RISK-BASED MONITORING USING EPISODE-OF-CARE ANALYTICS

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AGENDA

• Introduction
• SAS Healthcare Analytics Framework (HAF)
  • Episode analytics for value-based bundle payment models
  • Population analytics for patient care and risk management
• Risk analytics and segmentation models
  • The Likelihood-Frequency-Cost (LFC) predictive model for chronic condition episodes
  • Utilization of recommended core services (URCS)
  • Effect of URCS on potentially avoidable ED visits
• Condition episodes use cases: diabetes and asthma
• Summary
• Q&A
FOCUS ON ANALYTICS – GETTING PAST COLLECTION

• Healthcare Analytics:
  • Episode of Care/Cost of Care
  • Population Health Management
  • Quality of Care
  • Fraud, Waste, and Abuse
  • Clinical Research and Trials
  • Health Outcome Analysis
  • Patient Cohorts
  • Visualization & Reporting

Credits: http://kwfoundation.org
Can Episode Analytics help the transition from fee-for-service, volume based model to value based bundle payment reimbursement model?

Can Episodes Analytics impact patient care cost?

Can Episode Analytics impact quality of care?

Can we solve for \( \text{Value} = \frac{\text{Quality}^*}{\text{Cost}^{**}} \)

* Determined by patient outcomes, safety, and experiences
** Determined by cost of services, and operational costs
TRANSFORMING RAW DATA INTO REAL WORLD EVIDENCE-BASED ACTIONABLE INFORMATION

**DATA MAPPING & PREPARATION**
- Process claims/EMR/clinical trials data
- Data reconciliation and consolidation
- Episode-of-care metadata

**EPISODE CONSTRUCTION**
- Episode definitions & signal logic
- Service assignment & cost allocation
- Episode association & dependency detection

**PROVIDER ATTRIBUTION**
- Episode attribution rules
- Provider-level metrics for costs/resource use

**HEALTHCARE/RISK ANALYTICS**
- Derive risk-adjusted typical and PAC costs
- Member risk score and profile analytics
- Subpopulation risk segmentation

**BUDGETING & V-ANALYTICS**
- Bundled payments & contracts negotiation
- Care patterns & underuse gap analyses
- Population health management models

**SAS® EPISODE ANALYTICS** (component of SAS® Healthcare Analytics Framework)
Complications depend on perspective

Consider a year in the life of a diabetic patient
<table>
<thead>
<tr>
<th>Condition</th>
<th>Episode Total Cost</th>
<th>Episode Cost Trend</th>
<th>Episode PAC Cost</th>
<th>Episode PAC Cost Trend</th>
<th>Level</th>
<th>Condition Class</th>
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<tbody>
<tr>
<td>Allergic Rhinitis/Chronic Sinusitis</td>
<td>$34,466.04</td>
<td></td>
<td>$9,906.92</td>
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<td>Level 1</td>
<td>Chronic Conditions</td>
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<tr>
<td>Arrhythmia / Heart Block / Conduction Diseases</td>
<td>$78,426.40</td>
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<td>$13,669.22</td>
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<td>Asthma</td>
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<td>$11,669.40</td>
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<tr>
<td>Bipolar Disorder</td>
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<td>$2,784.60</td>
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<tr>
<td>Chronic Obstructive Pulmonary Disease</td>
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<td>$12,885.33</td>
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<td>Congestive Heart Failure</td>
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<td>$752.36</td>
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<td>Coronary Artery Disease</td>
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<td>$1,955.76</td>
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<td>$21,468.40</td>
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<td>Chronic Conditions</td>
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<td>Diabetes</td>
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<td>$30,260.45</td>
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<td>Chronic Conditions</td>
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<td>Gastro-Esophageal Reflux Disease</td>
<td>$58,204.51</td>
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<td>$21,958.45</td>
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<td>Chronic Conditions</td>
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<td>Glaucoma</td>
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<td>$1,381.21</td>
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<td>Chronic Conditions</td>
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<td>Hypertension</td>
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<td>$31,573.42</td>
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<td>Chronic Conditions</td>
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<td>Low Back Pain</td>
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<td>$21,570.48</td>
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<td>Osteoarthritis</td>
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<td>$4,616.15</td>
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<td>Chronic Conditions</td>
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</table>
HOLISTIC VIEW OF PATIENT COSTS BASED ON EPISODES ASSOCIATIONS

Episode Timeline for Patient Ranking

Condition Description
- Upper Respiratory Infection
- Preventive Care
- Gastro-Esophageal Reflux Disease
- Chronic Obstructive Pulmonary Disease
- Arrhythmia / Heart Block / Conduction Abnormality
- Allergic Rhinitis/Chronic Sinusitis

Episode Timeline:
- Sep 2009: 1937, 1931
- May 2010: 1934
- Dec 2011: 1935, 1936
- Sep 2012: 1938, 1940
- May 2013: 1943

Member ID
- 0000843589

Episode ID
- 754, 753, 755, 756, 758, 759, 760
- 761, 757, 763, 764, 765, 766, 767

Member ID
- 0000299805

Episode ID
- 754, 753, 755, 756, 758, 759, 760
- 761, 757, 763, 764, 765, 766, 767
Patient-centric Clinical Alignment of Claims

Provider Attribution

Bundled Budgets

Case Mix Adjustment

SAS® Episode Analytics Engine

Input Tables

- IP Claims
- PRO/OP Claims
- Rx Claims
- Member
- Enrollment
- Providers
- Budget Targets (Optional)

Visual Analytics Reports

Output Data

Clinically Aligned Data
Includes PAC & Risk Adjustment
### Using Episode-of-Care Data to Address Population Health Questions

#### SAS® Healthcare Analytics Framework

<table>
<thead>
<tr>
<th>Enterprise Data</th>
<th>Descriptive Profiling</th>
<th>Epidemiological / Clinical Profiling</th>
<th>Predictive/Precision Profiling</th>
<th>Prescriptive Profiling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Providers</td>
<td><strong>Patient-Like-Me/ Similarity Rules</strong></td>
<td><strong>Condition/Disease Anomaly Detection</strong></td>
<td><strong>Predictive Models/ Machine Learning</strong></td>
<td><strong>Patient / Provider Engagement</strong></td>
</tr>
<tr>
<td>Members</td>
<td>For profiling KNOWN patterns</td>
<td>For DIAGNOSTIC and PROGNOSTIC patterns</td>
<td>For detecting COMPLEX and UNKNOWN patterns</td>
<td>For evaluating ACTIONABLE patterns</td>
</tr>
<tr>
<td>Facilities</td>
<td>• Detect similar clinical/ health care behaviors across a patient population and treatments</td>
<td>• Detect individual and aggregated abnormal patterns vs peer groups</td>
<td>• Predict known and unknown complex cases</td>
<td>• Identify gaps in care</td>
</tr>
<tr>
<td>Claims</td>
<td>• Profile cost of care for patients with chronic conditions</td>
<td>• Investigate patterns and variations of care</td>
<td>• Hypotheses generation</td>
<td>• Detect non-compliance, and medication non-adherence</td>
</tr>
<tr>
<td>Referrals</td>
<td></td>
<td>• Compute disease incidence profile</td>
<td>• Root cause/what-if scenario analyses</td>
<td>• Out-of-norm behaviors</td>
</tr>
<tr>
<td>Financials</td>
<td></td>
<td>• Stratify patients based on disease risk</td>
<td>• Evaluate treatment patterns and outcomes</td>
<td>• Implement patient engagement rules</td>
</tr>
<tr>
<td>Clinical</td>
<td></td>
<td></td>
<td>• Reduce readmission rates</td>
<td>• Manage healthcare costs</td>
</tr>
<tr>
<td>Laboratory</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Genomics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd Party (Surveys)</td>
<td></td>
<td></td>
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</tbody>
</table>

#### Hybrid Approach

Proactively applies analytics to combined data from all sources across continuum of care: member, provider, facility, and network levels.
RISK MONITORING AND SEGMENTATION MODELS FOR CHRONIC CONDITION EPISODES

- **Risk monitoring objectives**
  - Define at-risk population, intervention program measures, and health outcomes of interest

- **Risk intervention program**
  - Measures: minimum/frequency/percent of recommended core services utilized
  - Models: propensity to seek care/utilization of recommended core services

- **Risk outcome events**
  - Measures: PAC-ED-Visits, hospitalizations, readmissions, surgical complications, etc.
  - Models: likelihood, frequency, and cost of potentially avoidable ER visits

- **Risk impact and hot-spot analysis**
  - Targets: actionable clusters and hot-spots - high-costs and super utilizers
  - Models: episode subpopulation analytics, risk stratification and segmentation
Methodology

- Retrospective analyses of a population-based cohort of members with a chronic condition of interest (e.g.: diabetes) for a defined study period
- Episode-of care analytics to derive condition episode-level data with:
  - member demographic information, treatment patterns, potentially avoidable complications
  - patient-level risk factors – measured prior to episode start/trigger
  - episode severity factors – measured during/after episode trigger
  - target outcomes – measured after episode trigger
- Assemble quality measures and recommended core services for each chronic condition (sources: AHRQ, NCQA)
  - analyze care patterns, gaps in recommended versus attributed core services
- Derivation of training/validation samples for the predictive model
  - bootstrapping/jackknife method for condition with episodes sample size<500
THE LIKELIHOOD-FREQUENCY-COST (LFC) PREDICTIVE MODEL

• Methodology
  • propensity models to adjust for observational data bias associated with attributed versus recommended core services
    • identify attributes of patients more likely to receive recommended core services
  • identify correlates and cost drivers of potentially preventable ER visits
    • logistic model/decision tree for the likelihood model of ER-visits
    • negative binomial (NB) or zero-inflated NB model for frequency of ER-visits
    • tweedie model for associated costs of PAC-ER visits
  • predict frequent users of ER based on their episode-of-care profiles?
  • proactively identify high risk members for targeted care outreach?
UTILIZATION OF RECOMMENDED CORE SERVICES (URCS)

**Diabetes**
- **Physician Services - PCP**
  - URCS: 80%
- **Physician Services - Specialist**
  - URCS: 80%
- **Preventive / Rehab Services - Diabetes**
  - URCS: 60%
- **Foot Exam**
  - URCS: 90%
- **Preventive / Rehab Services - Individual**
  - URCS: 56%
- **Lipid panel**
  - URCS: 41%
- **HbA1c**
  - URCS: 51%
- **Preventive / Rehab Services - Case Mgmt**
  - URCS: 60%
- **Preventive / Rehab Services - Cardiac**
  - URCS: 10%
- **Eye Exam**
  - URCS: 10%
- **Urine protein**
  - URCS: 51%

**Asthma**
- **Physician Services - PCP**
  - URCS: 85%
- **Physician Services - Specialist**
  - URCS: 59%
- **Preventive / Rehab Services - Individual**
  - URCS: 85%
- **Preventive / Rehab Services - Case Mgmt**
  - URCS: 53%
- **Preventive / Rehab Services - Cardiac**
  - URCS: 14%
- **Lung function test**
  - URCS: 34%
- **Preventive / Rehab Services - Diabetes**
  - URCS: 34%
- **Chest X-Ray**
  - URCS: 16%

URCS: 50% Utilization of recommended core services
UTILIZATION OF RECOMMENDED CORE SERVICES (URCS)

**Coronary Artery Disease**

- Metabolic panel: 60%
- Physician Services - Specialist: 28%
- Preventive / Rehab Services - Diabetes: 54%
- Lipid panel: 65%
- Preventive / Rehab Services - Case Mgmt: 51%
- Electrocardiogram: 86%
- Urine protein: 17%

**Congestive Heart Failure**

- Metabolic panel: 78%
- Physician Services - Specialist: 39%
- Preventive / Rehab Services - Diabetes: 74%
- Lipid panel: 82%
- Preventive / Rehab Services - Case Mgmt: 88%
- Electrocardiogram: 63%
- Urine protein: 46%

URCS: 50% Utilization of recommended core services
UTILIZATION OF RECOMMENDED CORE SERVICES MODEL

Propensity Score Analysis of Recommended Core Services Utilization condition-DMA

<table>
<thead>
<tr>
<th>Fit Statistics</th>
<th>Training</th>
<th>Validation</th>
</tr>
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<tbody>
<tr>
<td>-2 Log Likelihood</td>
<td>1288.98</td>
<td>833.13</td>
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<td>AIC (smaller is better)</td>
<td>1308.98</td>
<td>853.13</td>
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<td>AICC (smaller is better)</td>
<td>1309.20</td>
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<td>BIC (smaller is better)</td>
<td>1358.22</td>
<td>897.87</td>
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<td>Pearson Chi-Square</td>
<td>1024.85</td>
<td>675.24</td>
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<td>1.0188</td>
<td>1.0584</td>
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<tr>
<td>Average Square Error</td>
<td>0.2213</td>
<td>0.2251</td>
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Diabetes
LIKELIHOOD MODEL FOR PAC-EMERGENCY ROOM VISITS

Fit Statistics

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<tr>
<th>Measure</th>
<th>Training</th>
<th>Validation</th>
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<td>-2 Log Likelihood</td>
<td>675.82</td>
<td>426.60</td>
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<td>AIC (smaller is better)</td>
<td>697.82</td>
<td>448.60</td>
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<td>698.08</td>
<td>449.02</td>
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<td>BIC (smaller is better)</td>
<td>751.98</td>
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<td>Pearson Chi-Square</td>
<td>989.46</td>
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<td>Average Square Error</td>
<td>0.09756</td>
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Likelihood of Potentially Avoidable ED-Visit Model
condition=DIAB

Diabetes
FREQUENCY MODEL FOR PAC-EMERGENCY ROOM VISITS

Diabetes

Fit Statistics

<table>
<thead>
<tr>
<th></th>
<th>Training</th>
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<tr>
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<td>849.58</td>
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<td>514.98</td>
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<td>BIC (smaller is better)</td>
<td>903.74</td>
<td>563.78</td>
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<td>Pearson Chi-Square</td>
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<td>Pearson Chi-Square/DF</td>
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<td>Average Square Error</td>
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<td>0.1328</td>
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Frequency of Potentially Avoidable ED-Visits Model
condition=DIAB

Parameter Estimate
COSTS MODEL FOR PAC-EMERGENCY ROOM VISITS

Cost of Potentially Avoidable ED-Visits Model
condition=DIAB

-4 -2 0 2 4
Parameter Estimate

STDX10107 Obesity
STDX05324 Heart Failure,
Hyperlipidemia
age_group 65+
age_group 45-64
age_group 18-44
age_group 00-17
gender_cd M
gender_cd F
pct_room_core_group
propensity_core_group
Intercept

Fit Statistics

<table>
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<th>Statistic</th>
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### Variable Importance

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<td>epi_pop_cost_riskquadrant</td>
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<td>epi_age</td>
<td>0.2829</td>
<td>0.2130</td>
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<td>RF0527_Max</td>
<td>0.2130</td>
<td>0.1600</td>
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Subtree Starting at Node=0

- **Node 0**
  - N = 963 / 662
  - 2 / 0.7391
  - 1 / 0.3609

- **Node 2**
  - N = 625 / 423
  - 2 / 0.6648
  - 1 / 0.1952

- **Node 1**
  - N = 62 / 54
  - 1 / 0.6774
  - 2 / 0.3226

- **Node 4**
  - N = 159 / 96
  - 2 / 0.5190
  - 1 / 0.4810

- **Node 3**
  - N = 17 / 89
  - 2 / 0.8049
  - 1 / 0.1950

- **Node 17 AND BELOW**
  - N = 17 / 89
  - 2 / 0.8049
  - 1 / 0.1950

- **Node 8**
  - N = 215 / 126
  - 2 / 0.6648
  - 1 / 0.3352

- **Node 0**
  - N = 154 / 94
  - 2 / 0.6648
  - 1 / 0.3352

1. min_core_srvs_pathway_status=MET
2. min_core_srvs_pathway_status=NOT MET
• Episode-of-care analytics
  • provide meaningful framework to evaluate differences in risk profiles of patient population with chronic conditions
• For diabetic episodes:
  • gaps-in-recommended versus attributed care have a significant impact on potentially preventable ER visits
  • risk drivers of likelihood of and frequency of PAC-ER visits are mostly episode-severity factors controlling for age, gender, and episode duration
• For asthma episodes:
  • propensity to seek care is influenced by age and patient-level risk factors
• Risk monitoring predictive models:
  • may help to uncover gaps in care and identify patient segments and episode subpopulation for targeted care in order to reduce preventable ER visits
QUESTIONS?