

Real World Patients: The Intersection of Real World Evidence and Episode of Care Analytics

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ABSTRACT

SAS Institute recently released two products, SAS® Episode Analytics and SAS® Real World Evidence, which enable healthcare organizations and pharmaceutical companies to leverage the power of real-world data and episode analytics to solve real-world health care questions. Insights gained from constructed episodes can be used to measure cost and quality of care, evaluate care pathways, and monitor efficiency of healthcare resources utilization. Further analyses of the episodes can be undertaken by exporting the episodes data into SAS Real World Evidence. This paper examines two business use cases that highlight the episode analytic capabilities of SAS Episode Analytics and SAS Real World Evidence. We also develop two risk adjustment models – an episode cost prediction model and a readmission likelihood model for patients in the diabetes and COPD episode cohorts.

INTRODUCTION

The healthcare system in the United States is rapidly evolving as the healthcare reimbursement model transitions from a fee-for-service (FFS) to a pay-for-value (P4V) model. For most patients receiving care under the FFS reimbursement model, healthcare delivery operates more like an 'a la carte' model (that is, you pay as you use). The FFS model is service-centric and volume-based because it is structured around the way providers deliver care in contrast to how patients actually receive care. Under this model, the patient gets coordinated but fragmented services with each provider focusing only on the fractional part of the overall patient health outcome or wellness experience. In contrast, the P4V model offers a bundled episode-of-care approach that enables care coordination amongst several entities (providers, payers, and so on) all working together to achieve common goals: cost reduction, higher quality care, and a better experience for the patient. Under this model, the patient becomes the center of care and providers are held accountable for the care provided. This was the theme of the keynote address given by the Center for Medicare and Medicaid Services (CMS) Administrator, Seema Verma, at the recent 2018 HIMSS Conference. She announced the launch of a new initiative called 'MyHealthData' that will empower patients by giving them control of their healthcare data, and allowing it to follow them through their healthcare journey (Hagland, 2018).

CMS is one of the proponents and early adopters of the bundled payment model. They have tested different episode-of-care based bundles that represent a mix of chronic, acute, surgical, and medical conditions, with the goals to curtail cost, optimize provider efficiency, and achieve better patient health outcomes. Other payers and accountable care organizations in the commercial and private healthcare markets have adopted or are considering adopting bundled payment models for some chronic conditions given that they have the potential to demonstrate cost savings and improve patient outcomes. For example, in the State of Tennessee, adoption of episode-based bundle payments for managing asthma exacerbations in the Medicaid population lowered costs by about 9% (Tennessee Division of Health Care Finance and Administration, 2018).

SAS recently released two products, SAS Episode Analytics and SAS Real World Evidence, which enable health care organizations and pharmaceutical companies to use real-world data to define and construct episode-of-care profiles for different clinical and medical conditions. Insights gained from constructed episodes can be used to measure cost and quality of care, evaluate care pathways, and monitor efficiency of healthcare resource utilization. Learning which of the care pathways, for example, in the management of patients with type-2 diabetes and reduction in HbA1c levels, can be accomplished by creating an index study cohort of patients with diabetes episode followed through time, and then compare

the effectiveness of the different pathways against this HbA1c goal. This paper examines two business use cases that highlight the episode analytic capabilities of SAS Episode Analytics and cohort creation and discovery of SAS Real World Evidence. We also develop two risk adjustment models – an episode cost prediction model and a readmission likelihood model for patients in the diabetes and chronic obstructive pulmonary disease (COPD) episode cohorts. In subsequent sections, we present a generic profile of a typical episode-of-care journey for a simulated patient with a chronic diabetes condition and findings from the two use cases experiment. Furthermore, we show how to export episodes data from SAS Episode Analytics to SAS Real World Evidence for further analysis. A mortality prediction model add-in template is used to demonstrate this functionality.

A PATIENT'S EPISODE-OF-CARE JOURNEY

SAS Episode Analytics enables payers and providers to garner insights from episode-of-care profiles that describe the holistic view of each patient. For example, a patient's episode-of-care journey often consists of all provided services (diagnoses, procedures, prescriptions, laboratory tests, and so on) that span across a specified time window (a year is most often used). Consider a year in the life of an overweight diabetic patient (see Figure 1) who presents for preventive care at her primary provider's office. Her past medical history notes family history of diabetes, blood pressure of 148/92 mmHg, repeated occurrences of fasting blood sugar of 148 mg/dL, laboratory test results for HbA1c of 8.1%, LDL cholesterol of 202mg/dL, HDL cholesterol of 28mg/dL, and triglycerides of 252mg/dL. Initial assessment and services provided during a primary care visit might include checking for signs and symptoms related to diabetes such as polyuria, polyphagia, polydipsia or impaired glucose tolerance, and other associated conditions such as diabetic neuropathy or peripheral vascular disease, and might be followed with additional lab tests, if necessary. Based on the lab results and other diagnostic tests, and taking into account the patient's comorbidity risk factors, the provider can establish a diagnosis and prescribe medications to treat the condition. The patient is monitored for adverse effects or complications associated with the type of treatment prescribed.

Services provided during the entire journey can be categorized as typical or complication. Most services during the presentation, diagnosis, and treatment phases are often considered as part of typical care, including concurrent episodes of conditions such as acute myocardial infarction (AMI), pneumonia, and stroke that are known to be associated with diabetes. However, admissions for such conditions or for uncontrolled diabetes would be labeled as complications. SAS Episode Analytics uses industry-standard episode-of-care or user-customized definitions to categorize all provided services as typical or complication for each episode. Derived episodes' data can then be used to develop risk adjustment models to predict cost of care or potentially avoidable complications.

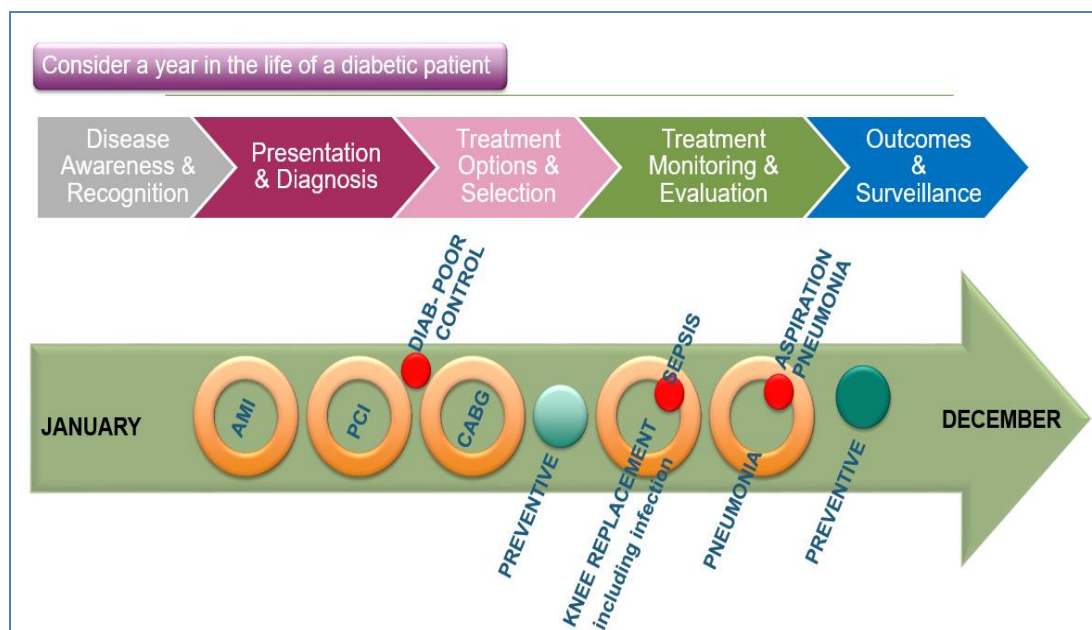
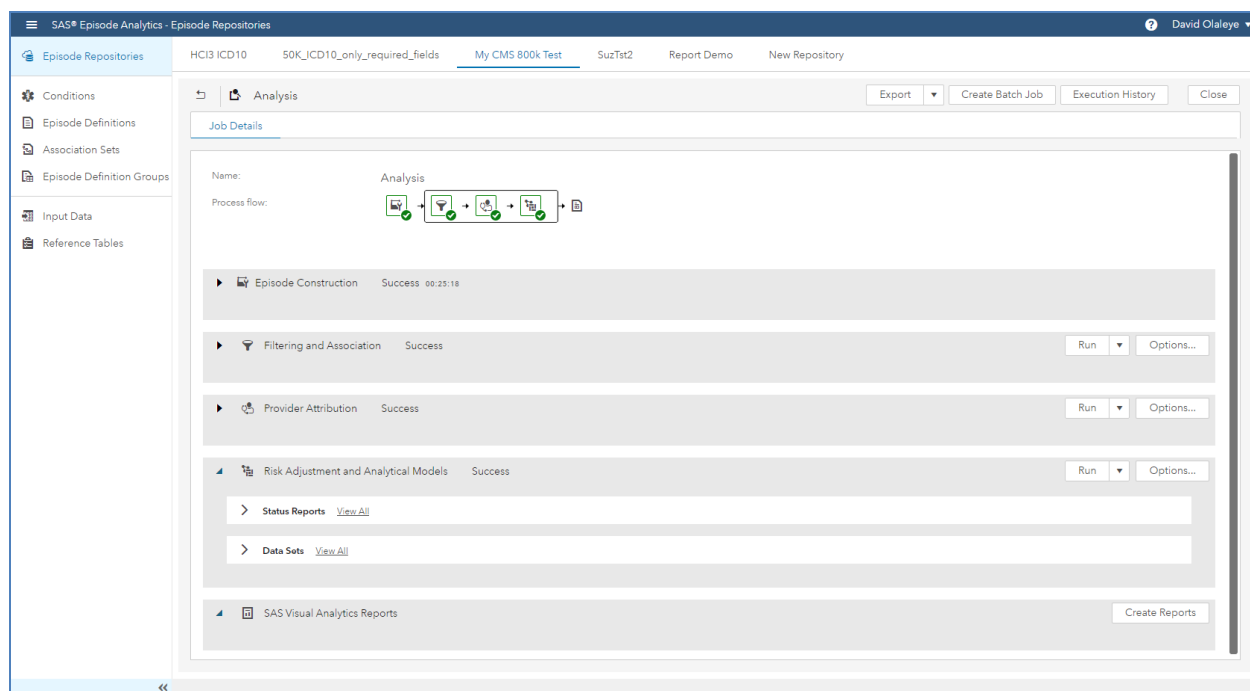


Figure 1: An episode of care journey for a synthetic diabetic patient

SAS EPISODE ANALYTICS

SAS Episode Analytics is an enterprise-level episode bundling solution for payers and providers and enables health care organizations to construct and analyze episodes derived from electronic health records or insurance claims data (see Display 1). An *episode* refers to all medical services that are provided for one patient's medical problem or condition during a specified time period. The application goes through all the professional, outpatient, inpatient, and pharmacy claims provided for each patient during the study period, looking for signals that an episode might exist for a patient. Episodes are then constructed based on one or more signaled events, which might include hospitalization, other facility services, or professional services. Further, episode identification logic determines which episodes exist during the study period and when those episodes begin and end. Clinical definitions and rules are used to define which services in a given time period are related to an episode and which services are unrelated. The associated services are categorized as typical (as part of routine care or treatment of the episode) or as complications or potentially avoidable complications (PAC) arising from that episode. Other benefits and components of SAS Episode Analytics include:

- an episode definition manager that provides flexibility in defining episodes based on customized rules and logic
- rapid construction of episodes, including episode association across multiple conditions, and identification of potentially avoidable complications
- cost allocation logic, which assigns money based on a claim or service to one or more episodes and then determines how the money should be distributed if the services are assigned to more than one episode
- episode filtering logic that enables users to define criteria and scenarios for including or excluding members or episodes for further analysis
- creation of physician accountability metrics for patient care with options to use different provider attribution rules
- calculation of expected episode costs and budget allocation based on flexible risk adjustment models (see Display 2)
- comparison of providers' performance and efficiency on similar episode types



Display 1: SAS Episode Analytics for episodes creation and processing workflow

SAS EPISODE ANALYTICS RISK ADJUSTMENT AND ANALYTICAL MODELS

The Risk Adjustment and Analytical Models step in SAS Episode Analytics enables users to build a cost prediction model that allows control of the different levels of medical risk that are presented by the population case-mix. The model also enables users to investigate variations in episode-of-care costs that are influenced by patient-specific risk factors that are neither under the control of nor influenced by providers. Constructed episodes can also be used to study population health related issues such as readmissions and provider cost profiling. Important features of the risk adjustment modeling component include (see Display 2):

- a parallel-processing analytic data preparation and model plug-in engine for rapid processing of episode data sets to create analytical-ready data sets
- choice of comorbidity risk factor set – including the standard risk factor set, CMS-hierarchical condition categories, Charlson, Elixhauser, and LACE
- flexibility in the type of cost prediction models - from level 1 cost modeling (baseline costs) for all conditions to level 3 for procedural conditions, level 4 for acute conditions, and level 5 for chronic conditions
- flexibility in the choice of modeling technique (one-part versus two-part model) and statistical method (normal, gamma, or Tweedie)
- population health focused models that include readmissions and provider cost profiling

The image shows two overlapping configuration windows. The background window is titled 'Global Settings' and contains three sections: 'Data Modeling Options' with a dropdown for 'Recent enrollee days to use in' set to 180 and a dropdown for 'Risk/comorbidity factors' set to 'Charlson Risk Factor Set'; 'Chronic Conditions Options' with a dropdown for 'Chronic condition model peric' set to 'Calendar quarter'; and 'Data Storage Options' with a checked checkbox 'Persist model input data for selected conditions'. The foreground window is titled 'Risk Adjustment and Analytical Models' and contains 'Global Settings' with 'Conditions...' and 'Settings...' buttons, a 'Cost' section with a checked checkbox 'Run cost models', a 'Model settings...' button, a dropdown for 'Cost distribution model method' set to 'Normal', a checked checkbox 'Run budget analysis', and input fields for 'PAC reduction target (%)' (50), 'Negotiated margin (%)' (2), and 'SRF reduction target (%)' (0). The 'Readmission' section has a checked checkbox 'Run readmission models' and a dropdown for 'All-cause readmission (days)' with options 3, 7, 30, 45, 60, and 90. Both windows have 'Save' and 'Cancel' buttons at the bottom right.

Display 2: Risk adjustment and analytical models options

EXPORT OF SAS EPISODES ANALYTICS FILES TO SAS REAL WORLD EVIDENCE

SAS Episode Analytics provides the mechanism to export episodes data to SAS Real World Evidence. Detailed data that include member, enrollment, prescriptions, services, service codes, laboratory tests, and vital information are included in the export package (see Display 3).

The image shows the 'Export Analysis' window. It has three input fields: 'Export name:' with the value 'MY CMS 800K', 'Export description:' with the value 'COPD_DIAB Episodes', and 'Email address:' with the value 'david.olaleye@sas.com'. Below these is a checked checkbox 'Only include data for the selected episodes' and a 'Filter' button. A table displays episode data with columns 'Code', 'Name', and 'Episode count'. The table has 10 rows, with the 9th row (DIAB - Diabetes) selected. The table data is as follows:

Code	Name	Episode count
PCIHIC3	Coronary Angioplasty (HIC3)	22000
CAD	Coronary Artery Disease	211632
DECUB	Decubitus Ulcer (SRF)	671
DVTPE	Deep Vein Throm/Pulm Embolism (SRF)	1420
DLRMEN	Delirium, Encephalopathy (SRF)	1220
DEPRSN	Depression	87412
DRMTIS	Dermatitis, Urticaria (SRF)	23
DIAB	Diabetes	246656
DMUNC	Diabetes, non-symptomatic (SRF)	751

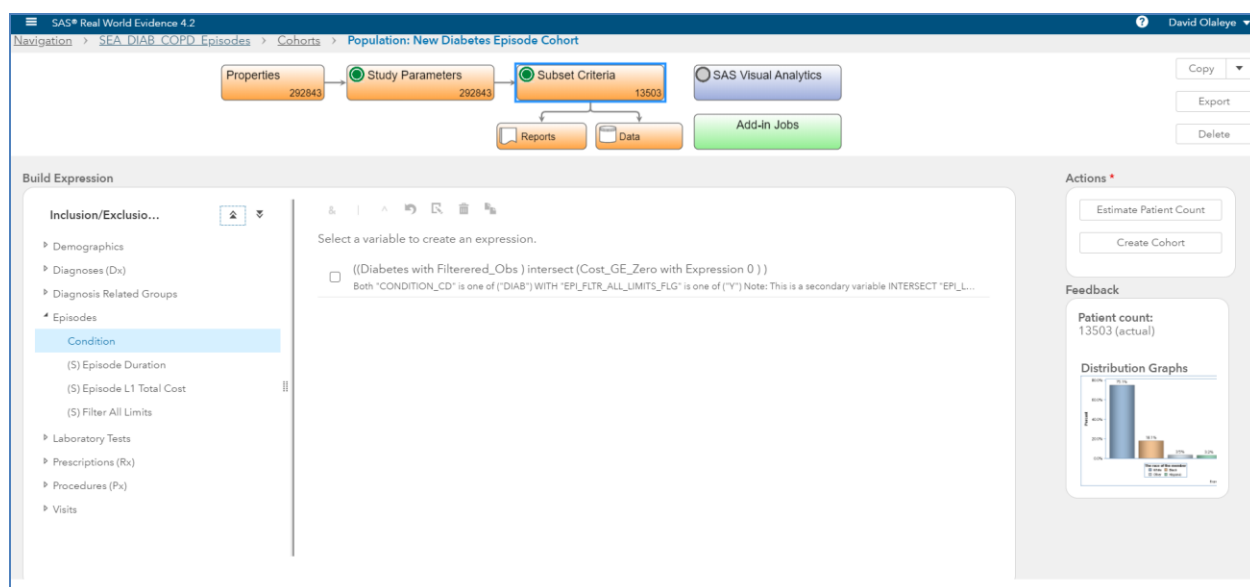
At the bottom right are 'Export' and 'Cancel' buttons.

Display 3: Export of SAS Episodes Analytics output files to SAS Real World Evidence

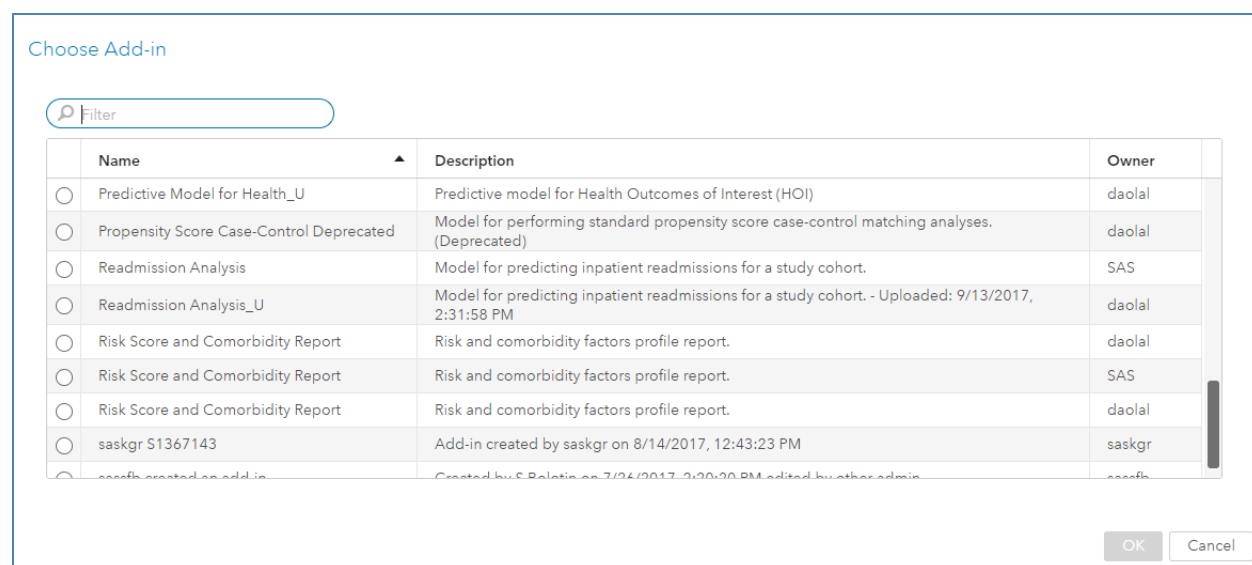
SAS REAL WORLD EVIDENCE

SAS Real World Evidence provides a platform to harness and leverage the power of real-world and health care data to gain insights that drive decisions about safety, efficacy, effectiveness, and costs. The platform workflows simplify the process of defining and building a cohort, which is a set of patients that meet some specific inclusion and exclusion eligibility criteria. Components and benefits of SAS Real World Evidence include:

- a common data submission model for managing real-world data that comes from multiple sources and vendors
- rapid creation and processing of cohorts of patients based on simple and complex query logic and rules that are customized to address different clinical scenarios and temporal relationships across different event codes - diagnoses, procedures, prescriptions, vitals, and laboratory tests (see Display 4)
- an easy-to-navigate point-and-click user interface to assist a variety of users with exploring and querying large data sources
- add-in models and report templates that run against cohort outputs and leverage the power of advanced analytics to gain insights and real-world evidence from real-world data (see Display 5)
- an add-in builder that allows users to develop and execute customized or user-written SAS code against cohort outputs



Display 4: SAS Real World Evidence for cohort discovery and processing workflow



Display 5: SAS Real World Evidence add-in model job

METHODS

DATA SOURCE AND PATIENT POPULATION

The data used for this study comes from the publicly available 2008-2010 CMS Synthetic PUF Medicare data. SAS Episode Analytics is used to create episodes for the two cohorts, which consist of patients with diabetes and COPD. A random sample of 800,000 members is obtained from the 2.3 million member population represented in the CMS data sets. As mentioned in the 'SAS Episode Analytics' section of this paper, episode definition rules and logic are applied to create episodes for all case mixes of chronic, acute, and procedural conditions that are represented in the data. For this paper, analyses are restricted to COPD and diabetes episodes only, which number 6,094 and 13,503 patients, respectively.

COMORBIDITY RISK FACTORS AND EPISODE OUTCOMES

For the risk adjustment models presented in this paper, both the demographic characteristics and comorbidity risk factors are considered as potential factors that could influence episode costs, readmission, and mortality. Risk factors are patient characteristics (identified using claim codes) that are expected to have some clinical relevance to the incidence and severity of the episode being modeled. For each condition, both Charlson and Elixhauser comorbidity index diagnosis codes are used to capture the patient's comorbidity status prior to the start of the episode. The comorbidity risk factors are derived as binary variables based on information that is known prior to the episode start date. A value of 1 indicates that the risk factor is present, and a value of 0 indicates that it is not present. Demographic factors include the patient's age and gender.

For the study outcomes of interest, episode costs and 30-day readmission risk are examined. Readmissions are currently assigned only when they are for subsequent stays that are relevant to the episode's condition and that occur during the episode. An anchor claim is an initial inpatient stay and has a positive allocation amount. The anchor claim is used to understand timing for a readmission. (Note that this logic is different from the current Medicare 30-day, all-cause readmissions penalties.) Episode costs are the final allocated costs after all services have been allocated to the episode, including complication costs arising from episode association and leveling.

For the exported episodes data used to create the population study cohort in SAS Real World Evidence, the effects of demographic and risk factors on mortality are examined using the health

outcomes predictive model add-in template shipped with the product. Mortality status is assessed during the episode duration window with 1 indicating death and 0 otherwise.

STATISTICAL ANALYSES

The descriptive summary statistics that are used to describe the episodes data are provided in Table 1. Findings are reported for patients' demographic and comorbidity characteristics using frequency and percentage distribution, while mean, median, and standard deviation are used to describe continuous and cost variables. For the episode cost prediction model use case, SAS Episode Analytics allows different types of statistical methods such as normal distribution, gamma distribution, and Tweedie distribution to be fitted. For this use case, a gamma model is used. The readmission and mortality risk adjustment models use a logistic model to fit the likelihood of 30-day readmission and mortality for a patient with diabetes (or COPD).

RESULTS

STUDY POPULATION

Based on the 2008-2010 CMS SynPUF administrative claims data, the total number of patients, which also equals the number of generated episodes during the study period, in the diabetes and COPD cohorts are 13,503 and 6,094, respectively. Table 1 gives the summary description of the patients contained in both cohorts. The sample generated twice as many diabetes episodes as COPD episodes. Gender and age distributions of patients are similar across episode type with a higher proportion for females and patients aged 55 or less. Charlson clinical and comorbidity characteristics (assessed in the 6-12 month period before the episode start date) of the whole sample by condition type suggest that chronic pulmonary disease, peripheral vascular disease, and rheumatic/connective tissue disease tend to be the most frequently observed risk factors.

Among patients with COPD episodes, unadjusted and adjusted mean episode costs are US\$2325 and US\$2360, respectively. Similarly, an unadjusted cost of US\$3201 and adjusted cost of US\$3253 are found for patients in the diabetes episode cohort (Table 2).

Table 3 presents the overall and breakdown by gender and age group of the percentages of admissions and readmissions. In total, there are 2204 (16.3%) and 1165 (19.1%) index admissions in diabetes and COPD cohorts, respectively. Of the total admissions in each cohort, about 1.5% and 1% resulted in 30-day readmissions. In both episode cohorts, higher percentages of readmissions are observed among males aged 55 or more.

Characteristics		Diabetes		COPD	
		N	%	N	%
Number of patients / episodes		13503	100	6094	100
Gender	Female	7078	52.4	3259	53.5
	Male	6425	47.8	2835	46.5
Age Group	55+	7258	53.8	3222	52.9
	<55	6245	46.2	2872	47.1
History of:					
Cancer	Yes	886	6.6	466	7.7
Cerebrovascular disease	Yes	592	4.3	365	6.0
Congestive heart failure	Yes	646	4.8	411	6.7
Chronic pulmonary disease	Yes	2306	17.1	979	16.1
Dementia	Yes	26	0.2	19	0.3
AIDS/HIV	Yes	206	1.5	124	2.0
Myocardial infarction	Yes	422	3.1	242	4.0
Mild liver disease	Yes	620	4.6	330	5.4
Moderate/severe liver disease	Yes	132	1.0	78	1.3
Paraplegia and hemiplegia	Yes	68	0.5	65	1.1
Peripheral vascular disease	Yes	1081	8.0	609	10.0
Renal disease	Yes	905	6.7	472	7.8
Connective tissue/rheumatic disease	Yes	1212	9.0	607	10.0

Table 1: Distribution of patient characteristics and baseline comorbidity risk factors by cohort type.

Medical Condition	Label	N	Mean	Median	Std Dev
COPD	Episode Cost	6094	2325.621495	1015.000000	4869.380205
COPD	Risk-adjusted Episode Cost	6094	2360.600392	1240.289186	3990.483269
DIAB	Episode Cost	13503	3201.752768	1475.000000	6089.271173
DIAB	Risk-adjusted Episode Cost	13503	3253.273150	1788.974488	5384.328070

Table 2: Summary statistics of observed and risk-adjusted episode costs

Condition	Gender	Age Group	Number of Episodes	Number of Admissions	Number of Readmissions	Percent of Episodes	Percent of Admissions	Percent of Readmissions	Percent of Admissions in Group	Percent of Readmissions in Group
DIAB	F	55+	3939	611	7	29.17	27.72	21.88	15.51	1.15
DIAB	M	55+	3319	548	12	24.58	24.86	37.50	16.51	2.19
DIAB	F	<55	3139	536	7	23.25	24.32	21.88	17.08	1.31
DIAB	M	<55	3106	509	6	23.00	23.09	18.75	16.39	1.18
DIAB			13503	2204	32	100.00	100.00	100.00	16.32	1.45
COPD	F	55+	1789	327	1	29.36	28.07	8.33	18.28	0.31
COPD	M	55+	1433	288	4	23.51	24.72	33.33	20.10	1.39
COPD	F	<55	1470	285	4	24.12	24.46	33.33	19.39	1.40
COPD	M	<55	1402	265	3	23.01	22.75	25.00	18.90	1.13
COPD			6094	1165	12	100.00	100.00	100.00	19.12	1.03

Table 3: Percent distribution of admission and readmission by gender and age group in the diabetes and COPD episode cohorts

EPISODE OF CARE JOURNEY PROFILE

Over the entire course of an episode journey, a patient being treated for diabetes might also manifest and be treated for other types of medical conditions. SAS Episode Analytics generates episode data for each of the conditions found in the claims data. Figure 2 shows the consolidated view of the episodes for multiple conditions generated for selected diabetic patients with other concomitant medical conditions, concomitant episode complications (marked with the [*] symbol, for example, pneumonia and stroke), and other adverse treatment effects experienced during the episode duration window (marked with the [**] symbol). The red (*) symbols indicate the start dates and end dates of diabetes episodes.

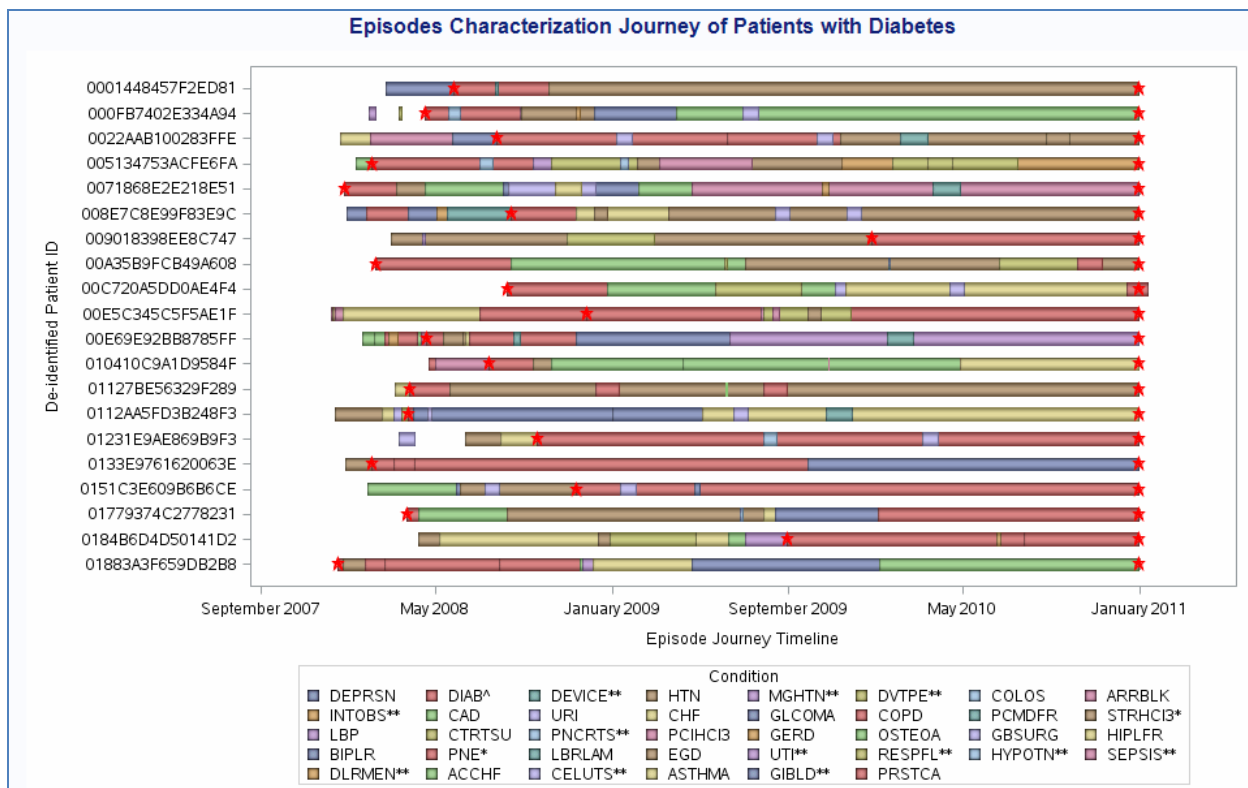


Figure 2: Episode characterization profiles of diabetic patients

EPISODE COST RISK ADJUSTMENT MODEL

Table 4 displays the results of the generalized gamma regression model of episode costs. Both the demographic variables and comorbidity risk factors show positive effects on cost. Patients in the lower age group, patients who experienced complications during the course of episode treatment, or patients who had prior heart failure, vascular disease, and renal disease, amongst other risk factors are more likely to have higher episode costs on average relative to those who did not have these comorbidity risk factors. The findings are somewhat similar for patients with COPD episodes as well (table not shown).

Medical Condition	Model Parameter	Model Estimate	Lower Confidence Limit	Upper Confidence Limit	Pr > Chi-Square
DIAB	Intercept	4.76988	4.64708	4.89269	0.00000
	Sex (Female)	-0.02788	-0.06571	0.00995	0.14857
	age_group 55+	-0.06117	-0.09941	-0.02292	0.00172
	age_group <55	0.00000	.	.	.
	died_ind	0.97329	0.67127	1.27532	0.00000
	Enrolment status > 180 days	0.15124	0.09643	0.20604	0.00000
	Episode duration (months)	0.05669	0.05285	0.06053	0.00000
	Episode complication status (Y)	0.61949	0.50833	0.73066	0.00000
	Care setting (institutional/non-institutional)	0.89133	0.82995	0.95270	0.00000
	Cancer	-0.00072	-0.07792	0.07649	0.98544
	Cerebrovascular disease	0.01950	-0.07612	0.11512	0.68939
	Congestive heart failure	0.18259	0.09067	0.27452	0.00010
	Chronic pulmonary disease	0.11207	0.05787	0.16627	0.00005
	Dementia	0.10474	-0.30980	0.51928	0.62046
	AIDS/HIV	0.30805	0.15277	0.46334	0.00010
	Myocardial infarction	0.03894	-0.07283	0.15070	0.49473
	Mild liver disease	0.37278	0.27606	0.46950	0.00000
	Moderate/severe liver disease	-0.03149	-0.22325	0.16028	0.74760
	Paraplegia and hemiplegia	0.34370	0.07400	0.61340	0.01250
	Peripheral vascular disease	0.24064	0.16808	0.31319	0.00000
	Renal disease	0.78797	0.70851	0.86743	0.00000
	Connective tissue/rheumatic disease	-0.00413	-0.07331	0.06506	0.90693
	Dispersion	0.87591	0.85400	0.89838	.
	Power	2.00000	.	.	.

Table 4: Regression estimates from episode cost risk adjustment model for diabetes cohort patients

READMISSION RISK ADJUSTMENT MODEL

A logistic regression model is fitted to evaluate the relative importance and effect of demographic and comorbidity risk factors on the likelihood of readmission for patients being treated for diabetes or COPD. The results are shown in Table 5. For the diabetes cohort, male gender, older age group, myocardial infarction, pulmonary disease, renal and vascular diseases are all positively associated with elevated risk of readmission. However, none of the effects of comorbidity risk factors are found to be

significant. Table 6 shows similar results for COPD episodes. In separate models, the effects of Elixhauser comorbidity risk factors on readmission likelihood are evaluated (results not shown). Like the Charlson comorbidity factors, these variables demonstrated non-significant positive elevated risk on readmission.

Logistic Regression Model Estimation										
Condition	Risk Factor Type	Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square	Odds Ratio Estimate	Lower 95% Confidence Limit for Odds Ratio	Upper 95% Confidence Limit for Odds Ratio	RISK_FACTOR_GROUP_DESC
DIAB	CHAR	CHAR_CANCER	-0.8207	1.0359	0.6276	0.4282	0.440	0.058	3.352	Cancer
DIAB	CHAR	CHAR_CHF	-0.0596	0.7650	0.0061	0.9379	0.942	0.210	4.220	Congestive Heart Failure
DIAB	CHAR	CHAR_COPD	0.4553	0.4338	1.1017	0.2939	1.577	0.674	3.690	Chronic Pulmonary Disease
DIAB	CHAR	CHAR_HIV	0.7455	1.0504	0.5036	0.4779	2.107	0.269	16.515	AIDS/HIV
DIAB	CHAR	CHAR_MI	0.5294	0.7663	0.4774	0.4896	1.698	0.378	7.624	Myocardial Infarction
DIAB	CHAR	CHAR_PVD	0.3144	0.5645	0.3102	0.5776	1.369	0.453	4.140	Peripheral Vascular Disease
DIAB	CHAR	CHAR_RD	0.0277	0.5603	0.0024	0.9606	1.028	0.343	3.083	Renal Disease
DIAB	CHAR	CHAR_Rheum	-1.0741	1.0316	1.0841	0.2978	0.342	0.045	2.580	Connective Tissue Disease/Rheumatic Disease
DIAB	CHAR	Intercept	-4.3259	0.2237	374.0908	<.0001
DIAB	CHAR	agegp 55+	0.1487	0.1818	0.6693	0.4133	1.346	0.660	2.746	Age Group
DIAB	CHAR	sex F	-0.1661	0.1804	0.8475	0.3573	0.717	0.354	1.455	Gender

Table 5: Regression estimates from readmission risk adjustment model for diabetes cohort patients

Logistic Regression Model Estimation										
Condition	Risk Factor Type	Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square	Odds Ratio Estimate	Lower 95% Confidence Limit for Odds Ratio	Upper 95% Confidence Limit for Odds Ratio	RISK_FACTOR_GROUP_DESC
COPD	CHAR	CHAR_CANCER	0.3872	1.0651	0.1321	0.7162	1.473	0.183	11.880	Cancer
COPD	CHAR	CHAR_COPD	0.0542	0.7870	0.0047	0.9451	1.056	0.226	4.937	Chronic Pulmonary Disease
COPD	CHAR	CHAR_RD	-0.2409	1.0587	0.0518	0.8200	0.786	0.099	6.260	Renal Disease
COPD	CHAR	Intercept	-4.6044	0.3394	184.0936	<.0001
COPD	CHAR	agegp 55+	-0.2293	0.2954	0.6027	0.4376	0.632	0.199	2.012	Age Group
COPD	CHAR	sex F	-0.2145	0.2947	0.5300	0.4666	0.651	0.205	2.067	Gender

Table 6: Regression estimates from readmission risk adjustment model for COPD cohort patients

MORTALITY RISK ADJUSTMENT MODEL

A logistic regression model is fitted to evaluate the relative importance and effect of demographic and risk factors on a patient's likelihood of dying during the episode duration window for the diabetes episode cohort. The SAS Real World Evidence health outcomes prediction model add-in template is shown in Display 6 and the model results are shown in Table 7.

Predictive Model for Health_U

Data Preparation | **Model Selection and Estimation**

Target variables

Health outcome of interest (HOI):
 ▶ **_IV_Death_Flag**

Input variables

☒ Include age group
 Age group binning method:
 Age

☒ Include risk/comorbidity factor group
 Risk/comorbidity factor group type:
 Standard

Create risk factors as:
 Binary variable

☒ Include user-defined input variables
 User-defined input variables:
 ▶ **_IV_Rosiglitazone, _IV_Metformin**

Data Preparation | **Model Selection and Estimation**

Minimum number of events for training and test sets:
 5

☒ Perform data partition
 Percentage of cases for training data set:
 60

Model selection

Binary target model:
 Logistic Regression

Input variable selection method:
 Stepwise

☒ Include model evaluation(ROC)

OK **Cancel**

Display 6: SAS Real World Evidence add-in template for health outcomes predictive model

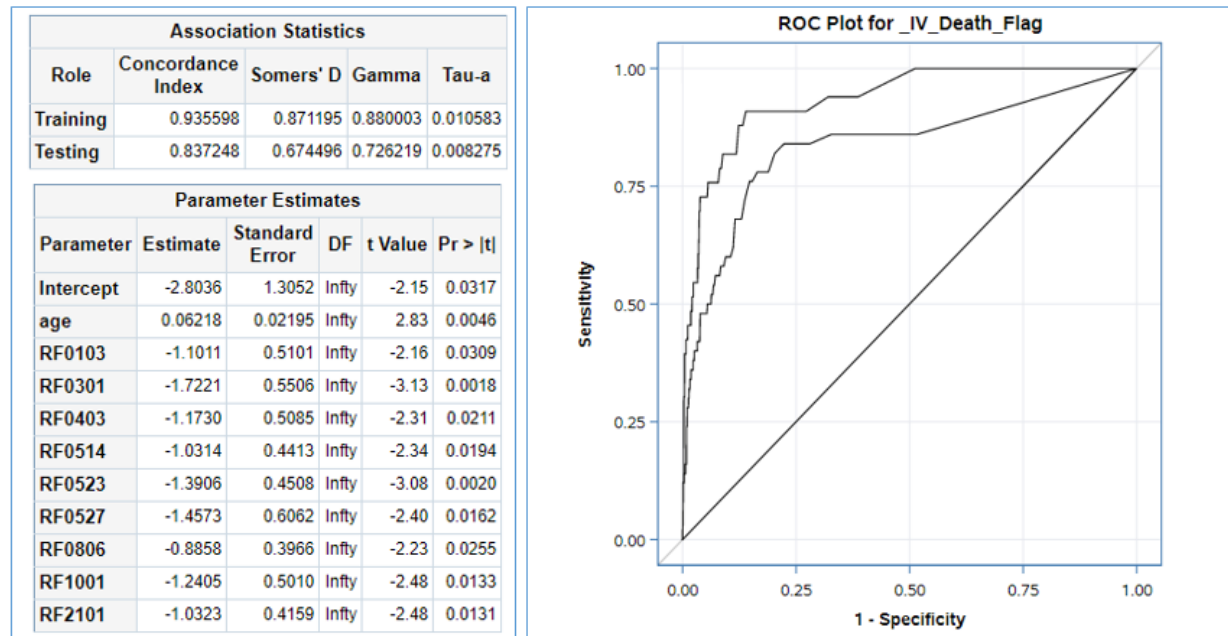


Table 7: Regression estimates from the mortality add-in model for diabetes cohort patients

[Note: RF0103 - Previous Stroke, Paralysis, RF0301-ENT, Upper Respiratory Problems, RF0403 - Empyema, bronchiectasis, Pneumonias, RF0514 -Hyperlipidemia, RF0523 - Cardiomyopathy, valve disorders, RF0527 - Other Cardiovascular Disease, RF0806 - Other arthropathies, RF1001 - Diabetes, poor control, RF2101 - Drug Reactions, long term use of drugs]

CONCLUSION

The adoption of episode-based bundled payment models by some providers and payers in private and government sectors suggests that they see the potential promise and value that this payment strategy holds over prior alternative payment models. The study conducted by McKinsey & Company highlights 7 business areas that health insurers could benefit from if they were to take advantage of the episode analytical capabilities afforded by the bundled payment model. The benefit areas include: (1) innovative payment models guided by episode-based payment, (2) referral management, (3) information sharing with providers to inform and support providers' decision-making, (4) case management and care coordination, (5) ability to use data-driven insights to enhance care guidelines and protocols for treatments and medications, (6) power for consumers and employers to make cost- and value-conscious healthcare purchase decisions, and (7) more informed network design via insights on risk-adjusted provider performance for certain conditions and procedures. With the rapid processing and creation of episodes using real-world data and episode-based risk adjustment models capabilities, SAS Episode Analytics and SAS Real World Evidence solutions are well-positioned to assist health insurers to gain insights and benefits from episode analytics.

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