Case Finding Web Application for Care Management Programs

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Abstract

Care management programs for high-cost patients with complex medical and social needs are seen as an opportunity to improve quality of care, promote health, and reduce costs. However, mixed evidence of intervention effectiveness and a lack of supportive technologies limit the ability of programs to properly target patients and significantly impact health service use. This study presents a series of analytics tools designed to improve case finding for care management programs.

Introduction

Care management programs targeting patients with complex needs are proliferating despite mixed evidence of effectiveness and a lack of robust tools to guide program operations. This study synthesizes nearly two years of experience developing data applications to support population health management programs at a primary care clinic to improve case finding of high utilizer patients for enrollment in a complex care management program.

Care management and coordination has been defined as "the deliberate integration of patient care activities between two or more participants involved in a patient's care to facilitate the appropriate delivery of health care services"[1]. These programs attempt to avoid wasteful duplication of diagnostic testing, perilous polypharmacy, and conflicting care plans for patients receiving care from multiple providers. Most care management research has occurred in the Medicare setting, with varied results[2-8]. However, successful programs share several characteristics: they serve as a communications hub between providers and patients; they use behavior-change techniques and motivational interviewing to help patients follow recommendations; lastly, they have reliable information about patients' medications and implement a comprehensive approach to transitions from hospital to home[3].

Attention is shifting from reducing costs for elderly Medicare patients to reducing costs for high utilizing Medicaid patients, with an emphasis on treating mental illness and substance abuse[9]. Sixty percent of high-cost Medicaid patients have co-morbid physical and behavioral health conditions and Medicaid patients with mental illness in addition to common chronic illness incur costs that are 60-75% higher than those without a mental illness[10,11].

In 2011, a performance services analyst at the largest adult Medicaid primary care clinic within the Duke University Health System (DUHS) found similar results that revealed an opportunity to improve care for Medicaid beneficiaries. Nearly all constellations of disease for patients at this clinic with high levels of 30-day hospital readmissions included both mental and physical health comorbidities. For example, 54% of hospital admissions for patients with diabetes, hypertension, and mental illness/substance use were followed by a readmission within 30 days. By comparison, only 28% of hospital admissions for patients with coronary artery disease, diabetes, heart failure, and hypertension (without mental illness/substance abuse) were followed by a readmission within 30 days.

To address the complex needs of high utilizing Medicaid patients, "super-utilizer" programs have emerged to provide intensive outpatient care management to patients whose medical, behavioral, and social needs are unmet[14]. These programs incorporate behavioral health services into primary care, but the extent of service integration and resultant outcomes vary greatly[9]. In response to analysis of its own administrative data, DUHS launched "HomeBase," its first unified primary care and behavioral health intervention targeting high utilizer Medicaid enrollees, in August, 2013.

The HomeBase program was created at a safety net, resident-run primary care clinic to shift care for high utilizer male and female Medicaid beneficiaries from the high-cost hospital environment to the low-cost outpatient primary care setting by improving treatment of mental illness and addressing unmet social needs. The behavioral-physical care management team consists of a nurse care manager, a social worker, a mental health-trained advanced practice provider, and a dually trained medicine-psychiatry attending.

Case Finding

HomeBase began enrolling in August 2013, based on Medicaid enrollment status, levels of ED use, and referrals from primary care providers. The care management team subsequently performed manual chart reviews to assure continued use of healthcare services. Priority was given to patients with comorbid mental health or substance abuse disorders, but a number of patients with significant chronic medical illness were also enrolled.

Over the first six months, thirty-seven patients were enrolled in the program. To evaluate the impact of the program on health service use, a case-control study using propensity score matching was completed to compare outcomes for program participants with outcomes for similar high utilizer patients not engaged in care management[15]. However, preliminary results revealed a very heterogeneous treatment group, which made it difficult to find well-matched control patients and brought into question whether or not the program was appropriately targeting patients. For example, the average number of emergency department (ED) visits in the year pre-intervention for program participants was 11.63 visits/year with a standard deviation of 8.26 visits/year. ED use trajectories for the first thirty-four patients enrolled in the program are illustrated in Figure 1. Nearly a quarter of the patients enrolled (e.g., patients 2 and 12) had an average of less than two ED visits per six-month period in both the pre- and post-intervention periods, limiting the measured impact of a program intended to target only high utilizers.
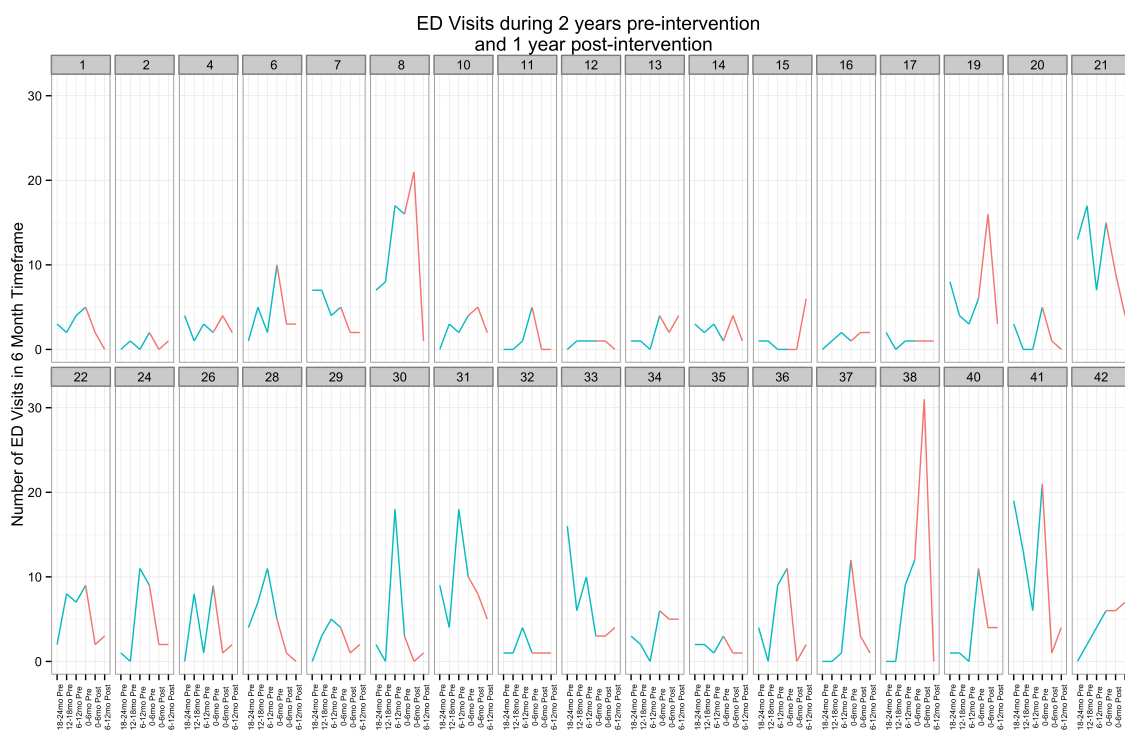

Figure 1. ED use trajectories for the first thirty-four patients enrolled in the program. Each data point is the total number of ED visits over a six-month period. Blue data points span the two years pre-intervention and red data points span the one-year post-intervention.

The identification of patients most likely to benefit from care management, referred to as case finding, is essential for both the effectiveness and cost-efficiency of care management programs[16,17]. For HomeBase, reliance on provider referrals likely resulted in enrollment of patients who did not demonstrate sufficient levels of health service use to show a significant impact on cost of care. But while primary care providers have limited ability to predict future levels of health service use[18,19], predictive modeling can result in the identification of patients who are often unwilling or unable to participate[20]. The tools described below attempt to resolve the tension between using either chart review or a numeric risk score exclusively by presenting health record data in novel ways that enable providers to quickly analyze data.

Design
To address the lack of data-driven case finding, a series of analytics tools were developed to support the HomeBase program and population health efforts at the clinic more broadly. Mark started attending clinic redesign meetings every-other-week in September, 2013, to support the population health management programs as a data analyst and he received credit for his evaluation of the HomeBase program as his Masters in Public Policy thesis.

To begin with, clinic leadership didn't have the necessary data to guide population health management program operations. To understand the landscape of meaningful measures, we assembled a compendium of the hundreds of data elements included in validated hospital readmission prediction models[21,22,23,24]. The list sufficiently covered medical conditions and encounter histories, but clinic providers wanted to include additional socioeconomic and behavioral health data. In response, we built a validated chronic pain phenotype[25], agreed on a list of five socioeconomic ICD9 codes to monitor, and built a validated socioeconomic status index that incorporates seven census tract data elements[26]. Next, providers wanted better data on childhood trauma, a major driver of disruptive health service use in adulthood, and better measures of patient engagement. In response, two ICD9 code variables were built for child and adult abuse and HomeBase was advised to use the Patient Activation Measure as part of the intake process for new patients[27]. After the list of variables was set, we developed R scripts to transform raw data extracted from the administrative data warehouse into the meaningful features. We were granted access to the administrative data warehouse via DEDUCE, an online guided query tool built at Duke,[28] and the data cleaning required regular meetings with data warehouse staff and clinic providers to vet the output. A list of the variables is included in the supplementary material.

Once meaningful data elements were identified, clinic providers needed a way to interact with the population health data. One provider recommended we use REDCap, an electronic data capture tool built to support clinical research[29], so we worked with a health system SAS programmer to launch an interactive REDCap database in June 2014. This tool enabled the HomeBase team and clinic leaders to generate lists of high-risk patients based on a very rich set of data, without requiring the time and support of a data analyst. Clinic leadership and the department of medicine found the tool so helpful that resources were dedicated to update the database quarterly and to create a new database each year for adjusted clinic panels. However, the database had a limited impact on clinic operations. We wanted to create a usable analytics tool that could support the day-to-day operations of population health management programs, but we learned after 6 months that the database became a rarely used administrative reporting tool. Providers wanted more real-time data, not quarterly measures, and they did not want to interact with tables of data.

Based on this feedback, we strived to build a user interface that demonstrated actionable data. Clinic providers wanted visualizations that detected disruptive patterns of health service use, so that high-risk patients stood out from the population. Providers wanted to incorporate total cost of care and ED reliance, a measure validated in the pediatrics population[30], into the analysis. We also built a custom variable that calculated the percentage of ED visits that result in hospital admission. The goal was to find patients who excessively relied on the ED for healthcare and for whom ED encounters rarely result in hospital admission. Care for these patients, the team hypothesized, could more easily be shifted to the outpatient setting. During this time, we worked closely with RJ Andrews, creator of the InfoWeTrust data visualization blog, to design new graphics for the population health data. The HomeBase team and clinic leadership were most excited about a plot of ED reliance versus hospital admission percentage and a healthcare utilization timeline. Software was developed in R to print 5-page PDF reports for the costliest 100 clinic patients. A sample report is included in the supplemental materials and the source code can be found in the github repository: https://github.com/mpdakkak/AMIA_SDC_2015.

The visualizations in the PDF report generated tremendous excitement among clinic and department leadership. This tool successfully allowed clinic providers to quickly understand an individual patient's health service use patterns across years of time and hundreds of data points. One provider at the clinic told us that the visualizations challenge providers to think differently about their patients, demonstrating that we accomplished much more than was possible with chart review or tables of data. Small revisions were made to the plot based on feedback, including changes to the color scheme and the addition of subspecialty visits.

Within weeks of sending a pilot report, a faculty in family medicine requested running the report on a different cohort, which prompted extension of the code to enable flexible cohort and timeframe selection.

The major limitation of the PDF report was lack of interactivity. Clinic providers wanted to see the top diagnosis codes for each encounter, which can be easily added as a hover-over feature, but is much more difficult to add to a static image. In addition, the tool is ultimately meant to build a cohort of individuals to intervene on and a static image does not allow the inclusion or exclusion of individual patients from the plot. In response to this feedback, development of an interactive web application began in March, 2015, using the R Shiny framework. The application includes healthcare utilization timelines, ED use trends, and comorbidity data. Viewing twenty-five patients at a time, HomeBase and clinic providers can now identify which patients appear to have disruptive health service use patterns and can quickly assess whether or not underlying mental illness or substance abuse drives those patterns. The source code for the web application and a video demo can be found in the github repository: https://github.com/mpdakkak/AMIA_SDC_2015.

The Duke Institute for Health Innovation is now funding the deployment of the interactive web application. The front-end development and analytics for the pilot are complete, but the back end infrastructure still needs to be put in place. A data mart with the clean data must sit below the visualizations and feeds must be established to update the data mart on a monthly basis. Servers must also be provisioned to create a sandbox where web applications that display protected health information to providers can sit behind the firewall. A schematic of the plan moving forward has been assembled with input from health information security office representatives as well as health system developers and is included in the supplemental materials. Ultimately, integrating with Fast Healthcare Interoperability Resources (FHIR) will enable the web application to sit alongside the electronic health record and access data in real-time.

The initial pilot of the web application will be from August 1, 2015 – October 31, 2015 for the HomeBase team. We will continue to attend clinic redesign meetings every month and a standing item on the agenda will be to receive feedback on the tool. To test usability, we will measure site visits and time spent on the site, with hopes that the HomeBase team visits the site once per month. To test the impact of the tool on case finding, the distribution of historical health service use (i.e., mean and variance) will be measured for all new waves of enrollment. Upon completion of the initial pilot, the web application will be launched at a family medicine clinic and an interdisciplinary clinic for adolescent and young adult patients with chronic illness that seeks to improve their transition from pediatric to adult care. Both sites run care management programs and leaders at both sites have provided feedback on the initial prototype and have advocated for broader dissemination.

The web application is the next iteration of analytics tools to support case finding, but we do not expect this tool to dissolve the gap between analytics and program operations. Visiting an extra website does not fit seamlessly into existing workflows. The quality of socioeconomic data, patient engagement data, and trauma history continue to be limited. However, despite these limitations, the set of tools being developed go beyond anything previously available to providers to enable data-driven case finding. Alternatives to this application include those described above that were tested during our iterative process and proved to have significant limitations, such as tables of data generated from a health system analyst, the REDCap database, and use of the PDF reports; or increased intensive in person screening, used in other care management programs. The strength of this application over alternative options include the utility of clear data visualizations, the ability to use this data in near-real-time, and the richness of the variable space. These strengths allow care management programs to select and reach the patients that need it most.

Conclusion
The analytics tools described in this study have enabled data-driven case finding for a care management program embedded in a primary care clinic. Relying too heavily on provider referrals during initial program enrollment resulted in a mix of patients that made it especially hard to significantly impact health service utilization and show cost savings. By optimizing case finding, the tools described in this study can significantly improve program effectiveness. Usability challenges have demanded iterative refinements to the analytics tools, culminating in the development of a prototype web application. At Duke, the tools are being piloted at a single primary care clinic with plans to disseminate the tools to two new sites in late 2015. With health systems across the country increasing investment in population health programs,

technologies such as these must be developed and deployed to support program operations and improve clinical care for patients with complex medical needs.

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