$S_OR~combined$N_OR))
summary(South.North)
```

Figure 7: R code for calculating linear regression models.

Linear regression modelling was undertaken comparing the OR in the following morbidity profiles in order to ascertain how different the effects are between the regions, and the statewide profile (Figure 7):

- Statewide vs Southern region
- Statewide vs Northern region
- Southern region vs Northern region

4.4.7 Stage 6b – Network visualisaton

At this stage, a variety of network graphs is created utilising R (see Figure 8). Simplification of the network graph is also undertaken at this point to filter out less significant / relevant edges.

```
#====
#Plot Network graph with selected parameters
library('igraph')

#Create function for network graph plot
plot.graph = function(edges.plot) {
  net<-graph_from_data_frame(d=edges.plot[,c(1,2,5)], vertices=nodes, directed=F)
  #Set colours
  colours = c("No" = "yellow", "Yes" = "red")
  V(net)$color<-colours[V(net)$SoPI]

  #set parameters
  plot(net,
       vertex.shape = "circle",
       vertex.size=nodes$Value/1000,
       vertex.frame.color = "white",
       vertex.label.cex = 1.0,
       vertex.label.family="Gill Sans",
       edge.curved=0,
       edge.width=edges$nEdge/1000,
       edge.arrow.size=0,
       edge.color = "red",
       layout = layout.star(net)
  )
}

#Stipulate filtering requirements for network graph
s<-edges[edges$OR>1.25
         & edges$SoPI_Edges=="YesYes"
         & edges$Significance_f=="Signficant"
         ,]

#Plot the graph
plot.graph(s)
```

Figure 8: R code to create network graph.

5 Results

5.1 Descriptive statistics

The age distribution of the cohort is shown below:

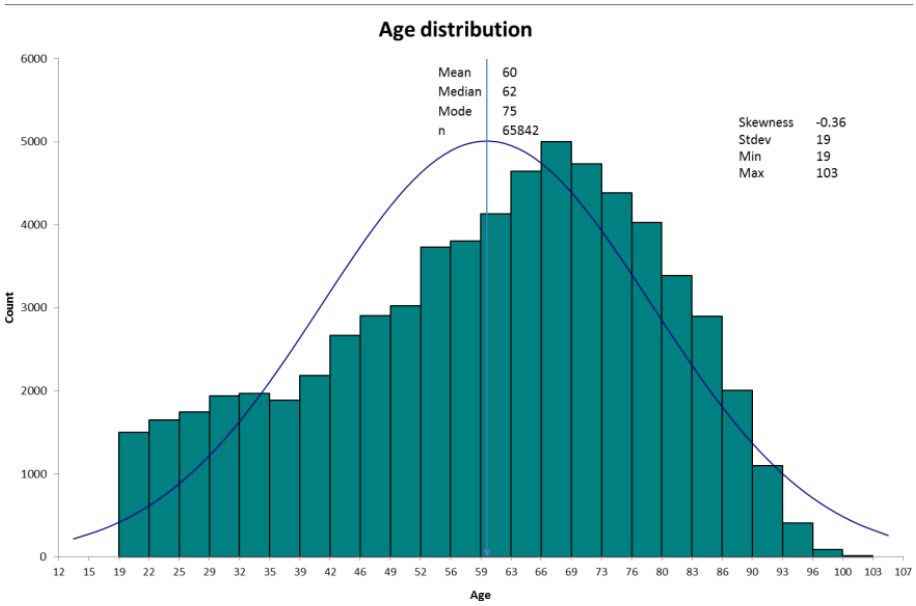


Figure 9: Age distribution of the cohort included in the analysis.

The geographical distribution of persons, with chronic conditions, admitted to acute facilities across the state is shown below:

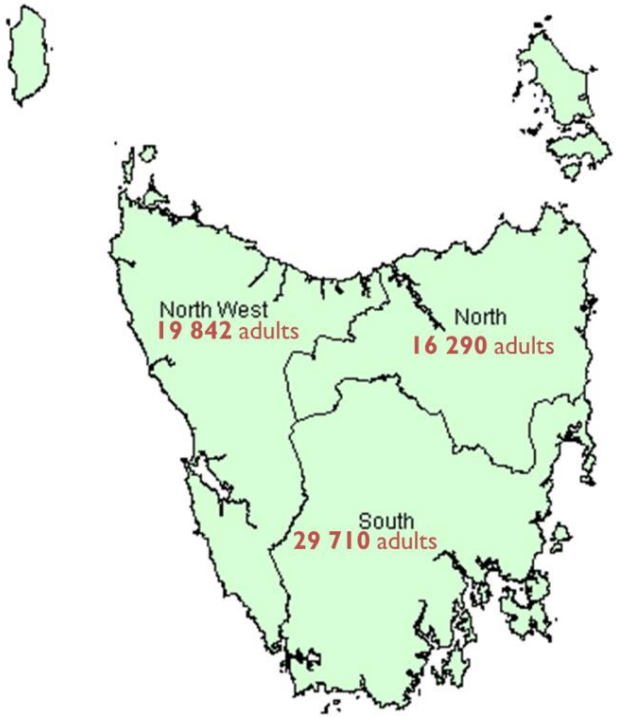


Figure 10: Cohort numbers by LGA region of people admitted to acute facilities with chronic conditions over 2015/16 and 206/17 financial years.

5.2 Linear regression analysis

North and Northwest were combined to form one region (North) to mirror the governance structure of the Tasmanian Health Service (THS). See Figure 10.

Three simple linear regression models were generated (Statewide vs Northern region, Statewide vs Southern region and Southern vs Northern region) in order to ascertain how close each of the models were and to reach a conclusion whether separate models would need to be generated for each region or whether a statewide model be used for both regions.

The edge Neuro_Inf&Con (Neurological Conditions and Infant and Congenital Disorders) has been excluded from the regression plots due to the high Odds Ratio skewing the plots. This edge has however been included in the regression models. The values for the Neuro_Inf&Con edge are provided in the label for each figure.

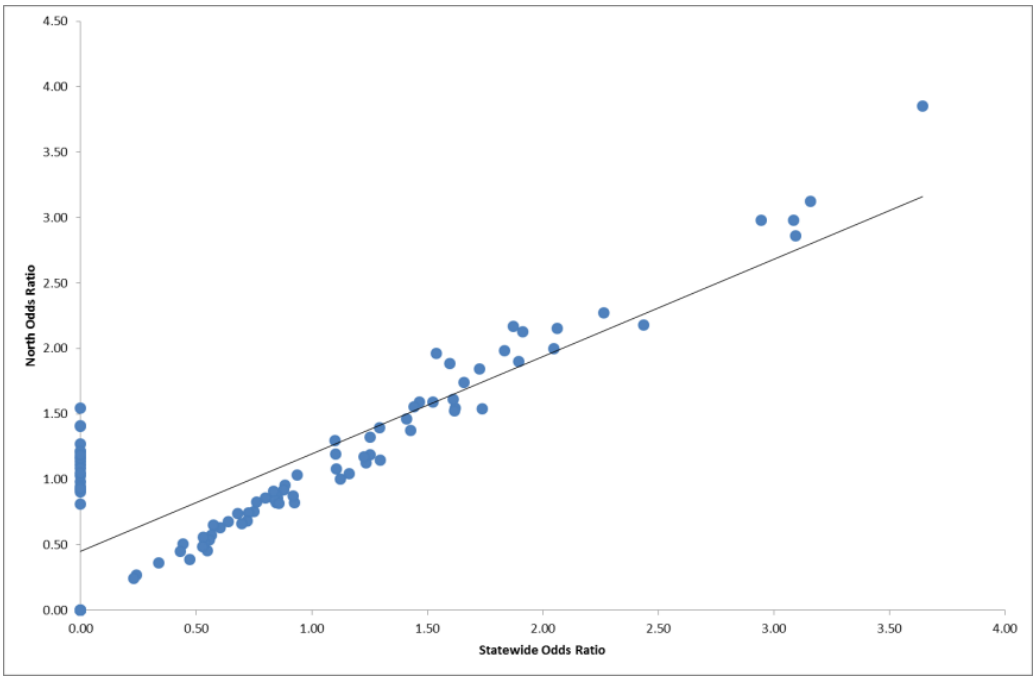


Figure 11: Scatterplot for Statewide vs Northern region. Edge *Neuro_Inf&Con* has been excluded from this plot. The OR values for the Statewide and Northern region are 13.54 and 16.95 respectively.

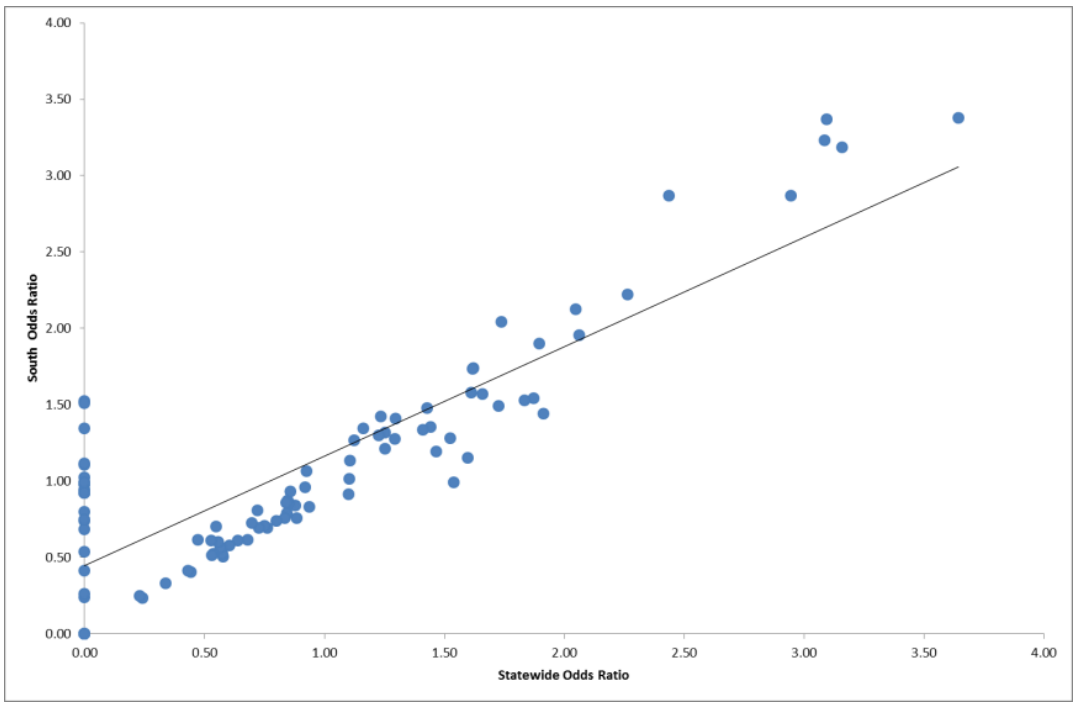


Figure 12: Scatterplot for Statewide vs Southern region. Edge *Neuro_Inf&Con* has been excluded from this plot. The OR values for the Statewide and Southern region are 13.54 and 11.87 respectively.

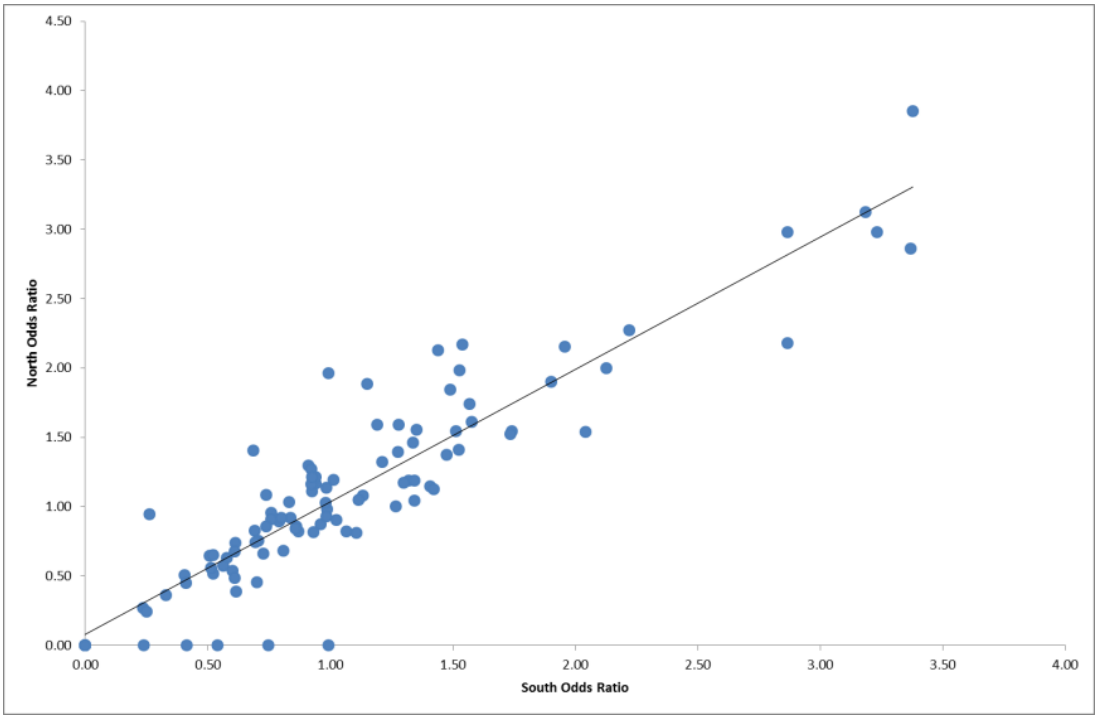


Figure 13: Scatterplot for the Southern region vs the Northern region. Edge *Neuro_Inf&Con* has been excluded from this plot. The Odds Ratio values for the Southern and northern regions are 11.87 and 16.95 respectively.

Table 2: Linear regression results for the three morbidity profile models.

	Intercept	Slope	Std Error	Adjusted R^2	F statistic	p
Statewide vs Northern region	-0.049	0.828	0.027	0.903	957.7	0.0000
Statewide vs Southern region	-0.323	1.120	0.036	0.906	996.6	0.0000
Southern region vs Northern region	0.272	0.718	0.018	0.939	1584	0.0000

Linear regression modelling indicates that there are no significant differences between the statewide morbidity profile and the Northern and Southern morbidity profiles (Table 2). Thus it can be concluded that the statewide profile can be used to model multimorbidity across the state of Tasmania.

Based on the linear regression results, only statewide data was used to analyse and draw conclusions about the morbidity profile across the state.

6 Morbidity Profile Visualisation

Statewide edge and node data was loaded into SocNetV-2.1 and progressively refined and visualised (Figure 14 and 15).

Table 3: Network graph key (Figure 14, 15 and 16) showing DHHS Statement of Purchaser Intent (SoPI) priority and non-priority conditions.

SoPI Priority conditions		Non SoPI Priority conditions	
Ca	Cancer and neoplasms	Gast	Gastroenterological conditions
CVD	Cardiovascular conditions	Bl&Met	Blood and Metabolic disorders
End	Endocrine conditions	Renal	Renal conditions
H&V	Hearing and Vision conditions	Inf&Con	Infant and Congenital conditions
MH	Mental Health and Substance Abuse	Infect	Infectious diseases
mSkelet	Musculoskeletal conditions	Rep&Mat	Reproductive and Maternal conditions
Neuro	Neurological conditions	Skin	Skin disorders
Resp	Respiratory conditions		

Figure 14 shows the full morbidity profile of the state which includes both SoPI and non SoPI priority conditions. This graph includes all significant OR (See Appendix 2 for full listing).

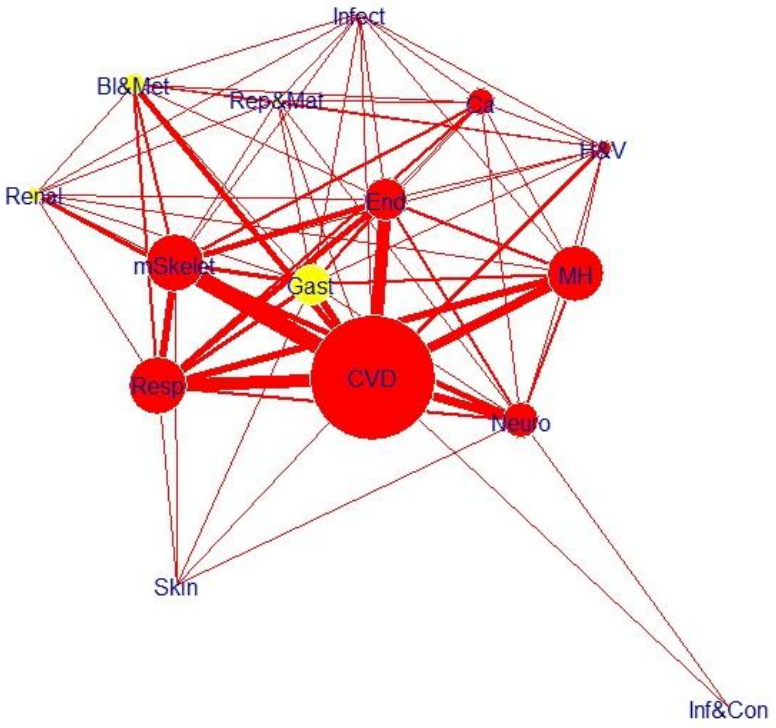


Figure 14: Network graph illustrating the statewide morbidity profile for patients admitted to an acute hospital with a chronic condition in Tasmania over the two years 2015/16 and 2016/17. Node labels refer to AIHW Burden of disease groupings. Edges are weighted according to Odds Ratio. Only significant (p<0.05) edges have been included.

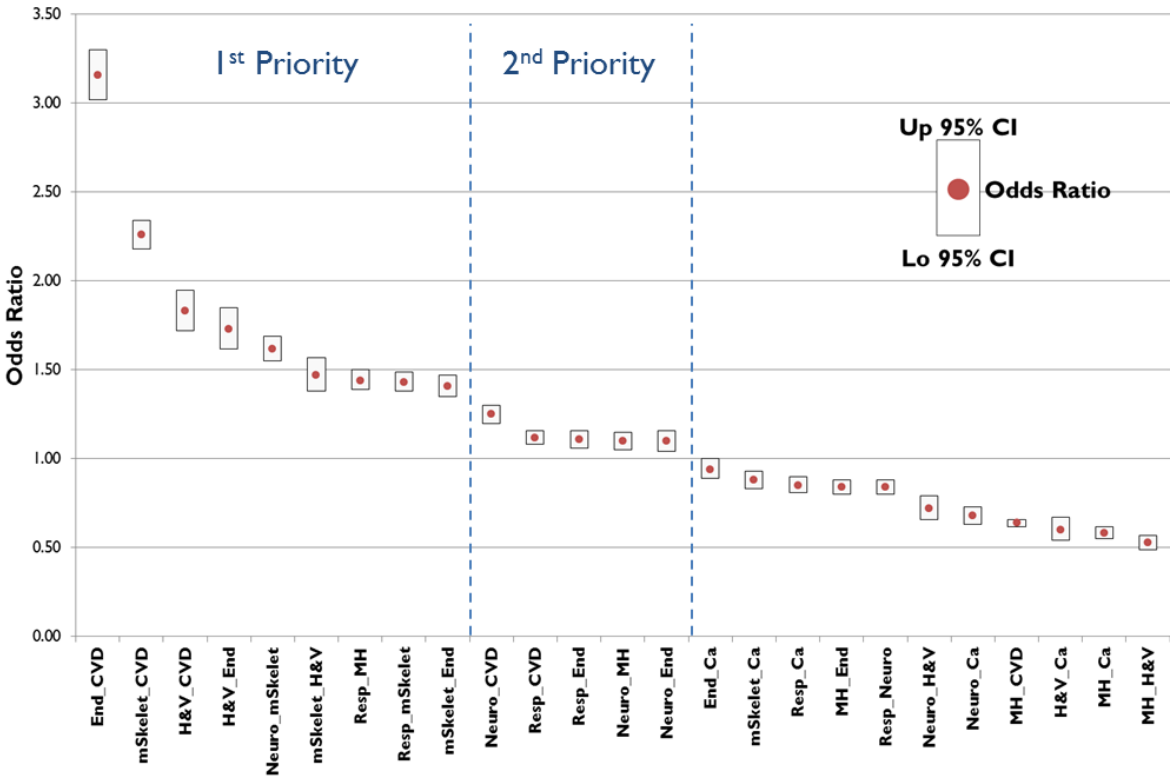


Figure 15: Odds Ratios and 95% Confidence Intervals for significant (p<0.05) edges connecting SoPI priority conditions.

In order to focus and prioritise those conditions with the strongest links, further analysis of the OR was undertaken. Figure 15 shows the OR and 95% Confidence Intervals for all edges that are significant and link SoPI priority conditions. They are grouped in turn into 1st Priority and 2nd Priority groupings. 1st Priority edges are shown in Figure 16.

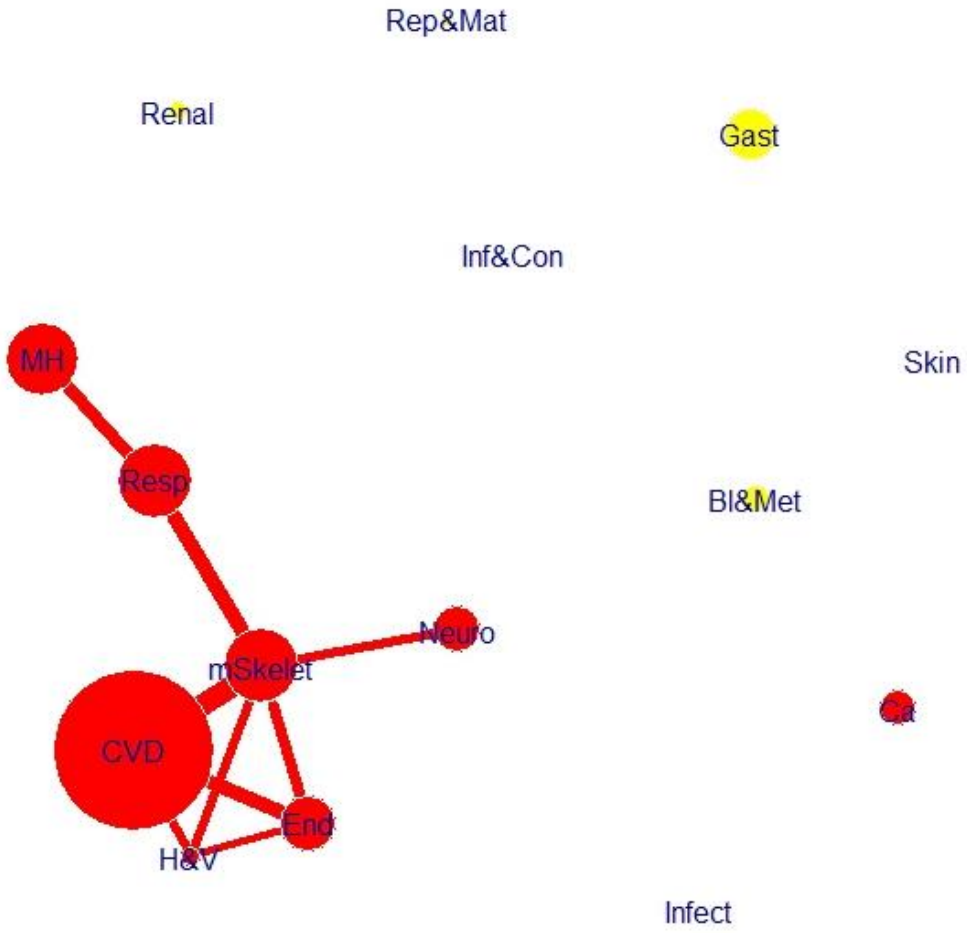


Figure 16: Statewide network graph illustrating the morbidity profile for patients admitted to an acute hospital with a chronic condition in Tasmania over the two years 2015/16 and 2016/17. Edges shown are those that connect SoPI priority conditions, are significant and have an Odds Ratio >1.25.

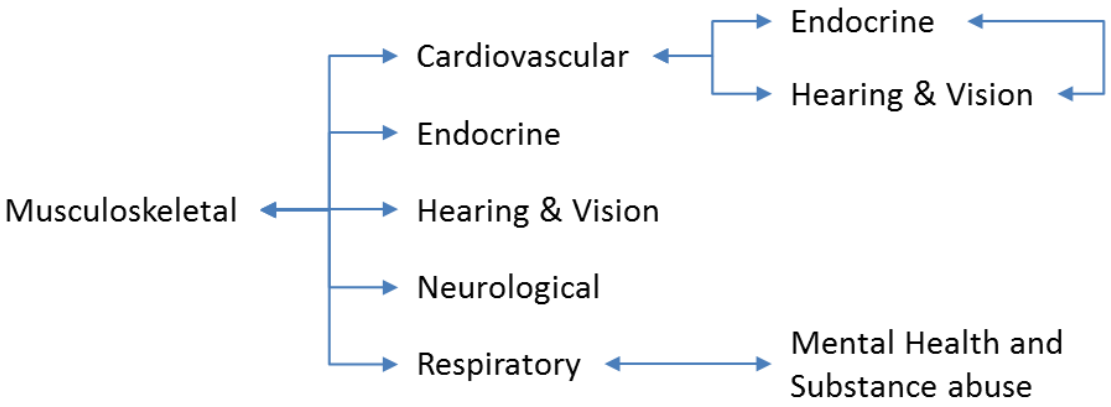
7 Service Planning

7.1 Which shared conditions should we focus on in Tasmania?

In addressing this question, two principles were applied:

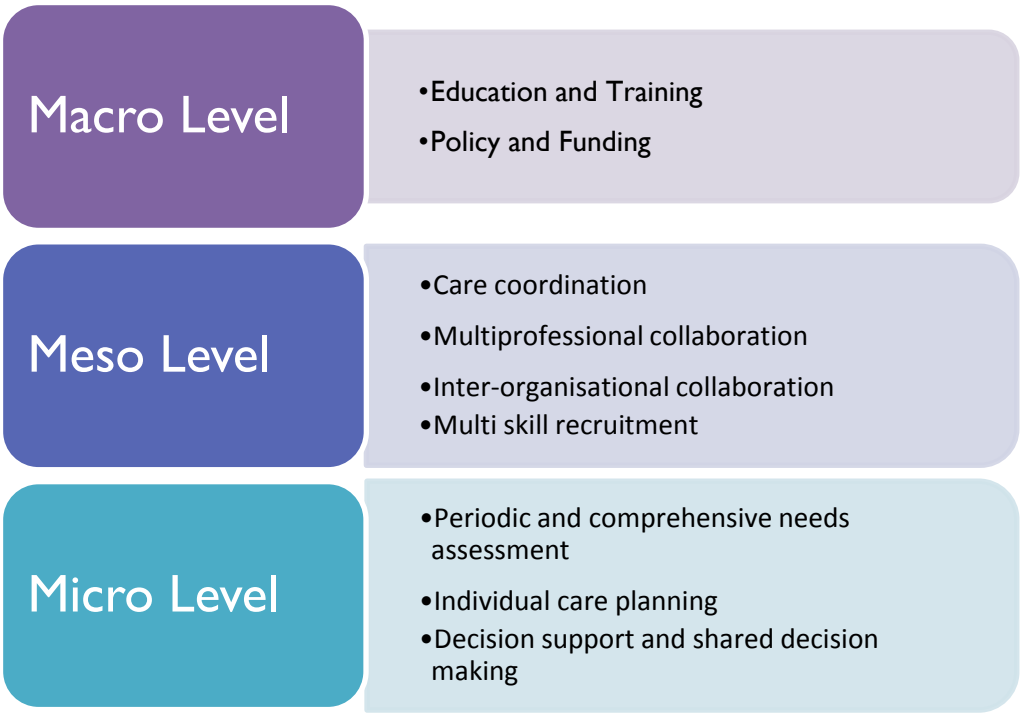
- Those conditions providing the greatest burden of disease would be prioritised i.e. those conditions highlighted in SoPI 17_18.
- Those shared conditions that have the strongest statistical associations i.e. significant ($p<0.05$) odds ratio > 1.25.

The analysis would suggest that in order to facilitate provision of services in the acute sector for those with multimorbidity, strengthening collaboration between the following combinations of services should be prioritised:



7.2 What are the options for responding to multimorbidity?

Options for responding to multimorbidity at a various levels are provided by Rijken et. al (2017) in a policy brief cofounded by the Health Program of the European Union. These are summarised below.



7.3 Future development

Further work is required in order to provide a more mature and robust approach to multimorbidity. These include but are not restricted to:

- A definitive list of chronic conditions and associated ICD 10 codes.
- A better understanding of the morbidity profile in the primary care sector. Is this vastly different to the acute sector presented here? If so, it may have service planning implications along the continuum of care.
- What does multimorbidity mean for service providers?
- What does multimorbidity mean for service users?
- Development of a framework to improve care for people with multimorbidity.

8 Appendices

Appendix1: Chronic Conditions List

Appendix 2: Odds Ratios and p values for all conditions

Appendix 1 - Chronic Conditions List

Conditions List	Kohler (2014)	(Knox et al. 2008)	(Salisbury et al. 2011)	(Goodman et al. 2013)	(van den Bussche et al. 2011)	(Orueta et al. 2014)	(Rocca et al. 2014)	(Bahler et al. 2015)	(Fabbri et al. 2015)	(Knesebeck et al. 2015)	(Tonelli et al. 2015)	(Ramond-Roquin et al. 2016)	(Rillamas-Sun et al. 2016)	(Wang et al. 2017)
Acid related disorders								I						
Allergies	I									I				
Anaemia	I							I	I	I				
Anxiety	I	I				I				I				
Arthritis	I	I		I	I		I			I	I			
Asthma / COPD	I	I	I	I	I	I	I	I	I	I	I	I	I	I
Atherosclerosis	I				I					I				
Atrial Fibrillation			I			I					I			
Autism spectrum disorder				I										
Cancer	I	I	I	I	I	I	I	I	I	I	I	I	I	I
Cardiac arrhythmias	I			I	I		I			I				
Cardiac insufficiency	I									I				
Cardiac Valve disorders	I									I				
Cardiovascular diseases		I						I						I
Chronic cholecystitis / Gall stones	I									I				
Chronic Gastritis / GERD	I									I				
Chronic Kidney Disease	I		I	I			I		I	I	I			I
Chronic Pain	I	I			I			I		I	I	I		
Cirrhosis											I			
Colon problem												I		
Congestive heart failure		I				I	I		I		I	I		
Coronary artery disease	I		I	I			I			I		I	I	

Conditions List	Kohler (2014)	(Knox et al. 2008)	(Salisbury et al. 2011)	(Goodman et al. 2013)	(van den Bussche et al. 2011)	(Orueta et al. 2014)	(Rocca et al. 2014)	(Bahler et al. 2015)	(Fabbri et al. 2015)	(Knesebeck et al. 2015)	(Tonelli et al. 2015)	(Ramond-Roquin et al. 2016)	(Rillamas-Sun et al. 2016)	(Wang et al. 2017)
Dementia / Alzheimers / Parkinsons	I		I	I			I	I	I	I	I		I	
Depression	I	I	I		I	I	I		I	I	I	I	I	
Diabetes (Types I and II)	I	I	I	I	I	I	I	I		I	I	I	I	I
Diverticulosis	I									I				
Dizziness	I									I				
Epilepsy			I					I			I			
Frequent falls													I	
Gynaecological problems	I									I				
Haemorrhoids	I									I				
Hearing loss	I									I		I	I	
Heart failure			I	I										
Hepatitis				I			I				I			
High Cholesterol												I		
Hip Fracture									I				I	
HIV				I				I						
Hyperlipidemia	I	I		I	I		I	I		I				
Hypertension	I	I	I	I	I	I	I		I	I	I	I		
Hyperuricemia / Gout	I				I			I		I				
Hypotension	I													
Hypothyroidism											I			
Inflammatory bowel disease											I			
Insomnia	I	I								I				
Intestinal inflammatory diseases								I						

Conditions List	Kohler (2014)	(Knox et al. 2008)	(Salisbury et al. 2011)	(Goodman et al. 2013)	(van den Bussche et al. 2011)	(Orueta et al. 2014)	(Rocca et al. 2014)	(Bahler et al. 2015)	(Fabbri et al. 2015)	(Knesebeck et al. 2015)	(Tonelli et al. 2015)	(Ramond-Roquin et al. 2016)	(Rillamas-Sun et al. 2016)	(Wang et al. 2017)
Irritable bowel syndrome											I			
Ischemic Heart Disease		I			I	I			I					
Learning disability			I											
Liver disease	I									I				
Mental health problems		I	I	I			I	I						I
Migraine / Chronic headache	I							I		I				
Multiple sclerosis											I			
Myocardial infarct											I			
Neuropathies	I									I				
Osteoarthritis		I										I	I	I
Osteoporosis	I			I	I		I	I		I		I		I
Other Joint Diseases									I			I		
Overweight / Obesity	I		I							I		I		
Peptic ulcer disease											I			
Peripheral vascular disease		I									I			
Prostatic hyperplasia	I									I				
Psoriasis	I									I				
Rheumatoid Arthritis	I	I								I		I		
Rheumatological disorders								I						
Severe constipation											I			
Sexual dysfunction	I													
Smoking	I													
Somatoform disorders	I									I				

Conditions List	Kohler (2014)	(Knox et al. 2008)	(Salisbury et al. 2011)	(Goodman et al. 2013)	(van den Bussche et al. 2011)	(Orueta et al. 2014)	(Rocca et al. 2014)	(Bahler et al. 2015)	(Fabbri et al. 2015)	(Knesebeck et al. 2015)	(Tonelli et al. 2015)	(Ramond-Roquin et al. 2016)	(Rillamas-Sun et al. 2016)	(Wang et al. 2017)
Stomach problem (incl GOR)		I										I		
Stroke / Cerebrovascular	I	I	I	I		I	I		I	I	I	I	I	
Substance abuse				I			I				I			
Thyroid disease	I		I		I			I		I		I		
Tuberculosis								I						
Urinary Incontinence	I									I			I	
Urinary Tract calculi	I									I				
Varicosis	I				I				I	I				
Vision loss	I				I			I		I		I	I	

Appendix 2 – Odds Ratios and p values for all conditions

Edge_Label	Statewide		Southern region		Northern region	
	OR	p	OR	p	OR	p
Neuro_Inf&Con	13.54	0.0000	11.87	0.0000	16.95	0.0000
MH_Infect	3.64	0.0000	3.38	0.0000	3.85	0.0000
End_CVD	3.16	0.0000	3.19	0.0000	3.13	0.0000
Renal_CVD	3.10	0.0000	3.37	0.0000	2.86	0.0000
Renal_Bl&Met	3.09	0.0000	3.23	0.0000	2.98	0.0000
Renal_End	2.94	0.0000	2.87	0.0000	2.98	0.0000
Skin_mSkelet	2.44	0.0000	2.87	0.0001	2.18	0.0001
mSkelet_CVD	2.26	0.0000	2.22	0.0000	2.27	0.0000
Ca_Bl&Met	2.06	0.0000	1.96	0.0000	2.15	0.0000
Gast_Bl&Met	2.05	0.0000	2.13	0.0000	2.00	0.0000
CVD_Bl&Met	1.90	0.0000	1.90	0.0000	1.90	0.0000
Rep&Mat_Neuro	1.87	0.0000	1.54	0.0000	2.17	0.0000
H&V_CVD	1.83	0.0000	1.53	0.0000	1.98	0.0000
Rep&Mat_Renal	1.74	0.0000	2.04	0.0000	1.54	0.0000
H&V_End	1.73	0.0000	1.49	0.0000	1.84	0.0000
mSkelet_Bl&Met	1.66	0.0000	1.57	0.0000	1.74	0.0000
Neuro_mSkelet	1.62	0.0000	1.74	0.0000	1.55	0.0000
End_Bl&Met	1.62	0.0000	1.74	0.0000	1.52	0.0000
mSkelet_Renal	1.61	0.0000	1.58	0.0000	1.61	0.0000
mSkelet_H&V	1.47	0.0000	1.19	0.0022	1.59	0.0022
Resp_MH	1.44	0.0000	1.35	0.0000	1.56	0.0000
Resp_mSkelet	1.43	0.0000	1.48	0.0000	1.37	0.0000
mSkelet_End	1.41	0.0000	1.34	0.0000	1.46	0.0000
Neuro_CVD	1.25	0.0000	1.21	0.0000	1.32	0.0000
Resp_Renal	1.25	0.0000	1.32	0.0000	1.19	0.0000

Edge_Label	Statewide		Southern region		Northern region	
	OR	p	OR	p	OR	p
Resp_Bl&Met	1.23	0.0000	1.30	0.0000	1.17	0.0000
Resp_CVD	1.12	0.0000	1.27	0.0000	1.00	0.0000
Resp_End	1.11	0.0000	1.13	0.0003	1.08	0.0003
mSkelet_Gast	0.89	0.0000	0.76	0.0000	0.95	0.0000
mSkelet_Ca	0.88	0.0000	0.84	0.0000	0.92	0.0000
Resp_Ca	0.85	0.0000	0.86	0.0003	0.86	0.0003
Gast_End	0.85	0.0000	0.87	0.0011	0.82	0.0011
MH_End	0.84	0.0000	0.79	0.0000	0.90	0.0000
Resp_Neuro	0.84	0.0000	0.86	0.0000	0.84	0.0000
MH_Gast	0.83	0.0000	0.76	0.0000	0.91	0.0000
MH_Renal	0.80	0.0000	0.74	0.0000	0.86	0.0000
Rep&Mat_Ca	0.76	0.0000	0.69	0.0003	0.83	0.0003
Gast_CVD	0.75	0.0000	0.71	0.0000	0.76	0.0000
Neuro_H&V	0.72	0.0000	0.81	0.0033	0.68	0.0033
Renal_Gast	0.70	0.0000	0.73	0.0000	0.66	0.0000
Neuro_Ca	0.68	0.0000	0.61	0.0000	0.74	0.0000
MH_CVD	0.64	0.0000	0.61	0.0000	0.68	0.0000
H&V_Ca	0.60	0.0000	0.58	0.0000	0.63	0.0000
MH_Ca	0.58	0.0000	0.51	0.0000	0.65	0.0000
Infect_End	0.58	0.0000	0.52	0.0000	0.65	0.0000
Gast_Ca	0.57	0.0000	0.56	0.0000	0.57	0.0000
Rep&Mat_H&V	0.55	0.0000	0.70	0.0234	0.46	0.0234
H&V_Gast	0.54	0.0000	0.52	0.0000	0.52	0.0000
MH_H&V	0.53	0.0000	0.51	0.0000	0.56	0.0000
Rep&Mat_Gast	0.47	0.0000	0.62	0.0000	0.39	0.0000
mSkelet_Infect	0.44	0.0000	0.40	0.0000	0.50	0.0000

Edge_Label	Statewide		Southern region		Northern region	
	OR	p	OR	p	OR	p
Neuro_Gast	0.43	0.0000	0.41	0.0000	0.45	0.0000
Infect_CVD	0.34	0.0000	0.33	0.0000	0.36	0.0000
Infect_H&V	0.24	0.0000	0.24	0.0000	0.27	0.0000
Skin_Resp	1.91	0.0001	1.44	0.2915	2.13	0.2915
Neuro_MH	1.10	0.0001	0.91	0.0083	1.30	0.0083
Rep&Mat_mSkelet	1.16	0.0002	1.34	0.0000	1.04	0.0000
Neuro_End	1.10	0.0002	1.01	0.7404	1.19	0.7404
Rep&Mat_Bl&Met	1.23	0.0004	1.42	0.0001	1.13	0.0001
Resp_Gast	0.92	0.0004	0.96	0.2786	0.87	0.2786
Renal_Infect	0.56	0.0004	0.60	0.0266	0.54	0.0266
Infect_Gast	1.29	0.0008	1.28	0.0250	1.39	0.0250
Rep&Mat_Infect	0.53	0.0015	0.61	0.0853	0.49	0.0853
Infect_Ca	0.73	0.0030	0.69	0.0115	0.75	0.0115
H&V_Bl&Met	0.86	0.0064	0.93	0.4576	0.82	0.4576
Skin_CVD	1.60	0.0084	1.15	0.7166	1.89	0.7166
Infect_Bl&Met	1.30	0.0094	1.41	0.0082	1.15	0.0082
Inf&Con_CVD	0.23	0.0095	0.25	0.0408	0.24	0.0408
End_Ca	0.94	0.0320	0.83	0.0001	1.03	0.0001
Skin_Gast	1.53	0.0328	1.28	0.6100	1.59	0.6100
Skin_Neuro	1.54	0.0345	0.99	1.0000	1.97	1.0000
Rep&Mat_CVD	0.93	0.0379	1.06	0.3100	0.82	0.3100
Neuro_Renal	0.00	0.0577	0.94	0.3721	1.21	0.3721
CVD_Ca	0.00	0.0647	0.94	0.0720	1.17	0.0720
Inf&Con_End	0.00	0.0778	0.00	0.1506	0.00	0.1506
Resp_Rep&Mat	0.00	0.0812	1.11	0.1542	0.81	0.1542
mSkelet_Inf&Con	0.00	0.0848	0.24	0.2316	0.00	0.2316

Edge_Label	Statewide		Southern region		Northern region	
	OR	p	OR	p	OR	p
Neuro_Bl&Met	0.00	0.0876	0.99	0.7938	1.14	0.7938
Skin_Bl&Met	0.00	0.1022	1.51	0.4324	1.55	0.4324
Renal_Ca	0.00	0.1032	0.93	0.3125	1.21	0.3125
Neuro_Infect	0.00	0.1147	0.80	0.0673	0.92	0.0673
MH_Bl&Met	0.00	0.1542	0.92	0.0797	1.16	0.0797
Rep&Mat_MH	0.00	0.1719	1.12	0.1027	1.05	0.1027
Skin_Ca	0.00	0.1998	0.26	0.0719	0.94	0.0719
Inf&Con_Ca	0.00	0.2112	0.00	0.2848	0.00	0.2848
Resp_Inf&Con	0.00	0.2387	0.54	0.6126	0.00	0.6126
Inf&Con_Gast	0.00	0.2932	0.41	0.6082	0.00	0.6082
Skin_Rep&Mat	0.00	0.3047	1.52	0.7237	1.41	0.7237
Rep&Mat_End	0.00	0.3159	1.02	0.7873	0.90	0.7873
Inf&Con_H&V	0.00	0.4774	0.00	0.7510	0.00	0.7510
Renal_Inf&Con	0.00	0.5214	0.00	0.7168	0.00	0.7168
Skin_H&V	0.00	0.5291	0.69	0.8253	1.41	0.8253
Skin_End	0.00	0.5312	0.92	0.9687	1.27	0.9687
Skin_Renal	0.00	0.5475	1.34	0.7853	1.19	0.7853
Skin_Infect	0.00	0.5850	0.99	1.0000	0.00	1.0000
Rep&Mat_Inf&Con	0.00	0.7104	0.00	0.9548	0.00	0.9548
Renal_H&V	0.00	0.7242	0.98	0.9183	0.93	0.9183
Resp_H&V	0.00	0.7966	0.99	0.8611	0.98	0.8611
Resp_Infect	0.00	0.8468	0.92	0.4655	1.11	0.4655
Inf&Con_Bl&Met	0.00	0.8967	0.75	1.0000	0.00	1.0000
MH_Inf&Con	0.00	0.9930	0.74	0.8679	1.08	0.8679
mSkelet_MH	0.00	1.0000	0.98	0.5196	1.03	0.5196
Skin_Inf&Con	0.00	1.0000	0.00	1.0000	0.00	1.0000

Edge_Label	Statewide		Southern region		Northern region	
	OR	p	OR	p	OR	p
Infect_Inf&Con	0.00	1.0000	0.00	1.0000	0.00	1.0000

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