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Health Program Quality Evaluation to Identify Program Improvement Opportunities

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Health Program Quality Evaluation

To Identify Program Improvement Opportunities

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Abstract

Objective: to identify Health Program improvement opportunities including reducing risk of unplanned visits.

Background: Health Program is a program in a Midwest community assisting persons with diabetes and Medicaid to help patients better self-manage their diabetes and connect with community resources. Communities are challenged with helping a growing number of persons with diabetes with multiple chronic conditions, medications, and increased use of unplanned visits. Information was needed to understand unmet needs of this population associated with unplanned visits to develop program improvements.

Methods: In a quality evaluation of a single center, a model of baseline prognostic factors associated with risk of unplanned events was developed. A total of 98 cases enrolled 2011-2017 with PH Medicaid insurance had adequate data available for modeling diabetic patients. Descriptive analysis was conducted comparing two PCP groups (SH, non-SH): T-tests were used to compare means, Chi-square tests for proportions. Survival analysis was conducted using multivariable Cox regression with stepwise selection to derive a predictive model of unplanned events. Schoenfeld residuals tests ensured the Cox proportionality assumption was met. A modified bootstrapping method was used to validate the model.

Results: A total of 41 patients had unplanned events and 57 were censored. PCP group was not a significant predictor of unplanned events; evidence of differences between PCP groups were only found in medications prescribed, and one chronic condition. Survival analysis provided evidence of significant association ($P<.001$) between freedom from unplanned visits and several predictors: diagnosed schizophrenia/bi-polar (HR 4.6, $p=.0085$), depression medication (HR 3.6, p=.0035), statins (HR 2.8, p=.0068), A1c<7.0 (HR .24, p=.0023), A1c>9.0 (HR .20, p=.0004), pain medication (HR .09, p=<.0001), COPD also included in the model for clinical value (HR .140, p=.0609). The highest risk patient groups were identified by distinct separation in survival curves for these covariate sets: (1) at highest risk: schizophrenia/bi-polar diagnosis with pain meds (none: depression meds, statins, COPD diagnosis), (2) schizophrenia diagnosis with no other meds or COPD, (3) depression and pain meds (no schizophrenia or COPD diagnosis or statins), (4) schizophrenia/bi-polar diagnosis with pain meds. Modified bootstrapping validated this model to have 68% sensitivity, and 86% specificity.

Conclusions: To improve outcomes for Health Program enrollees and reduce unplanned visits, initiatives that address unmet needs of the highest risk groups could be most successful for both the patient and the health care system. Suggestions include: (1) equipping the care team nurse to facilitate appointment scheduling with patients and mental health (MH) providers including med reconciliation by the mental health provider, and an option for in-home via telehealth MH sessions, (2) the model could be packaged into a tool for nurses to estimate risk for individuals perhaps an app, spreadsheet, or an auto-flag in EHR report for new referrals, (3) if preceptor IRB were to provide authorization for sharing some information in this evaluation with the scientific community and other community health systems, other communities could benefit toward progress in improving outcomes and reducing risk of unplanned visits for diabetic Medicaid populations.

Introduction

<u>The Placement Site</u>

This research was conducted in a multi-hospital health care system, serving the Midwestern urban community. Health Program was established in 2009 to help patients better self-manage their diagnosed diabetes chronic condition (primarily), and to connect with community resources.

Referrals are further screened for a few additional qualification criteria (living in the geographic service area, adults, readiness to make changes), and exclusion criteria (end stage HF or CKD, receiving dialysis, active cancer treatment, LTC residence, or pregnancy) (Health, 2016).

This community health intervention provides free in-home visits by a Health Program Care Team which consists of and a nurse lead (R.N), a social worker (MSW), and the helping hands of community health workers (CHW). The aim is empowering the patient by learning new ways to self-manage their chronic condition to improve health and quality of life. The care team serves the individual patient by assisting with developing an individual plan based on goals set by physician and patient, monitoring progress, and connecting with community resources (Health, 2016). The program is free and voluntary. Patients are discharged when the patient (together with the Health Program Team member) determine they are ready to 'graduate'--typically 6 months duration. Patients are welcome to return to the program when they would like additional help in the future.

The Issue

Qualitative insight from Health Program leadership and the care team suggests the complexity and acuity of health of both referrals and enrollees limits the progress individuals can make with self-managing their diabetes. This is anticipated to have a key role in unplanned visits, and also possibly preventing as many as 50% of referrals from participating in the program. Within the U.S., the cost of care is known to increase substantially for each additional chronic condition, and adherence to medications decreases with each additional daily dose.

Importance of Evaluation to Preceptor and the Scientific Community

Insight is needed to assess how to best serve this population toward improved outcomes and utilization. Evidence for potential improvements was anticipated to emerge from two group comparisons: PCP groups, and chronic condition groups.

An initial plan for a longitudinal data analysis was developed for this evaluation was included in the authorized Service Learning/Capstone Experience (SL/CE) proposal. With the overall goal of the SL/CE to identify program improvement opportunities, needed data for the pre-defined analysis was found to be unexpectedly not available, and although attempts were made toward needed authorizations, we concluded the original analysis plan was not possible within the time frame for this experience. To accomplish the original goal within the time frame available, I reviewed the data that was available and conducted an alternative analysis using an iterative approach involving both the site preceptor and Jiangtao Luo (UNMC). The alternative analysis resulted in a robust evaluation using survival analysis to develop a model of prognostic predictor sets of the patient groups at highest risk for unplanned events.

Goals and Objectives

The goal of this SL/CE is to evaluate a community health intervention program and to suggest opportunities for improvement using Preceptor's Triple Aim Criteria: health, health care, relative cost. Spiegelman provides a framework of 'Best Practices' used within the U.S. and globally to define the objectives in evaluating public health interventions as defined below (Spiegelman, 2016).

Primary Objective	I. **Comparative effectiveness analysis** of 'Health Program' delivered to two PCP cohorts: (1) subjects seeing a SH PCP, (2) subjects seeing non-SH PCP.
Secondary Objective	II. **Implementation science** toward identification of possible improvements that help Health Program patients by further synergizing the communication between patient, public health care team, and clinical care providers. Key factors to assess for association with unplanned visits include: 19 chronic conditions defined by CMS (CMS, 2017), 5 medication classifications of interest to the physician overseeing this program (Pain, and subset of Opioids, Depression, Psychotics, Statins, Non-statins), Labs (A1c, LDL, total cholesterol), age, PCP Group.

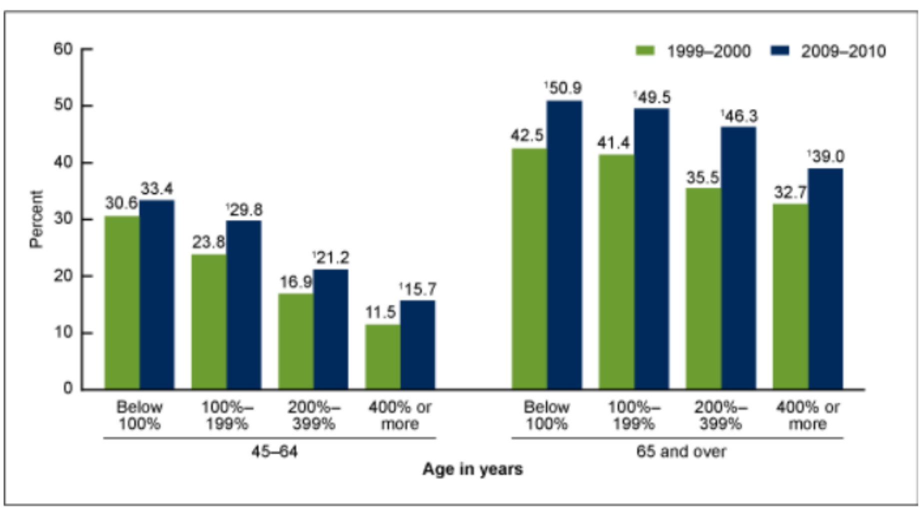
Background Information

More than 25% of the U.S. population reports living with multiple chronic conditions (MCC) (Falci L, 2016). MCC is on a growth trajectory in the U.S., and disparities exist among elderly, lower economic levels, and Hispanic ethnicity (Freid V, 2012). The prevalence of multiple chronic conditions is likely to continue to increase at an accelerated rate with an increase in the proportion of people over age 65, and an increasing proportion of younger people with chronic conditions of obesity and diabetes—see Figure 2. (Note: CDC Prevalence of U.S. population shown below is based on 2 or more of 9 chronic conditions; this under states the prevalence of multiple chronic conditions when compared to the list of 19 chronic conditions as used by CMS.)

Figure 1. 10-Year Trend in the Prevalence of 2+ Chronic Conditions

CDC NHIS Self Report Survey Tracking 9 Chronic Conditions

2000-2010: Age by Poverty Level

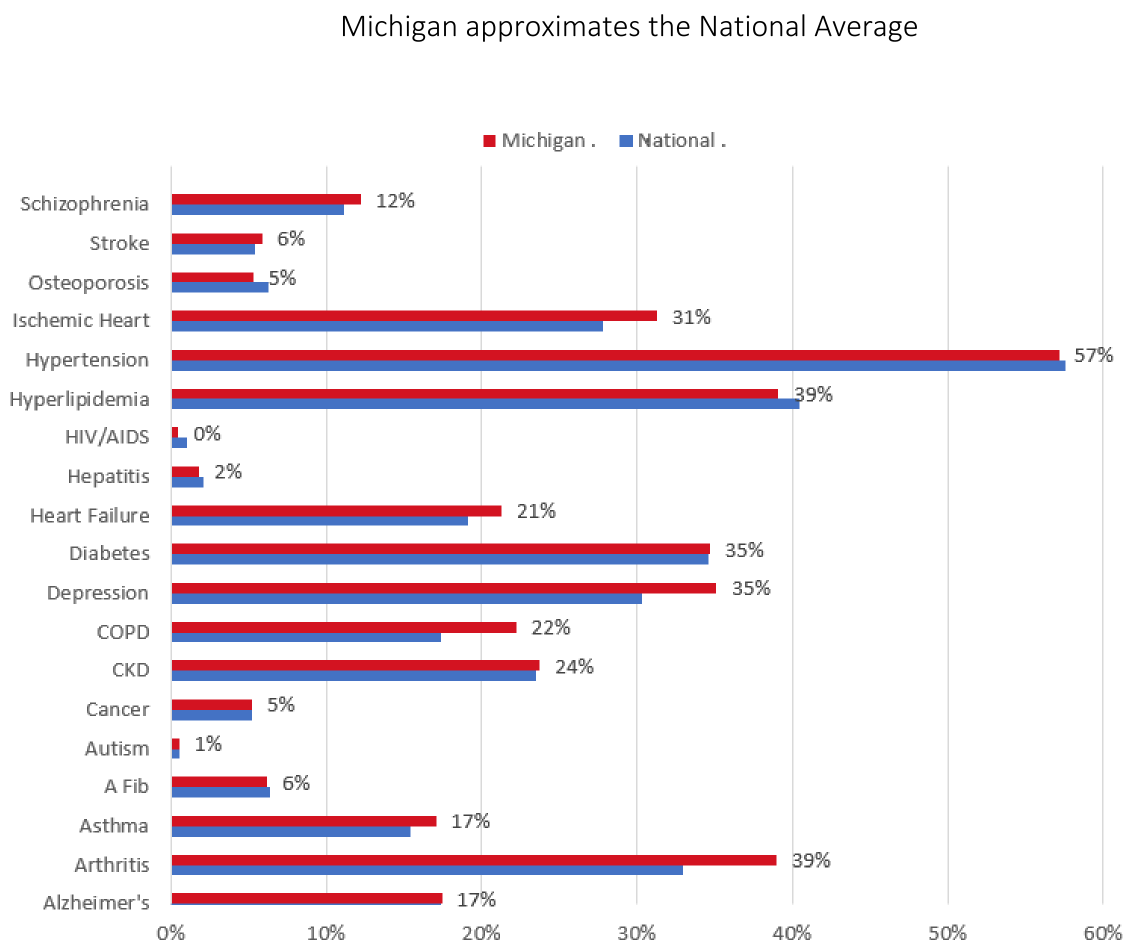


Source: (Freid V, 2012)

A paucity of scientific evidence exists for managing patients with multiple chronic conditions. A solid body of evidence exists relating to the prevention of individual chronic conditions with agreement among the medical community on 7 risk factors which contribute to developing a chronic disease (alcohol, blood glucose, blood pressure, cholesterol, insufficient physical activity, obesity/overweight, tobacco use), (WHO, 2016). A large body of evidence exists for successful interventions that modify risk factors with respect to smoking cessation, healthy eating, and exercise.

The traditional health care system in the U.S. is configured to deliver care, including treatments, medications, and other insurance payable services, based on one primary diagnosis at a time per physician encounter. This system has been adequate to meet the needs of individuals with a single chronic condition. With the prevalence of individual chronic conditions so high it is reasonable to expect the prevalence multiple chronic conditions is also quite high as shown in Figure 2.

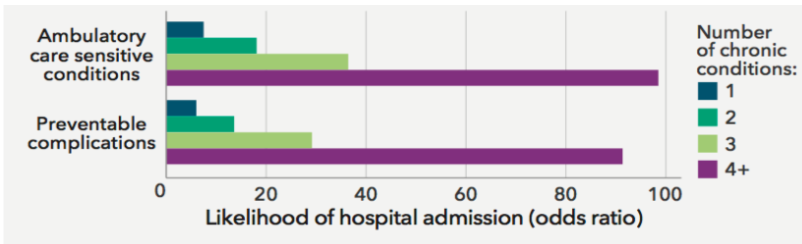
Figure 2. 2015 MCC Prevalence Among Medicare/Medicaid Persons



Source of data: (CMS, 2017)

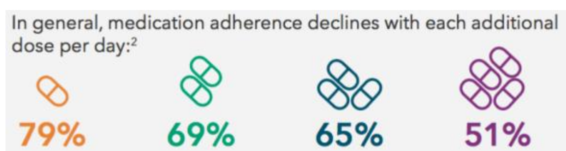
For persons with chronic conditions, the odds ratio for hospital admission increases exponentially with each additional chronic condition (Figure 3). And compliance with prescribed medications decreases substantially with each additional dose (Figure 4).

Figure 3. Number of Chronic Conditions and Hospital Admissions



(TEVA Pharmaceuticals, 2017)

Figure 4. Number of Medication Doses and Adherence



(TEVA Pharmaceuticals, 2017)

Nurse case managers and nurse navigators are trained to assist physicians with coordinating care for only a portion of those patients with complex conditions. It is significant that MCC patients are unique in needing multiple, highly-specialized physicians and pharmacists to determine patient priorities and to provide oversight for treatments and medicines. However, for many patients with MCCs, neither physicians nor patients can manage their MCCs in an optimal manner, and neither patients nor the payers are prepared to cover the exponential cost increase for each patient's additional chronic condition.

Effective Management of Multiple Chronic Conditions

The U.S. Department of Health and Human Services (DHHS) considers multiple chronic conditions an escalating and major public health and medical challenge with recommendations including a call to optimize health and reduce burdens of individuals with health care and public health system changes, maximizing use of effective self-management care, and (cooperative) shared responsibility between public health and health care systems (U.S. DHHS, 2010) (U.S. DHHS, 2011) (Hajat C, 2017) (Bayliss E, 2014) (Hayek S, 2017).

Two recent European models, ICARE4EU and Horizon2020EU project SELFIE, appear to be the most advanced models of integrated care for persons with MCC, relying on patient-centered care as the key call to action (Rijken M, 2018) (Struckmann V, 2018) (Van Der Heide I, 2018). 'Patient-centered care' is perhaps one of the most powerful shared vision statements that align public health with health care delivery systems to champion the system-wide transformation that is needed over the next decade.

The Centers for Disease Control are encouraging wide-spread adoption of self-management programs for individuals with multiple chronic conditions with the aim of long term improvements in hypertension, diabetes, and obesity; interventions with healthy diet, physical activity, medication adherence for high blood pressure or diabetes, self-management of blood pressure and diabetes, and increased breastfeeding (Park B, 2017).

Effective Interventions for Chronic Conditions

Risk factors for developing chronic disease are widely agreed upon in the medical community including: high blood pressure, high fasting plasma glucose, high total cholesterol, smoking, obesity, exposure to high ambient particulate matter (Hajat C, 2017). Public health professionals have identified the most modifiable risk behaviors that account for substantially worse outcomes in mortality, morbidity, and disability: “tobacco use, poor nutrition, physical inactivity, alcohol abuse, drug abuse, and poor mental health” (Calitz C, 2015). Among evidence-based interventions available for public health initiatives, patient self-management interventions with healthier eating, physical activity are commonly known to be successful during the intervention, although longevity of effect after completion of the intervention is relatively unknown.

Diabetes in the U.S. has a prevalence of 17 million cases with an incidence of 1 million cases diagnosed per year, and an annual cost of $98 billion; it is considered the leading cause of disability and death in the U.S. (U.S. DHHS, 2012). Evidence based interventions include self-management programs, and clinical based interventions of defining a care pathway for this single condition of diabetes, with one primary physician and care team that includes nurses, case managers, nurse navigators, pharmacists; with indicators of success often being reduction of HbA1c $> 9\%$ to reduced levels $\leq 9\%$; while multiple conditions are actually present but not addressed like hypertension and heart disease, (U.S. DHHS, 2012) (RWJ Foundation, 2017).

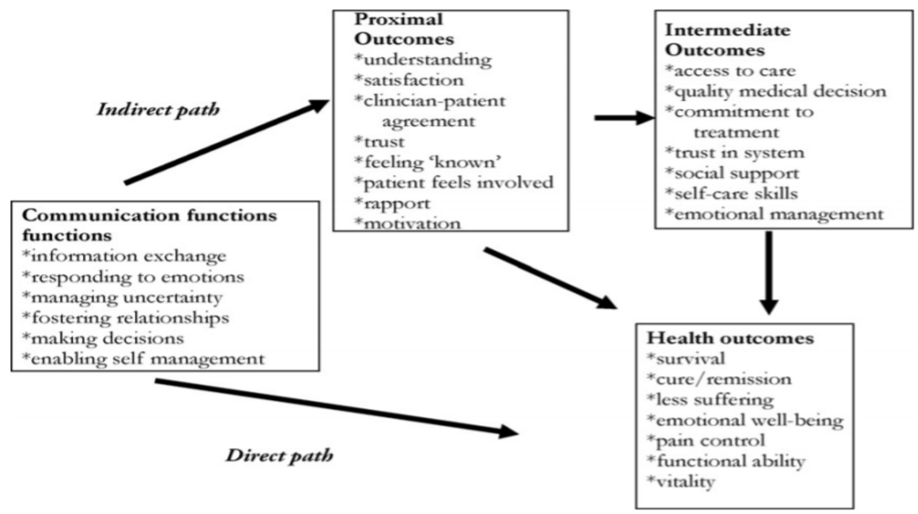
Obesity has numerous evidence based prevention programs for adults and children using self-management programs that increase nutrition and increase physical activity (RWJ Foundation, 2017). Obesity has also attracted significant federal funding as an individual condition with the interventions through schools for children, and as part of a multiple chronic conditions when combined with heart disease/stroke (Park B, 2017).

Conceptual Framework:

The Patient-Provider Communication framework was selected for two reasons. First, the MCC patient has an inherent need for expertise of multiple specialists at a single point in time to determine best holistic treatment plan that includes preferences of the individual patient. This is especially evident for medications prescribed from multiple providers in different disciplines, and the patient struggling to adhere to complex medication plan from multiple sources, with unknown impact of drug-drug interactions. Communication is imperative between the patient and multiple providers toward a shared decision on treatment priorities as evidence exists of association between provider-patient interactions and improved adherence to treatment plans, especially with shared decision-making model (Duggan A, 2015).

Second, the 'Health Program' intervention is designed around the relationship between a Care Team member and patient during monthly in-home visits to monitor, guide in setting goals with a plan, and connecting to community resources (Duggan A, 2015). Use of the patient-provider communication framework (Figure 5) is expected to facilitate identification of mechanisms needed for indirect and direct communication between patient and providers (Street R Jr, 2009). This proposed study of Health Program is expected to provide insight on critical points where improved communication is needed including indirect communication using IT solutions convenient to both the patient and providers.

Figure 5. Conceptual Model: Pathways from Communication to Health Outcomes



(Street RL Jr, 2009)

Methods

A quality evaluation of Health Program enrollees between 2011 and 2017 with one Medicaid insurance plan was conducted. The source of data from this study was a retrospective records review of health system EHR primarily relying on: encounters, diagnosed conditions in problem list and medical history, medications, and labs. While 198 subjects represented the total enrolled during the timeframe of interest, data was not fully available on all subjects reducing the number of subjects represented in some summary tables. Several subjects did not have available data for critical fields to be included in this analysis: 24 subjects with no data on any encounter following date of enrollment (no censor or event date), 38+ with no record of any meds (of any kind not just the categories of interest in this study) and assumed to be receiving their health care in another system, 22 missing lab data (A1c, LDL, or total cholesterol). A very few subjects not representative of the core diabetes population with high risk of unplanned events were found to contribute noise preventing identification of useful predictors for the diabetic population and were therefore removed from model development: 10 heart failure only (no diagnosis of diabetes), 5 hepatitis, 1 LDL>190. (Several subjects had multiple of the exclusion criteria above were counted one time to enable direct accounting of all selected subjects from the original population.)

UNMC IRB provided a confirmation letter waiving IRB oversight to proceed as a quality initiative. The site preceptor was firm and clear it was a quality initiative, with results to be held confidential between Preceptor and UNMC unless additional authorization if provided by Preceptor.

Vulnerable populations are excluded from this study as they are also excluded from participation in the Health Program. Program exclusion criteria screened out: pregnant women, adults unable to consent, persons age < 18 years. Incarceration status is unknown and will not be further screened to keep this factor fully unknown to researchers.

To protect confidentiality of subjects, all data records were de-identified by preceptor site. Each subject's record was pre-indexed with a 6-digit random unique ID (UID) for this evaluation. Dates were converted to days +/- date of referral. All other HIPAA identifiable information was removed prior to analysis.

Qualitative research was conducted during the early stages of this project on-site at Preceptor through discussion with Health Program leadership, care team members, shadowing a care team member at-home visit with a patient, and others serving on the school nurse telecommunications program team. This phase was essential to provide contextual understanding to the study, more clearly frame in priority items of interest, identify the most meaningful measures, and understand the in-home interface of Health Program care team with a patient. The scope of the evaluation was developed in collaboration with Preceptor, UNMC committee members, literature review, and suggested analytical frameworks for analyzing MCCs and/or conducting public health intervention evaluations (CDC, 1999) (Academy Health, 2017) (Spiegelman, 2016) (PAHO, WHO, 2017).

Definitions of key terms for this study is provided in Table 1.

Table 1. Definition of Key Terms

Term	**Operational definition**
Enrolled	Subjects participating in 2 or more in-home visits with Health Program care team members. Non-enrolled are subjects choose not to participate directly or indirectly by not responding to 3 follow-up calls made by referral in-take coordinator, or information mailed to their address.
SH PCP Group	SH PCP is the PCP listed in EPIC on the date of referral to Health Program.
Non-SH PCP Group	The Non-SH group is based on the PCP of record in EPIC on the day of referral to Health Program.
Unplanned events	We coded 'encounters' data from EHR that was available on subjects, unplanned visits represented ED and UCC visits occurring after date of referral.
Chronic Conditions	We classified EHR text of diagnosed conditions at time of referral qualitatively into CMS defined 19 Chronic Conditions. "A Medicare beneficiary is considered to have a chronic condition if the CMS administrative data have a claim indicating that the beneficiary received a service or treatment for the specific condition. Chronic conditions are identified by diagnoses codes on the Medicare claims" (CMS, 2017) (ICD10 Codes were preferred but unable.)
Multiple Chronic Conditions	CMS defined as more than one Chronic Condition (CMS, 2017)
Meds: Opioids, Other pain, Depression, Psychotic/other MH, Statins, Non-statins for cholesterol	The medication classes of interest to the physician overseeing this program were operationalized using the med classifications defined by AHFS (American Society of Health-system Pharmacists).
Total medications	Count of all medications of any kind (beyond the classifications listed above) +/- 90 days of referral

Results

Descriptive Analysis

An overall profile of the sample is provided for demographics, courtesy of Preceptor (Table 2). Overall the median age is 50.1 years, with nearly ¾ female (72%). Two races were most prevalent: African American (38%), and Caucasian (37%). The median education was 'Graduated High School', and noteworthy are nearly 10% of adults have 'Elementary' or less.

Table 2. Sample Demographics

Demographics
(n=198)

	SH PCPs n=121	non-SH PCPs n=77	Total n=198
Age (median)	50.2	49.9	50.1
Female (%)	70.2	75.3	72.2
Race (%)			
White	45.5	24.7	37.4
African American	33.1	45.5	37.9
Hispanic	15.7	22.1	18.2
Other	5.7	7.7	6.5
Education (%)			
K or less	1.7	0.0	1.0
Elementary	10.7	5.2	8.6
Some High School	9.1	18.2	12.6
Graduated High School	32.2	24.7	29.3
Some College	21.5	20.8	21.2
Graduated College	4.1	3.9	4.0
Unknown	20.7	27.3	23.3

Data source: Preceptor

Subjects with SH PCPs were compared to non-SH PCPs on 19 chronic conditions, medication classifications, and labs; significant findings are summarized in the Table 3. For medications, SH PCPs appear to have 4x more subjects with 10+ meds (p<.001), 2x more depression class meds (p=.022), 2x more statins (p=.005), and 2.5x more with psychotic class meds (p=.039). For chronic conditions, arthritis was the only chronic condition of 19 CMS defined where evidence of a difference was found: arthritis was 2.5x higher with SH PCPs than non-SH (p=.026). For labs (A1c, LDL, total cholesterol), no differences were found between PCP groups.

Table 3. PCP Group Comparison

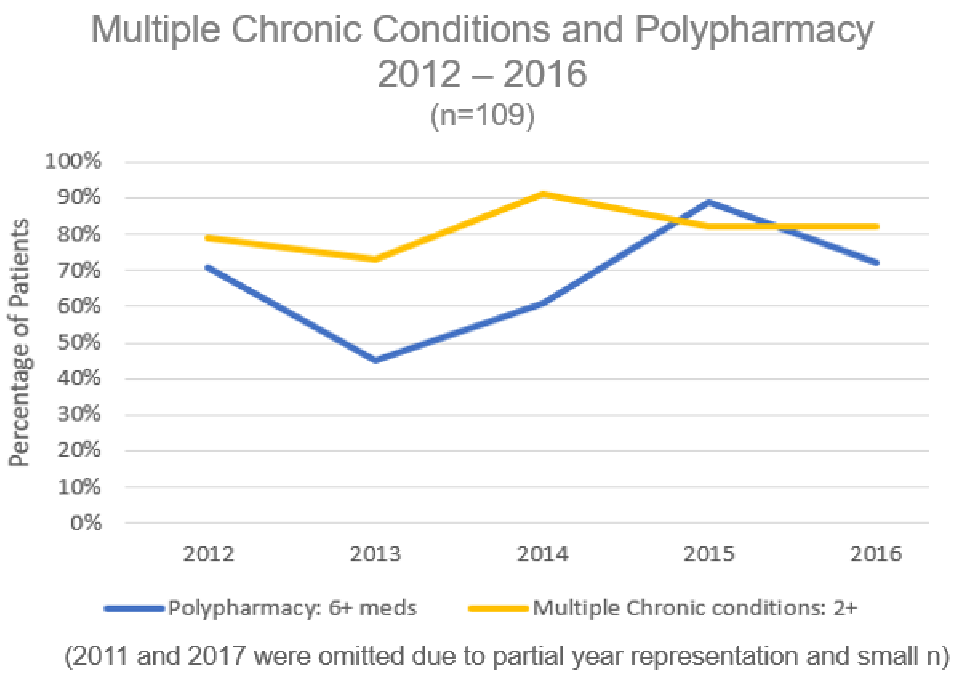
Medications (+/- 90 Days of Referral)

	SH PCPs	non-SH PCPs	P-value	(n)
Medications				
10+	45%	11%	<.001	118
Statins Class	46%	17%	.005	118
Depression Class	42%	20%	.022	118
Psychotic Class	25%	9%	.039	118
Chronic Conditions				
Arthritis	23%	9%	.026	174

Note: Chi-square tests at 95% Confidence Level

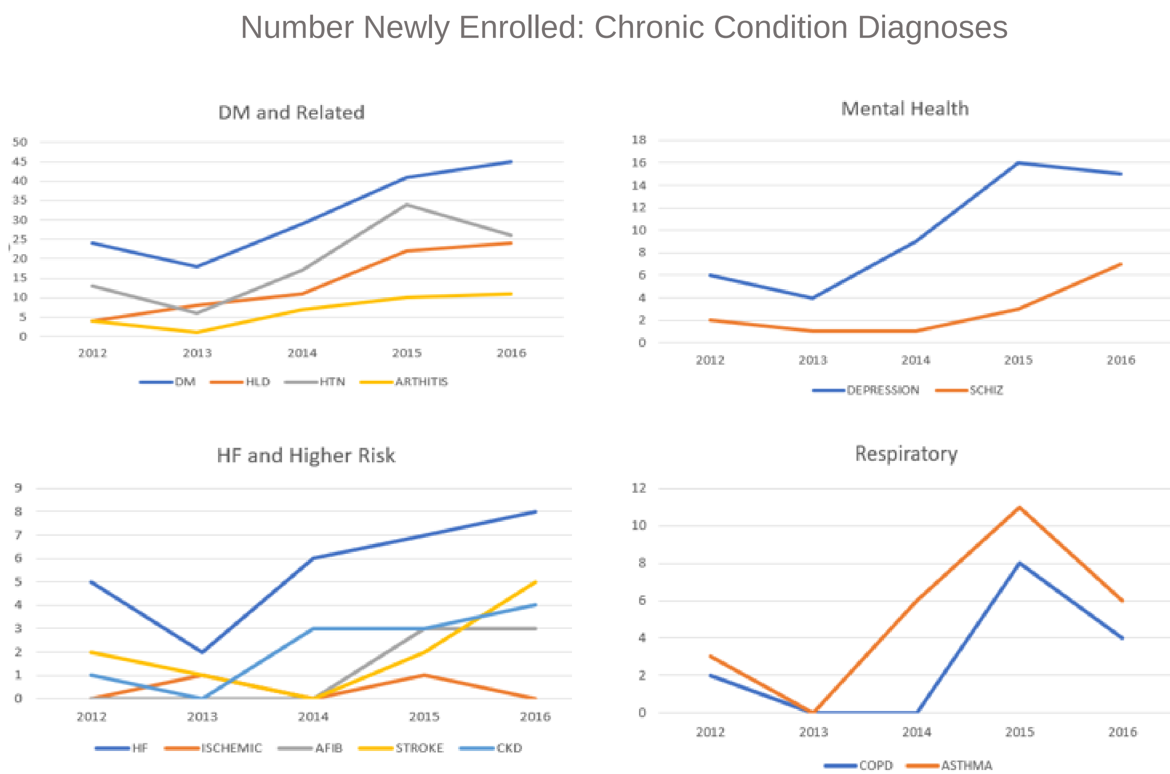
Complexity of diabetic patients is high and continues to increase (Figure 6). Over 2012-2016 the prevalence of new enrollees who have multiple chronic conditions increased from upper 70% to low 80%, while polypharmacy also increased.

Figure 6. Enrollee Trends at Referral: Complexity



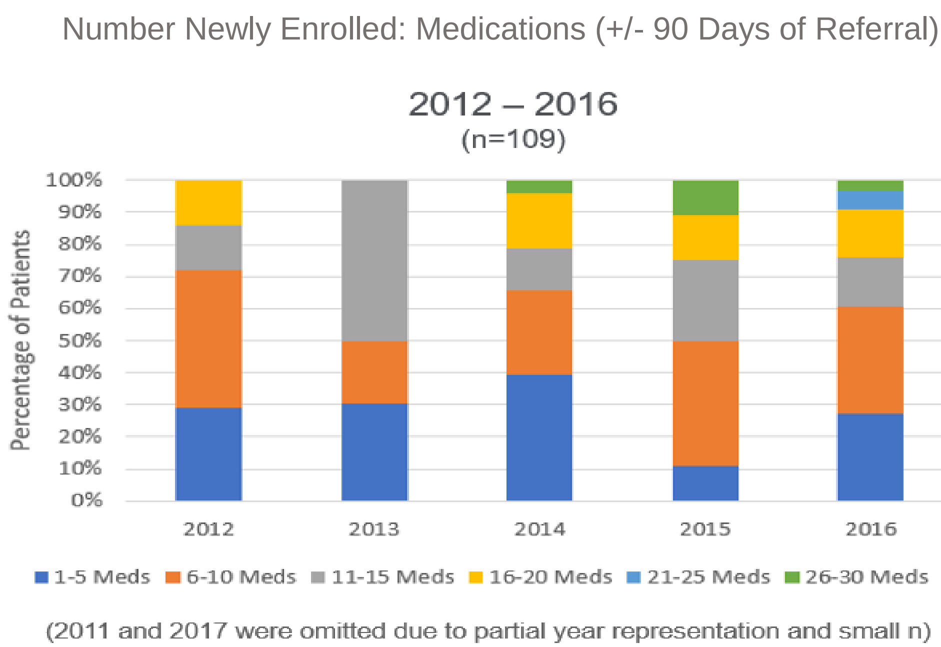
A closer evaluation of individual chronic conditions by the number of cases of new enrolled subjects each year is provided in Figure 7 below. Faster than average growth seems evident among these conditions: HF (heart failure), stroke, depression, schizophrenia.

Figure 7. Enrollee Trends at Referral: Conditions



The trend in number of medications over time is increasing substantially (Figure 8). Newly enrolled patients with 16+ meds grew from about 12% in 2012 to 20-25% in the most recent 3-year period 2014-2016. Noteworthy is the existence of patients who have 26-30 medications taken/prescribed within a very short time window.

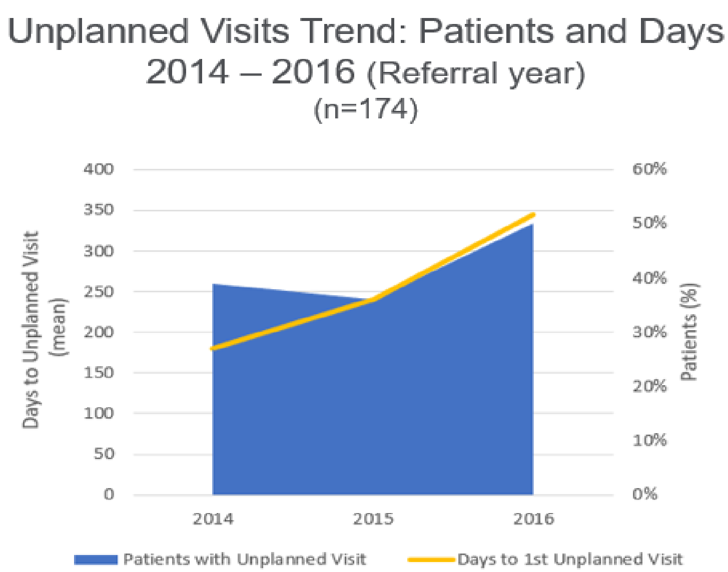
Figure 8. Enrollee Trends at Referral: Medications



For the outcome of unplanned visits, there is an increasing trend--more recently enrolled patients are more like to have an unplanned visit. The rate has increased from 39% in 2014 to 50% in 2016 (Figure 9).

Simultaneously there is an improvement in the time for first unplanned visit. In 2014 the mean time to unplanned visit was 265 Days (about 9 months), and by 2016 the mean time has lengthened to 326 days (about 11 months).

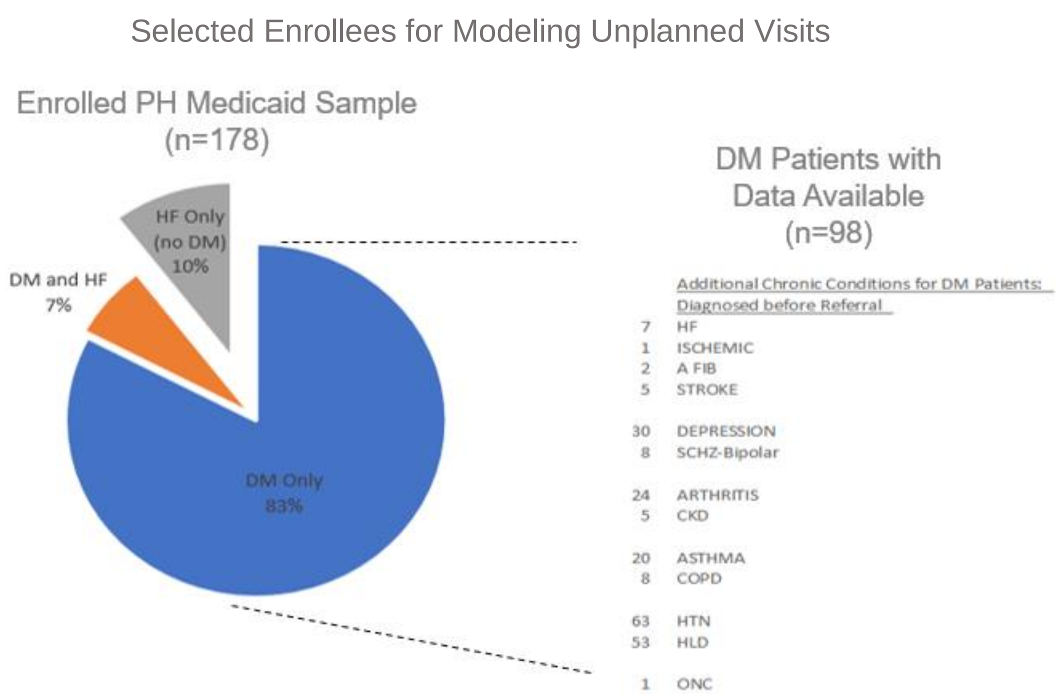
Figure 9. Enrollee Trends at Referral: Unplanned Visits



<u>Survival Analysis--Model Development</u>

To develop a model for the Health Program population with diabetes, immersion in the underlying relationships in the data and multiple discussions with preceptor site was imperative to determine how to best handle missing data, and data outliers. The process was iterative moving forward and backward with varying definitions of subjects and potential predictors to clarify the true core predictive pattern for unplanned visits. A total of 98 cases were determined to be usable for model development (described fully in the methods section) that would represent the diabetes population with multiple chronic conditions and multiple medications and labs to predict unplanned events as shown in right side of Figure 10.

Figure 10. Modeling Unplanned Visits



The potential predictors evaluated included chronic conditions, medications, labs, age, and PCP group. The chronic conditions covered are the 19 CMS defined chronic conditions. Medications were modeled as a total count per person of any type of medication (duplicates were not counted) in the medication classes of interest to physician overseeing Health Program: Pain, and subset of Opioids, Depression, Psychotic, Statins, Cholesterol reducing Non-statins. For labs, A1c was significant and it was modeled as two indicator variables to match program targets: A1c > 9.0, and A1c < 7.0. Age as a continuous variable violated the proportionality assumption; transformation to an indicator variable ≥ 45 years satisfied the proportionality assumption.

Preliminary Model

The result was a significant survival model (p<.001) shown in Table 4. All predictors had individual hazard ratios (HR) p <.05 except COPD which was included at the request of preceptor for clinical value.

Table 4. Preliminary Predictive Model: Unplanned Visits

Preliminary Model (n=98)
Cox Survival Key Predictors – Stepwise Selection
(p <.001)

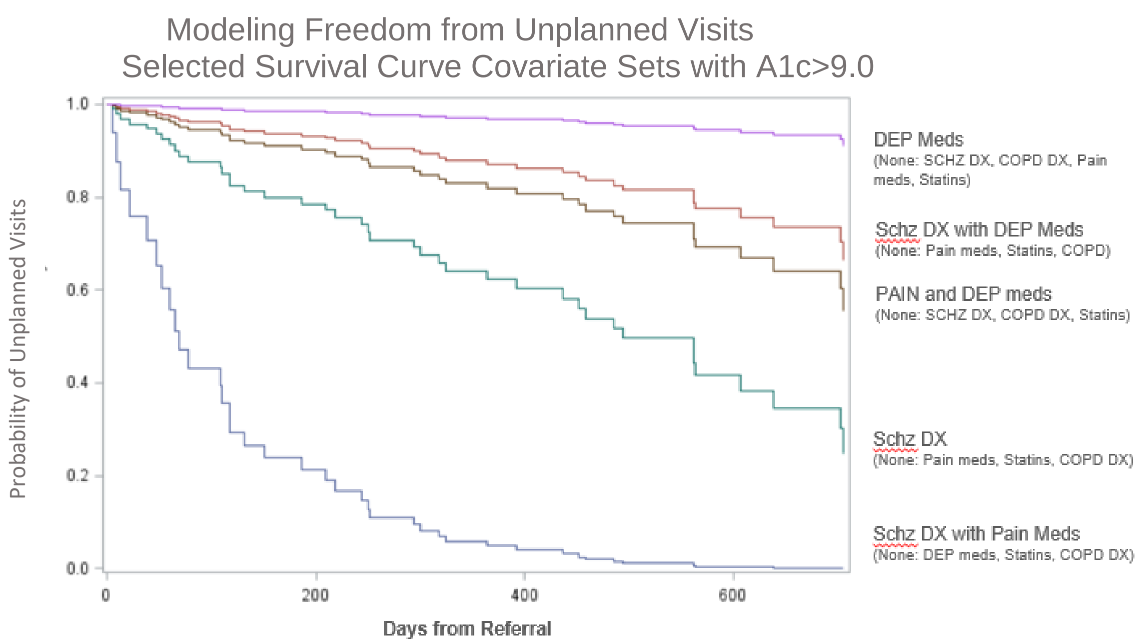
Predictor	Beta	P-Value	Hazard Ratio
Schz-Bipolar DX	1.15192	.0085	4.569
Depression Meds	1.27585	.0035	3.582
Statins Meds	1.02495	.0068	2.787
A1c < 7.0	-1.41411	.0023	0.243
A1c > 9.0	-1.62337	.0004	0.197
COPD DX	-1.96671	.0609	0.140
Pain Meds	-2.39675	<.0001	0.091

(COPD DX was included with p<.10 as request of preceptor due to clinical value)

Highest Risk – Unplanned Visits

Survival curves representing distinct values of predictors (covariate sets) enabled identification of prognostic factors for patients with the highest risk of unplanned events as shown in Figure 11. The lowest curve (blue) is the highest risk of unplanned visits 'schizophrenia diagnosis with pain meds' (no depression meds or statins, and no diagnosis of COPD) with events occurring primarily within the first 6 months of referral. The next highest risk is 'schizophrenia diagnosis only'. The third highest risk group with 'depression meds and pain meds' (no schizophrenia/bi-polar diagnosis, COPD, or statins).

Figure 11. Predictive Model: Highest Risk Groups (A1c > 9.0)



Model Validation

This model was validated using a modified bootstrapping method. Ten iterations of the model were developed with a subset of cases based on a randomly selected hold out sample for each iteration. The hold out cases for a specific model iteration were randomly determined by the last digit of a randomly generated 6-digit number for each subject. For each of the 10 models, covariate values for each subject in the hold out sample were used to estimate probability tables for each covariate set. Individual subjects were predicted to be free of an unplanned event if the corresponding hazard probability table representing that person's covariate set was less than 50% (greater than 50% probability of survival). Predicted unplanned visits were compared to actual unplanned visits resulting in 68% sensitivity, 86% specificity.

To maximize sensitivity additional variables were added to the model. These variables included predictors found to be significant during exploring modeling of sub-populations, and time segments. A total of 20 predictors and missing value indicators were included in the model for predicting risk of unplanned events for individuals (Table 5).

Table 5. Model Validation: Predictors and Indicator Variables

Diagnosed	Med Classes	Indicator Missing Data Yes/No
DEP	Dep	Yes
SCHZ	Psychotic	Yes
	Pain	Yes
	Opioids	Yes
	Statins	Yes
COPD		
	Labs	
	A1c>9.0	Yes
	A1c<7.0	No
	Other	
	Age $\leq$ 45	No
	PCP Group: SH, non-SH	No
	Interactions	
	Psychotic meds with Age < 45	Yes
	Psychotic meds with PCP Group	Yes

Discussion

Opportunities for Program Improvements

Opportunities for Health Program improvements based on this evaluation are regarding meeting more of the unmet needs of patient groups at highest risk of unplanned visits. The high-risk patient groups are defined by specific combinations of mental health and medication classifications.

The highest risk group has a diagnosis of schizophrenia/bi-polar with pain medications (no depression medications, no statins, no COPD diagnosis). This group is most likely to have unplanned visits within the first 6 months of referral to Health Program. To further estimate the size of this sub-population in the program, if we think broadly of this group to also include persons on psychotic medications (possibly undiagnosed mental health disorders) the size of this highest risk group is about 10-20% of the enrolled Health Program population.

The second highest risk group is persons with diagnosis of schizophrenia/bi-polar but without medications for pain, depression, statins. It is possible these patients may also be without needed medications or MH care to be able to utilize planned visits rather than have their conditions escalate and need unplanned visits.

The third highest risk group is persons with both depression medication and pain medication. Potentially these patients may have unmet needs for MH provider counsel and/or med reconciliation—which includes both MH meds and all other prescribed meds. An estimate of this sub-population is 20-30% of the enrolled population.

To assess the urgency of program refinements, it might be helpful to consider two trends identified in this evaluation: the incidence of unplanned visits is increasing, and the number of cases of enrolled diabetic patients who also have depression or schizophrenia is also increasing.

Some ideas for improving the Health Program could include: (1) equipping the care team nurse to facilitate appointment scheduling with patients and mental health (MH) providers including med reconciliation by the mental health provider, and also having an option for in-home via telehealth MH sessions, (2) operationalizing the predictive model's calculation into a spreadsheet, an auto-flag in EHR report for new referrals, or even a pop-up application on a mobile device to empower team nurses to supplement other information by having an estimate of risk of unplanned visits before meeting with new enrollees.

Opportunities for Additional Insight

Additional quality evaluations or research that could potentially help with additional decision support for Health Program improvements include:

- Specific information of interest to clinicians
- Re-occurring events, heavy users
- Specific models for ED visits

It is expected an investment in additional model development would strengthen predictive power. This is a reasonable expectation as exploratory analysis in the current evaluation developed an alternative model to predict events > 120 days post referral was validated to have improved power at 86% sensitivity and 100% specificity (using a 30% hold out sample).

Considerations – Limitations

The power of this model to predict unplanned visits could possibly be strengthened with validation from additional sites, and insurance plans.

This model offers a starting point to dynamically monitor Health Program population needs, and proactively reduce risk of unplanned visits. Ongoing development will provide SH management a robust tool for improved health outcomes for patients and the delivery system.

Conclusion

Evidence exists of an increasing incidence of unplanned visits. A model was developed to predict unplanned events which enabled the identification of prognostic baseline factors, as well as high risk patient groups. The model was validated using a modified rigorous bootstrapping method (68% sensitivity and 86% specificity).

Service Learning/ Capstone Experience Reflections

Experience at Placement Site

At my placement site I discovered that although they serve persons who are at the mercy of everyone, they are given what appears to be top priority among health system data requests and ample resources to help those persons in need. It was quite nice to discover that people within the Evaluations Department team are open-minded, and very positive about considering and trying new analytical techniques; very positive synergy, and easy to synchronize with their team work.

When I started the project, I expected to have a very tightly defined problem and access to very restricted dataset. This preceptor site however, provided me with substantial flexibility to collaborate with them and explore potential access for the most useful data. The original plan relied heavily on claims data from one Medicaid plan and considerable extra work was done to try to secure needed authorizations. However, when it became clear this data would not become available within the scope of this SL/CE, we quickly reframed the problem and within an amazingly short amount of time, the preceptor site provide several data extracts from the EHR which I was able to synthesize into a meaningful dataset for their quality evaluation. This adjustment of data scope/availability also required adjustments to the analytical methods that would be most insightful with the data, changing from a mixed effects longitudinal modeling approach to a survival analysis, requiring a substantial amount of analysis to be conducted in a very short amount of time.

Also, at on-set of study I understood from preliminary conversation that we were doing an IRB approved study; after I arrived on-site I quickly realized the evaluation was a non-IRB approved quality evaluation. With this new constraint, I was careful to establish processes that would enable us to easily adhere to HIPAA regulations for quality (non-research) initiatives.

SL/CE Activities

SL/CE activities were performed in a combination of on-site at preceptor location (4 weeks), and at my residence (several months). Thoughout the entire experience I was in regular contact with my Preceptor. Preceptor provided excellent theoretical and conceptual framing as I worked through this project, including supplemental reading materials. He explored important dimensions with me including how to assess power, validate the model, and strengthen sensitivity of the model. His pre-existing knowledge about the population was extremely valuable in sifting through intermittent results to determine what was most meaningful to him. I met one time with Jiangtao Luo on-site at UNMC and talked/emailed with him at critical points in the analysis regarding analytical methods and interpretations. Chris Wichman provided support and feedback regarding the SL/CE standard checkpoints, and Fabio Almeida provided content expertise of diabetic population challenges and interventions. The site preceptor was very supportive with providing office work space, a dedicated laptop, data storage location, and software applications (SAS, Word, Excel); it all worked every time I needed to use it. A complete list of activities is included in the time log (attached Appendix B).

Deliverables

The primary deliverable was a survival model to predict freedom from unplanned visits for the diabetic Medicaid enrolled population. A power-point presentation was prepared for site preceptor which included identification of highest risk groups of patients for unplanned visits, and identification of baseline prognostic factors. In addition, contextual information was provided on trends in chronic conditions, medications, and unplanned visits. This PowerPoint was reviewed by Preceptor, and UNMC SL/CE committee members. Refinements were made to the final PowerPoint based on their feedback.

I've offered to present the findings to Preceptor's team; we do not have a scheduled presentation at this time. Preceptor has requested narration be added to the PowerPoint; I've prepared a version with audio narration.

Service Learning

During the on-site Service Learning, my activities revolved around observational learning and Q&A directly with the Health Program care team and how they interface with patients, Evaluations team, physician overseeing the program, and Preceptor. Substantial amount of time was needed to collaborate and frame in the problem. A few data scientists at Preceptor site were extraordinary in thinking through how we can best access the needed data from EHR and the data warehouse including requesting entirely new EHR report builds that were completed within very short amount of time, extracting several very different types of data, and coding chronic conditions.

The issue of IRB authorizations arose early in my time on-site as the scope of the study changed from an anticipated 'research initiative' to an internal 'quality initiative' using only internal clinical and program data. I worked together with Preceptor toward possibility of securing needed authorizations to use claims data by writing a proposal 'Sensitive Data Sharing' Use Case for the work to be considered by preceptor site's legal team together with the insurer, and work toward preparing a draft protocol that could be submitted to preceptor's IRB. After a few weeks we reassessed the time required to secure IRB approval would be beyond the scope available for this SL/CE experience.

If there was one way that I've contributed to the Health Program/Preceptor team is possibly in framing in research questions that might be valuable from a different perspective, and scoping in data needs to answer those questions from a different analytical perspective.

My greatest challenge with this experience is not wanting it to end. This could easily be an extended internship of 1-2 years where I could work with Preceptor and his team, to further strengthen my skillset and conduct additional analyses for decision support.

UNMC Learning

Perhaps one of the most significant areas with moving from classroom into real-time community service are the important boundaries that need to be protected in public health initiatives that involve clinical data. HIPAA and ways of de-identifying clinical data. IRB authorization and clear boundaries for quality versus research studies, and internal only information versus information that can be shared publicly. Data Use Agreements (DUA's) that would be needed for sharing any type of data between organizations. These areas were addressed in the research methods class, and re-affirmed in the SL/CE process, with a dedicated step for UNMC IRB review in addition to or regardless of preceptor site IRB involvement, and

Laura Vincent making herself available through the SL/CE curriculum to discuss this important topic.

My view of public health practice has changed with this learning experience. Specifically, with work on this project I have evidence I can assist with tangible assessment needs within the community setting. I've learned that my newly learned analytical biostatistics tools are relevant to help provide insight to decision makers to help identify opportunities to improve health outcomes and utilization. I've also discovered that people serving in a community health capacity have hearts of gold to help others in need in our community.

Also, I was quite surprised to learn the value of conducting a comprehensive literature search before arriving at preceptor site. This provided a lens through which I assimilated what I observed and understood, in addition to the course work of the entire UNMC MPH Biostats curriculum.

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Preceptor Site
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Appendix

A. Public Health Competencies (separate document)
B. Activity Log (separate document)