How To Measure Multimorbidity? Ask the Experts!

Mary Charlson, MD (Cornell)
Anne Elixhauser, PhD (AHRQ)
Arlene Ash, PhD (UMass Medical School)
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1. Event info Tab:

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  - Type your questions in the Q&A box:

- Hosts will acknowledge questions in order
Comorbidity: Why Measure it?

Mary E. Charlson, MD
Chief, Division of Clinical Epidemiology and Evaluative Sciences Research
Executive Director, Center for Integrative Medicine

AGING Initiative
Multimorbidity Measures Webinar
November 16, 2015
What I will talk about:

Comorbidity
Why measure it?

Mary E. Charlson, MD
Chief, Division of Clinical Epidemiology and Evaluative Sciences Research
Executive Director, Center for Integrative Medicine
What I was supposed to talk about:

Multimorbidity...

But what is it?

Mary E. Charlson, MD
Chief, Division of Clinical Epidemiology and Evaluative Sciences Research
Executive Director, Center for Integrative Medicine
Disclosure:
Cornell University has filed a patent for the use of the enhanced comorbidity index to predict future costs.
Higher Comorbidity

Objective

- Prognostic burden of chronic disease
- Predict mortality

Developmental population

- Medical inpatients 1 year mortality
  - Validation population
- Breast cancer patients 10 year mortality
<table>
<thead>
<tr>
<th>Chronic disease</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cerebrovascular disease</td>
<td>1</td>
</tr>
<tr>
<td>Congestive heart failure</td>
<td>1</td>
</tr>
<tr>
<td>COPD or Asthma</td>
<td>1</td>
</tr>
<tr>
<td>Dementia</td>
<td>1</td>
</tr>
<tr>
<td>Depression</td>
<td>1</td>
</tr>
<tr>
<td>Diabetes without end organ damage</td>
<td>1</td>
</tr>
<tr>
<td>Hypertension</td>
<td>1</td>
</tr>
<tr>
<td>Mild liver disease</td>
<td>1</td>
</tr>
<tr>
<td>Myocardial infarction</td>
<td>1</td>
</tr>
<tr>
<td>Peripheral Vascular disease</td>
<td>1</td>
</tr>
<tr>
<td>Rheumatic disease</td>
<td>1</td>
</tr>
<tr>
<td>Ulcer disease</td>
<td>1</td>
</tr>
<tr>
<td>Hemplegia</td>
<td>2</td>
</tr>
<tr>
<td>Moderate/severe renal disease</td>
<td>2</td>
</tr>
<tr>
<td>Diabetes with end organ damage</td>
<td>2</td>
</tr>
<tr>
<td>Any tumor</td>
<td>2</td>
</tr>
<tr>
<td>Skin ulcers/cellulitis</td>
<td>2</td>
</tr>
<tr>
<td>Takes warfarin</td>
<td>1</td>
</tr>
<tr>
<td>Leukemia</td>
<td>2</td>
</tr>
<tr>
<td>Lymphoma</td>
<td>2</td>
</tr>
<tr>
<td>Moderate/severe liver disease</td>
<td>3</td>
</tr>
<tr>
<td>Metastatic solid tumor</td>
<td>6</td>
</tr>
<tr>
<td>HIV/AIDS</td>
<td>6</td>
</tr>
</tbody>
</table>
Higher Comorbidity

- Worse physical and mental health
- Greater disability
- Higher morbidity and mortality
- Higher hospitalization and readmission

13,166 citations
Why understanding comorbidity is key to population health management
Population level utilization

- 181,984 health workers
- Prospective use of comorbidity to predict costs, hospitalization and readmission
Yearly health cost rises steadily with increasing comorbidity
In employed populations, a relatively low percent of patients have high comorbidity.

Charlson et al. PLOS One 2014
Hospitalization rates rise steadily with increasing comorbidity

Average hospitalizations per year

Charlson et al PLOS One 2014
Repeated hospitalization also rises with increasing comorbidity

Charlson et al PLOS One 2014
Percent of beneficiaries and costs

- % beneficiaries
- % costs

Comorbidity
- 0-1
- 2-3
- 4
- >5
Costs according to comorbidity and number of hospitalizations

Yearly cost

Comorbidity

Number of Hospitalizations

None

One

Two

Three or more

Charlson et al PLOS One 2014
Reducing costs

- Hospitalization is the principal driver of costs.
- Average hospitalization costs are $25-30K.
- Patients with high comorbidity have the greatest potential for cost reduction by reducing hospitalizations.

Charlson et al PLOS One 2014
Charlson et al BMC Health Services Research 2014
Comparisons with other predictors

Prior year
- Costs
- Comorbidity
- DCG Score
- Hospitalizations

Statistical methods
- Two stage regression
- Quantile regression –5% and 10%
- ROC analysis
- Positive Predictive Value using logistic regression
## Two stage regression models

<table>
<thead>
<tr>
<th>Prior year</th>
<th>Adults $R^2$</th>
<th>Children $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Costs</td>
<td>0.31</td>
<td>0.20</td>
</tr>
<tr>
<td>Comorbidity</td>
<td>0.20</td>
<td>0.17</td>
</tr>
<tr>
<td>DCG</td>
<td>0.20</td>
<td>0.07</td>
</tr>
<tr>
<td>Prior year hospitalization</td>
<td>0.11</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Controlling for age, gender and mental health diagnosis
Predictors of the adults and children who would have the top 5% of costs

<table>
<thead>
<tr>
<th>Prior year</th>
<th>Adults Pseudo $R^2$</th>
<th>Children Pseudo $R^2$</th>
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</thead>
<tbody>
<tr>
<td>Costs</td>
<td>.13</td>
<td>.11</td>
</tr>
<tr>
<td>Comorbidity</td>
<td>.12</td>
<td>.10</td>
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<tr>
<td>DCG</td>
<td>.12</td>
<td>.10</td>
</tr>
<tr>
<td>Hospitalization</td>
<td>.04</td>
<td>.09</td>
</tr>
</tbody>
</table>

Controlling for age, gender and mental health diagnosis
Predictors of the adults and children who would have the top 10% of costs

<table>
<thead>
<tr>
<th>Prior year costs</th>
<th>Adults Pseudo R²</th>
<th>Children Pseudo R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comorbidity</td>
<td>.134</td>
<td>.12</td>
</tr>
<tr>
<td>DCG</td>
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<tr>
<td>Prior year hospitalization</td>
<td>.12</td>
<td>.09</td>
</tr>
<tr>
<td></td>
<td>.04</td>
<td>.03</td>
</tr>
</tbody>
</table>
## Classification of likelihood of membership in Top 5% or 10% of costs

<table>
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<tr>
<th>Prior year</th>
<th>Top 5%</th>
<th>Top 10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Costs</td>
<td>.66</td>
<td>.68</td>
</tr>
<tr>
<td>Comorbidity</td>
<td>.65</td>
<td>.65</td>
</tr>
<tr>
<td>DCG</td>
<td>.66</td>
<td>.67</td>
</tr>
<tr>
<td>Hospitalization</td>
<td>.56</td>
<td>.55</td>
</tr>
</tbody>
</table>

Controlling for age, gender and mental health diagnosis
Most programs have not reduced costs

- Disease management programs
- Coordinated care/case management programs

*Because...*
- They targeted the wrong patients and ended up spending more than they saved.
Why understanding comorbidity is key to population health management
Total costs for specific chronic diseases according to the adjusted comorbidity index

Total yearly cost

Adjusted Comorbidity

- Cancer
- CHF
- CVA
- Asthma/COPD
- Diabetes
- Hypertension
- MI
- PVD
- Rheumatic
Percent of patients according to comorbidity

- Asthma/COPD
- Hypertension
- Cancer
- Diabetes with end organ
- Rheumatic
- Diabetes
- Liver
- CVA
- PVD
- MI
- CHF
- Renal

Percent of patients

Adjusted comorbidity index
All patients should receive the same HgA$_{1c}$ or BP target.
On the assumption that reducing variability in process will improve outcomes.
OR...
Maybe not the same rules

- Three patients... all 75 year old men s/p MI scheduled for colorectal surgery.
  - Labs are the same.
  - ASA ranks are the same.
- By industrial process assessment, they are the same.
- But by your assessment, are their risks the same?
- Why are you more worried about the recent widower?
Why did we buy into the theory that industrial processing rules that result in less than 1 in 1 million errors in manufacturing lightbulbs apply to patient care?
Maybe patient variability is the driver of outcomes
Higher comorbidity

- Different outcome metrics
- Separate from quality reports
Sources for comorbidity data

- Questionnaire (5-10 min)
  - Patient
  - Interviewer
- Medical records
- Registries
- Repositories

- Claims data
  - ICD-9
  - ICD-10
For questions:

Mary Charlson MD

mecharl@med.cornell.edu
Diagnostic Cost Groups (DCGs) and Hierarchical Condition Categories (HCCs)

Arlene S Ash, PhD
University of Massachusetts Medical School
Dept. of Quantitative Health Sciences (QHS)
Worcester, MA
arlene.ash@umassmed.edu
A mathematician, I have worked in risk modeling and payment reform since 1984

- DCG-HCC modeling family includes
  - Public models, e.g., CMS-HCC and HHS-HCC
  - DxCGs (updated and licensed by Verisk Health (VH))

- A founder of DxCG Inc, now part of VH
  - I have no current ownership interest in any risk tool
  - I consult for VH and use DxCG models in research

- I am currently exploring adding social determinants to DxCG models for MassHealth (Medicaid)
Outline

- DCG Chronology
- Functionality as a “grouper”
- Functionality as a risk score/predictive tool
- Strengths and limitations
  - Of the publicly available CMS-HCC models
  - Of Verisk Health’s DxCG models
Late ‘80s – Diagnostic Cost Groups (DCG) risk models developed for payment in “Medicare Advantage”

Early ‘90s – Hierarchical Condition Categories (HCCs) modeling structure introduced

Late ‘90s – DCG-HCC models extended to commercial and Medicaid populations

1996 DxCG, Inc. founded – now the science division of Verisk Health (VH)

2000 - 2004 CMS-HCC models introduced for capitated payments to Medicare health plans

2014 HHS-HCC models used for ACA small-group market pricing
Use ICD-9 (10) diagnoses, usually from a year of claims (or encounter records) to:

1. Classify each person’s individual morbidities
2. Create a summary morbidity profile
3. Predict: Outcome = f(age, sex, morbidity profile)

Can predict many outcomes, including:

- Total medical expense (TME) next year
- TME in the same year that the morbidities were recorded
- Resources needed to supply comprehensive primary care
- Probability of an ED visit in the next 6 months
- Probability of death w/in 30-days of an AMI admission

Predictions often given as “relative risk scores” (RRS)

For TME, RRS = 1.5 means expected cost is 50% higher than the average in a benchmark population
1. A useful classification of (14,000 to 68,000) ICD-diagnosis codes into “condition categories” (CCs)
   - DxCG maps all codes into 394 CC
   - CMS-HCC only maps ~3,000 codes into ~80 CCs

2. A clinically informative organization of CCs
   - By chronicity: chronic versus not (eg, heart failure vs. AMI)
   - By body systems: 31 Aggregated CCs (eg, “liver”)
   - Through hierarchies among related CCs: eg, keep the upper respiratory infection (URI) only absent more serious lung disease
     
     CC: URI = 1 and COLD =1 becomes →
     
     HCC: URI = 0 and COLD =1

3. Risk scores, benchmarks and predictive models for: cost, utilization, quality, morbidity and mortality outcomes
Which doctor is most efficient?

<table>
<thead>
<tr>
<th>Provider</th>
<th>Actual Cost/Patient</th>
<th>Predicted Cost/Patient</th>
<th>Ratio (Actual/Expected)</th>
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<td>Dr A</td>
<td>$4,190</td>
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<td>$4,840</td>
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<td>0.82</td>
</tr>
<tr>
<td>Dr C</td>
<td>$4,270</td>
<td>$3,710</td>
<td>1.15</td>
</tr>
<tr>
<td>Dr D</td>
<td>$10,275</td>
<td>$11,350</td>
<td>0.91</td>
</tr>
<tr>
<td>Dr E</td>
<td>$7,328</td>
<td>$6,540</td>
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Provider A is least expensive; whereas Provider D is most expensive.
## With Risk Adjustment

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Provider B is most efficient; whereas Provider C is least efficient.
Key inputs are: age, sex and diagnoses

Models are fit to huge databases
- Commercial, Medicare, Medicaid

Modeling strategies address:
- Influential outliers (through top-coding)
- Partial years of eligibility (through annualizing)
- Interactions (e.g., among diseases, of diseases with age-sex groups, ...)
- Differences in the implications of chronic and acute condition for current and future utilization and cost
RRS = \( A + \text{RiskIndicator}_1 \times \text{RiskWeight}_1 + \ldots \)

<table>
<thead>
<tr>
<th>A</th>
<th>Intercept</th>
</tr>
</thead>
</table>

**Risk Indicator**
- Demographic characteristics
- Clinical conditions (HCC)
- Disease interactions
- Age x disease interactions

**Risk Weights**
Incremental risk assigned based upon the presence of a particular risk indicator
Accruing Risk Weights

Components:
- Morbidity
- Interactions
- Medical
- Demographic

Risk Indicators:
- No Claims
- Diabetes
- CHF
- Diabetes and CHF
Enrollment Information

- 60 Years Old
- Male
- Full Year of Enrollment

Medical Claims

- Regular Check Up: $100
  - Uncomplicated Diabetes
  - Congestive Heart Failure
  - Diabetes w/ Renal Manifestation

- Hospital Admission: $5,200
  - Diabetes w/ Acute Complications
  - Various Lab Tests
  - Hospitalized for 3 days

Risk Adjustment

- Age and Gender: 3.250
- All Medical: 10.975
Limitations of DCG-HCC models

- Rely on claims and enrollment data
  - Aggressive coding is rewarded; can distort risk scores
  - Risk calculation requires a claims history
- Models can only be fit to large databases
- Availability
  - Verisk Health’s DxCG models require licensing
  - Public models are “coarse” (ignore many diagnostic codes, use <100 CCs)
- Only capture socioeconomic risks (eg, poverty) only through resultant disease
Strengths of DxCG-HCC models

- Can predict “almost anything” from age, sex and ICD-9-CM or ICD-10 codes
  - Useful for setting benchmarks, assessing performance
- Models that have been fit to large populations can be applied to, and work well, in new data
  - Models are stable over time, age-sex groups, region, and health plan types
  - Easy to extend: Outcome = f(age-sex, RRS, rf₁, rf₂,...)
- Classification system is comprehensive and clinically rich; its models capture multi-morbidity
- Reduced-price licensing for researchers
Selected References

- Chen J; Ellis RP; Toro KH; Ash AS. 2015. Mispricing in Medicare Advantage Risk Adjustment. Inquiry.
- Ash S; Ellis RP. 2012. Risk-Adjusted Payment and Performance Assessment for Primary Care. Medical Care.
The Elixhauser Comorbidity Measures and development of indices to predict mortality and readmissions using nationwide data

Anne Elixhauser, PhD
Senior Research Scientist
Agency for Healthcare Research & Quality
Claudia Steiner, Bob Harris, and Rosanna Coffey
- Comorbidity Measures for Use with Administrative Data. *Medical Care* 1998;36:8-27

Brian Moore, Susan White, Raynard Washington, and Natalia Coenen
- Comorbidity Indices for Identifying Risk of Readmission or In-Hospital Mortality Based on Administrative Data. *(Manuscript in process)*
Overview

- Elixhauser Comorbidity Measures – original development
- Detour: Chronic Condition Indicator
- Development of indices to measure in-hospital mortality and hospital readmissions
Comorbidities need to be controlled when using administrative data

Can be handled various ways:
- Stratify patients into groups
- Individual binary indicators for discrete conditions
- Summarize comorbidities into single index or score

Charlson comorbidity index
- Based on 600 breast cancer patients
- Predicting 1-year mortality
- Applied to administrative data by others
Romano pointed out precautions with indices
- Must account for complexity of ICD coding
- Weights should be estimated for different populations and different outcomes
- Ensure list of comorbidities is comprehensive

1998 study: Developed and tested measures
- Specifically for use with administrative data
- Predicting charges, length of stay, in-hospital mortality
- Overall and for selected diagnostic subgroups
How the original comorbidity measures addressed illness burden

- Primary reason for stay: principal diagnosis
  
  Limit search for comorbidities to secondary diagnoses

- Severity of principal diagnosis

  Count comorbidities only if not related to the DRG

- Complications resulting from care

  Exclude ICD codes that reflected acute medical misadventures

- Conditions present on admission with trivial impact on outcomes

  Eliminate conditions unrelated to outcomes

- **Comorbidities not related to principal diagnosis with impact on outcomes**

  Clinical condition existing before admission, not the same DRG, not a complication, related to outcomes of interest

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**AGING initiative**
Defining the comorbidity list

- 41 comorbidities initially identified through published studies and review of ICD codebook
- Series of analyses to refine list
  - Too infrequent – dropped
  - Statistically unrelated to outcomes – dropped
  - Too heterogeneous – partition further
  - Weak when separate but stronger when combined – combine
  - Algorithm to avoid double-counting – only count the more severe of two related comorbidities

31 comorbidities
Study population

- Healthcare Cost and Utilization Project (HCUP) State Inpatient Database (SID) for California, 1992
  - 3.6 million records from 438 hospitals
  - Up to 29 secondary diagnoses
  - 18 years and older
  - Admitted to acute care hospital
  - Not transferred

- All stays and 10 specific conditions
  - Breast cancer, AMI, asthma, appendicitis, hernia, biliary tract disease, low back pain, pneumonia, DM with complications
Methods for original measures

- OLS regression for logged LOS and charges
- Logistic regression for in-hospital mortality
- Controlled for age, race, payer, emergency admission, complications
Results on the original measures

- Ended up with 30 comorbidity measures including:
  - Mental disorders, drug and alcohol abuse, obesity, weight loss, fluid and electrolyte disorders
- Independent effects on LOS, charges, and mortality
- Suggested using the measures as independent variables in models based on administrative data
  - Feasible because of generally large sample sizes
- Dropped cardiac arrhythmias, so 29 comorbidities currently
- Other researchers have:
  - Examined use of present on admission (POA) indicators (e.g., Stukenborg)
  - Developed indices (e.g., van Walraven, Thompson)
    - Valid substitutes for individual measures
    - Powerful way to condense comorbidity information
  - Extended use of comorbidity measures to other outcomes, e.g., readmissions
- Small convenience samples
- Maintained at: [http://www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp](http://www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp)
Based on work for MEPS

- Clinical panel designated all 3-digit ICD diagnosis codes as chronic or not chronic
- Specific definition of “chronic”

Began with that list and expanded to all diagnosis codes

- Includes a body system indicator (follows ICD chapters)

http://www.hcup-us.ahrq.gov/toolssoftware/chronic/chronic.jsp
Purpose: Develop comorbidity indices for administrative data

HCUP SID, 2012
- New HCUP product: Nationwide Readmissions Database
  - Can make national estimates
- 1,714 community hospitals from 18 states
- 10.8 million records
  - Drawn from states with ~45% of U.S. population/discharges
  - Encrypted patient linkage numbers to identify readmissions

Outcomes
- In-hospital mortality
- 30-day readmissions
Methods for deciding which comorbidities to include

- Logistic regression using maximum likelihood fit
- Bootstrapped to decide which comorbidities would appear in the final models
  - Backward stepwise regression models
    - Also tested forward regression – negligible differences
  - 100 replications with 5 percent random samples (alpha inclusion: 0.01)
Criterion: Comorbidities appearing in 20% or more of the models were included in final model on full sample

Excluded comorbidities based on this criterion

- Acquired immune deficiency syndrome*
- Rheumatoid arthritis*
- Uncomplicated DM*
- Peptic ulcer disease*†
- Hypothyroidism*†
- Valvular disease*†

* Dropped from mortality model
† Dropped from readmission model
Parameter estimates with significant effects were assigned a weight =
  - Regression coefficient ÷
  - Absolute value of the smallest regression coefficient
  - Rounded to nearest integer

Comorbidity index score =
  - Weighted sum of each comorbidity variable in model
Validation tests of the index

- Validation sample
  - 2011 data from 1,802 hospitals, 11.1 million records
- Diagnostic subgroups based on principal diagnosis grouped using Clinical Classification Software (~240 diagnosis categories)
Summary of results: Weights

- Mortality model
  - Weights ranged from -7 (drug abuse) to 14 (metastatic cancer)
- Readmission model
  - Weights ranged from -3 (obesity) to 21 (metastatic cancer)
- Comorbidities with “protective” effect (negative signs)
  - Alcohol abuse*
  - Deficiency anemias*
  - Chronic blood loss anemia*
  - Depression*
  - Diabetes with complications*
  - Drug abuse*
  - Hypertension*†
  - Obesity*†
  - Psychoses*

* In mortality model
† In readmission model
### Comparing c-statistics

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<thead>
<tr>
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<th>Mortality</th>
<th>Readmission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Final mortality index</td>
<td>0.78</td>
<td>0.63</td>
</tr>
<tr>
<td>29 individual binary comorbidity variables</td>
<td>0.78</td>
<td>0.63</td>
</tr>
<tr>
<td>Count of comorbidities</td>
<td>0.68</td>
<td>0.61</td>
</tr>
<tr>
<td>Van Walraven index</td>
<td>0.76</td>
<td>0.60</td>
</tr>
<tr>
<td>Thompson index</td>
<td>0.78</td>
<td>0.59</td>
</tr>
</tbody>
</table>

**Summary of results:**

- Mortality performance: Index performs as well as individual binary variables.
- Unweighted count of comorbidities performs worst.
- Comparable to results using alternative weights.
### Comparing c-statistics

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- **Index performs as well as individual binary variables, but not as well as for mortality**
- **Again, unweighted count of comorbidities performs worst**
- **Results with alternative weights not as good**
Comparable performance in 2011 validation sample

Subpopulation analysis on all CCS diagnoses

- For principal diagnoses with the greatest number of in-hospital deaths, c-statistics ranged from 0.60 (stroke) to 0.72 (pneumonia)
- For principal diagnoses with the greatest number of readmissions, c-statistics ranged from 0.54 (schizophrenia) to 0.63 (complication of device, implant or graft)
Mortality index weights and model performance were similar to van Walraven and Thompson
- Stable across a range of populations
- Index performed as well as individual comorbidity variables

First time a comorbidity index was created for readmissions
- Better performance than simply applying mortality weights to readmission outcome
ICD-10 version available

Comorbidity Software for ICD-10-CM

The Comorbidity Software is one in a family of databases and software tools developed as part of the Healthcare Cost and Utilization Project (HCUP), a Federal-State-Industry partnership sponsored by the Agency for Healthcare Research and Quality. HCUP databases, tools, and software inform decision making at the national, State, and community levels.

Contents:
- Overview of the Comorbidity Software for ICD-10-CM Tool
- Description of the Comorbidity Software for ICD-10-CM Tool
- Technical Guidance for the Comorbidity Software for ICD-10-CM Tool
- Downloading Information for the Comorbidity Software for ICD-10-CM Tool
- Publications Using the Comorbidity Software for ICD-10-CM Tool
- For More Information, Comments, or Questions About the Comorbidity Software for ICD-10-CM Tool

Overview of the Comorbidity Software for ICD-10-CM Tool

The Comorbidity Software for ICD-10-CM assigns variables that identify comorbidities in hospital discharge records using the diagnosis coding of ICD-10-CM. This Web page describes the software that created the original ICD-9-CM comorbidity measures reported by Elixhauser et al. 1

The Comorbidity Software for ICD-10-CM consists of two SAS computer programs for personal computers. Although these programs are written in SAS, they are being distributed in ASCII so that they can be readily adapted to other programming languages.

The first program, Creation of Format Library for Comorbidity Groups, creates a SAS format library that maps diagnosis codes into comorbidity indicators. Additional formats are created to exclude conditions that may be complications or that may be related to the principal diagnosis.

- Comformat2016.txt is designed for files that include ICD-10 MS-DRG version 33.

The second SAS program, Creation of Comorbidity Variables, applies the formats created above to a data set containing administrative data and then creates the comorbidity variables:

http://www.hcup-us.ahrq.gov/toolssoftware/comorbidityicd10/comorbidity_icd10.jsp
Questions/Comments?
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AGING Initiative Website

More information about the AGING Initiative, as well as a link to a recording of the webinar can be found at: http://www.hcsrn.org/en/Collaboration/Consortia/AGING_Initiative.html

For Questions Contact:

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