Identifying Patients at Risk of High Healthcare Utilization

Lincoln Sheets,[1,2] MD, Lori Popejoy,[3] PhD, APRN, GCNS-BC, Mohammed Khalilia,[1,4] PhD, Greg Petroski[1], PhD, Jerry C. Parker[1], PhD

1. University of Missouri School of Medicine
2. University of Missouri Informatics Institute
3. University of Missouri School of Nursing
4. University of Missouri College of Engineering

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This project was funded by the Center for Medicare and Medicaid Services (CMS) to expand the scope of services to a population of CMS beneficiaries, so the Health Sciences Institutional Review Board deemed the project to be a quality improvement initiative that did not require a formal patient consent process since the explicit purpose of data use was to improve patient care; the IRB number is 1212477.QI. The authors have no conflict of interest to declare.

ABSTRACT

Objective. To develop a systematic and reproducible way to identify patients at increased risk for higher healthcare costs. *Methods.* Medical records were analyzed for 9,581 adults who were primary care patients in the University of Missouri Health System and who were enrolled in Medicare or Medicaid. Patients were categorized into one of four risk tiers as of October 1, 2013, and the four tiers were compared on demographic characteristics, number of healthcare episodes, and healthcare charges in the year before and the year after cohort formation. *Results.* The mean number of healthcare episodes and the sum of healthcare charges in the year following cohort formation were higher for patients in the higher-risk tiers. *Conclusions.* Retrospective information that is easily extracted from medical records can be used to create risk tiers that provide highly useful information about the prospective risk of healthcare utilization and costs.

INTRODUCTION

The Chronic Care Model[1] proposed improving the effectiveness of interactions between patients and providers as a way of promoting the "triple aim" of healthcare:[2] (a) better health, (b) better care, and (c) lower costs.[3] These positive outcomes may be anticipated on the basis of improved interactions between informed, activated patients and prepared, proactive providers [1]. Evidence also has shown that patients with care coordinators have fewer emergency department and urgent care episodes,[4] hospital admissions,[5] and readmissions.[6]

Care coordination is "… the deliberate organization of patient care activities between two or more participants (including the patient) involved in the patient's care to facilitate the appropriate delivery of health service…"[7] [2]. Care coordination is increasingly being used across the healthcare system to improve patient outcomes for populations of patients and is a core element of both the triple aim and the Chronic Care Model. In order for care coordinators to manage populations of patients, they must be able to identify the patients who are most in need of their services; one approach to this challenge is risk stratification. Indeed, risk stratification is crucial for effective population health management[8] because it provides care coordinators the opportunity to focus their work on those patients who will benefit the most.[9-11] By bridging the implementation gaps in the Chronic Care Model, well-designed risk stratification supports the transition from the traditional "reactive" model of medical care[12] to one of maintaining health and avoiding preventable conditions. Risk stratification is a potentially powerful tool for predicting population health outcomes, and previous healthcare utilization has been shown to be a useful predictor of future healthcare needs.[13]

Although the literature contains many studies and reviews of condition-specific risk stratification, most predictive indices have less than 90 percent accuracy[14] and relatively few attempts have been made to stratify entire primary care populations. Notable examples include the Scottish SPARRA risk index for readmission of patients who had been recently discharged from the hospital[15] and the Welsh Prism risk index for emergency admissions.[16] In the United States, the Michigan Primary Care Transformation Project[17] defined four functional tiers upon which intensity of services was based, rather than relying on a predictive index. The tiers are as follows: (a) Navigating the Medical Neighborhood, (b) Transition Care, (c) Care Management, and (d) Complex Care Management. The Senior Segmentation Algorithm,[18] developed by the Kaiser Permanente healthcare system, also used four tiers that were more descriptive than functional; those were (a) Without Chronic Conditions, (b) With One or More Chronic Conditions, (c) With Advanced Illness or End-organ Failure, and (d) With Extreme Frailty or Nearing the End of Life. The Senior Segmentation Algorithm, while objective and reproducible, has been validated only in patients aged 65 years and older. Other models that have been applied to community-dwelling populations with varying degrees of success are Dr. Chad Boult's work on risk scores to identify high risk patients from Medicare data,[19] the Charlson and Elixhauser comorbidity indices,[20] and the work by Dr. Hal Luft on the yearly stability of Medicare utilization and costs.[21]

In this study, the objective was to develop a systematic, reproducible way to identify subgroups in a managed population at risk for higher utilization of healthcare resources as measured by healthcare episodes and charges.

METHODS

Population

In February of 2013, the LIGHT2 project (Leveraging Information Technology to Guide Hi- Tech and Hi-Touch Care, pronounced "light squared") began enrolling adults who were primary care patients in the University of Missouri Health System and who were already enrolled in Medicare and/or Medicaid. LIGHT2 was a Health Care Innovation Award from CMS (Centers for Medicare and Medicaid Services) to achieve the Triple Aim of better health, better care, and lower costs by using advanced information technology and care coordination.[22] In order to define a stable cohort, this study limited data analysis to 9,581 patients who were enrolled before the first three months of care coordination was completed on July 1, 2013, and who were still enrolled when patients were first evaluated for risk stratification on October 1, 2013.

Primary Care Setting

Adult primary care in the University of Missouri Health System (UMHS) is provided by approximately 133 primary care physicians who practice in nine regional clinics; the Department of Family and Community Medicine operates five local outpatient clinics and two in nearby communities, and the General Internal Medicine section of the Department of Medicine operates two local clinics. This community-based, primary care focus is supported by an extensive UMHS tertiary-care system of six hospitals and more than 50 clinics, staffed by approximately 550 university physicians.

Data Source

All data on diagnoses, outpatient visits, and hospital episodes and charges were retrieved from the University of Missouri Health System electronic medical record as maintained by clinicians and staff between 2012 and 2014.

Rationale for Categorical Approach

For the purpose of differentiating levels of care coordination intensity, a categorical approach has some advantages over an index. Each category can receive a customized level of care coordination in a manner similar to the "functional tiers" of the Michigan Primary Care Transformation Project.[17] One potential disadvantage to some previous approaches[9,14] is that they sometimes rely on socioeconomic and other data for which characteristics can vary widely across settings. In order to predicate the risk tiers on more universally reproducible criteria, socioeconomic factors were not included in the development of risk tiers for this study using the general criteria of diagnoses and utilization. Specifically, the 27 chronic conditions that are included in the Chronic Conditions Data Warehouse[23] provide a standard set of diagnoses that are relevant to population health management of Medicare/Medicaid patients in a primary care setting (see Figure 1). In addition, healthcare utilization was extracted for (a) outpatient visits, which may be encouraged or even increased as part of care coordination, and (b) the more costly hospital-based episodes, which include emergency department episodes, observation stays, and hospital admissions.

Number and Definitions of Tiers

Tier Definitions. The definitions of the four LIGHT2 risk tiers are shown in Table 1. These tiers were conceptualized to be generally similar to the "functional tiers" developed by the Michigan Primary Care Transformation Project[17] and the "care groups" used in the Senior Segmentation Algorithm.[18] For the purposes of risk stratification, the LIGHT2 tiers were defined as (1) No Chronic Conditions, (2) Chronic Conditions, Stable, (3) Chronic Conditions, Unstable, and (4) Chronic Conditions, Complex. These broad categories of chronic-disease acuity describe all members of a managed adult population with some specificity, but the categories also are general enough to be applied to a variety of environments and conditions.

Tier Calculations. The breakpoints between tiers were determined deductively in an effort to reflect the intent of the functional tier definitions. The lowest or "No Chronic Conditions" category (Tier 1) was reserved for enrollees who had none of the 27 diagnoses included in the CMS Chronic Conditions Data Warehouse.[23] For those enrollees with one or more chronic conditions, placement in either Tier 2, 3, or 4 was based on the frequency of outpatient clinic visits and hospital episodes (including emergency department episodes, observations stays, and hospital admissions) during the 12 months prior to analysis. Patients with one or more of the 27 CMS chronic conditions were stratified as "Chronic Conditions, Stable" (Tier 2) if they had four or fewer outpatient visits and no hospital episodes associated with their chronic conditions in the preceding 12 months. Based on the clinical experience of two authors (LS, LP), patients were stratified as "Chronic Conditions, Unstable" (Tier 3) if they had 5 to 12 outpatient visits or one hospital episode related to any chronic conditions during the preceding 12 months, and were stratified as "Chronic Conditions, Complex" (Tier 4) if they exceeded 12 related outpatient visits or had two or more related hospital episodes during the preceding 12 months.

Data Collection

Cohort Formation. In order to test the ability of these queries to predict risk for higher utilization of healthcare resources, the population was divided into tiers based on their clinical history as of a given date (October 1, 2013) and was treated thereafter as four fixed cohorts. For each cohort, the healthcare episodes and charges were calculated retrospectively for the 12 months before cohort formation (October 1, 2012, to September 30, 2013) to provide a baseline, and then prospectively for the subsequent 12 months (October 1, 2013, to September 30, 2014) to examine the utility of the risk stratification methodology.

Cohort Attrition. Attrition (e.g. death, relocation) during the 12 months after cohort formation reduced the size of the cohort by 208 patients, or 2.2%. Because excluding these patients was likely to bias the data collection toward healthier patients, their outcomes were included for those months in which they were alive and enrolled in the LIGHT2 program. A patient enrolled for one month after cohort formation, therefore, would contribute one-twelfth as much to the mean episodes and charges for his or her tier subgroup as another patient who was enrolled for the entire 12 months.

Inflation Adjustment. In order to compare baseline and prospective charges, all charges were adjusted to 2014 dollars. Since healthcare charges were adjusted upward by 3% on April 1 of each year during the study period, charges billed from April 1, 2013, to March 31, 2014, were adjusted by multiplying times 1.03. Charges billed from October 1, 2012, to March 31, 2013,were multiplied by (1.03 x 1.03) or 1.061.

Statistical Methods

Statistical comparisons of outcomes between tiers used the Kruskal-Wallis Test, a nonparametric analogue of the standard one-way ANOVA. Statistically significant ($p < 0.05$) overall tests were followed by pairwise rank-based comparisons;[24] all comparisons were two-sided.

RESULTS

Demographic Description of the Cohort

Of 9,581 patients in the cohort, 63% (n = 6,014) were in Tier 2 on October 1, 2013, while Tiers 1 and 3 comprised 16% each (n = 1,554 for Tier 1; n = 1,555 for Tier 3), with the remaining 5% (n = 458) in Tier 4. More than three-fourths of the Tier 1 enrollees were younger than 65, but fewer than half of the enrollees in the other tiers were under 65. Overall, 4,185 of the 9,581 patients (44%) were younger than 65 years old. Approximately three-fifths of the enrollees in every tier were female. Figure 1 shows the prevalence of the Chronic Conditions Data Warehouse[23] diagnoses in the LIGHT2 population.

Baseline Analyses of Hospital Episodes by Tier

During the 12 months before cohort formation, the mean number of emergency department episodes was 0.20, 0.18, 0.52, and 1.45 in each tier respectively; observation stays averaged 0.10, 0.09, 0.41, and 1.16 respectively; and there were 0.09, 0.09, 0.47, and 1.86 mean inpatient admissions in each respective tier. The number of episodes was significantly different overall among the tiers ($p < 0.001$) and progressively higher in successive tiers in pairwise comparisons ($p < 0.001$ for all comparisons), except that there were no significant differences between numbers of episodes in Tiers 1 and 2 ($p = 0.304$ for emergency, $p = 0.967$ for observation, and $p = 0.739$ for inpatient). Because the data were skewed, the median number of episodes of all types was zero for Tiers 1, 2, and 3. For Tier 4, the median number of emergency episodes was zero, and the median number of observation and inpatient episodes was 1. The median values of zero indicate that over half of the lower tier patients had no hospital episodes during the baseline year.

Baseline Analyses of Healthcare Charges by Tier

During the 12 months before cohort formation, mean healthcare charges in the four tiers (respectively $6,208, $10,889, $43,059, and $115,228) were significantly different overall and in pairwise comparisons ($p < 0.001$ overall and for all comparisons). Median charges in each tier (respectively $658, $2,641, $19,707, and $66,182) were likewise significantly higher in higher tiers ($p < 0.001$ overall and for all pairwise comparisons). Tiers 3 and 4, comprising only 21% of the total population, accounted for 61% of total healthcare charges. Because lower tiers were defined by fewer or no healthcare episodes, the finding that enrollees in these tiers had fewer mean hospital episodes and lower charges was expected. However, these numbers show the magnitude of the differences between the subgroups in each tier at baseline, and they provide the basis for tier categorization on the date of cohort formation (October 1, 2013).

Prospective Analyses of Hospital Episodes by Tier

Figure 2 shows the mean number of hospital episodes by type, within each tier, during the 12 months following cohort formation. For all episode types, the overall differences remained significant ($p < 0.001$). Tier 4 enrollees had significantly more episodes on average than Tier 3 patients; they, in turn, had significantly more episodes than Tier 2 or Tier 1 patients ($p < 0.001$ for all comparisons). There were no significant differences between Tier 1 and Tier 2 emergency episodes ($p = 0.279$), but the numbers of observation and inpatient episodes were significantly different between these two tiers ($p < 0.001$ for each type). For all tiers, the median number of episodes of all types was zero.

Prospective Analyses of Healthcare Charges by Tier

Figure 3 shows the mean and total healthcare charges by tier during the 12 months after cohort formation. Tiers 3 and 4, comprising 21% of the total population, accounted for 43% of total healthcare charges. Overall differences were significant ($p < 0.001$). Tier 4 enrollees had significantly higher charges on average than Tier 3 patients, which had significantly higher charges than Tier 2 patients; and these in turn where significantly higher than for Tier 1 patients ($p < 0.001$ for all comparisons). Median charges in each tier (respectively $0, $2,343, $8,662, and $20,412) were likewise significantly different overall ($p < 0.001$) and higher in the higher tiers ($p < 0.001$ for all comparisons).

DISCUSSION

The primary conclusion is that the LIGHT2 risk stratification methodology successfully met the objective of identifying which subgroups of Medicare/Medicaid patients were at risk of utilizing more healthcare resources. Specifically, information about healthcare utilization and charges over the previous twelve months provided highly useful information about what is likely to occur going forward. This finding confirms the expectation that past utilization is a good predictor of future utilization. When viewed through a population health lens, the extraction of readily available retrospective data can provide care coordinators with useful information that allows them to focus their efforts on those patients who care needs are most expensive, and who may require more intensive management.

A second observation is that the risk tiers created in this study were defined on the basis of diagnoses that are included in the Chronic Conditions Data Warehouse[23] and on utilization categories that are in general use in healthcare systems. Because these are easily reproducible, the LIGHT2 risk stratification framework is potentially applicable to other healthcare systems.

A third observation is that there were no differences between Tier 1 patients and Tier 2 patients in the mean number of hospital episodes during the retrospective (i.e., baseline) period. Similarly, in the prospective period, there was no difference in mean number of emergency department episodes between Tiers 1 and 2. Accordingly, the cost and utilization patterns of Tier 2 patients are, in some ways, not notably different from Tier 1. Therefore, from a population health standpoint, time and resources devoted to keeping Tier 2 patients from evolving into the much more costly Tier 3 category would appear to be a useful care coordination strategy.

Finally, Tiers 3 and 4, comprising only 21% of the total population, accounted for 61% of total baseline healthcare charges and 43% of total prospective healthcare charges. The decrease in this difference from the baseline to the prospective measure reflects that prior healthcare episodes and charges are not a perfect, but nevertheless, highly useful predictor of prospective utilization. Specifically, the consumption of a large proportion of healthcare resources by a relatively small minority of the population (Tiers 3 and 4), even in the prospective year, underscores the importance of the early identification of those patients (or subgroups) who are most “at risk” for high healthcare utilization.

Limitations

Measurement of baseline and prospective utilization included only healthcare episodes that occurred within the University of Missouri Health System. Accordingly, these results likely under-report utilization by excluding healthcare episodes at other local or out-of-town facilities; inclusion of this additional data could possibly improve the accuracy of risk stratification. In addition, healthcare charges were used as a proxy for healthcare costs, although claims data would be a more accurate source of cost information. Lastly, the generalizability of the LIGHT2 risk stratification methodology to other settings remains an empirical question. The study sample included only adults who received Medicare or Medicaid services in central Missouri, which may limit the generalizability of these findings to the wider US population.

Future Research

This preliminary work would be strengthened by validation against other populations that may have different prevalence of chronic conditions, age-adjusted death rates, or rates of relocation as well as different distributions of race/ethnicity, educational attainment, economic status, and literacy. Because the data used in the LIGHT2 risk stratification methodology is available in any healthcare system, replication of this four-tier methodology in other settings would be instructive. Additional studies that incorporate claims data also could be conducted to examine whether the accuracy of risk stratification could be improved. While this study demonstrates the predictive power of a tiered model, continuous risk scoring may be even more powerful, and development of such a model would also be helpful.

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TABLES

Table 1: Operationalized Queries

Tier	Definition (based on healthcare episodes in the past 12 months)
1: No Chronic Conditions	Zero chronic conditions listed in the Chronic Conditions Data Warehouse
2: Chronic Conditions, Stable	One or more chronic conditions AND (hospital episodes = 0 AND outpatient visits < 5)
3: Chronic Conditions, Unstable	One or more chronic conditions AND (hospital episodes = 1 OR outpatient visits from 5 to 12)
4: Chronic Conditions, Complex	One or more chronic conditions AND (hospital episodes > 1 OR outpatient visits > 12)

FIGURES

Figure 1: Prevalence of 27 Defined Chronic Conditions

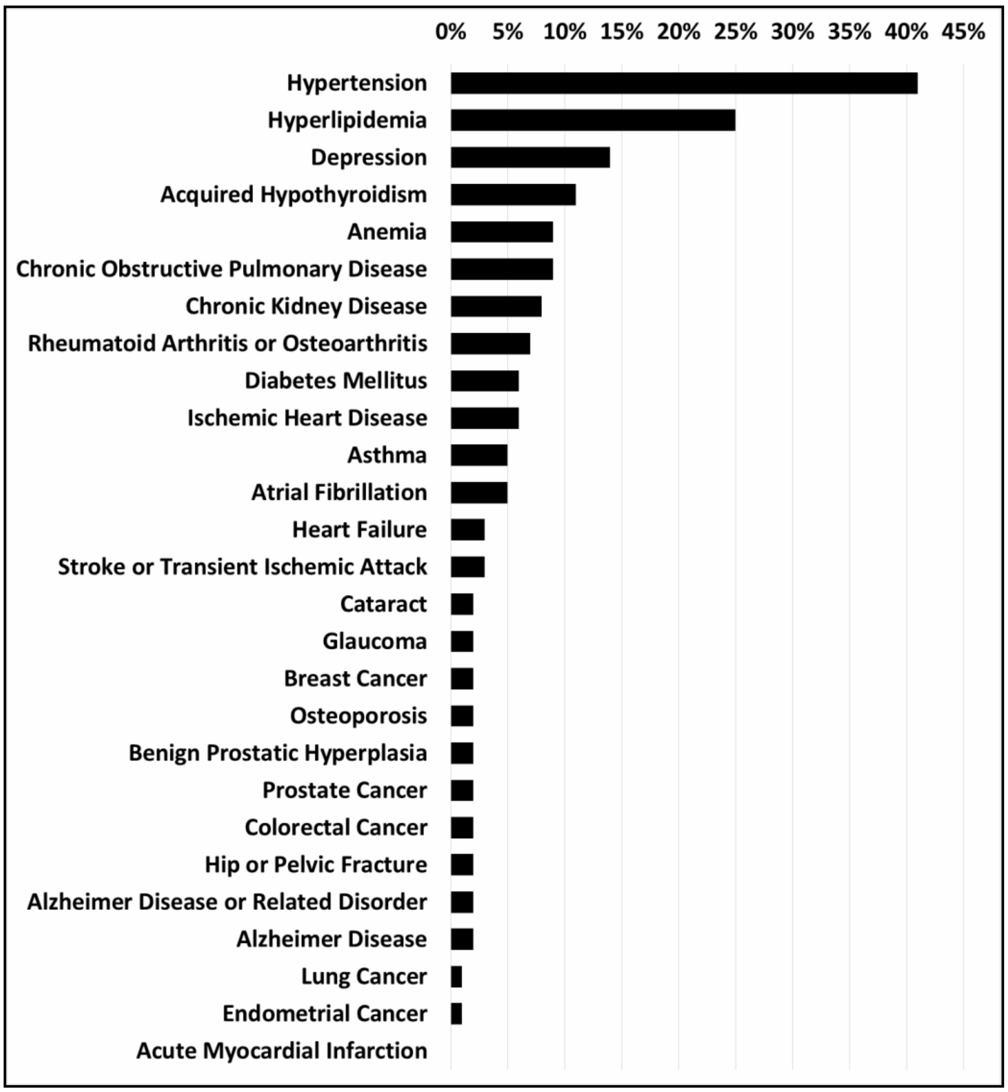

Figure 2: Prospective Hospital Episodes by Tier

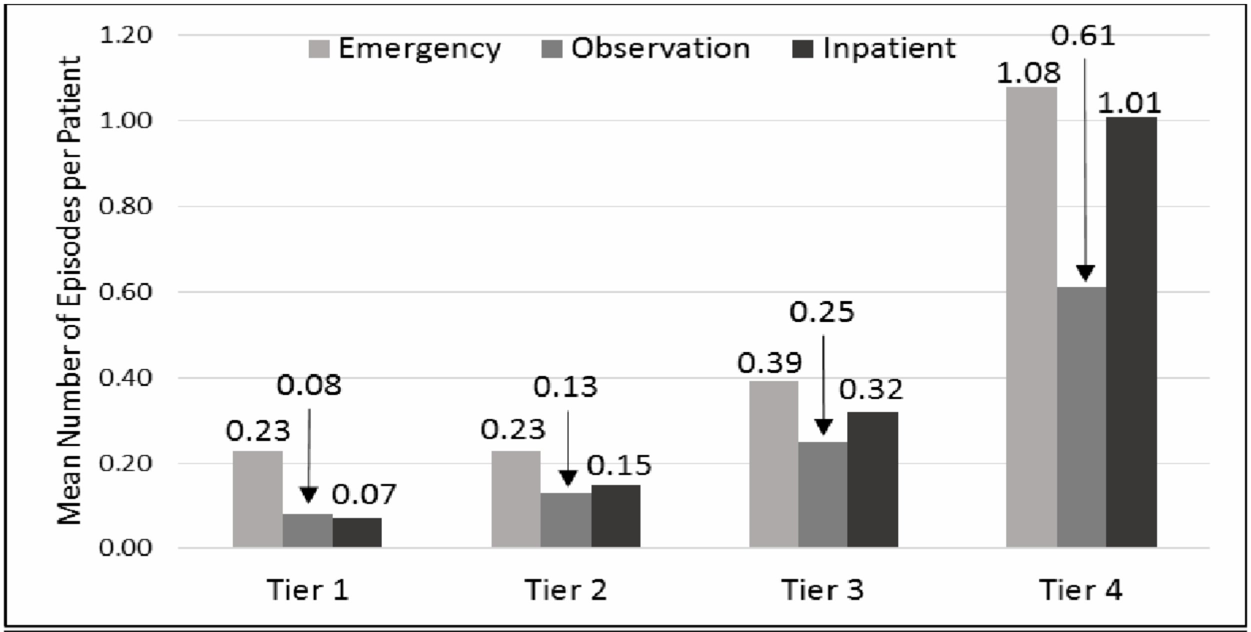

Figure 3: Prospective Healthcare Charges by Tier