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The Relationship Between Social Determinants of Health and Healthcare Utilization

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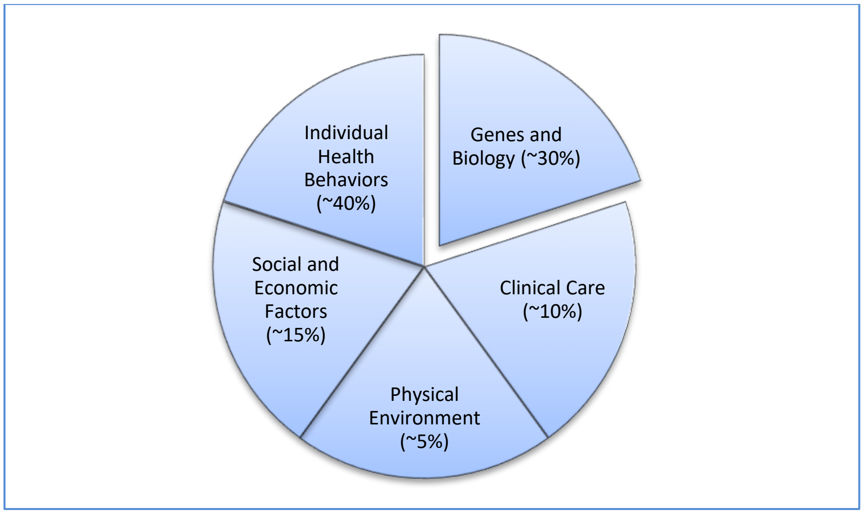
ABSTRACT

Decades of research has documented the effect of various social factors on health status and health outcomes. This research project examines the relationship between three measures of social determinants of health (SDoH) and two measures of avoidable outcomes of care. The SDoH measures include a validated, self-reported survey called AssessMyHealth (AMH), a subset of ICD-10 supplemental Z-codes related to patient social/psychosocial factors from claims data, and 3M's Neighborhood SDoH Scoring tool using publicly-available small area data. Avoidable outcome measures used are 3M's Potentially Preventable Readmissions (PPR) and Potentially Preventable Emergency Room Visits (PPV). The study population is enrollees in a Midwest Medicaid plan. Patients will be stratified according to clinical risk for outcomes using 3M's Clinical Risk Grouper, with covariates including age and sex. Statistically modeling of these outcomes will allow for calculation of predictive probabilities and model diagnostics from an underlying categorical regression model. Predictive probabilities will then be compared for each singular tool and in combination using standard model selection processes. A training set of approximately 65% of the response data will be used to test the modelling. The remaining 35% will be used as a verification data set. Implications for risk adjustment using SDoH will be discussed as well as methodologies for comparing predictive probabilities for model selection.

Keywords: Analytics, Population and Public Health, SAS Base, SAS/STAT Software, Health Care, Social Determinants of Health, Machine Learning, Latent Class Analysis, Principal Components Analysis, HPSplit, Classification Model

INTRODUCTION

The Centers for Disease Control and Prevention defines social determinants of health (SDoH) broadly as "Conditions in the places where people live, learn, work, and play". While data suggest that those with a low socioeconomic status (SES) are more likely to participate in unhealthy behaviors, such as smoking and alcohol consumption (Nandi et al., 2014), SES alone does not explain negative health outcomes. SDoH can provide a more complete picture than SES because it measures socioeconomic status as well as social, environmental and behavioral factors, and health and healthcare. Recent research estimates that social, environmental, and behavioral factors account for 60% of the determinants of health, with genetics and healthcare accounting for 40% (Figure 1) (Schroeder, 2007). Adverse social determinants considered in this analysis include unstable housing, low income, unsafe neighborhoods, or low educational achievement (CDC, 2018).



Error! Reference source not found. Determinants of Health (Adapted from Schroeder, 2007)

METHODOLOGY

This paper assesses the association between three measures of Social Determinants of Health (SDoH) and two measures of avoidable outcomes of care. The SDoH measures include a validated, self-reported survey called AssessMyHealth (AMH), a subset of ICD-10 supplemental Z-codes related to patient social/psychosocial factors from claims data, and 3M's Neighborhood SDoH Scoring tool using publicly-available small area data. Outcome measures used are 3M's Potentially Preventable Readmissions (PPR) and Potentially Preventable Emergency Room Visits (PPV). The study population includes enrollees in a Midwest Medicaid insurance plan. Patients are stratified according to clinical risk for outcomes using 3M's Clinical Risk Grouper, with covariates including age and gender. Implications for risk adjustment using SDoH are discussed as well as methodologies for comparing predictive probabilities for model selection.

Objectives

It is hypothesized that there are different strata within the three SDoH measures which have different use patterns and requirements of the healthcare system. The goal is to identify a methodology and analysis process, which detects those thresholds in a manner that could be easily applicable to policy and to how healthcare systems best implement those policies.

Data

The claims database used in this analysis is from a Midwest Medicaid Insurance Payer and spans from [October 2016 to March 2017] and provides healthcare utilization measures (PPR and PPV) which will be used as outcomes of interest in this analysis.

3M's AssessMyHealth is a health risk assessment tool that helps providers and patients work together to achieve better outcomes. It uncovers the risk factors that often go unnoticed but have deep impact on a patient's health (Wasson, et al., 2018). Data was from July 1, 2017 to December 31, 2018.

A new category of supplemental codes, labeled Z-codes, were created with the advent of the International Classification of Diseases Tenth Revision (ICD-10). In the ICD-10 classification scheme, Z-codes are found in Chapter 21, "Factors influencing health status and contact with health services (Z00-Z99)" (CMS, 2016). Among these new Z-codes is the following series related to potential hazards due to family and social circumstances impacting health status: Z55-Z65 - Persons with potential health hazards related to socioeconomic and psychosocial circumstances (ICD-10 Data.com, 2016).

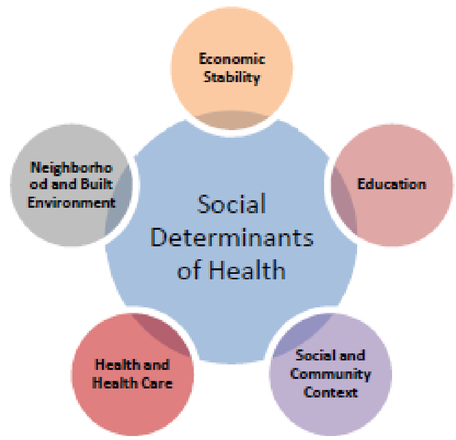


Figure 2. Healthy People 2020 SDoH Domains

The 3M Social Determinants of Health (SDoH) Neighborhood Score is a composite score, which includes variables from five SDoH domains as outlined by Healthy People 2020: Economic Stability, Education, Social and Community Context, Health and Healthcare, and Neighborhood and Built Environment (Figure 2). Healthy People 2020 further breaks down each domain into additional categories. For example, Neighborhood and Built Environment is further divided as access to healthy foods, quality of housing, crime and violence, and environmental conditions.

Analysis Data Set

A systematic random sample of the data was conducted after merging the SDOH scores with the claims data. This sample was selected using the SurveySelect Procedure. Stratification was set to zip code, with the control set to Patient Segmentation. Rate of selection was set to 30% which resulted in a sample of approximately 150,000. While AMH survey had a response sample of approximately 1,000 subjects, these responses were extrapolated to claims data persons within the same zip code to create simulated data for this exercise to assess the capability of the HPSPLIT Procedure and to match the AMH and Neighborhood scores. The Z-codes have approximately 13,000 individuals (out of approximately 625,000 unique individuals in the master data file) with at least one documented diagnosis code falling within the Z-code definition.

Statistical Methodology

Summary statistics of the outcomes and factors are presented using standard frequentist descriptive measures. Visualizations are produced using the SGPLOT Procedure and include boxplot/jitter scatter plots and heatmaps. Each of the three SDOH data sources are analyzed in different ways to produce an index score. The AMH survey is assessed by creating a matrix of polychoric correlations followed by Principal Components Analysis (FACTOR Procedure) to create an index of weighted percentiles ranging from 0-100 (Carlson, 2016). Similar to the AMH data score analysis, the 3M SDoH Neighborhood Score is assessed using Principal Components Analysis (PCA) and also ranges 0-100. The PCA uses a correlation-based model to measure the relationships between the variables and within the domains to create an SDoH index, called the 3M SDoH Neighborhood Score. The healthcare claims based Z-codes are assessed using a Logistic Regression (LOGISTIC Procedure), to estimate Propensity Scores and create an index of probabilities which are converted to percentages, ranging 0-100.

To determine a baseline fixed effects model, a general linear model logistic regression is used to model the scores and covariates to the PPV and PPR outcomes, respectively. The final modeling step uses the scores as factors in a classification tree (HPSPLIT Procedure) to identify the relationships and thresholds between the three SDoH related indexes and healthcare utilization, represented by 3M's Potentially Preventable Visits (PPV) and 3M's Potentially Preventable Readmissions (PPR) measures. The use of tree techniques in modeling these complex variables is useful given the detailed insights generated from a relatively simple coding technique ((http://support.sas.com/documentation/cdl/en/stathpug/68163/HTML/default/viewer.htm#stathpug_hpsplit_examples04.htm). Training data is the first step in developing the model and traditionally follows the machine learning rule-of-thumb by using 70% of the data, while the remaining 30% is used as a validation data step. These results are compared to those as estimated by the fixed effects general linear model.

DATA SUMMARY AND GRAPHICAL ANALYSIS

Using SGPLOT Procedure, a heatmap and boxplot/jitter scatter plot were created. The heatmap (Figure 3) shows the frequency of SDoH score by the three different data source types. The darker areas show the greatest frequency of data. The AMH measure appears to have greater variance than the Neighborhood Score measure (Table 1). The boxplot/jitter scatter plot (Figure 4) demonstrates the distribution and variability which is not often visualized as cleanly in a simple histogram or summary table.

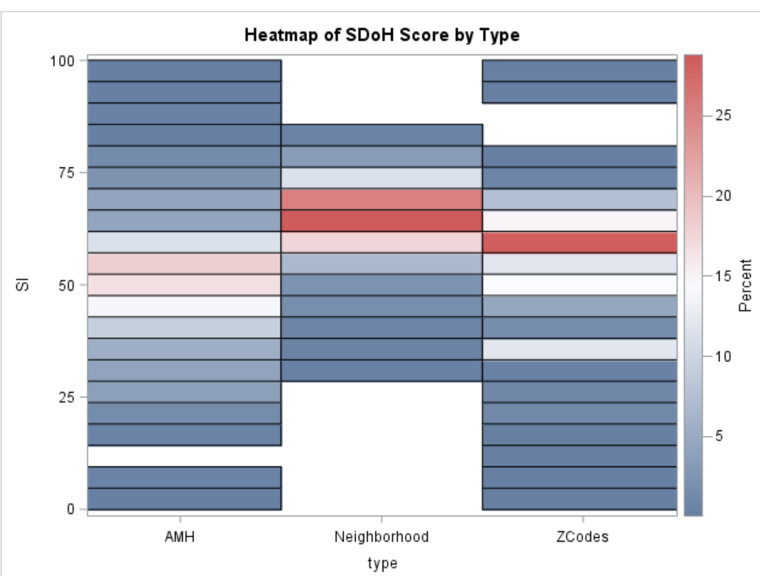


Figure 3. Heatmap of SDoH by Data Source Type

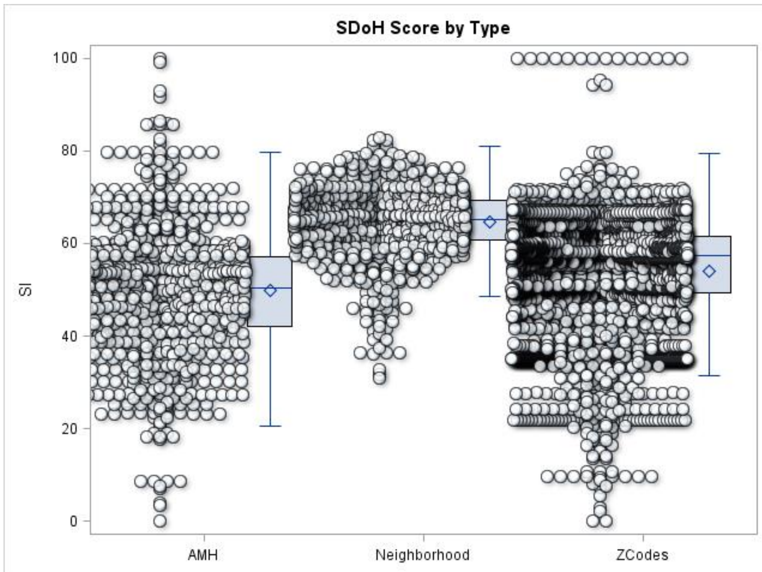


Figure 4. Boxplot/Jitter Scatter Plot of SDoH by Data Source Type

	Mean	Lower 95% CL for Mean	Upper 95% CL for Mean	Median
AMH	49.75	48.98	50.51	50.27
Z-Codes	54.48	54.46	54.51	57.33
Neighborhood	64.57	64.12	65.04	65.13

Table 1. Descriptive Statistics of SDoH Score by Data Source Type

The distributions of the scores and probabilities are usually displayed in standard histograms, which lack the depth of information presented in the heatmaps and boxplot/jitter scatter plots. It is good practice to develop a variety of visualizations, which can give insights into the data prior to any planned analyses. Histograms of the three SDoH data source types were created using the SGPANEL procedure (Figure 5).

Figure 5. Histograms of SDoH by Data Source Type

SDOH INDEX CREATION AND MODELING OF OUTCOMES

Social Determinants of Health are widely acknowledged as major contributors to health and quality of life, but measuring SDOH requires collecting a wide range of data and also insights into healthcare practices, social and health behaviors, and external and internal environments. Measuring SDoH is often complicated, and it can be difficult to find SDoH data and to analyze real-world latent variables. 3M's SDoH Neighborhood score measures at a small area level metrics that tie into the domains established in HealthyPeople 2020 and has been documented as a useful index of social determinants of health at the census tract level (Butterfield, Gottschalk, LaBrec, 2017, 2018). The AssessMyHealth survey attempts to measure similar SDoH domains and incorporate additional important domains at a personal level through self-identification and self-report (Soloway and Horak, 2019). The Z-codes measure, from the perspective of the healthcare provider-patient interaction, reveals what social and psychosocial determinants may be present/lacking medically (for a complete listing see appendix A). The distributions and summaries of these scores are shown in the previous section.

Conducting statistical modeling can be a complex and tedious exercise. The wide range of options for modeling that are now available via advanced statistical systems like SAS allow for insights into data that were previously not possible. This paper demonstrates the range of modeling which yields a high amount of information and can be used in support of policy decisions and intervention designs. Identifying and using social determinants as an early system warning for potential health concerns could be a useful and cost saving approach to prevention.

GENERAL LINEAR MODEL RESULTS

Traditionally, binary outcomes are modeled using a logistic regression. This is done here to establish a baseline association between the predictor set and the outcomes of interest. The following code was used:

```
proc glimmix data=zcode.claims_zcode_AMH_sample ;
   class Age Gender Patient_Segment;
   model PPV_bin= SI Age Gender Patient_Segment / link=cumlogit;
   run;
```

Using just F-value and p-values as a decision tool, (which is often done in healthcare), one can see that the variables almost all have a significant relationship to the outcomes with some exceptions of PPR and the Neighborhood SDoH score (Table 2).

Outcome	***Fixed Effects***

PPV with Neighborhood-SDOH score

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
SI_mean	1	114000	71.61	<.0001
Age	1	114000	726.68	<.0001
Person_Gender	1	114000	613.84	<.0001
Patient_Segment_Desc	6	114000	366.97	<.0001

PPR with Neighborhood-SDOH score

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
SI	1	149000	1.58	0.2090
Age	1	149000	733.68	<.0001
Person_Gender	1	149000	7.77	0.0053
Patient_Segment_Desc	6	149000	43.64	<.0001

PPV with AMH-SDOH score

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
SI_mean	1	114000	72.96	<.0001
Age	1	114000	701.10	<.0001
Person_Gender	1	114000	605.96	<.0001
Patient_Segment_Desc	6	114000	362.43	<.0001

PPR with AMH-SDOH score

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
SI_mean	1	114000	4.71	0.0300
Age	1	114000	400.48	<.0001
Person_Gender	1	114000	83.16	<.0001
Patient_Segment_Desc	6	114000	36.91	<.0001

PPV with Z-Code-SDOH score

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
ps_n	1	749000	21318.3	<.0001
Age	1	749000	54.76	<.0001
Person_Gender	1	749000	3543.54	<.0001
Patient_Segment_Desc	6	749000	2259.19	<.0001

PPR with Z-code-SDOH score	Type III Tests of Fixed Effects				
	Effect	Num DF	Den DF	F Value	Pr > F
	ps_n	1	749000	21318.3	<.0001
	Age	1	749000	54.76	<.0001
	Person_Gender	1	749000	3543.54	<.0001
	Patient_Segment_Desc	6	749000	2259.19	<.0001

Table 2. Fixed Effect Model Results

CLASSIFICATION TREE Model using PROC HPSPLIT

This procedure uses tree-based statistical models to create classification trees which model a categorical response. This is shown as an add on to the traditional use of logistic regression, as the interaction between categorical and continuous variables can be complicated when modeling. This approach can be extended to the continuous case, with the process falling under the regression-tree heading. From description in the SAS documentation (see link in recommended readings), this model allows for non-overlapping partitions of the predictor variable space to be specified. While there are limitations to tree-based models, the proposed function in this paper is to develop insights into the relationships between SDoH measures and utilization outcomes while accounting for influences from sex and age, which naturally occur in healthcare.

Sample Code:

```
proc hpsplit data=zcode.claims maxdepth=10;
   class PPV Gender Patient_Segment;
   model PPV(event='1') = SI Age Gender Patient_Segment;
   prune costcomplexity;
   partition fraction(validate=0.3 seed=1313);
…
run;
```

The full classification trees are given as part of the standard output from the procedure. While this offers a macro view, which is usable for comparison, it is the next set of figures which offer insight into the clusters of the data (Figure 6).

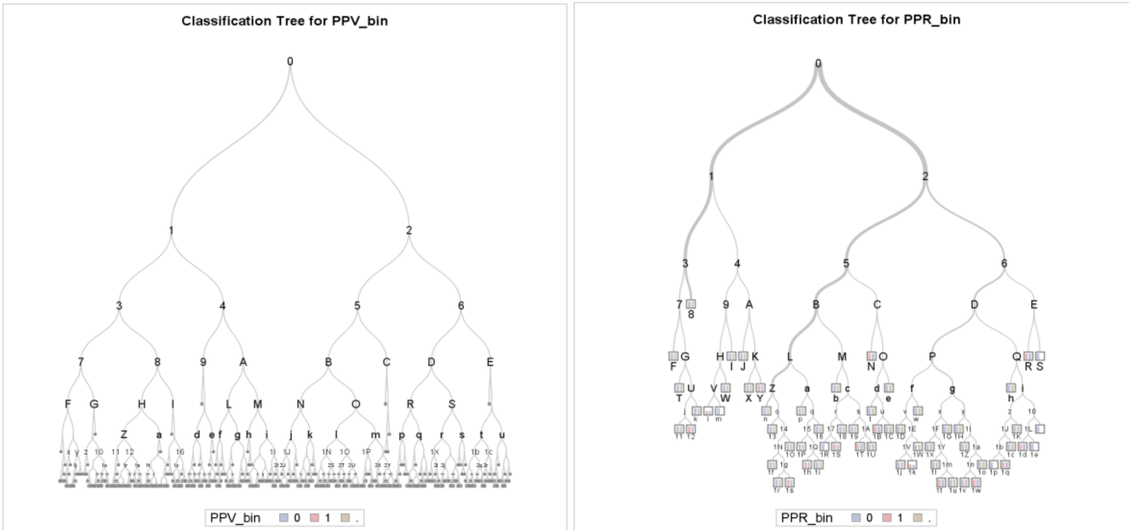


Figure 6. PPV and PPR (Neighborhood score): Tree-models with nodes, branches, and leaves

In an effort to compare directly, the branches at Node 0 are presented for discussion, the remaining information from the model can be found in the Code and Rules files which are output as part of the standard procedure (Figure 7).

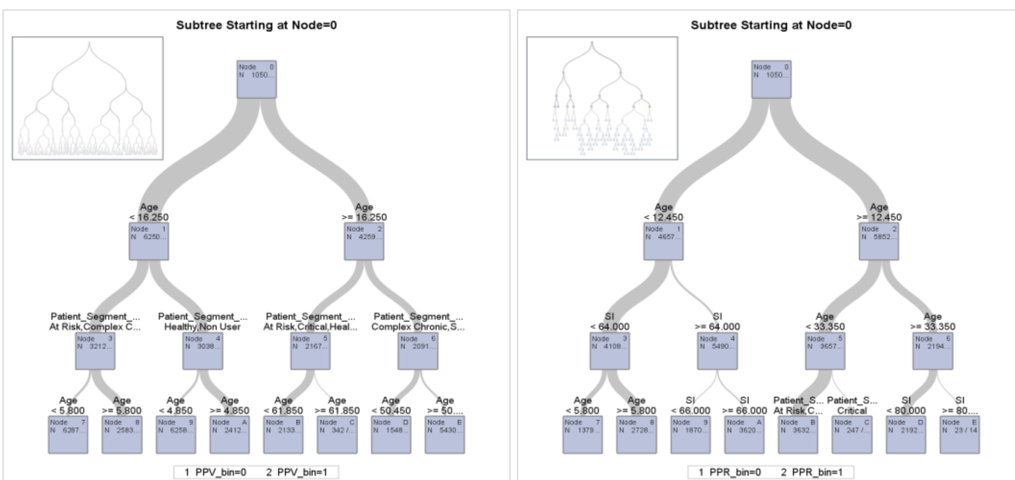


Figure #. PPV and PPR (comm data): Zoom in on node 0 and corresponding branches, and leaves.

The Fit statistics for the PPV outcome indicate a better fit than those for the PPR outcome (e.g. Entropy higher) (Table 7). The sample of branches presented, though, offers some insight which is suggestive that while the predictor set of variables are heavily associated to the outcomes (at least in this sample), there are thresholds of these variables in relationship to the others that offer greater insights into the makeup of the data.

Fit Statistics for Selected Tree (Neighborhood Score)						
PPV Outcome	**N Leaves**	**ASE**	**Mis-class**	**Entropy**	**Gini**	**RSS**
Training	285	0.1948	0.3035	**0.8139**	0.3896	40941.3
Validation	285	0.1972	0.3100	**0.8188**	0.3926	17500.7
PPR Outcome						
Training	61	0.0104	0.0109	**0.0682**	0.0207	2179.4
Validation	61	0.00969	0.0102	**0.0651**	0.0193	860.0
Fit Statistics for Selected Tree (AMH)						
PPV Outcome	**N Leaves**	**ASE**	**Mis-class**	**Entropy**	**Gini**	**RSS**
Training	322	0.1865	0.2848	**0.7791**	0.3729	29775.9
Validation	322	0.1898	0.2934	**0.7860**	0.3772	12802.6
PPR Outcome	**N Leaves**	**ASE**	**Mis-class**	**Entropy**	**Gini**	**RSS**
Training	75	0.00855	0.0092	**0.0551**	0.0171	1365.1
Validation	75	0.00845	0.0090	**0.0546**	0.0168	570.1
Fit Statistics for Selected Tree (Z-Codes)						
PPV Outcome	**N Leaves**	**ASE**	**Mis-class**	**Entropy**	**Gini**	**RSS**
Training	399	0.1871	0.2946	0.7806	0.3742	196396
Validation	399	0.1885	0.2971	0.7846	0.3765	84519.7
PPR Outcome	**N Leaves**	**ASE**	**Mis-class**	**Entropy**	**Gini**	**RSS**
Training	85	0.00950	0.0101	0.0612	0.0190	9975.9
Validation	85	0.00926	0.0098	0.0601	0.0185	4151.6

Table 3: Fit statistics for tree models

The SDOH Neighborhood score shows up as the second most important variable for each outcome, with a greater impact for the PPV outcome than for PPR. Looking at the relationship between AMH and PPV/PPR, there are similar patterns of results for the AMH data as the modeling of the Neighborhood score. For AMH, the PPV outcome demonstrates more well-defined branching than the PPR and higher entropy scores. The results from the AMH model are similar to the Neighborhood score. Table 4 displays the results of the Z-codes model with PPV/PPR.

Variable Importance (Neighborhood Score)						
PPV Outcome					**Relative Ratio**	**Count**
	Relative	**Importance**	**Relative**	**Importance**		
Age	1.0000	**70.7389**	1.0000	**45.8037**	1.0000	96
Social Det. Score	0.9264	**65.5326**	0.8865	**40.6059**	0.9569	149
Patient Segment	0.5173	**36.5902**	0.5078	**23.2587**	0.9817	19
Person Gender	0.3286	**23.2470**	0.3240	**14.8388**	0.9858	20
PPR Outcome						
Age	1.0000	**15.7074**	1.0000	**11.7259**	1.0000	24
Social Det. Score	0.9940	**15.6131**	0.8617	**10.1044**	0.8669	24
Patient Segment	0.5359	**8.4169**	0.4916	**5.7649**	0.9175	11
Person Gender	0.2983	**4.6856**	0.2957	**3.4677**	0.9914	1

Variable Importance (AMH Score)						
PPV Outcome					**Relative Ratio**	**Count**
	Relative	**Importance**	**Relative**	**Importance**		
Age	1.0000	**70.7389**	1.0000	**45.8037**	1.0000	96
Social Det. Score	0.9264	**65.5326**	0.8865	**40.6059**	0.9569	149
Patient Segment	0.5173	**36.5902**	0.5078	**23.2587**	0.9817	19
Person Gender	0.3286	**23.2470**	0.3240	**14.8388**	0.9858	20
PPR Outcome						
Age	1.0000	**15.7074**	1.0000	**11.7259**	1.0000	24
Social Det. Score	0.9940	**15.6131**	0.8617	**10.1044**	0.8669	24
Patient Segment	0.5359	**8.4169**	0.4916	**5.7649**	0.9175	11
Person Gender	0.2983	**4.6856**	0.2957	**3.4677**	0.9914	1

Variable Importance (Z-Code Score)						
PPV Outcome					**Relative Ratio**	**Count**
	Relative	**Importance**	**Relative**	**Importance**		
Age	1.0000	163.3	1.0000	**105.3**	1.0000	145
Social Det. Score	0.9513	155.3	0.9486	**99.8723**	0.9972	164
Patient Segment	0.6034	98.5215	0.6123	**64.4618**	1.0147	51
Person Gender	0.3604	58.8425	0.3607	**37.9754**	1.0009	38

PPR Outcome						
Age	1.0000	40.1900	1.0000	**25.9747**	1.0000	38
Social Det. Neighb Score	0.9288	37.3280	0.9314	**24.1936**	1.0028	23
Patient Segment	0.6175	24.8180	0.6010	**15.6106**	0.9732	18
Person Gender	0.3354	13.4787	0.3514	**9.1278**	1.0478	5

Table 4: Variable Importance from tree model by outcome

Of the variables included in the model, only age showed to be more important than each of the three social determinants of health scores. In examination of the tree models, age, SDoH, and Patient Segmentation thresholds are useful in determining risk of potentially preventable healthcare events. The additional information gathered from the use of the HPSPLIT procedure is invaluable in building guidelines and policies related to interventions designed to offset the burden of some social determinants on the population's health.

CONCLUSION

The intent in developing a quantitative based social determinants of health model is to accurately assess and capture the public health environment on a broader spectrum and with greater sensitivity to the factors that are associated with health inequalities. The 3M SDoH Score can be used as a proxy for measuring SDoH in a population and can provide a greater understanding of inherent health gradients and disparities existing both within and between communities. Incorporating claims data as well as publicly available data creates a more meaningful view of the impact SDoH has on the individual's health. It is important to note that the AMH score is based on self-reported survey data and may offer insights that are not available via other methods. Caution should be exercised when making policy decisions based on survey data. Each of the SDoH score approaches demonstrate that social determinants have a higher level of importance on the outcomes than perhaps even sex does. However, as this was a random systematic sample, generalization of results should be limited to conclusions related to this sample only and not the population at large. Further development of this process is needed but offers insights into techniques which can be useful for creating thresholds of importance and for garnering insights into actionable policy.

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RECOMMENDED READING

- *https://support.sas.com/resources/papers/proceedings17/0689-2017.pdf*
- *http://support.sas.com/documentation/cdl/en/stathpug/68163/HTML/default/viewer.htm#stathpug_hpsplit_overview.htm*
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Appendix A:

Table 1A: Z-codes and Descriptions From ICD-10

Z551	="Schooling unavailable and unattainable"
Z552	="Failed school examinations"
Z559	="Problems related to education and literacy, unspecified"
Z591	="Inadequate housing"
Z603	="Acculturation difficulty"
Z605	="Target of (perceived) adverse discrimination and persecution"
Z62820	="Parent-biological child conflict"
Z629	="Problem related to upbringing, unspecified"
Z655	="Exposure to disaster, war and other hostilities"
Z550	="Illiteracy and low-level literacy"
Z553	="Underachievement in school"
Z554	="Educational maladjustment and discord with teachers and classmates"
Z558	="Other problems related to education and literacy"
Z566	="Other physical and mental strain related to work"
Z5689	="Other problems related to employment"
Z595	="Extreme poverty"
Z599	="Problem related to housing and economic circumstances, unspecified"
Z604	="Social exclusion and rejection"
Z608	="Other problems related to social environment"
Z609	="Problem related to social environment, unspecified"
Z6222	="Upbringing away from parents - Institutional upbringing"
Z62821	="Parent-adopted child conflict"
Z639	="Problem related to primary support group, unspecified"
Z658	="Other specified problems related to psychosocial circumstances"
Z659	="Problem related to unspecified psychosocial circumstances"
Z6221	="Upbringing away from parents - Child in welfare custody"
Z6229	="Upbringing away from parents - Other upbringing away from parents"
Z6332	="Absence of family member - Other absence of family member"
Z6379	="Other stressful life events affecting family and household"
Z560	="Unemployment, unspecified"
Z569	="Unspecified problems related to employment"
Z572	="Occupational exposure to dust"
Z5731	="Occupational exposure to environmental tobacco smoke"
Z578	="Occupational exposure to other risk factors"
Z579	="Occupational exposure to unspecified risk factor"
Z592	="Discord with neighbors, lodgers and landlord"
Z593	="Problems related to living in residential institution"
Z594	="Lack of adequate food and safe drinking water"
Z596	="Low income"
Z597	="Insufficient social insurance and welfare support"
Z598	="Other problems related to housing and economic circumstances"
Z600	="Problems of adjustment to life-cycle transitions"
Z602	="Problems related to living alone"
Z620	="Inadequate parental supervision and control"
Z621	="Parental overprotection"
Z62810	="Personal history of physical and sexual abuse in childhood"
Z62811	="Personal history of psychological abuse in childhood"
Z62812	="Personal history of neglect in childhood"
Z62819	="Personal history of unspecified abuse in childhood"
Z62822	="Parent-foster child conflict"
Z62891	="Sibling rivalry"
Z62898	="Other specified problems related to upbringing"
Z630	="Problems in relationship with spouse or partner"
Z634	="Disappearance and death of family member"
Z635	="Disruption of family by separation and divorce"
Z636	="Dependent relative needing care at home"
Z640	="Problems related to unwanted pregnancy"
Z641	="Problems related to multiparity"
Z651	="Imprisonment and other incarceration"
Z653	="Problems related to other legal circumstances"
Z654	="Victim of crime and terrorism"
Z590	="Homelessness"

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Z6372   ="Alcoholism and drug addiction in family"
Z638    ="Other specified problems related to primary support group"
Z561   ="Change of job"
Z562 ="Threat of job loss"
Z563 ="Stressful work schedule"
Z564 ="Discord with boss and workmates"
Z565 ="Uncongenial work environment"
Z5681 =" Sexual Harassment on the job"
Z570 ="Occupational exposure to noise"
Z5739 ="Occupational exposure to air contaminants"
Z574 ="Occupational exposure to toxic agents in agriculture"
Z575 ="Occupational exposure to toxic agents in other industries"
Z623 ="Hostility towards and scapegoating of child"
Z626 ="Inappropriate (excessive) parental pressure"
Z6281 ="Personal history of physical and sexual abuse in childhood"
Z62890 ="Parent-child estrangement NEC"
Z631 ="Problems in relationship with in-laws"
Z644 ="Discord with counselors"
Z650 ="Conviction in civil and criminal proceedings without imprisonment"
Z652 ="Problems related to release from prison"
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