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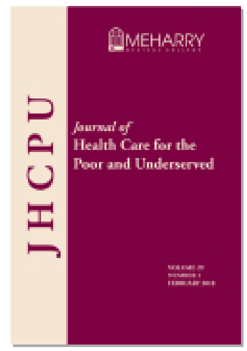

Junjun Xu, Arletha Williams-Livingston, Anne Gaglioti, Calvin McAllister, George Rust

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A Practical Risk Stratification Approach for Implementing a Primary Care Chronic Disease Management Program in an Underserved Community

Junjun Xu, MPH
Arletha Williams-Livingston, PhD, MPH
Anne Gaglioti, MD
Calvin McAllister, MPH
George Rust, MD

Abstract: The use of value metrics is often dependent on payer-initiated health care management incentives. There is a need for practices to define and manage their own patient panels regardless of payer to participate effectively in population health management. A key step is to define a panel of primary care patients with high comorbidity profiles. Our sample included all patients seen in an urban academic family medicine clinic over a two-year period. The simplified risk stratification was built using internal electronic health record and billing system data based on ICD-9 codes. There were 347 patients classified as high-risk out of the 5,364 patient panel. Average age was 59 years (SD 15). Hypertension (90%), hyperlipidemia (62%), and depression (55%) were the most common conditions among high-risk patients. Simplified risk stratification provides a feasible option for our team to understand and respond to the nuances of population health in our underserved community.

Key words: Primary care, risk stratification, PCMH, community health management.

Payment priorities in the United States (U.S.) health care system are changing from volume metrics to value metrics, which are driven by whole person outcomes.[1] However, most primary care providers (PCPs) do not have access to the full spectrum of value metrics, including outcomes data on emergency department (ED) visits, hospital bed days, and medical costs[2–3] for their entire panel across all payers. Instead, PCPs are often dependent on payer-initiated population health care management incentives,

***JUNJUN XU** is affiliated with the National Center for Primary Care at Morehouse School of Medicine. **ARLETHA WILLIAMS-LIVINGSTON** is affiliated with the Department of Family Medicine and the Department of Community Health and Preventative Medicine at Morehouse School of Medicine. **ANNE GAGLIOTI** is affiliated with the National Center for Primary Care and the Department of Family Medicine at Morehouse School of Medicine. **CALVIN MCALLISTER** is affiliated with the Department of Community Health at Morehouse School of Medicine. **GEORGE RUST** is affiliated with the Department of Behavioral Science and Social Medicine and the Center for Medicine and Public Health at Florida State University College of Medicine. Please address all correspondence to Junjun Xu, Morehouse School of Medicine, 720 Westview Drive SW, Atlanta, GA 30310.*

with varied content and quality of data and a myriad of performance standards for population health management across payers.[4–5] This can lead to practices implementing payer-specific metrics, programs, and information technologies (IT) even though a practice's patient panel is covered by a variety of payers.

In order to manage practice-level panels, rather than payer-specific sub-groups of panels, the primary care practice must develop its own information technology solutions and its own collaborative care management strategies. To ready our primary care practice for this shift in payment structure, we developed the Patient Centered Medical Home and Neighborhood Project (PCMHN). Addressing social complexities for patients in Neighborhood context adds the N (*neighborhood*) to the classic PCMH model of team-based care, panel based management, and whole person outcomes.[6–7] The goal of the PCMHN model is to improve health outcomes and decrease costs for a high-risk/high-cost patient population.[8–12] Implementation of this program required development of a cost-efficient risk stratification system based on internal data sources. In this paper, we describe our approach to developing and implementing this algorithm in our urban, underserved primary care clinic.

The Morehouse Healthcare Comprehensive Family Healthcare Center (CFHC) is an academic family medicine practice located in East Point, Georgia, a community in the Atlanta metropolitan area. The clinic serves a predominantly African American population, and both medical and social complexities are common among our patients. Thirty-five percent of patients have at least two comorbid chronic diseases. Patients in the clinic's panel are older, lower-income, and more likely to rent their home than other Fulton county residents. In Fulton County, 10 of the 11 leading causes of morbidity—including mental and behavioral disorders—are most prevalent in African American residents.[13] Clinicians include faculty and resident primary care physicians.

The goal of this paper is to describe the development and application of a cost-effective risk stratification algorithm based solely on internal data, designed to target population health and care management strategies for panels of patients defined at the practice-level, regardless of payer.

Methods

Data source and study population. The cohort for the risk stratification algorithm and PCMHN program included patients seen at the CFHC. We included those with at least one visit since 2013 who were 18 years or older and resided in ZIP codes surrounding the clinic (30344, 30331, 30311, 30349, 30315, 30354, or 30310). Health information was obtained from the patient management system (IDX) and the internal electronic health record (Practice Partner 11.0, McKesson Technologies, 2014) database. A risk stratification algorithm based on diagnosis codes was developed to select a panel of patients for inclusion in the initial program.

Risk stratification algorithm. The risk stratification process was initiated with compilation of an exhaustive list of ICD-9 codes[14] for every CHFC patient who met the inclusion criteria above. Elixhauser comorbidity index[15] conditions and chronic health conditions (developed internally based on Elixhauser comorbidity index and adjusted with results from previous researches and target population[16–18]) have been shown to predict health outcomes.[19] ICD-9 codes were used to indicate whether a patient had any health condition from these two groups (Table 1). Chronic behavioral conditions including depression, schizophrenia, dementia, and alcohol abuse were extracted separately. We calculated total number of conditions for each patient. Patients with at least one behavioral condition and two or more physical conditions were identified

Table 1.

LIST OF BEHAVIORAL/MENTAL AND PHYSICAL COMORBIDITIES

	Elixhauser Comorbidity Index	Chronic Conditions
Behavioral/Mental Conditions	Alcohol Abuse	Affective Disorder
	Drug Abuse	Schizophrenic Disorders
	Psychoses	Dementia
	Depression	Alcohol Abuse
Physical Conditions	Congestive Heart Failure	Asthma
	Cardiac Arrhythmia	COPD
	Valvular Disease	Hypertension
	Pulmonary Circulation Disorders	Diabetes
	Peripheral Vascular Disorders	Coronary Artery Disease
	Hypertension Uncomplicated	Stroke
	Hypertension Complicated	Hyperlipidemia
	Paralysis	HIV/AIDS
	Other Neurological Disorders	Sickle Cell
	Chronic Pulmonary Disease	Breast Cancer
	Diabetes Uncomplicated	Prostate Cancer
	Diabetes Complicated	Colorectal Cancer
	Hypothyroidism	Lung Cancer
	Renal Failure	Arthritis
	Liver Disease	Congestive Heart Failure
	Peptic Ulcer Disease excluding bleeding	Disease of Arteries, Arterioles, and Capillaries
	AIDS/HIV	Kidney Failure
	Lymphoma	Lung Failure
	Metastatic Cancer	
	Solid Tumor without Metastasis	
	Rheumatoid Arthritis/collagen	
	Coagulopathy	
	Obesity	
	Weight Loss	
	Fluid and Electrolyte Disorders	
	Blood Loss Anemia	
	Deficiency Anemia	

as high-risk. Low-risk patients had no behavioral conditions and at most one physical condition. Others were categorized as medium-risk. We based the approach for developing this risk stratification approach on the well documented increased risk of morbidity and mortality associated with co-occurring chronic mental and physical health conditions.[20,21]

Our risk stratification algorithm was designed for widest applicability to any primary care practice with an electronic health record (EHR) system and an integrated or stand-alone patient registration / management information system (MIS), using the following a priori principles:

1. Algorithm uses only data available in the patient registration and electronic clinical records on the practice's own computers.
2. Algorithm uses only fixed field variables (not free text) from EHR clinical data (e.g., ICD-9 diagnosis codes, systolic blood pressure) and from MIS patient registration data (e.g., age, gender, and insurance status).
3. Project assumes that no data from hospital or health system utilization will be available.
4. Project assumes that no data from administrative claims or insurance data will be available, other than the billing submissions generated internally from the practice. Even when such data are available from payers, they are usually in a payer-specific format and not tightly integrated into the EHR dataset.
5. EHR is assumed not to have an automated population health management or panel-based care management module.

Although we generated risk stratification profiles through direct Structured Query Language (SQL) queries of the Oracle database within our electronic health record system, we used simple selection of variables, simple calculation of an unweighted Elixhauser comorbidity score, plus the addition of a behavioral health diagnosis variable, which clinicians had previously described as adding a qualitatively different layer of complexity to primary care case management. Keeping the algorithm simple was done purposefully to design an approach that could be easily replicated by care managers in any primary care practice whose EHR's custom reporting module allowed for generating custom patient profiles or variables (risk score) from within their own data. Although modest gains in predictive accuracy have been demonstrated for more complex predictive models using prescription profiles[19] and past patterns of hospital or emergency department use, we assumed that many practices would not have access to these data nor to the predictive analytics necessary to apply them to new practice settings. Once a practice establishes a simple algorithm for automatically risk-stratifying patients for care management, then future gains in accuracy could be achieved as data links become available, by adding variables related to polypharmacy, hospital utilization, and a geo-coded neighborhood risk deprivation index.

Care management and coordination. High-risk patients were offered enrollment in the PCMHN program. The PCMHN care team included a nurse care manager, community health workers (CHW), a licensed clinical social worker (LCSW), a community support liaison and a physician. The patient intervention included: one clinic visit with the PCP, four home visits with a CHW and behavioral health assessments provided by the LCSW. During each one to two-hour home visit, CHWs assessed vital signs, behavioral health, medication adherence, self-management skills, patient satisfaction, health goals and connected the patients to community support programs. Digital dashboards were developed which provided a snapshot view of patient health information to the care management team. This included demographic characteristics, recent vital signs and lab results, problem list, hospital visits, members of the care team and health maintenance (Figure 1). The care coordination team reviewed dashboards prior to and after home visits.

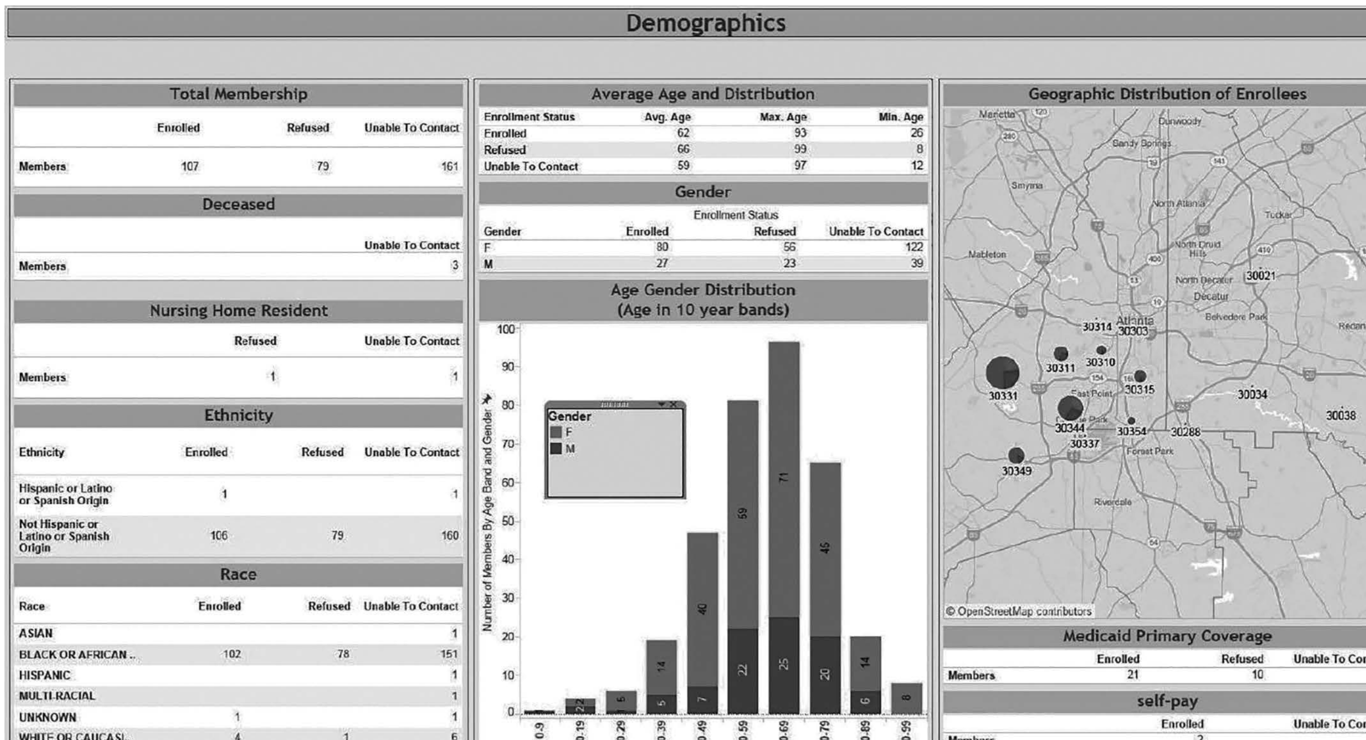
Community intervention led by support liaison and CHW included the following components. 1) Cultivate healthy lifestyle activities, chronic disease support groups, church health promotion, and connection of high-risk patients with these resources. 2) Teach patients realistic self-management of chronic disease in home, family and community contexts. 3) Maintain active relational connection with patient using community health workers as patient navigators and peer counselors. 4) Facilitate training to access health information through patient outreach and community education program outreach. 5) Identify community resources for psychosocial and logistical support. 6) Weekly *care and outcomes optimization team meetings* to review rapid-cycle feedback loop data. 7) Mobilize community resources in behavioral health specific to patient needs.

Statistical analysis. We combined demographic characteristics and health information to generate a list of high, medium, and low-risk patients. We conducted descriptive statistics to characterize each group. Frequency distribution was performed on insurance status and demographic factors. Based on prevalence, top-ranked conditions, dyads (combinations of two health conditions), and triads (combinations of three health conditions) illustrated overall health status of high-risk patients. All analyses were performed using SAS 9.3 (SAS Institute, Cary, NC). The Morehouse School of Medicine Institutional Review Board found this study to be primarily a quality improvement program, and therefore exempt from human subjects review.

Results

There were 347 patients classified as high-risk out of the 3,360 member CHFC patient panel (Table 2). Average age was 59 years (SD 15). Most patients in the high-risk group were females (74%), resided in ZIP code 30331 (29%), and were enrolled in Medicare (43%). Compared with medium and low-risk patients, the high-risk subgroup was older, had more female, and more likely to be covered by Medicare. Hypertension was the most common physical health condition among high-risk patients (90%), followed by hyperlipidemia (62%), obesity (39%), and type II diabetes (34%). More than half of the high-risk group had depression (55%). Other relatively common behavioral conditions were alcohol abuse (12%), dementia (10%) and psychosis (9%).

Among the high-risk patient panel, the most common comorbidity dyad was hypertension and hyperlipidemia (204 patients), followed by depression and hypertension (172 patients) and depression and hyperlipidemia (113 patients). Among the triads, the most frequently occurring was depression, hypertension and hyperlipidemia (109 patients).


Demographics
Total Membership
Enrolled Refused Unable To Contact
Members 107 79 161
Deceased
Unable To Contact
Members 3
Nursing Home Resident
Refused Unable To Contact
Members 1 1
Ethnicity
Ethnicity Enrolled Refused Unable To Contact
Hispanic or Latino or Spanish Origin 1 1
Not Hispanic or Latino or Spanish Origin 106 79 160
Race
Race Enrolled Refused Unable To Contact
ASIAN 1
BLACK OR AFRICAN .. 102 78 151
HISPANIC 1
MULTI-RACIAL 1
UNKNOWN 1 1
WHITE OR CAUCASI.. 4 1 6
Average Age and Distribution
Enrollment Status Avg. Age Max. Age Min. Age
Enrolled 62 93 26
Refused 66 99 8
Unable To Contact 59 97 12
Gender
Enrollment Status
Gender Enrolled Refused Unable To Contact
F 80 56 122
M 27 23 39
Age Gender Distribution
(Age in 10 year bands)
Number of Members By Age Band and Gender
Gender
F
M
0-9
10-19
20-29
30-39
40-49
50-59
60-69
70-79
80-89
90-99
Geographic Distribution of Enrollees
Marietta
Dunwoody
Sandy Springs
Smyrna
North Atlanta
Tucker
Mableton
North Druid Hills
North Decatur
Decatur
Belvedere Park
Redan
Atlanta
East Point
Forest Park
Riverdale
30314
30303
30311
30310
30315
30331
30344
30354
30337
30288
30349
30021
30034
30038
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Medicaid Primary Coverage
Enrolled Refused Unable To Contac
Members 21 10 4
self-pay
Enrolled Unable To Contac
Members 2

Figure 1.

Table 2.

CHARACTERISTICS OF HIGH-RISK PATIENT PANEL

	N (%) / Mean (SD)		
	High Risk N=347	**Medium Risk N=1546**	**Low Risk N=1467**
Age	59.0 (15.3)	58.5 (16.9)	32.6 (21.9)
Sex			
Female	258 (74%)	1018 (66%)	933 (64%)
Male	89 (26%)	528 (34%)	534 (36%)
ZIP Code			
30310	25 (7%)	117 (8%)	100 (7%)
30331	41 (12%)	206 (13%)	151 (10%)
30315	36 (10%)	130 (8%)	136 (9%)
30331	100 (29%)	439 (28%)	333 (23%)
30344	78 (22%)	347 (22%)	378 (26%)
30349	44 (13%)	215 (14%)	271 (18%)
30354	23 (7%)	92 (6%)	98 (7%)
Health Insurance			
Medicare	166 (48%)	646 (42%)	139 (9%)
Medicaid	88 (25%)	300 (19%)	763 (52%)
Commercial	93 (27%)	577 (37%)	520 (35%)
Self-pay	0 (0%)	23 (1%)	45 (3%)
Most Common Physical Conditions			
Hypertension	311 (90%)	1254 (81%)	174 (12%)
Hyperlipidemia	214 (62%)	876 (57%)	54 (4%)
Obesity	137 (39%)	529 (34%)	184 (13%)
Diabetes	118 (34%)	494 (32%)	4 (0%)
Most Common Behavioral/Mental Conditions			
Depression	191 (55%)	108 (7%)	0
Dementia	35 (10%)	6 (0%)	0
Alcohol Abuse	41 (12%)	11 (1%)	0
Psychoses	31 (9%)	17 (1%)	0

Discussion

We describe how a simplified risk stratification approach implemented in a primary care clinic that serves an underserved, medically and socially complex population can be used to implement a clinic-to-community multidisciplinary care management program. With such an approach, a care team can quickly react to different intensities of illness in their panel and proactively manage risk. This approach allows a multidisciplinary care team to target high-risk patients inside the walls of the clinic and the communities where they live.

This approach is easily replicable and low-cost, requiring input that is easily derived from an EHR, which are now prevalent primary care settings.[22–25] In contrast, several existing risk-stratification instruments are not transparent and not necessarily affordable for the primary care setting. For example, Adjusted Clinical Groups (ACGs), which has an algorithm that incorporates disease patterns, pharmaceutical information, and claims data, requires licensed software and has considerable charge for end-users.[26,27] Additionally, measurement of the population management, registry, and quality measures can be customized by the approach presented here and leveraged to meet requirements across a variety of payers, for meaningful use requirements, and towards National Committee for Quality Assurance (NCQA) status qualifications. This approach enables a practice to implement a population health management tool for their whole patient panel, rather than managing multiple sub-panels defined by specific payers.

These strategies are in the interest of patients, clinicians, and payers, but the implementation is best managed on a practice-wide level, rather than creating multiple programs and solutions for each subset of the practice patient panel divided by various payer segments. The fully-implemented Patient-Centered Medical Home (PCMH), as measured by NCQA certification, has already been demonstrated to have significant (although variable) benefits as measured by health outcomes improvement and financial return on investment (ROI).[28] Addressing behavioral and social complexity through integrated care with behavioral health professionals, social workers, and community health workers, also adds value to this model.[29,30]

Clearly there is an opportunity to build on this simple risk stratification model to test and then potentially strengthen the predictive power of the risk stratification algorithm. Our most common chronic conditions (hypertension and hyperlipidemia) are important targets of secondary prevention, but may have limited impact on short-term outcomes of interest to payers, such as near-term costs, emergency department visits, and hospital bed-days. Focusing on the combination of heart failure, chronic lung disease and renal insufficiency, for example, would be a triad that would be expected to generate a greater one-year return on investment (ROI) than cardio/metabolic risk reduction in otherwise healthy patients. Similarly, not all behavioral health conditions carry the same risk of morbidity. The combination of schizophrenia and diabetes, for example, is a potent dyad which leads to increasing utilization with each added comorbid condition.[21] Weighting the risk stratification by annual costs or inpatient bed-day rates associated with each disease (or each dyad or triad), for example, would generate a different "high-risk" cohort and one-year ROI. County-specific Medicare cost and utilization data related to specific diseases or dyads are now available on-line for generating these weighting factors, and are available for public use by primary care clinicians on-line from the Centers for Medicare & Medicaid Services (CMS).[31]

Limitations. This approach has limitations. Payers' outcome data are still needed for better care management. This will ultimately require real-time data feeds from payers and/or hospitals to generate actionable information. Weighting of comorbidities by impact on near-term and longer-term utilization, costs, and outcomes, will be essential. While payer agreement is not assured, this approach will allow the primary care practice to negotiate based on the ability to manage outcomes, rather than simply submitting to multiple programs, interventions, and IT solutions imposed by multiple payers.

Future work. Next steps will include a detailed evaluation of the current algorithm that takes into account cost, utilization, and patient and provider perceptions of the program. Additionally, we plan to incorporate more detailed patient home visit information and claims data for patients receiving services outside CHFC into a refined dashboard. An enhanced patient engagement dashboard will be designed to support patient self-management, enhance health literacy, and encourage shared decision-making. Additionally, a care coordination toolkit and clinical support services will be developed to extend care coordination/clinical dashboard support services to small practices throughout the region.

Conclusion. The risk stratification algorithm presented here, built upon internally available EHR and billing system data, provides a feasible option for beginning the process of engaging in population health management in a safety-net primary care practice. Implementing this algorithm as the foundation for a Patient Centered Medical Home and Neighborhood initiative located in a high-need, high-disparity neighborhood enabled our team to understand and respond to the nuances of population health in our underserved community.

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