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High-Risk-Patient Identification

Strategies for Success

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Association of
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High-Risk-Patient Identification: Strategies for Success

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The project summarized in this report was a collaborative effort between the AAMC and the National Association of Accountable Care Organizations (NAACOS). The purpose of the project was to enhance the dialogue about and the practice of risk assessment for hospitals, physician practices, and integrated networks that assume financial risk in alternative payment models.

Participants included both hospitals and providers that were participating in risk-based payment programs at the time of the interviews. The programs included accountable care organizations (ACOs), the Medicare Shared Savings Program (MSSP), the Bundled Payment for Care Improvement (BPCI) program, and other value-based payment models.

The AAMC and NAACOS contracted Validate Health to summarize the project's findings in this report, *High-Risk-Patient Identification: Strategies for Success*.

The AAMC supports teaching hospitals and faculty physicians in continuously improving care. It is a facilitator-convener for the BPCI program and other alternatives to fee-for-service payment models.

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PROVIDER STRATEGIES AND LESSONS LEARNED

Introduction

The Patient Protection and Affordable Care Act (ACA) includes numerous provisions that encourage or require health care providers to implement or expand a variety of value-based care initiatives. The ACA created the Hospital Value-Based Purchasing program, which ties payment to quality, the Medicare Shared Savings Program (MSSP), the largest Medicare accountable care organization (ACO) program, and the Center for Medicare and Medicaid Innovation, which tests the impact of new delivery and payment models on expenditures and clinical outcomes. These alternative payment models shift financial risk from payers to providers by rewarding those who achieve quality and cost thresholds and penalizing those who fail to do so.

The proliferation of these new reimbursement models has accelerated providers' efforts to focus on population health management (PHM). A cornerstone of PHM is the use of data-driven care interventions to improve the health of and lower the care costs for a population. Across all models, the identification, stratification, and management of high-risk patients is central to improving quality and cost outcomes. The use of predictive modeling to proactively identify patients who are at highest risk of poor health outcomes and will benefit most from intervention is one solution believed to improve risk management for providers transitioning to value-based payment. The patient-identification process may include the use of both predictive modeling and manual, clinical selection of patients through health provider or family referral.

This section of the *High-Risk-Patient Identification* report summarizes lessons from 17 provider organizations with experience in risk-based payment models. Although approaches to risk assumption vary, these providers share a disciplined approach to identifying high-risk patients who would most benefit from interventions. These organizations share several commonalities: strong organizational structure and leadership, investment in analytics, experimentation with several proprietary tools and homegrown solutions, deep investment in complex-care management, and recognition of the impact social determinants have on health.

Study Background

Interviewer Team

An interdisciplinary interview team was assembled to conduct qualitative interviews. A physician executive and informaticist with significant experience in provider risk programs and IT, an experienced managed-care consulting actuary, and an actuarial data scientist investigated the use of predictive models in academic medical centers (AMCs) and ACOs to support value-based-care initiatives.

The dialogues with interviewees challenged all previous assumptions about how predictive models are being used in the clinical arena, despite the clinical and administrative expertise of the interview team.

Organization Selection Criteria

A representative sample of AMCs and ACOs were selected using the following criteria:

1. A wide range of geography, representing most regions of the United States
2. A nearly equal number of AMCs and ACOs (some AMCs participated in an ACO and were counted as both AMCs and ACOs)
3. Both hospital and physician-led organizations
4. AMCs and ACOs experienced or successful in risk arrangements
5. Diverse payer perspectives, including Medicare, Medicaid, and commercial

Participation

Over 30 AMCs and ACOs received interview invitations. Some organizations declined, did not respond, or were unable to schedule an interview within the interview deadline. There were no common features among the nonparticipating organizations that indicate selection bias. Interviews were completed for 18 AMCs and ACOs. One interview was discarded due to incomplete participation beyond the interview. Successful interviews occurred for 17 organizations.

Process

Initial qualitative interviews lasting about one hour took place between October 27, 2015, and December 17, 2015. The discussions were semistructured, meaning that standard questions were asked of all interviewees, and related follow-up questions were formulated and asked during the interview. The standard interview questions appear in Appendix A. The interviews were recorded, transcribed, and summarized using a profile

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format. An initial review period occurred during January 2016 in which interviewees could provide feedback about their profile. Follow-up questions and interviews with some interviewees offered further clarification. A second review period occurred in March 2016 before the release of this study.

Confidentiality

All AMCs and ACOs and specific interviewees were de-identified. Population health management and electronic medical record (EMR) software vendors discussed during the interviews appear below but are not associated with individual organizations.

Acknowledgments

We thank the AAMC and the National Association of ACOs (NAACOS) for defining, guiding, and funding this research project, as well as all interviewees who volunteered their time and insight. We recognize the indispensable input from specific interviewees, including Christine Vogeli, Peter Slavin, and Timothy Ferris.

Organization Backgrounds

Types of Organizations Interviewed

A diverse selection of AMCs and ACOs were interviewed. Some physician-led ACOs consolidate risk nationally across many health care markets, whereas most AMCs serve their local markets. Physician-led ACOs tended to focus on implementing administrative strategies, compared with AMCs, which embraced significant care redesign. Table 1 designates de-identified organizations by a number and lists the corresponding organization type. Of the interviewees, four were ACOs only, five were AMCs only, and eight were both AMCs and ACOs.

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Table 1. Types of Organizations Interviewed

Organization Code #	Type of Organization
1	ACO only
2	AMC only
3	Both ACO and AMC
4	AMC only
5	Both ACO and AMC
6	Both ACO and AMC
7	Both ACO and AMC
8	Both ACO and AMC
9	AMC only
10	Both ACO and AMC
11	ACO only
12	ACO only
13	Both ACO and AMC
14	AMC only
15	ACO only
16	AMC only
17	Both ACO and AMC

Organization Risk Background

Table 2 displays the organizations and their self-reported risk contracts as of the interview date. The most common type of risk contract was with commercial payers. Some participated in Medicaid risk contracts. State regulations largely determined the level of provider Medicaid risk. A few organizations participated in early Medicare value-based care programs, such as the Physician Group Practice Demonstration, the Care Management for High-Cost Beneficiaries Demonstration [Org 13], and the Pioneer ACO program [Orgs 8, 13]. Many organizations are participating in a Medicare Shared Savings Program (MSSP) ACO. All organizations serving a Medicare fee-for-service population were subject to Value-Based Purchasing and/or the Physician Quality Reporting System (PQRS) program.

The amount of revenue from risk-based contracts is likely to increase in the future for the interviewed organizations. Some organizations will participate in the mandatory Comprehensive Care for Joint Replacement (CJR) bundled payment program [Orgs 10, 14]. The new Medicare Access and CHIP Reauthorization Act (MACRA) is likely to

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impact all of these organizations. Some will be affected by aggressive transition to increasing levels of risk in some state Medicaid programs [Orgs 16, 17].

Table 2. Types of Risk Contracts

Organization	Currently Contracted Risk Agreements						Provider-Sponsored Health Plan / Direct to Employer
	Self – Funded Employee	Medicare Advantage	Medicare Bundled Payment for Care Improvement (BPCI)	Medicare ACO**	Medicaid ACO	Commercial ACO	
1				X		X	
2					X		
3	X	X	X	X	X	X	X
4	X		X	X	X***	X	
5				X	X	X	X
6					X	X	
7	X			X		X	
8					X	X	
9	X		X		X	X	
10	X	X		X		X	
11				X		X	
12		X				X	
13				X	X	X	
14	X	X				X	
15		X*		X			
16			X		X	X	
17		X		X	X***		
Total	6	6	4	9	10	14	2

*The department managing Medicare Advantage plans was not interviewed.

**Includes Pioneer and MSSP ACOs.

***Subject to mandatory Medicaid risk within the next three years.

Most organizations assumed upside risk only under alternative payment models [Orgs 2, 10, 11, 17]. Others had minor exposure to downside risk contracts [Orgs 1, 15]. Organizations with self-insured employee populations assumed full risk. Some interviewees expressed plans in the future to move toward downside risk [Orgs 9, 12]. The upfront collection of care-coordination fees was also an important consideration for some organizations to be able to transition to risk-based payment [Orgs 2, 11].

Commercial insurers have approached several of the physician-led ACOs that are achieving early success under MSSP ACOs. The private payers are interested in risk-based contracts that will achieve similar results for their commercial population [Orgs 1, 12]. Achieving early success has allowed these providers to expand their at-risk population and reinvest in infrastructure improvements, such as predictive analytics and IT [Org 12].

Themes and Strategies

All interviewees were focused on the Triple Aim as defined by 1) improved patient experience of care, 2) improved health of populations, and 3) reduced per capita cost of health care. However, there is not a single path to effectively managing population health. All the programs were innovative in their own way and demonstrated best practices in population health management. Despite varied approaches, common themes emerged and are described in the following section of the report.

Strong Foundations

Organizational Structure and Leadership

Introduction

The leaders interviewed were highly pragmatic and focused on program execution in light of multiple challenges. They displayed the ability to lead cross-functional teams and credited their teams for success. Leaders were results-oriented and innovative, despite the complexity that they faced.

ACOs often provide centralized systemwide data and tools to participating hospitals or physician practices. The individual providers participating in the ACO are responsible for local implementation of tools to achieve their objectives [Orgs 7, 13, 17].

A Multidisciplinary Approach

Multidisciplinary teams led important PHM initiatives. At larger organizations, clinical, analytics, IT, and financial representatives engaged in shared decision making when purchasing PHM software [Orgs 3, 5, 17]. One organization established local “change committees” in which representatives from clinical, financial, and IT departments jointly developed new care-management protocols. Change Committees discussed metrics and desired quality outcomes for patient-focused initiatives [Org 7].

Physician Relations and Care Compacts

Several organizations created physician compacts to increase physician buy-in for PHM implementation efforts. The physician compact details the manner in which the hospital will support physicians and how physicians will partner with the hospital. One organization framed every meeting between the hospital and the physicians around the physician compact to remind both parties how to best work with one another [Org 7]. Another organization used a physician-compact agreement to enforce specific rules about specialist referrals and mandatory collaboration with local social organizations [Org 1].

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Executive Leadership

One interviewee cited sustained tenure of senior leadership as a critical success factor. Lasting commitment by senior leadership is required to manage the multiyear timeframe required for population health transformation [Org 4].

Planning and Funding

Planning

Successful organizations regarded investing early in data warehousing, business intelligence, and care-management staff as a strategic move that would pay off as value-based care contracting increases [Org 9]. Implementing such aspects early, before an ACO performance period, provided for effective execution of PHM strategies during the first performance year. Sustained reinvestment built on early successes will create long-term viability [Org 12].

Required Capital

Limited care-management and IT resources pose significant challenges to the successful implementation of PHM strategies. A few organizations addressed this limitation by collecting an advance lump-sum investment from insurers to help fund care-management improvements [Orgs 2, 11]. Insurers were then repaid through a portion of the shared savings or through a direct repayment schedule. One example is the Centers for Medicare and Medicaid Services (CMS) Advance Payment ACO model. Other organizations had access to capital to support infrastructure improvement [Org 3].

Long-term Investment

Providers often face a disincentive to investing significant resources in optimizing patient care in light of the fact that many patients may leave their market or change insurers [Org 9]. This means that it is often more prudent to make long-term investments for populations such as Medicare Advantage or self-funded employees, given the longer-term nature of their commitment within the plan. Theoretically, if all providers were required to manage the care of their patients using minimum quality standards, then all providers would benefit from new entrants managed by a previous provider, supporting the systemwide benefit of short-term care management.

Innovative Use of Existing Resources

The scarcity of resources available to execute population health strategies demands that successful organizations exhibit resourcefulness. For example, one organization closely collaborates with their school of public health and has academic researchers and data scientists participate in applied projects when developing predictive models that also benefit the health system [Org 17].

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Testing and Experience

Testing Using the Self-Funded Health Plan

Successful organizations have used their self-insured employees as the innovation test bed for risk modeling and risk-contract performance [Orgs 3, 7]. They describe the advantages of control over health-risk-assessment content, access to claims, ability to rapidly diffuse innovations, and optimal size of populations to measure cause and effect. A full-risk self-funded plan eliminates the complexity of attribution and shared risk calculation. Additionally, there is the benefit of increasing productivity and reducing absenteeism of managed employees.

Organizations reported an important governance transformation in shifting organizational accountability and responsibility of self-insured populations from contracting, finance, or benefits departments to a collaboration with or leadership by the population-health-management department [Org 3]. Shifting the emphasis from benefits, co-pays, and deductibles to risk stratification and interventions has created immediate value in organizational expense control, as well as built-in capabilities used for other risk populations.

However, interviewees were careful to indicate that there may be difficulty with directly applying the self-insured employer model to the broader population because of the lack of comprehensive claims data, the inability to stimulate new business through new-patient incentives, and greater ACO-network leakage. Additionally, employees are likely to remain enrolled in the self-funded health plan longer than other plans, thus justifying long-term investment in interventions that do not have immediate financial or clinical outcomes.

Experience

Several of the organizations interviewed have decades of experience either running a health plan or executing managed-care agreements from the 1990s [Orgs 5, 8, 10, 15]. This is in stark contrast to health systems or ACOs that are just entering into risk-sharing agreements. One interviewee stated that their predictive-risk model is the result of years of refinement of predictive-risk factors [Org 8].

Data Infrastructure and Partnerships

Introduction

A wide variety of internal and external data sources are aggregated in a central location to support direct patient-care improvement and population health initiatives. In many cases,

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data consolidation occurs in a general-purpose data warehouse and a vendor population-health-management system. AMCs and ACOs are consolidating data sources for reasons other than patient identification, such as utilization pattern and provider performance analyses. The types of data being consolidated vary with the stage of the risk contracting and organizational priorities. Local factors, such as the availability of local health insurance exchanges and the willingness of insurers to share data, also affect the availability of raw-data ingredients for predictive modeling.

Table 3 lists data sources that can be integrated into the data warehouse or population-health-management platform. One interviewee uses a “four quadrants” data model that incorporates biometric, behavioral, social, and functional data [Org 3]. Data collection for many useful data sources is still manual. For example, data about patients’ health-risk assessment were commonly collected manually. Useful data-collection workflows for determining root causes of variation include documenting the root cause of each readmission [Org 7] and investigating the root cause of each death [Org 4]. A strong clinical IT infrastructure and strong partnerships with payers can help ease the burden of manual data collection.

Table 3. Data Sources Encountered During the Interviews

Paid claims
Electronic medical record (EMR) data
Private health-information exchange (HIE)
State or regional HIE
Pharmacy fill
External laboratory
Patient-reported outcomes
Health assessment
Enterprise resource planning (ERP)
Real-time monitoring data
Prior authorization

Clinical Information Systems and Challenges

Interoperability

Interoperability refers to the ability of different electronic medical record (EMR) systems to share data between systems. Participating physician practices are commonly allowed to choose their own EMR as long as it complies with meaningful use practices and can

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share data [Orgs 1, 9, 12]. Many of the large clinically integrated networks with independent community-based physicians need to extract data from over a dozen different EMR vendors. In one organization's clinically integrated network, 30 to 35 different EMRs were deployed [Org 10]. Many respondents identified extraction of data from EMRs as a significant challenge due to the lack of interoperability standards, costs, and vendor business practices. One organization stated that patient care would be light years ahead if the interoperability problem were solved [Org 10].

The need to aggregate and analyze data for population health management is as important a driver for interoperability standards as the need to exchange clinical data for real-time care. The lack of interoperability standards and the need for customized interfaces add enormous time and cost to data acquisition. Customized interfaces can delay data use by a year or more from project inception. Point-of-care EMR tools alerting physicians to care gaps, while useful, are limited because the alerts are based solely on clinical EMR data sources [Org 10]. Despite close partnerships with external providers, top-performing ACOs still struggle to share data with postacute providers [Org 7].

One physician-led ACO whose physician members have multiple EMRs requires each potential member to have their data mapped to the ACO's [Org 1]. The ACO uses programmers to write a custom interface for each primary-care provider's practice. They ask the primary-care physician's (PCP) office for a backup of its data and then work with that dataset to create a process that extracts and standardizes appropriate data. The initial data-mapping requirement for a physician practice to join the ACO has resulted in successful integration into one central data warehouse across multiple, different EMR formats.

Health-Information Exchange

HIEs offer one solution to the interoperability problem. An HIE allows for the appropriate and safe exchange of patient information between organizations. HIEs can be integral data sources in event-based programs, such as readmission reduction or emergency department (ED) utilization management, by offering near real-time data to help manage a health care event and guide care follow-up. HIEs can be publicly offered at the state or regional level. Additionally, provider-owned clinically integrated networks may establish private HIEs. Some public HIEs allow for timely intervention with high-risk patients [Orgs 2, 11, 12], while others are not as useful for care-management purposes [Org 10]. High-functioning HIEs are able to provide notice of admission and lab results from hospitals within a day of patient admission so that patients are managed in a timely fashion [Org 2]. Discharge summaries are also shared by some HIEs quickly after patient discharge. One organization emphasized the importance of a master patient index to identify unique patients across providers [Org 10]. A couple of organizations focused

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on an 80% solution by connecting the top three most popular EMRs to the HIE first; physicians who used EMRs used by less than 20% of the physician population were not initially connected to the HIE [Orgs 9, 12].

Disease Registries

Disease registries represent an additional tool for consolidating critical patient data. Most disease registries are used to support care management for groups of patients with one or more chronic diseases, such as diabetes, congestive heart failure, and asthma. Similar to an HIE, a disease-registry system can normalize data from disparate EMRs to function as a central repository for patient information that is critical for patient identification.

Utility of Clinical Information for Modeling

The use of different EMR vendors and software versions causes challenges to data normalization, which is necessary for predictive modeling. EMR customization also makes data normalization more difficult [Org 13]. System transitions resulting in shifting business rules make it challenging to build consistent predictive models [Org 16]. EMRs contain unstructured data that require an additional step to transform the data into a structured format for predictive modeling. One organization was unable to find unstructured-data experts to process clinical data and reverted to using claims data for modeling [Org 13]. Finally, data-quality issues affect the ability to perform analytics and patient care. For example, one organization identified inaccurate medication-reconciliation information, which led to errors and higher readmission rates [Org 10].

The Future of EMRs in Population Health Management

Despite these challenges, many organizations are looking to their EMR vendors for long-term population health strategies and are installing their EMR vendor's population-health-management modules. One interviewee said that their EMR vendor is employing data scientists to develop predictive models for ED utilization [Org 10]. Organizations are hopeful that their EMR vendor will add more predictive models to the EMR but recognize that usefulness is limited by the comprehensiveness of that EMR's data.

Payer Relationships and Challenges

The strength of payer relationships varied greatly among organizations. Commonly encountered issues appear below. To manage patients prospectively, some organizations have weekly care-management calls and share data [Orgs 9, 10]. One interviewee sends an upcoming appointment list to the payer daily, and the payer identifies which patients should be targeted for additional care management [Org 10]. In addition, that organization has weekly calls with the payer to discuss upcoming patients who have psychosocial issues or are in need of enhanced care coordination.

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Risk-Contract Construction

Almost all interviewees report underlying issues with risk-contract construction, making it difficult to focus on the appropriate patients. Insurers do not allow adequate time between the release of risk-contract details and the performance period for providers to implement necessary infrastructure design. Many organizations are discovering that it is difficult to control postacute cost, which is often included in the total cost of care but is challenging to manage [Org 16].

Risk Adjustment

Lack of transparency about risk-adjustment-model definitions increases the difficulty of reconciling financial results. In addition, each risk contract uses a different risk-adjustment model to equalize benchmarks and capitation payments, a process that causes confusion and adds administrative burden [Org 6]. It is important to understand the risk-adjustment model for patient identification since the financial opportunity of managing the patient depends on the expected cost after care management relative to the risk-adjusted benchmark.

Patient Attribution

Patient attribution is the identification of the patient population for which a provider accepts financial risk under a risk-contract or alternative payment model. Attribution rules are unclear and difficult to manage [Orgs 2, 9]. Issues arise with dually eligible patients and newly expanded Medicaid populations about how and whether they are attributed. It is important to know how to predict patient attribution because it defines the base population and affects savings [Orgs 9, 17].

Changes in patient attribution can have a large financial impact on an ACO.

Organizations reported annual member-attribution change in the 15% to 20% range [Orgs 9, 15]. Healthy members are more likely to change providers compared with unhealthy members who are involved in ongoing clinical episodes of care.

Out-of-Network Expense and Member Churn

Some organizations are actively managing the out-of-network expenses associated higher billing rates. Out-of-network utilization also causes longer claims-data lag times, which affects the predictive power of models [Orgs 9, 17].

Member churn occurs when the patient exits the health plan. This is in contrast to changes in patient attribution, which results in a patient no longer being assigned to an ACO. Medicaid populations are more susceptible to member churn due to Medicaid-eligibility rules. It is important to recognize the impact of member churn and how it can affect the efficacy of population health initiatives.

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Non-ACO Expense and ACO-Network Leakage

ACOs add an extra layer to a preferred provider organization (PPO) network structure. Patients are allowed to receive services from non-ACO providers, which leads to ACO-network leakage. ACO-network leakage is a large problem for some organizations. When many services are provided outside the ACO, member attribution becomes more difficult to manage. Non-ACO service utilization also causes data leakage, which limits the data foundation the ACO can use to identify and manage patients [Org 9]. Several prominent teaching hospitals had high rates of ACO-network leakage, up to 45% of services [Orgs 3, 4, 9]. Figure 1 illustrates the ACO concepts of patient attribution and out-of-network utilization.

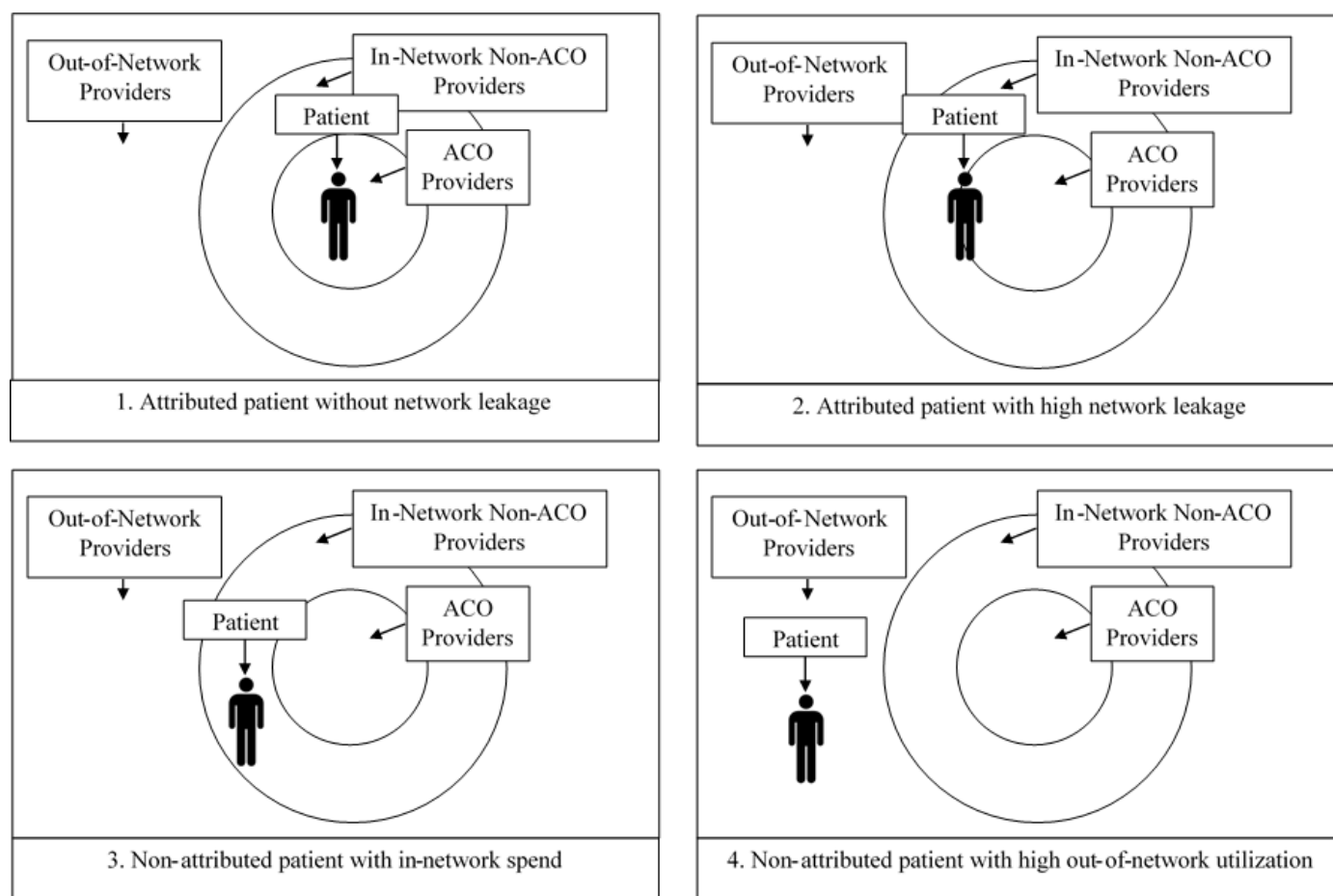


Figure 1. Illustration of patient attribution, ACO-network leakage, and out-of-network utilization.

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Payer Data—Lack of Standards

Many organizations use claims data as the basis for predictive modeling [Org 13]. Despite the fact that many commercial ACO contracts contain similar provider incentives, commercial payers vary in their data-sharing practices. Most organizations have multiple risk contracts. These organizations receive claims data from different commercial payers that vary by dates of service, subsets of data elements, price details, and inclusion-exclusion criteria. Issues include lack of uniform standards, deficient payer resources, and confidentiality issues affecting data sharing for certain metrics. For example, claims for behavioral health and substance abuse may be omitted from claims-data sources despite their critical influence on patient risk. One Medicaid organization manages confidentiality issues by abstracting claims data to form a mental health and substance abuse indicator. The indicator can be shared with other providers and care managers to indicate that more investigation into the patient's behavioral health history is appropriate [Org 6].

Payer Data—Data Delays

Many organizations stated that the long delay in receiving claims data limited the data's use in predictive analytics. A large health system with a dominant position in its health care market was able to use clinical data sources and avoided claims data [Org 4]. Another organization used preadjudicated claims data from the billing system in their predictive analytics models and, similarly, avoided the need for payer claims data [Org 1].

Population-Health-Management Vendor Relationships and Challenges

Most organizations are either searching for or have installed a commercially available population-health-management (PHM) platform. However, there is not a complete reliance on commercial solutions because there is no perfect solution that performs all PHM tasks well for all types of organizations [Orgs 4, 7, 17]. The PHM software market is in its infancy and is highly dynamic. Organizations voiced concerns about purchasing a complicated and expensive PHM solution when they are only in the initial stages of taking financial risk [Orgs 2, 4, 15, 12].

If the organization decides to purchase a vendor solution, it is important to have a strong sense of the objectives for the system [Orgs 3, 14]. Customers using commercial tools with embedded risk models are promised very high levels of predictive power. Yet, the marketing claims of improved predictive power are largely theoretical and unproven. Proprietary systems that market unpublished claims of superiority should be treated with

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skepticism. A more sophisticated software solution can be purchased as organizations earn savings and begin to assume larger amounts of financial risk [Org 12].

Care-Management Programs

Types of Care-Management Programs

While common approaches to complex patient care emerged throughout the interviews, the types of strategies and interventions depended on the target population. For example, Medicaid contracts frequently focus on behavioral health, social needs, and ED use. Types of programs encountered, including complex-case management, ED-utilization management, readmission reduction, postacute-care management, end-of-life, and preventive care and wellness programs, are summarized below.

Care management or care coordination, provided by a variety of types of health and social service professionals, is used by most interviewees for specific populations. Care management frequently informs care-redesign efforts to improve patient care or process flow in areas such as surgical safety, hospital-acquired infections, early home discharge, and telemonitoring. Complex-case management is an enhanced level of intervention for the costliest and sickest patients. Most interviewees stratify patient populations by risk scores and intensely manage those with the highest scores. Some organizations are focused on specific interventions to reduce ED use or avoid readmissions. One organization used dentists in the ED to triage dental issues for their Medicaid population [Org 6]. Another organization implemented home monitoring through the use of a home tablet computer as part of their readmissions-reduction program [Org 7]. Nurses monitored blood pressure, weight, pulse oximetry, and glucose levels. When nurses observed changes in vital signs, they performed direct outreach to patients to potentially prevent readmissions.

Progressive organizations are working to increase access to palliative and hospice care, as well as partnering with postacute-care (PAC) providers. Recognizing that medical expenses during end-of-life account for a large portion of Medicare expenses, many organizations are implementing comprehensive palliative-care models [Orgs 4, 8, 10, 17]. Some states now require discussion of advanced directives in the primary-care setting [Org 10]. Most organizations have relationships with skilled nursing facilities (SNFs) or inpatient rehabilitation facilities, and the organizations interviewed described their efforts to forge more effective partnerships with PAC facilities. Narrow network approaches are extensive as hospitals temporarily or permanently remove poorly performing PAC facilities from their network [Org 7]. Other organizations created preferred postacute

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networks using quality-of-care data [Org 8]. One physician-led ACO embedded nurses in SNFs so that they could perform advanced procedures onsite and prevent costly hospital admissions [Org 1].

Leveraging community services for the appropriate patient populations offers an efficient way to further support patients. One organization partners with its county outreach staff to help develop and execute a shared care plan by providing county outreach staff access to their EMR. This approach has had significant impact by engaging difficult-to-reach patients in care-management programs and improving outcomes [Org 6]. Another organization uses community partnerships for transportation and housing resources [Org 17]. These organizations recognize that maintaining healthy patients' health status is as essential as managing the highest-risk patients. One organization focuses on obesity management for its self-funded employee population [Org 3]. Another redesigned the Medicare annual wellness visit using a custom health-risk assessment to collect and integrate clinical and psychosocial-risk factors into their risk score [Org 10].

Managing Patients With Emerging Risk

Successful organizations are moving from managing patients with historical risk to managing patients with emerging risk. In general, this practice involves focusing more on patients with gaps in care than on patients who have experienced recent increases in cost and/or utilization. Intervening in the care of rising-risk patients is challenging because these individuals can remain rising-risk for extended periods of time, making it difficult to know when and how to intervene. Some patients have great difficulty having an impact on their chronic conditions, such as obesity or diabetes. Focused interventions that use motivational intervention techniques with patients have gained increasing acceptance [Org 15]. Instead of commanding patients to change health behaviors, motivational intervention techniques motivate patient engagement by linking health goals to social goals. For example, a care manager practicing motivational intervention would motivate a diabetic patient to control their blood sugar levels so that patient can spend more time doing activities with their grandchild.

Social Determinants

There is strong consensus among leaders of successful health care organizations that social determinants account for a large portion of health risk. However, the data to support this are not available in diagnosis-based risk models. Accounting for social determinants represents an opportunity to address previously unknown risks. A diverse list of critical social determinants that arose during the interview discussions appears in Table 4.

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Table 4. Specific Social Determinants Encountered During the Interviews

Addiction and mental health comorbidities
Being labeled noncompliant or nonadherent in the EMR
Financial distress, level of income
Frequent appointment no-shows
Health literacy
Immigration status
Language issues
Legal issues
Living alone
Motivation to change, patient activation
Strength of social supports
Transportation barriers
Unstable housing, homelessness
Use of social services

Organizations serving a large Medicaid population have traditionally paid more attention to the impact of social determinants. Many successful organizations are collecting this information and plan to incorporate it within enhanced risk models over time [Orgs 3, 6, 13, 16, 17]. Many organizations are addressing social determinants through innovative community partnerships and patient incentives and by fostering trusting, sustained relationships with patients.

Standards for Social-Determinant Data

Over a decade ago, the National Quality Foundation (NQF) created a policy that excluded social determinants in quality measurement because of the lack of evidence that social determinants affect quality and concerns about lowering performance standards for providers serving at-risk populations. However, many were concerned that as a result of this policy, risk-adjusted readmission rates for hospitals serving low-income populations were potentially unfairly adjusted. Related concerns about the increased use of outcome measures to modify payment prompted revision of the NQF policy.

The NQF convened an expert panel in 2013 to examine the inclusion of social determinants in quality measurement and ultimately recommended the incorporation of sociodemographic factors. These recommendations were adopted by NQF in 2014 during a trial period. Congress subsequently passed the IMPACT Act, which requires

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examination of the effects of adjusting for socioeconomic status on quality and resource use. The legislation also required the Institute of Medicine (IOM) (now the National Academy of Medicine) to define socioeconomic status, sociodemographic factors, and valid methods for the use of the factors in Medicare quality measurement and payment. In March 2016, CMS released an interactive Medicare map of geographic disparities in chronic disease focused on disparities in health outcomes, utilization of services, and spending by race and ethnicity and location. “Racial and ethnic minorities experience disproportionately high rates of chronic diseases, and are more likely to experience difficulty accessing high quality of care than other individuals. The identification of areas with large differences in the proportions of Medicare beneficiaries with chronic diseases is an important step for informing and planning health equity activities and initiatives” (CMS 2016).

Incorporating sociodemographic factors in quality-measure adjustments and payment models is likely to have a profound effect on value-based payments; it will allow organizations participating in advanced-payment models to target and serve subpopulations with innovative social and nonmedical interventions. One organization’s EMR vendor is releasing a standard update to incorporate Centers for Disease Control and Prevention (CDC) and IOM standard elements into physician documentation flow sheets, better standardizing the collection of social-determinant data [Org 6]. The same organization developed its own housing index by using local data so that care managers can determine the level of housing instability using the patient’s addresses. Enterprise analytics vendors are already exploring opportunities to create new models that incorporate claims and clinical and sociodemographic data. It is expected that this rapidly evolving field will further contribute to the pursuit of better outcomes for all.

Establishing Socially Focused Goals

It is important for care managers to collect social data elements and understand the impact of social factors and patient preference on clinical goals. One organization viewed social goals as more important than clinical goals [Org 5]. For example, dementia patients benefit from setting and achieving social and personal goals, given the lack of effective medical solutions.

Implementation

Risk Model Implementation

Organizations had differing lengths of experience in alternative payment models, level of investment in IT, and degrees of risk assumption. The population health initiatives undertaken by organizations were strikingly similar, but the tactical implementation details differed. All showed high levels of execution despite facing various implementation challenges.

Patient Relationships

Some interviewees stated that their success was more highly dependent on robust care management and patient relationships than on predictive-risk calculations [Org 15]. They said that while some patients do not agree to participate in the care-management program, most organizations continue to develop new ways to partner with these patients. Awareness of cultural issues and care-manager motivational training positively affect care managers' ability to execute care plans [Org 15].

Change Management

Successfully implementing a PHM strategy requires a strong change-management infrastructure that supports the efficient planning, prioritizing, and monitoring of organizational-process improvements. Many organizations used a formal change-management infrastructure that was promoted by senior leadership. For example, one organization used the Baldrige Excellence Framework to guide its change-management process [Org 4]. Another used lean change-management techniques [Org 16]. Other organizations followed more informal change-management processes.

Physician Education

Physician education was another key ingredient to success. One physician-led ACO offered weekly webinars to physicians, staff, care managers, and administrators. Education topics included patient identification, risk scoring, quality measures, and disease management. The webinars were produced in-house and led to more effective partnerships with participating physicians [Org 11].

Physician Incentives

Organizations use a variety of financial incentives to engage physicians. Savings generated through physician-led ACOs are often redistributed directly to doctors [Org 12]. One Medicaid ACO paid PCPs for each follow-up appointment completed within seven days of hospital admission [Org 2]. Another physician-led ACO used withhold penalties for physicians who are noncompliant with new programs and guidelines. Those

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physicians have an opportunity to alter their practice to meet the new guidelines and receive the appropriate payment. If they do not fully engage, the amount in escrow is then distributed to other participating physicians.

Meanwhile, continuously improving physician skills and providing better care through population health are the main motivators for some AMCs [Org 3]. One AMC uses the academic incentive of the opportunity to publish research based on population health management [Org 14].

Care-Management Duplication

Because of the proliferation of care-management programs, patients can be assigned to multiple care managers from multiple organizations. Interviewees at one organization described plans to change the process for assigning care managers to reduce the likelihood of duplicative work by multiple care managers [Org 6]. They said that it was not uncommon to identify seven care coordinators from a variety of organizations addressing the same patient.

Incremental Success

Commercial insurers approached several of the successful physician-led Medicare ACOs to partner in achieving similar results for a commercial population [Orgs 1, 12]. Early success allows program expansion and reinvestment in infrastructure improvements such as predictive analytics [Org 12]. The analytics' improvement process is iterative, with the continual refinement of data-warehouse capabilities and predictive-model performance [Org 1].

Supporting Analytics

The Analytics Necessity

Analytics within a care-management context encompasses both retrospective analysis and predictive modeling. Several interviewees cited the need to use retrospective population-level analytics to identify root causes of utilization patterns. Managers are unable to monitor what they cannot measure. One example of the use of this kind of analytics was a 36-month retrospective claims study that identified the top five most expensive diabetes utilization patterns driven by other comorbidities [Org 9]. The discovery that diabetes comorbidities were the root-cause issue for high utilization helped inform the design of care-management intervention for that organization. Another example was the use of data analysis to find that 50% of ED high utilizers who were assigned a PCP had untreated pain or substance abuse [Org 4]. Other organizations discovered that a similar assumption

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about ED high utilizers who did not have an assigned PCP—that they had comorbidities that caused high utilization—was incorrect [Orgs 6, 12]. In these ways, retrospective analytics helped reset assumptions and guide the future design of interventions so that root causes were addressed.

Organizations were at different stages of implementing predictive modeling for patient identification. One organization is focused on planning and modeling its limited-risk contracts and has not yet focused heavily on specific patient-identification models [Org 14]. Another organization was installing its EMR-based PHM software solution and had experience with population-level retrospective analytics but not with prospective individual-patient identification [Org 4]. A third organization had a separate department for alternative payment models [Org 16]. It had considerable population-level retrospective bundled payment expertise but limited focus on prospective individual-patient identification.

Predictive modeling is necessary but not sufficient for achieving successful quality and cost outcomes. A predictive identification model is needed early on, and this can improve over time [Org 15]. Positive outcomes can be achieved even if the data sources and predictive models are still evolving. Other interviewees cited their respect for predictive analytics, but they did not believe it was the sole reason for their success [Org 12]. Predictive modeling is a work in progress.

Other Predictive-Modeling Opportunities

During the interviews, topics beyond patient identification emerged as relevant opportunities for predictive or descriptive analytics. Exploring these opportunities through analytics could result in lower medical cost and improved care-management impact:

- **Patient Matching and Care-Manager Profiling.** Chances for success under care-management programs depend on linking care-management resources to unique patient needs. For example, some patients may be more suited to work with a social worker, and others, with a nurse or community navigator. Matching the patient to the correct resource can improve the chance of success. One organization was very focused on the ability of its care-manager staff to form meaningful connections with patients, yet one challenge was the variation in the ability of individual care managers to create strong patient relationships [Org 15].
- **Resource-Type Matching and Optimal Case Load.** The volume of cases and the patient-acuity mix should be optimally matched to the experience of the care manager [Org 8].

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- **Patient Activation and Motivation.** The degree to which a patient will actively participate once identified and enrolled in care management is another opportunity to leverage predictive analytics.
- **Patient Graduation.** Ultimately, care-management programs are designed to move patients toward self-sufficiency. It is important to assess the right time for “graduation.” One organization noted the dilemma of patients or care managers who want to prolong the relationship beyond recovery [Org 3].

Care-Management IT Infrastructure

Population health care is a complex activity involving multiple stakeholders, IT systems, and evidence-based interventions. A strong IT strategy is essential to being able to consolidate data sources and create an efficient workflow for care managers. Three IT systems often serve as an IT foundation for PHM: an internal data warehouse, commercial platforms, and an EMR with embedded population health capabilities.

Internal Data Warehouse

The internal data warehouse may include claims, pharmacy, demographics, preauthorization, diagnoses, EMR, and patient-satisfaction data. It offers the flexibility and control to include external data sources beyond the EMR. It is usually highly customized for the organization’s needs.

Commercial Population-Health-Management Software

The organizations that have taken on risk for decades had to develop their own IT solutions because of the lack of mature commercial alternatives [Orgs 8, 10]. Some of these organizations developed homegrown solutions. Others are now actively searching for a commercial solution that can augment their high degree of historical competence with population health analytics, which could include finding additional efficiencies and selectively adding commercial products to their existing infrastructure. Many described the current dilemma of not being able to fully rely on commercial solutions because a perfect solution has not been found that meets all their needs [Orgs 4, 7, 17]. Most vendor systems excel at managing clinical data or claims data, but not both.

IT Infrastructure Approaches

There are generally three analytics infrastructure-development approaches. Table 5 describes the IT strategies for population health management.

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Table 5. IT Infrastructure

Development Approach	Internal Data Warehouse	EMR-Based Population-Health-Management Software	Commercial Population-Health-Management Software	Ideal Organization
I. Fully Homegrown	Yes	No	No	<ul style="list-style-type: none"> • Large organization or multiple health systems • Many years of experience with data • Adequate internal IT resources • Experience with risk contracts
II. Homegrown and Commercial Software	Yes	Yes (one or both)*	Yes (one or both)*	Searching for a balance between flexibility and ease of execution
III. Commercial Software	No	Yes	Yes	<ul style="list-style-type: none"> • Low on IT or clinical talent • New to risk contracts

*Either EMR-based PHM software or commercial PHM software, or both.

Table 6 shows the specific analytics strategy used by each organization interviewed. The level of IT sophistication and automation used in the patient-identification process varied. Most organizations use a combined approach of an internal data warehouse and stand-alone vendor software or EMR-based population-health-management software solution. This dual approach achieves the flexibility and control inherent in a data warehouse while seeking the ease, power, and speed to implementation of vendor solutions [Org 17]. However, there are examples of successful implementation and execution using all three of these strategies.

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Table 6. Care-Management IT Infrastructure, by Organization

Organization	Approach*	Internal Data Warehouse	EMR-based Population-Health-Management Software	Commercial Population-Health-Management Software
1	I	Yes	No	No
2	I	Yes	No	No
3	II	Yes	Epic Healthy Planet	Optum One, MedInsight, Explorys
4	II	Yes	Epic Healthy Planet	No
5	II	Yes	No	Cerner HealtheIntent
6	I	Yes	No	No
7	II	Yes	No	The Advisory Board Company (Crimson)
8	I	Yes	No	Actively searching, and The Advisory Board Company (Crimson)
9	I	Yes	No	Optum One
10	II	Yes	No	Actively searching
11	III	No	No	McKesson
12	II	Yes	No	Storan Technologies
13	II	Yes	No	Optum Impact Pro
14	I	Yes	No	Actively searching
15	II	Yes	No	Specific vendor names were not provided at request of organization
16	II	Yes	No	McKesson, Evolent
17	II	Yes	Epic Healthy Planet	Lightbeam with Tableau

*Roman numerals correspond to the IT infrastructures described in Table 5.

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Model Construction

Differing Model Goals

It is necessary to identify the primary objectives for risk prediction before developing, applying, or purchasing models [Org 3]. The ultimate goal is not simply to identify high-cost patients, but to find the patients who will benefit from care management [Orgs 13, 15].

Organizations either develop or purchase claims-based models to predict patients who will generate high future claim costs. Cost-modeling approaches are consistent with actuarial methods of pricing and risk-adjusted financial-performance analysis. Some organizations use a clinically driven approach, incorporating previous hospital utilization, ED utilization, and the number of chronic conditions into measures of patient complexity. The hybrid approach relies on claims-based or patient-complexity models to predict which patients should be investigated further by a clinician to determine enrollment in care management.

Three broad modeling approaches were prevalent during the interviews. Organizations typically use all of these modeling approaches to support a variety of care-management interventions.

Claims-Based Models

Claims-based models are susceptible to bias because of factors that are not patient-specific, such as plan design and provider contracting comparability. For example, if claims-based models are not adjusted for different patient out-of-pocket levels, the health-plan-paid amount will appear lower for the plan with higher out-of-pocket cost sharing even if all other factors are identical. Accounting for these factors usually leads to multiple models for different payer contracts. Claims-based models are used by actuaries to predict future absolute claims cost by using past claims experience. However, patient identification requires only the relative prediction of patient risks. Despite the simplification of the objective, many of the standard models for patient-risk identification, such as Hierarchical Condition Categories (HCCs) and Chronic Illness and Disability Payment System (CDPS), are based on claims data. Wide availability makes claims-based risk modeling a default approach.

Complexity Models

Another approach is to use patient complexity to predict outcomes. This has been done as an alternative to cost modeling because of the limitations of claims data [Orgs 1, 2]. These models use past utilization and the number of chronic conditions and medications, which simplifies the models. LACE is a common readmission model that was not

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developed through the use of claims data. Instead, length of stay, acuity of admission, comorbidity, and ED utilization substitute as an easy-to-calculate and understandable proxy for future high cost. Other complexity-model logic was often developed using a clinical-consensus approach.

Hybrid Patient Identification

A hybrid model uses an automated predictive model followed by a manual post hoc review by physicians, nurses, or social workers. Credit is given to Haime et al. (2014) for the term “hybrid” model. This simplifies and improves the modeling process for several reasons. First, the objective of the model is no longer to predict high-risk patients. Instead, the objective is to predict which patients should be manually reviewed. Model accuracy is based on an automated predictive model, as well as clinical review. The hybrid models maintain a balance between human and predictive-model error, and the tradeoff is between accuracy and the burden of manual review. Secondly, reliance on expert judgment completes the data gaps for metrics that are not electronic or highly delayed. The hybrid model compensates for the commonly encountered data issues described earlier. Another benefit of the hybrid model includes enhanced physician participation, ownership, and feedback during the patient-identification process [Orgs 5, 13]. Conversely, one challenge is that the hybrid model is not fully automated, or standardized, which introduces both a manual-review burden and potential sources of error in its validity and reproducibility.

Single or Multiple Models

Patient-identification models are commonly tailored to a condition or to a specific risk contract. This results in the use of multiple models. For example, one organization used a readmission-risk model that incorporated the 3M company’s APR-DRGs (for all patients refined–diagnosis-related group) to triage discharged patients for different levels of care-management resources while using an entirely different approach to identify high-risk patients overall [Org 10]. As mentioned earlier, organizations expressed the desire to have a single IT platform for care managers, whereas multiple risk models are commonly tolerated [Org 7].

Internal Model Development versus Commercially Available Models

Some organizations developed their own predictive models instead of purchasing a commercially available one. There are three overall strategies for developing an internal model: using a statistical-only approach, a statistical-with-clinical-input approach, and a clinical-consensus approach. None of the interviewed organizations used a statistical-only approach, where relevant factors are solely determined through data analysis. Three organizations used a regression model combined with clinical experience to isolate

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significant factors and develop a clinically relevant model [Orgs 8, 15, 17]. The other organizations used a model that was defined only through clinician consensus rules where clinical expertise was the main method for selecting risk factors [Orgs 1, 2].

Event-Based Models

The attribution model for some risk contracts, such as bundled payments, is triggered by a clinical event, making event-based models particularly useful. Event-based models are simpler than other models. Event-based models help determine whether more-intense care-management resources are required to help a patient through their illness episode. Because the patient list is narrowed, the volume of patients becomes more manageable for manual review. Many of the event-based models in Table 7 involve manual steps for determining optimal intervention and intensity.

One organization uses a very effective model that is not mathematically complex but quickly identifies the patient [Org 2]. The model provides information to a clinical decision maker who determines whether to intervene after an inpatient admission or ED visit. This model depends on the availability of a comprehensive EMR or HIE to provide timely notification. This capability is still a technical challenge in some markets. The timeliness of the information allows a uniquely personal intervention to occur, in which a care coordinator visits the patient at their hospital bedside to initiate care management.

Two other event-based models depended on a combination of HIE data and other data elements to signal case-management intervention [Orgs 7, 12]. As the first stage of patient identification, one of these models uses an EMR-based risk score in combination with lab results to determine whether a patient is high risk and eligible to receive a tablet computer for remote monitoring after hospital discharge [Org 7]. Then, biometric readings from monitoring devices are reviewed by a nurse to determine whether patient outreach is needed as the second stage of patient identification. This model illustrates how data are used to make a two-stage determination for outreach for a recently admitted patient. Purely manual and purely automatic approaches are used by different organizations, which demonstrates how two different models can both achieve positive outcomes [Orgs 5, 10].

Another event-based model uses custom-developed clinical guidelines to identify three classes of patients in the ED who require different levels of treatment [Org 4]. The organization developed these guidelines through iterative retrospective analysis of utilization data. This model could be regarded as direct patient-care improvement instead of care management. The model was included because of the novel data-driven approach used.

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Table 7. Event-Based Models Encountered During the Interviews

Organization	Focus	Method	Automatic Steps	Manual Steps	Number of Care-Management Tiers	Unique Features
Organization 2	Inpatient readmissions and ED utilizers	Automatic using HIE data	Regional HIE ADT message from the previous day's admission	Discharge summary and lab-result review	2: Personal visit to the patient's bedside	The method of patient outreach is highly personal
Organization 4	ED high utilizers	Manual using clinical rules		-Chronic disease with pain issues -Untreated mental health -Drug-seeking	3: State database check, assignment to pain clinic staffed by psychiatrist	Custom stratification developed by locally investigating utilization patterns
Organization 5	Readmission risk	Manual using clinical rules		-Postdischarge assessment -Chronic-condition lists	2: Schedule a primary-care visit	
Organization 7	Readmission risk	Hybrid automatic risk score and manual monitoring	-EMR-based risk score -Lab results from an HIE	-Nurse monitors blood pressure, weight, and blood oxygen level to determine whether outreach is required	3: Top 5% are high risk. There are medium- and low-risk patients. The very complex patients receive a tablet for remote monitoring.	Remote patient-monitoring data are used
Organization 10	Readmission risk	Automatic using diagnosis data	Commercial severity-of-illness indicator	Risk evaluation within two days of discharge	3: Highest severity assigned to complex-care management or palliative care. Middle tier is assigned to aggressive readmission-risk-intervention program.	Exclusion of highest-risk patients

(continued)

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Table 7. Event-Based Models Encountered During the Interviews *(continued)*

Organization	Focus	Method	Automatic Steps	Manual Steps	Number of Care-Management Tiers	Unique Features
Organization 11	Readmission risk	Hybrid clinical and social judgment with clinical, cost, and utilization data	-Patient diagnoses -Medication lists -Problem lists -Recent inpatient and ED utilization -Cost of care	Case-manager and social-worker determination	2: 30-day follow-up and telephonic patient education for patients with high-risk of readmission	
Organization 12	ED high utilizers	Hybrid clinical judgment with clinical rules and utilization data	-Two or more ED visits in the past 12 months -Near real-time ED notification from regional HIE	Custom checklist: 1. Is the patient assigned to the PCP? 2. Does the PCP know about the admission? 3. What was the root cause? 4. What is the long- and short-term care plans? 5. Does the patient have access to medication? 6. Does the patient have a mental health disorder?	2: Schedule a primary-care visit	Uses a comprehensive root-cause checklist
Organization 17	Readmission risk	Automatic using utilization data	Greater than three inpatient or ED visits in the past 6 to 12 months OR assigned to the ACO	Daily monitoring, physician rounding, and discharge planning by a nurse or social worker	2: A follow-up PCP scheduled between 7 and 14 days from discharge	

Note: ED = emergency department; HIE = health-information exchange; ADT = admission, discharge, transfer; EMR = electronic medical record; PCP = primary care provider.

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Populationwide Models

Populationwide models are applied to the whole population and include high-risk and risk-stratification models. These are the most commonly encountered models in this study. They scan large patient populations and use multiple factors to stratify patients. The high-risk models differ from risk-stratification models because they focus only on the highest-tier patients.

High-Risk Models

High-risk models are populationwide models that focus on identifying the highest-risk patients and generally have only two tiers: complex-case management or no case management (Table 8). These models are generally more mathematically complex than event-based models. Two organizations developed their own internal risk-scoring model through regression [Orgs 8, 15]. This requires enough data to ensure that the model produces stable risk scores over time. Four other organizations used a commercially available claims-based risk-scoring model in combination with past utilization rules and measures of medical complexity to predict risk [Orgs 10, 11, 13, 17]. One organization incorporated multiple risk scores, including a standard claims-based model and an EMR vendor-derived risk score [Org 17].

Medical-complexity rules incorporate indicators of multiple chronic conditions and polypharmacy to identify complex patients. Medical complexity can be an alternative way to identify high-cost patients by relying on clinical data sources, such as EMRs, HIEs, and disease registries. Complexity models often do not require claims data. The viability of this shortcut is supported by the observed correlation of multiple chronic conditions with high cost. Often, the thresholds and rules for medical complexity are developed using a consensus-based approach among clinicians. One physician-led ACO focused on specific diagnosis-related groups (DRGs) to prioritize the patients who should be managed [Org 15]. Expert experience was then used to curate the DRG list. This organization included symptom DRGs, such as syncope and collapse and chest pain, which usually indicate that the root cause for an admission was not found, and the patient is likely to return for more medical services. DRGs that indicate a predictable disease progression, such as chronic kidney disease, were also selected for the model.

Several organizations manually incorporate social determinants into predictive models [Orgs 2, 10]. Other organizations are in the process of adding social determinants to the automatic portion of high-risk identification through patient-collection forms embedded in their EMR [Orgs 13, 17].

Due to the complex set of rules and high resource intensity required for high-risk-patient identification, organizations commonly use a hybrid automatic-and-manual approach

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[Orgs 10, 11, 15, 17]. Two organizations used a two-stage manual review by different stakeholders before enrolling the patient into a complex-case-management program [Orgs 10, 17]. One of these models calculated multiple risk scores to identify the patient for nursing review, followed by physician review to make a final determination [Org 17]. Another had weekly meetings with the insurance care managers to discuss upcoming patient appointments and to manually identify high-risk patients based on multiple data sources and payer-provider consensus. In one instance, after the patient was identified, a medical assistant visited the PCP practice to manually extract needed patient information to ease the burden on the PCP practice [Org 10]. This approach applied only to patients enrolled in a specific insurance plan.

One model produced more descriptive results than a predictive high-risk binary indicator did. The model took a novel prescriptive approach to automatically suggest different interventions from the patient’s claims-based risk score and condition list. Suggested interventions included the development of a customized patient-care plan, referral to expert case managers and/or centers of excellence, and the creation of an advanced-care plan [Org 11].

Table 8. High-Risk Models Encountered During the Interviews

Organization	Focus	Method	Automatic Steps	Manual Steps	Number of Care-Management Tiers	Unique Features
Organization 2	High-risk	Automatic using clinical data, social rules, and utilization data	-Two or more inpatient admissions in the past six months -Two or more chronic conditions -Five or more medications	Documented social barriers	2: Care-manager outreach	

(continued)

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Table 8. High-Risk Models Encountered During the Interviews *(continued)*

Organization	Focus	Method	Automatic Steps	Manual Steps	Number of Care-Management Tiers	Unique Features
Organization 8	High-risk	Automatic using claims data	Internally developed risk model: -Diagnostic category -Behavioral health -Substance abuse -Past utilization		2: Care-manager outreach	
Organization 10	High-risk	Hybrid clinical judgment with clinical data	-Standard risk model -Multiple chronic diseases -Polypharmacy	-PHQ-2 depression screening -Fall-risk assessment	2: Complex-case management	
Organization 10	High-risk (commercial risk payer-provider collaboration)	Hybrid clinical judgment and claims, clinical, and psychosocial data	Appointment lists are supplied by the provider. Payers use the list to report claims and patient information.	-A payer-provider weekly call is used to discuss patients and their psychosocial factors -Patients selected from the call have further information gathered by the individual PCP practice.	2: Complex-case management	There are multiple stages of manual judgment by diverse stakeholders

(continued)

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Table 8. High-Risk Models Encountered During the Interviews *(continued)*

Organization	Focus	Method	Automatic Steps	Manual Steps	Number of Care-Management Tiers	Unique Features
Organization 11	High-Risk	Hybrid clinical judgment with claims and clinical data	-Standard claims-based risk score -Diagnoses	-Physician determination is made as to how to intervene -Physicians are required to manually identify five additional patients on a quarterly basis	2-Tier: The model used is prescriptive describing potential patient interventions including development of a customized patient-care plan, referral to case managers, centers of excellence, or the creation of an advanced-care plan	-The model is more prescriptive than others -There is a limit of 10 patients per physician, per payer, per quarter -Physicians are required to add patients not identified
Organization 13	High-risk	Hybrid clinical judgment with claims and utilization data	-Standard claims-based risk score -Chronic illnesses -Utilization history -In the process of adding social determinants	Physician determination	2: Complex-case management	
Organization 15	High-risk	Hybrid clinical judgment with clinical rules and utilization data	-Internally developed risk score based on the number of admissions and emergency department visits determined by claims and ADT feeds	-Predictable disease progression (e.g., Chronic Kidney Disease DRG) -Symptom DRGs (e.g., Syncope and Collapse or Chest pain DRG) -Change in lab values	2: Eight-step care-coordination process for risk score of 60 and above	
Organization 17	High-risk	Hybrid clinical judgment with claims and clinical data	-Standard claims-based risk score -EMR-based risk score -In the process of adding social determinants	-Nurse determination -Physician review and determination	2: Care coordination	-Uses multiple risk scores from different data sources -There are two stages of clinical review

Note: PHQ-2 = Patient Health Questionnaire; PCP = primary care provider; ADT = admission, discharge, transfer; DRG = diagnosis-related group; EMR = electronic medical record.

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Risk-Stratification Models

A risk-stratification model is a populationwide model that performs identification of multiple risk levels simultaneously. Risk-stratification models search through broad patient population data and identify rising-risk, high-risk, and other levels of risk within a single model. These models return between three and five tiers of patients that help care coordinators perform targeted interventions. All but one risk-stratification model incorporated a standard claims-based risk score (Table 9). Another organization's model calculated the change in risk score instead of using the absolute risk score [Org 5].

One physician-led ACO strongly emphasized patient characteristics beyond health and sociodemographic status [Org 1]. A four-tier model uses patient past goal achievement to better incorporate patient motivation in the model. In addition, the organization included the number of chronic conditions and consensus-based selected conditions to determine patient tiers. Claims data were avoided.

An organization with a leading self-funded employee model took advantage of rich data sources for self-funded employees to address high and moderate risk; the use of patient incentives helped generate a service-containment rate within the health system of greater than 95% [Org 3]. The use of claims, clinical, and health-risk-assessment data sources aided in assigning high-risk patients to primary-care-based complex-case management. Moderate-risk patients were referred to insurer-driven low-touch interventions, such as a weight-management program. The identification of rising-risk patient populations identified patients before they became high-risk and attempted to close necessary care gaps. The interviewee did acknowledge that once the rising-risk population was identified, much work was required to close the high volume of care gaps. Rising-risk levels were further stratified by the required level of care-management support, such as the use of lower-cost medical-assistant resources and high-cost nursing resources.

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Table 9. Risk-Stratification Models Encountered During the Interviews

Organization	Focus	Method	Automatic Steps	Manual Steps	Number of Care-Management Tiers	Unique Features
Organization 1	Risk stratification	Automatic using clinical rules, patient-engagement data, and utilization data	<ul style="list-style-type: none"> -Number of chronic conditions -Past utilization -Whether or not goals are being achieved -In the process of adding social determinants 		4	Incorporates historical patient engagement into care-management programs
Organization 3	Risk stratification (self-funded employee population)	Automatic using claims data, clinical rules, psychosocial data, and utilization data	<ul style="list-style-type: none"> -Standard claims-based risk score -Medical and pharmacy claims -Custom health assessment including psychosocial factors or proxy psychosocial factors based on census data by zip code -External lab results 		3: 5%/15%/80% <ul style="list-style-type: none"> -Low- and moderate-risk patients have less-frequent contact by insurer -High-risk patients have more frequent contact with PCP 	Patient identification is highly automated and uses a variety of data
Organization 4	Risk stratification (entire risk-contracted population)	Automatic using clinical and utilization data	Rising-risk rules: <ul style="list-style-type: none"> -Currently not a high utilizer -Certain chronic diseases -Multiple gaps in care -Abnormal lab value in the past three years 		3: <ul style="list-style-type: none"> -Low-risk, no intervention -Moderate- or rising-risk, care gap closure by a medical assistant -High-risk, scheduled PCP visit 	Efficient use of resource tiering by using a medical assistant to close certain gaps in care

(continued)

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Table 9. Risk-Stratification Models Encountered During the Interviews *(continued)*

Organization	Focus	Method	Automatic Steps	Manual Steps	Number of Care-Management Tiers	Unique Features
Organization 5	Risk stratification	Hybrid clinical judgment with clinical rules and cost and utilization data	<ul style="list-style-type: none"> -Standard claims-based risk score -Change in lab values -Pharmacy -Disease-specific rules: level of condition, medication refills, which medications are prescribed -Change in risk score (movers) 	<ul style="list-style-type: none"> -Health-risk assessment -Recent prior authorization 	5	<ul style="list-style-type: none"> -Uses change in risk score as criteria -Combines the hybrid approach with disease-specific rules
Organization 6	Risk stratification	Automatic using claims and utilization data	<ul style="list-style-type: none"> -Standard claims-based risk score using EMR problem-list diagnoses -Inpatient and ED utilization -In the process of adding social determinants from custom-defined risk assessment 		4: <ul style="list-style-type: none"> -Low and moderate risk—no intervention -High risk—primary-care-based-care coordination -Extreme risk—intense-care coordination 	

Disease-Specific Models

Disease-specific models can support predictive models if appropriately designed. The advantage of these single-condition models is that it is easier to know which clinical intervention should be initiated once the patient is identified. Additionally, for organizations that are new to care management or have already identified conditions that drive adverse cost and clinical outcomes, stand-alone disease-specific models are easier to implement than populationwide models. However, in this study, disease-specific models were not as commonly encountered as event-based or populationwide models. In fact, a core value of one of the interviewed organizations is not to design disease-specific

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interventions [Org 2]. Most health care organizations recognize the prevalence of comorbidity across conditions and the relative lack of value in single-condition strategies.

Granted, exceptions exist. Organization 5 does use a risk-stratification model to identify nonadherent asthma patients based on medication use and compliance, as well as level of severity. Only one disease-specific model was used by an organization, which historically primarily achieved success through improvement in administrative efficiencies [Org 12]. The physician-led ACO is in the early stages of implementing PHM initiatives and is performing a targeted pilot effort to engage poorly controlled diabetic patients so they will attend primary-care office visits. The model used a hybrid approach to evaluate elevated glycated hemoglobin (HbA1c) and low-density lipoprotein (LDL) levels, medication nonadherence, and low frequency of primary-care visits to determine whether a primary-care visit was needed. It is too early to evaluate the results of the pilot [Org 12].

Stratification Levels

Predictive models usually result in multiple levels of risk that align clinically with different levels of intensity of intervention and/or resources. Many models report a three-tier stratification of risk: high, medium, and low. There are also four-tier [Orgs 1, 6] and five-tier systems [Org 5].

The risk-score thresholds of 5%, 15%, and 80% for a three-tier care-management program are industry standards [Org 3]. One method for determining the cutoff points is to begin with the maximum number of patients who can possibly be managed given the available resources for each tier's corresponding intervention. Those patient capacities translate to a percentage of all members that can then establish cutoff points.

Exclusions

Some models exclude conditions that are not modifiable by the care-management program. For example, cancer patients are high cost, but clinical resources are already maximally deployed [Org 2]. Some patients with severe behavioral health issues are excluded when the expertise is not present or when community resources provide more-skilled management. Patients may be excluded if they are too advanced in the progression of their illness [Org 10]. These patients may be assigned to a higher-intensity program or to end-of-life care. Exclusions are normally developed over time through clinical consensus and experience. However, another organization is in the process of implementing the Johns Hopkins Adjusted Clinical Groups (ACG) system, which uses EMR data to systematically address impactability by providing registered nurse (RN), certified nursing assistant (CNA), and pharmacy resources focused on patient needs [Org 17].

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Other Challenges

A portion of the population, even if identified, will not have accurate contact information or will not be interested in participating. Although some patients are contacted and agree to participate, some do not answer calls or keep appointments. One organization noted that 30% of identified patients failed to engage in or complete the program [Org 2]. Some patients are discharged from the program because they pose a safety threat to care managers [Org 2].

Patient-List Workflow Integration

EMR Integration

Full integration of the EMR, also known as interoperability, remains elusive. Interviewees pursue divergent approaches to bridge this gap. For example, when one physician-led ACO recognized that PCP practices were not able to contact enough patients on their lists, the ACO established a call center staffed by care navigators [Org 1]. The care navigators, who had access to the EMRs, helped make appointments for patients, thereby reducing administrative work for the practices.

Patient-List Delivery

Patient-list delivery refers to the electronic or physical workflow by which clinicians receive the identified patients for care management. Some organizations deliver patient lists in person through internal consultant resources [Org 12]. Some use a web-based portal to display lists [Orgs 2, 11]. A few organizations are able to import patient lists into their EMR and flag patients for care-manager referral [Org 9].

Almost all organizations partner with practices in using high-risk lists. Most organizations allowed manual physician referral or patient self-referral as ways to add to the list generated by the predictive model [Orgs 1, 2]. One organization engages in extensive manual interpretation of high-risk-patient lists [Org 13]. Additions and deletions are made by clinicians for various reasons, including whether the patient is actually high risk and would benefit from care management.

Some organizations had rigid rules about which patients would receive care management. For example, in one organization, every patient scoring over 60 on a 100-point scale enters into an eight-step care-management process [Org 15]. Other organizations had flexible lists; they presented patient lists that allow physicians and case managers to decide which patients would enter care management [Org 13].

One organization developed registries that delineate patients with chronic conditions who are achieving their goals, those not achieving their goals, and high-touch patients who

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continue to be extremely high cost [Org 1]. This organization developed unique strategies for patients identified as extremely high cost.

Limits and Other Adjustments

One organization assigns, at most, 10 high-risk patients per quarter per payer to each PCP, although physicians were able to view the full list [Org 11]. For example, if a practice had five PCPs, they would assign 50 high-risk patients. Limiting the number of high-risk patients given to the PCP allows physicians to focus on the patients who are most important.

Patient-Identification Transparency

It is crucial to be transparent about the factors used as clinical decision markers that place a patient on a high-risk-patient list. However, the extent to which this practice is met varies greatly across organizations. Some organizations presented patient lists to their physicians without specifying the reasons why the patients were on the list [Org 1]. Other organizations presented patient lists to the doctors with comprehensive reasons for inclusion on the list, such as chronic illnesses, utilization, and risk score [Orgs 5, 11, 13]. It was unclear whether a quantitative risk score supplements decision making [Org 11]. Another organization provided multiple risk scores to care teams [Org 17]. The care team then investigated sociodemographic factors and past utilization patterns to decide whether to perform patient outreach.

Model Validation

Evaluation approaches were widely variable, which is consistent with the variability in underlying modeling approaches. Many organizations did not statistically assess the validity of the model on a regular basis. If assessed, it was done either annually or infrequently due to the high degree of observed model stability [Orgs 3, 5, 8]. Organizations defended this position by stating that limited analytical resources are used effectively when evaluating outcomes of care-management programs or developing new models [Org 8]. There was need to validate the statistical predictive accuracy of the model when transitioning between models; otherwise, the models were mostly stable [Org 5].

A matching hybrid validation is recommended, similar to the suggestion to use a hybrid modeling approach. Clinicians need to periodically examine and record false positives and false negatives so that adjustments can be identified and incorporated into the model. Statistical analysis needs to be undertaken regularly to analyze the accuracy of the model and to benchmark accuracy against other models [Orgs 4, 5]. The hybrid evaluation approach helps classify and prioritize model improvements that can enhance clinical decision making.

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Sensitivity—Managing False Positives

Many models were overly sensitive, meaning that some identified patients were not always appropriate for care management due to false positives [Org 2].

It is more costly to not identify a high-risk patient than to falsely identify low-risk patients.

This asymmetry explains the proliferation of high-sensitivity models. One organization found that up to 40% of identified patients were deleted from the list due to administrative removals before the list was delivered to physicians [Org 13]. To conserve the time and energy of care managers, care-management programs were designed to quickly disconnect from the care-management contact in the event of a false positive. One organization determines whether the patient was appropriately identified as needing care management as the first step in the process [Org 15]. False positives are managed manually through the care-management process [Orgs 2, 8].

Specificity—Managing False Negatives

Manual approaches can correct for the lack of model specificity. This exemplifies one of the advantages of the hybrid approach. One physician-led ACO requires PCPs to manually add five patients every quarter who should have been on the list before but were not included [Org 11]. These manually determined patients are not yet used as feedback to predictive-model development for correcting systematic errors. Through physician validation, another organization identified a group of patients of whom physicians were unaware but the model identified [Org 3]. This demonstrates that predictive modeling is a necessary complement to clinical judgment and vice versa.

Model ROI

Despite the lack of rigorous statistical validation of the risk models, outcomes of holistic programs are measured continuously. Selected outcomes depend on the care-management program objective. Outcomes, such as the reconnection rate after an admission [Org 2] or overall readmission rate [Org 10], are regularly tracked to monitor overall program performance. Others measure program success by primary-care visits per thousand members [Org 11] or reduction in total cost of care [Org 6]. Most interviewees did not attribute their success to their predictive model alone [Org 5]. Instead, care-management success was attributed to the interventions, the staff, and patient readiness to change [Org 1].

Study Limitations

Several factors limit the applicability of findings and recommendations to other ACO or AMC providers, including:

- A limited number of experienced AMCs and ACOs were interviewed. Additional AMCs or ACOs in other markets and having less success may be able to provide further advice on what to avoid.
- The AMCs and ACOs interviewed have at least 30,000 to 200,000 members participating in risk arrangements. This large scale may have afforded the organizations resources that smaller hospitals and ACOs cannot replicate.

Conclusions and Recommendations

We investigated the use of predictive modeling to assist with managing risk and executing care-management programs. Several modeling approaches can be studied to enhance care-management program efficiency and improve outcomes. This report focused on the process for patient identification for high-risk management and how predictive modeling can enable automation and improvement.

Many practical challenges with payer, clinical, and patient-reported data sources still exist. Results from Haime et al. (2014) were reinforced and extended across health care geographies and types of organizations, whether they are large academic clinically integrated networks or physician-led ACOs. A hybrid automatic-and-manual patient-identification process provides a balance between accurately identifying patients who could benefit from care management and reducing the administrative burden of manually reviewing patient data. Additionally, the hybrid approach helps compensate for the litany of data challenges that currently exist in health care. The recommendation for a hybrid approach is especially important for high-risk-patient identification because of the extraordinary degree of intensity of resources and complex rules used to identify them. Some organizations have an extreme hybrid approach with multiple stages of manual review for high-risk-patient identification.

Every organization is generally focused on the same population health initiatives. However, each organization has a different approach to implementing programs, including the specific interventions involved in a program and the patient-identification process. Each organization had somewhat different goals and used a different mix of data sources, risk-scoring models, clinical rules, IT automation, and manual review to identify patients. These differences are explained by differing patient population needs, local

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health care issues, strength of data sharing across partnerships, and local regulation. Every model highlighted the need for financial and clinical decision making to be combined in order to best identify patients. The differing modeling processes revealed highly innovative ways to increase value for patients.

Full integration of the patient-identification process with EMRs remains a serious impediment to risk-based-model penetration. We observed creative methods for connecting models with clinical decision makers. Organizations interviewed frequently combined a highly customized data-warehouse approach with PHM-vendor solutions. Model-evaluation practices varied widely. A parallel hybrid-model evaluation process consisting of clinical review and statistical-predictive-model evaluation is recommended to match the hybrid patient-identification process.

Introducing advanced IT and predictive modeling to improve and automate the patient-identification process is a work in progress. Successful organizations have developed tailored and thoughtful approaches to meet their needs given the practical constraints. In the meantime, their program features, including pioneering leadership, robust change-management procedures, and a focus on creating strong patient relationships, have yielded early success.

Solutions to better aligning administrative procedures, improving data-collection standards, and refining value-based contracts should be investigated. One example is the recently passed Medicare Access and CHIP Reauthorization Act (MACRA), which contains provisions to better align administrative data with value-based care objectives by introducing Care Episode Groups, Patient Relationship Categories, and Patient Condition Groups. More research is needed to scientifically support alignment efforts. Concrete suggestions for research topics include the following:

1. Develop a standard taxonomy for all the various care-management interventions and program features,
2. Define data-collection standards for care-management enrollment data,
3. Revisit Meaningful Use to enforce IT-vendor standards that will help providers administratively meet value-based care demands,
4. Quantify the influence of social, behavioral, cognitive, and motivational factors on patient risk,
5. Conduct actuarial investigation of the financial implications of incorporating nontraditional risk factors in value-based contracts,
6. Conduct actuarial investigation into the optimal design and evaluation of hybrid risk-modeling algorithms.

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In conclusion, the actual data and methods being used by successful providers to manage risk are significantly different from those written into current value-based contracts and supported by current administrative procedures and IT standards. Financial incentives and penalties should reflect true provider-modifiable risk; otherwise, unexpected opportunities for financial arbitrage emerge that threaten the intent of value-based care.

Standard Interview Questions

I. Risk-Exposure Background (10 minutes)

- a) How long have you been participating in claims risk?
- b) In which risk-based payment models do you participate?
 - 1. Commercial, MSSP, Pioneer ACOs, MA, bundled payment, Medicaid HMO/ACO, Direct to Employer
 - 2. Are the contracts upside-only or two-sided risk?
- c) Approximately how many members are at risk?

II. Modeling Sophistication (15 minutes)

- a) How are you identifying high-risk patients? How many risk strata do you use?
- b) Which populations or conditions are modeled? On whom do you assess risk?
- c) Do you use commercial or homegrown tools or a combination? If you use commercial solutions, which one(s) and why did you choose that solution? Who decided this? What was the role of the clinicians?
- d) Do you use one or multiple models?
- e) What is the goal of your model? To assess total cost? Readmissions? Postacute-care use? A combination of factors?
- f) Are the tools embedded in the EMR? How do the tools integrate with workflows?
- g) What data sources do the tools pull from? How did you determine which risk factors to use?

III. Application of Results (20 minutes)

- a) Which clinical interventions are associated with the risk strata? What clinically happens with the scores? How are the scores applied?
- b) Describe data-acquisition, interoperability, lag-time, and other technical, operations, and human resource issues in using predictive modeling to drive performance improvement.
- c) Describe practical limitations you have encountered regarding model applicability (false positives, false negatives, exclusions, predictive-modeling applicability, impracticality for technical or operational reasons).

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- d) How are you evaluating the outcome of the intervention? Is the R^2 value important to you? If so, why? How satisfied are you with results?

IV. Financial and Clinical Outcomes (15 minutes)

- a) Do you believe that predictive modeling has enabled you to financially succeed under risk-based payment? Why or why not? How crucial is this to your overall performance in real life versus in theory?
- b) Compared with other success factors in assuming population and insurance risk, where does risk modeling and managing patient risk rank in importance? Explain; tell us more.
- c) What are your main concerns about vendor systems? What were the things that didn't work about the tool(s) that you were surprised about?
- d) What advice would you have for other organizations that are considering investing in predictive-modeling capabilities and are trying to determine the return on investment?

Selected Organization Profiles

Organization 1

Background

Organization 1 is a medical services organization that helps ease management burden for primary-care practices. The organization states that its data model empowers physicians to deliver high-value care while leveraging the company's management experience for increasing profitability.

The PCPs with whom the organization works participate in Medicare and commercial shared-savings contracts, primarily assuming upside-only risk. Successfully generating savings under Medicare ACO programs has allowed the organization to negotiate increased reimbursement for commercial programs.

Care-Redesign Process

The success of the organization's care model is due in large part to an initial standard compact with primary-care physicians. This agreement encourages PCPs and their practice to continually manage the patient population. Although the organization has some specialists under contract, the agreement is mostly with PCPs. The agreement includes guidelines and instructions for PCP referrals and for maintaining primary management of the patient after referral. Specialists fulfilling the referral cannot admit a patient to the hospital, refer the patient to other specialists, or change patient prescriptions without first notifying the PCP. Some specialists subscribe to the agreement, and others do not.

A second phase of the organization's approach is to integrate specialists into the practice. A PCP group may contract with a particular specialist for a certain number of days per week or per month. In those models, the specialist becomes an employee of the PCP practice.

As part of the agreement, the PCP practice must also connect with other community organizations, such as men's groups and entities that provide meals to those in need. The care coordinators use these local organizations when creating care pathways for their patients.

Individual-Patient Identification

The organization generates patient lists for providers and care coordinators in order to better focus their efforts. The lists do not include an exhaustive list of the clinical reasons for each patient's inclusion on the list because it is assumed that providers are aware

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when a patient is added to the list. Providers also have the ability to add patients to these lists.

The organization's risk-identification model uses data from registries of chronic conditions and patient utilization, and it stratifies patients into four levels. The first level includes a well, healthy population. The second level consists of patients with at least one registry indicator and who are generally achieving their health goals. The third level includes patients on a registry of patients who are not adherent to the treatment regimen. Finally, the fourth level includes the highest-risk patients, who are on multiple registries and who demand considerable care-management resources.

The risk stratification is unique because even though data are aggregated from multiple EMRs, the model can be executed in a timely fashion. When adding a new primary-care practice, ensuring successful data integration is key. Backups of the practices' databases are mapped into the organization's proprietary data warehouse to support patient identification. Many different data formats are successfully integrated into the organization's data warehouse.

Organization 1's care-navigation efforts originate with an internal call center. The organization created the call center in response to the fact that some physicians did not contact all patients on patient lists. Call centers provide scripts for care navigators and offer an efficient access point for patients trying to schedule appointments. Following a call, care navigators update patient tracking with a new task for the patient.

Organization 1 uses market-specific strategies for postacute-care improvement and skilled nursing facility (SNF) partnerships. For instance, in one market, a nurse is embedded in the facility to perform IV treatment for urinary tract infections in an effort to help prevent costly hospital admissions.

Advantages

Organization 1's approach is to encourage or require its doctors to use an EMR but allow the clinicians to use their preferred EMR. The clinicians can continue to use their current EMR while the data team maps the information to a specific format for reporting and analytics.

Challenges

Each health care market is unique. Certain aspects of the care model maintain consistency across markets, but there is still variation.

Future

Risk-modeling and data-warehouse capabilities continue to be automated and improved.

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Key Takeaways

- A simple risk-prediction model resulted in medical and supporting professionals' ability to execute focused care-management strategies.
- Adding resources, such as care navigators, who can relieve the administrative burden for the practice is integral to Organization 1's approach.
- A rigid care-model approach is not taken. Data formats and strategies for coordinating care are tailored to the local health care market environment.

Organization 2

Background

Organization 2 is a 501(c)(3) Medicaid ACO serving half the residents in its city. All patients in the ACO are attributed to a primary-care practice and are covered by Medicaid. Organization 2 coordinates care across three hospitals and 15 primary-care practices and partners with two major insurers for the Medicaid population. Both insurers pay lump-sum investments in advance and award shared savings (net of investment and no downside risk) to Organization 2.

Initiatives

Due to the complexity of the population, Organization 2 does not deploy single disease-specific interventions. Instead, it uses two separate programs that are guided by patient-identification models: a high-touch community-based care model and a transitional-care-management program.

The high-touch, community-based care-coordination model targets the most complex patients. A consensus approach is taken to define complex patients: those with two or more inpatient hospitalizations in a six-month period, two or more chronic conditions, five or more medications, and/or documented social barriers. Social-barrier flags identify patients who have had trouble accessing care and include documented language or transportation barriers, labels in the EMR such as “noncompliant,” frequent no-shows for appointments, lack of social support, addiction, and homelessness. The care-management model focuses on adults ages 18 to 80 years. To manage resource use and focus on risks that can be affected, there are certain exclusions for care management, such as cancer care.

Identified patients are incentivized to schedule a PCP visit 48 hours postdischarge and to maintain a PCP relationship for 90 days. Patients can graduate at any time. Organization 2 consistently admits more patients into the program than can be managed, and it manually adjusts the patient list later based on a number of factors. Challenges in locating

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and contacting patients, as well as patients declining care-management support, introduce practical barriers to effectively intervening in the care of all identified patients. In addition, some patients with severe behavioral health conditions are ultimately excluded due to lack of appropriate mental health system supports.

The second initiative is the transitional-care-management program. The aim of this program is to follow up with every patient after every hospital-inpatient or emergency department (ED) event. Organization 2 employees strive to meet all patients while they are in the hospital in order to discuss the importance of primary care. Organization 2 follows the “Seven-Day Pledge,” under which a primary-care follow-up appointment is scheduled within seven days of hospital-inpatient or ED discharge. This program is supported by a citywide health-information exchange (HIE) of all patients who were discharged the previous day from a hospital-inpatient or ED encounter. Discharge summaries and lab results are pushed into the HIE so that providers and care managers can use them rapidly.

Organization 2 recently launched a TrackVia software solution to assist with the transitional-care-management initiative. Participating PCPs can log in to view daily patient-outreach lists fueled by the HIE data. Excel-spreadsheet lists were previously sent through encrypted email to the practices, but Organization 2 has since created a cloud-based, HIPAA-compliant relational database for practice-specific patient-list viewing and documentation. The practices are required to enter patient-outreach attempts, scheduled appointments, and whether the patient showed up in the TrackVia system. Organization 2 has direct access to EMRs for two of the three local hospitals to help with further investigation and patient data collection.

Despite the presence of different EMRs across primary-care practices and the fact that some practices still use paper charts, Organization 2 was able to successfully train front-line PCP practice staff to use TrackVia. Practices are paid \$150 for every seven-day appointment that is completed. The transitional-care program has increased the reconnection rate for patients from 23% to 44% over the past year.

Advantages

Organization 2 cites the HIE as a helpful way for real-time interventions to occur. They receive discharge summaries and lab results from two of their three main hospitals within a day of discharge to help guide the triage process. All three hospitals provide admission, discharge, and transfer (ADT) feeds.

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Challenges

The shared-savings method used by private Medicaid payers is still a work in progress. Resolving contracting issues concerning whether dual-eligible populations or newly expanded Medicaid recipients should be included in the shared-savings method is an ongoing process. For example, there is doubt about whether it is fair to include Medicaid beneficiaries who recently gained coverage because the model's benchmark was established using a three-year historical period prior to Medicaid expansion.

The program-dropout rate for the high-touch, community-based care-coordination model is 30%. Patients are considered dropouts if they stop answering phone calls, are no-shows to appointments, or pose a threat to the care coordinators and are subsequently excluded.

Future

Organization 2 is a heavily data-driven organization and looks closely at utilization data for opportunities to improve care. The organization hopes to expand the seven-day follow-up visit to include Healthcare Effectiveness Data and Information Set (HEDIS) metrics for helping patients who experience gaps in care. It plans to use the TrackVia system, and it is seeking real-time data to help intercept patients while they are still in the ED.

Organization 2 is investigating commercial solutions to interface with the HIE. However, it is taking a cautious approach with off-the-shelf solutions that are not as customizable as homegrown solutions.

Lessons Learned

- It is important to focus on building relationships with patients instead of trying to implement too many interventions at once.
- Organizations must identify resources and use them to help define which patients are capable of receiving support through an intervention program.
- HIEs can allow more real-time notification of acute events than payer claims data can.

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Organization 3

Background

Organization 3 is a large multicenter, multispecialty academic hospital system founded in 1921. The system includes a large tertiary hospital, 9 community hospitals, and 18 family health centers, with additional locations in several states and countries.

The organization began assuming risk through its self-funded employee health plan in 2008, with about 80,000 employees and family members enrolled and with 95% of employee care performed within the health system.

Since 2012, Organization 3 has participated in value-based-care initiatives. Initially, it focused on Medicare Advantage with shared-savings and quality bonuses. The clinically integrated network, including affiliated physicians, is incorporated into the Medicare Advantage contracting. The hospital has an agreement with commercial payers similar to CMS value-based purchasing.

Organization 3 is participating as a Medicare Shared Savings Program (MSSP) ACO in the 2015 performance year. Some, but not all, physicians participate in the clinically integrated network. The health system is also accepting financial risk for major joint replacement of the lower extremity under the Bundled Payment for Care Improvement (BPCI) initiative. In addition, Organization 3 is responsible for the care of 30,000–40,000 adult Medicaid recipients. The organization contracts with at least six Medicaid managed-care organizations and is preparing for mandatory 30-day bundles under Ohio Medicaid.

Organization 3 is steadily increasing risk-contracting activity. One such effort is a partnership with a local insurer to provide a direct-to-employer co-branded insurance product as a pilot starting in 2016. This pilot is in addition to direct-to-employer bundled payment programs for coronary artery bypass grafting (CABG), cardiac valve replacements, and total joint replacements.

Care-Coordination Initiatives

Organization 3 began managing risk through the employee health plan. The plan is physician led, while human resources manages benefits and the plan's design. Following clinical integration and transformation efforts, the clinical transformation department oversees population health management.

A full medical claims dataset received by the third-party administrator and a pharmacy-claims dataset received by the pharmacy benefits manager are used for analytics. Clinical data from community paper charts and electronic charts are also combined for the

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analysis. The commercial vendor products, Optum Impact Intelligence and Optum Impact Pro, are used to combine the clinical and administrative data. This forms the backbone for patient identification, risk stratification, and financial and population health analytics. Episode Treatment Groups are used to group diagnoses for episode analysis.

The combination of the two commercial tools is powerful. Data from vendors managing other programs, such as an employee weight-management program, are also combined with the clinical and administrative data in an internal data warehouse. Model results from the Ingenix products are incorporated with traditional data feeds and put into the organization's data warehouse. A complete picture of the employee population is formed using claims and clinical data along with biometrics and health-risk-assessment data.

The health-risk assessment was developed internally through a health-visit form that contains objective data from a health care provider. The health-assessment data are extracted from paper and fed into the data warehouse along with the clinical and administrative data from the Ingenix products. Epic and Clarity tools are used predominantly to extract clinical data. Outside lab feeds are also incorporated into the employee-data warehouse.

Recently, Organization 3 has been shifting the data analytics programs from the Ingenix tools to Optum One, part of the same company, OptumHealth, which provides the Ingenix platform.

Some patient-reported outcomes are collected, as well, despite the subjectivity of the data source. A patient-entered-data strategy has existed for the past seven to eight years. Knowledge Program software communicates with Epic during workflows. Through that system, a variety of clinical areas completed relevant questionnaires including functional scores, depression screening, and the PROMIS 10 global health assessment. Organization 3 plans to incorporate the Knowledge Program software into risk modeling going forward through integration with Optum One.

The choice to expand the use of Optum One beyond the employee population was made by a collaborative team that included clinicians, HR, business intelligence, and data analytics. There was a discussion on the use cases, the needs, which solutions could fulfill the needs, and which solutions were available. Three different products were considered before Optum One was chosen through a due diligence process. Optum One is the primary clinical and claims tool but not the only vendor used for financial analytics. Milliman MedInsight is used for high-level actuarial work and additional risk-stratification tools. The team learned that it is essential to know the core questions that will be answered and what will be done with the model output before making an investment in a commercial solution.

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Risk Identification

The risk-identification algorithm uses a combined clinical-and-cost-risk approach. The objective is to search for high utilizers or soon-to-be high utilizers who have multiple or uncontrolled chronic conditions. A direct or proxy assessment of psychosocial-risk factors places patients at higher risk of preventable utilization and is incorporated into the model. The entire primary-care base is examined, and high-risk patients are identified as having a need for care coordination. The approach is not disease specific.

Under the current approach, patient-level social-determinant data are often not readily available. Instead, census data by zip code are used as a proxy to help inform the model. A relatively broad net is used to prioritize patients. The model prefers sensitivity over specificity. Clinician judgment helps determine whether the patient would benefit from care coordination.

The long-term approach is to capture data through a patient-entered-data strategy with health-risk assessment administered to self-funded employees and across the entire population. For example, patients can enter data on their partner status, living conditions, transportation, or financial barriers to filling medications. These elements are included in the model through Optum One or through homegrown analyses. Optum One is capable of receiving the data through Epic's patient-data-collection process and importing data elements as user-defined fields.

Some clinical and social considerations are unavailable in the data, such as whether the patient is amenable to care coordination. Resources are reserved for patients who would benefit or who do not have adequate home or community support and cannot navigate the health care system themselves. Care coordinators have formal training on health coaching, motivational interviewing, and collaboratively setting goals with patients to monitor progress.

Risk Stratification

There are three patient-risk strata in the employee health plan: low, moderate, and high. The high-risk patients require frequent contact and a high level of care coordination that is best managed from the primary-care office. The moderate- and low-risk strata are handled through the insurer. These patients require less-frequent contact than the high-risk patients do. An offshore model based on the primary-care system is used through a set of coordinators employed by the insurance plan.

From the broader population health perspective, Organization 3 is developing strategies to intervene with the larger population as risk contracting intensifies. The process is

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similar to the employee health plan in which rising risk and high risk are identified and interventions are guided by a care-coordination process.

The thresholds for risk are programmed into Optum One as low, moderate, and high or a 5%, 15%, and 80% set of thresholds, respectively. The 5%, 15%, and 80% thresholds were first used because they are an industrywide rule of thumb. The choice was validated by matching the volume of patients that would result in each stratum to the amount of resources available to intervene.

The models for rising risk differentially weight patients who are not currently high utilizers but have chronic disease and multiple care gaps. As part of the model for identifying risk, a variety of conditions has been identified, including the lack of ambulatory visits by patients. Clinical variables are also included in risk weighting (e.g., abnormal HbA1c). Closing care gaps is a central strategy for managing “rising-risk” patients. Patients at this level of risk use less-frequent and less-intense care coordination than high-risk patients.

Model Validation

The models are validated through two separate strategies. The first is clinical authentication by a physician-validation process that tests whether identified high-risk patients actually need care coordination. The second is a systematic cost and utilization validation of the Ingenix and Optum One tools.

Organization 3 is further formalizing the process of validating the risk-identification model. The Optum One lists are beginning to be generated based on models after the system transition from Ingenix. No validation cohorts are available, so clinician judgment is used as the most accurate source. The goal is to create a physician-specific list for physician review. The list contains the drivers or risk factors indicating the reasons the patient is included on the list. The physician formally provides feedback about the accuracy of the list. First, PCP attribution is clarified, and the physician is asked to describe the risk status of the patient. This feedback is captured and used to continue building a more accurate model through multiple iterations.

Three categories of patients have resulted from this process: 1) patients identified by the model who were also identified by physicians as high risk, 2) patients identified by the model who do not in fact need care coordination, and 3) patients identified by the model who were not initially identified by physicians. For example, in the last instance, the physician may not have been aware that high utilization was occurring outside the health system or that the patient was in the hospital for a long time due to uncontrolled chronic diseases.

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A more systematic analytical method of validation was also used. Internal analytics were performed by an actuary who assessed the validity of the risk identification. Both the populations who had the intervention and those who did not were used to retrospectively test model accuracy. The tools were determined to be fairly accurate. Reported results were not ideal but were better than expectations.

Workflow

Care-coordinator workflow is driven by analytics. Clinicians huddle regularly with care coordinators so that they can use the same information. The analytics are not integrated into physician workflow, but they can be obtained on demand.

Newer population-health-management tools from Epic's Healthy Planet application are being used by care coordinators to connect to high-risk-patient registries and operationalize care coordination within Epic. Patient lists fueled by Optum One are integrated into Epic. The patient list and the actionable drivers of high risk or care gaps appear in the summary view in Epic, including the last admission, last ER visit, and care-partner identification.

Physicians are not currently reimbursed through pay-for-performance bonuses or other financial incentives. Physician surveys show that 90% of physicians think that the biggest risk-management success is the care-team concept.

Data Sources

A four-quadrant data model is being tested for the at-risk population. The model uses biomedical, behavioral, social, and functional-status data sources. The EMR data populates the four quadrants so at any time, the physician or caregiver has a snapshot of the risk status. For example, recent Patient Health Questionnaire (PHQ-9) scores, past utilization of psychiatric services or substance abuse, health-risk-assessment data such as care partners, and marital status are all integrated into the EMR.

The Ohio-wide health-information exchange, called Clinisync, is used to share clinical information. The use of HIE data for population health management is still being explored. Physicians who participate in the clinically integrated network receive subsidized Epic through CommunityConnect. For those physicians not connected through Epic, the analytics vendor Explorys (IBM Watson Health) can connect the different EMRs. Explorys originated from Organization 3. The system can be used to run analytics for performance improvement, registries, and quality reporting. All that information is fed into Organization 3.

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Population-Level Analytics

Analytics are also used to guide system-redesign efforts. Organization 3 focuses on patterns of utilization and discovering comorbidity hotspots. The analytics aid in finding preventable high-utilization patterns associated with a condition and help allocate the resources that need to be deployed. For example, two years ago, 50 care coordinators were randomly assigned based on visit frequency to primary-care practices. Analytics are used to target resources toward concentrations of high-risk patients to streamline the deployment of additional resources.

Organization 3 is exploring a medical-neighborhood concept. A medical neighborhood is a co-management model between PCPs and specialists, such as cardiologists, who work in the same practice and treat the same patients. Analytics were used to isolate the two locations where it made most sense to establish a medical neighborhood. Population-level analytics present a huge opportunity for finding efficiencies. Individual-patient-level analytics may not present the same opportunity because of the limited ability to act on the results. This is due to constrained care-coordinator, social-worker, and home-care resources available to the front-line doctor.

Outcomes

There have been improvements in quality and reductions in utilization in the employee health plan in instances when the patient engaged with care-coordination interventions. There was far less increase in cost than would have been expected without care coordination, if not an actual reduction in cost. The real secret to bending the cost curve has been changing the delivery of care rather than just increasing co-insurance or co-pays. Additionally, the early success for the employee health plan helped earn executive buy-in to proceed with value-based reimbursement.

Challenges

While many health systems confront fragmented EMRs, Organization 3's employee health plan is on one EMR, which yields huge efficiencies. As the organization moves forward with more risk contracts with other payers, it will still have the advantage of a tight network but will not be able to use the same incentives for the broader population as it does with the employee population.

One challenge is the delay in insurer-claims data from outside the system. Optum™ deserves credit for working with the large payers to streamline the import of claims data. Many internal Organization 3 resources were used to ensure that the mapping was correct. Standardizing the claims data has been easier than expected through working with Optum™ One. There remain data gaps such as pharmacy-claims data. Payers remain reticent about supplying claims data even if they are committed to a value-based contract.

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Lessons Learned

- Medical management of the hospital's self-funded employee group provides valuable learning and executive buy-in to proceed with value-based-care initiatives.
- It is essential to determine what questions are being asked and how analytics output will be operationalized before making a large investment in an analytics solution.
- A risk-identification model based on data needs to be combined with clinician judgment to identify the patients who would benefit the most. Conversely, clinician judgment needs to be paired with data so that external information can inform the clinicians about patient issues they were unaware of.

Organization 4

Background

Organization 4 is an acute-care teaching hospital with more than 900 inpatient beds, a children's hospital, and two other regional hospitals.

Summary

Organization 4 currently uses descriptive and diagnostic analytics to support its care-redesign process. The process has yielded positive outcomes to date. An internal analytics team performs most of the analytics. The organization is in the early stages of implementing an EMR-integrated PHM platform.

Risk Programs

Organization 4 has a self-funded employee population and a state-mandated Medicaid risk program pending CMS-waiver approval. It is participating in a Medicare ACO with 46,000 beneficiaries, and it has also participated in commercial and government bundled payment programs for hip and knee replacements and percutaneous coronary intervention (PCI).

The Care-Redesign Process

The Organization 4 care-redesign model is a multistep process owned by a cross-disciplinary team that uses a formal documentation procedure for clinical redesign and outcomes tracking.

On a quarterly basis, new populations and processes are identified for redesign. Such opportunities are generally payer-agnostic and are instead targeted by condition or care

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setting. Initially, a consulting firm helped pinpoint opportunities by benchmarking costs relative to other AMCs through the use of a large populationwide claims dataset.

An internal analytics department now works with clinicians to run reports on populations of interest. The team identifies outliers by examining utilization patterns and proposes corresponding solutions. Quality, utilization, and patient satisfaction are monitored on an ongoing basis.

Example 1—Congestive Heart Failure (CHF)

Examination of CHF utilization patterns identified emergency room use as a source for concern. An outpatient same-day-access center for the CHF population was established as an alternative to the ER. The access center is staffed by a nurse practitioner who provides advanced treatment in an ambulatory setting. The project resulted in reduced readmission rates and ER utilization. Following the implementation of the same-day access center, high-cost CHF patients were further stratified for targeted interventions. CHF patients originating from skilled nursing facilities (SNF) had high ER and inpatient utilization. This observation resulted in a protocol change that allowed AMC nurse practitioners to round on patients at the SNF to help improve SNF medical management.

Example 2—ED “Familiar Faces”

Organization 4 also targeted patients who frequented the emergency department as an opportunity for care redesign. The organization defined these individuals as “familiar faces,” or patients who visited the ED at least once per month over the course of one year. Initially, the organization assumed that this population was largely uninsured and did not have a primary-care provider. However, retrospective analytics revealed that the majority of these “familiar faces” had insurance and a PCP. Analyses stratified the patients into three subgroups.

- The first stratum included patients presenting with a chronic illness, such as a cancer patient on high doses of opiates for pain relief. In many instances, the PCP was not comfortable with prescribing high doses due to the liability risk. As a result, the patient went to the ED to fill the prescription for their needed pain management.
- The second stratum included patients with a mental health and medical diagnoses as well as chronic pain, a challenging combination for primary care.
- The third stratum included patients with mental health and substance abuse diagnoses who were drug-seeking.

This stratification helped identify the appropriate steps for care redesign.

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Example 3—End of Life

Organization 4 is also experimenting with how to better manage patients in their last 30 days of life by focusing on the outpatient setting. Analytics are performed to understand what happens to patients during their last 30 days, what kind of resources are needed, what practices or specialties need to be involved, and how this preparation affects the final days of a patient's life. All deaths at the hospital are reviewed in detail to identify opportunities for improvement.

Advantages

Most of the patient data reside in the enterprise EMR because of the dominant position that Organization 4 has in its community, thus reducing the dependence on payer claims data. The organization's leadership also cites a long tenure for senior leadership in critical roles as being a key to the redesign program's success. Strong hospital and medical practice leadership and the support of the faculty practice in guiding change management is crucial.

Organization 4 does not typically rely on commercial predictive models for many reasons. One issue is the lack of transparency of the variables used in commercial predictive models and the inability to use it to validate their own experience. Another limiting factor is that nationally developed predictive models may not take into account the variations in local practice observed in the community. For example, patients in rural communities have less access to rehab and SNF, which may affect utilization patterns and risk strata.

Challenges

As part of the implementation of a care redesign, order sets are created and built in the EMR. Organization 4 uses a case-management system that is separate from its EMR because the current EMR cannot create or build order sets. Workflows are less efficient because of the lack of ability to import care-management data into the EMR.

Future

Organization 4 believes it is still facing a considerable learning curve in the development of predictive analytics. In-house analytics staff is developing a model for predicting risk of increased utilization and co-developing predictive models with surgeons to better understand which patient variables predict the risk of complications after surgery and end-stage renal disease. The organization has not yet embedded risk scores into their EMR across populations.

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Key Takeaways

- Organization 4 highlights the value to organizations of performing descriptive analytics and data visualization on their own data before developing predictive analytics or buying a commercial solution.
- A data-driven, root-cause investigation approach helps test initial assumptions about the types of patients who are high utilizers and more intelligently redesign care around the specific practice patterns.
- Sustained executive leadership and change management is a crucial ingredient to maintain stability of organizations in an unstable health care environment.

Organization 5

Background

Organization 5 is a physician-led health system with 30,000 employees, including 1,600 employed physicians, multiple hospital campuses, research centers, and a 500,000-member health plan. They have built their own subsidiary that offers analysis, care redesign, and technology tools. They have extensive experience managing risk through their own health plan and are increasing risk exposure through their ACO, a Medicare Shared Savings Program (MSSP) ACO, and with Medicaid managed care.

Initiatives

Organization 5 performs population health outreach for high-risk patients and uses predictive modeling and clinical expertise to target patients. The predictive model helps identify patients who are likely to be high cost, and clinical judgment subsequently helps determine which patients can benefit most from case management. The organization has a readmissions initiative in which patients are contacted within 24 to 48 hours after discharge, and a follow-up PCP visit is scheduled for five to seven days after discharge. A postdischarge assessment is manually administered to all patients. All Medicare inpatient patients are considered at risk for readmission. Claims-based risk-prediction tools are supplemented with chronic-condition lists and other real-time data to proactively perform patient intervention.

Patient Identification

Organization 5 has used MedAI, now LexusNexis, to predict a high-cost-risk score for patients. It is in the process of reexamining its prospective-risk-score approach to incorporate cost and utilization factors into the determination of whether to provide case management to a patient. A collaborative clinical, analytical, and financial team made the decision to reevaluate the risk-modeling approach.

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Claims, lab, and pharmacy data are used to select patients who would benefit most from case management. Health-risk-assessment data are collected (when available) but not incorporated into the predictive-modeling portion of the model. Instead, they are used separately to inform clinical judgment. For example, patients with asthma are ranked based on factors such as whether they refill medications, whether they are on steroids, and the intensity of their asthma symptoms, as well as a risk score. Patients whose risk score significantly increases over time are also identified as potential case-management candidates. To enhance the model, the internal actuarial informatics department is experimenting with HCC scoring for populations. No other EMR fields are used at this time.

Organization 5 uses a five-tier risk-stratification system when assigning patients to different levels of resources, with 5 being the most complex patients. The high-cost risk score is only one piece of the information used to assign a case-management referral. Other patient information is considered once it is determined which patients are likely to be helped by case management. Case-management and prior-authorization data are used in addition to the risk scores to help identify patients more quickly. Several risk models have been used. The most important aspect of the models is risk-score transparency and the score's meaning to clinicians. It is important for clinicians to immediately see the top three to five diagnoses associated with the risk score. Additionally, case managers need to understand the level of risk and the rationale behind the scores.

Validation

Model oversensitivity is expected, and models are designed to expect some false positives. Organization 5 assessed the accuracy of the claims-based industry-standard models. Predictions from different models were compared. An R^2 of around .25 was typical across populations from the best models and similar to levels of accuracy found by the Society of Actuaries in 2007. Measuring the model's predictive accuracy is only one piece of the process for recommending care management, given that the return on investment (ROI) is calculated from the combination of risk score and care-management interventions.

Population-level Analytics

Two activities are performed to better manage postacute-care population dynamics: 1) CMS data on the relative performance of the local SNFs and rehab sites, such as length of stay, cost, readmission rates, and ED use, pinpoint the higher-performing postacute providers in the network and 2) nurse practitioners and physician assistants are placed in key nursing homes so that an advanced provider is available 8 to 10 hours a day to evaluate high-risk patients.

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Results

It is difficult to measure the ROI of the predictive model alone because it is intertwined with case-management outreach and effectiveness. Organization 5's case-management process has proven to be very successful, but it cannot determine what portion of the ROI to attribute to the predictive model. Predictive modeling alone has not been proven to result in shared savings.

Challenges

Risk-score lag is an issue because of claims lag. Lag is overcome at Organization 5 through clinical judgment and use of other data sources. If there were more real-time data, it would be easier to identify patients with certain medication patterns, increased specialist utilization, and other prospective indicators of risk. Overlaying real-time EMR data, such as changes in lab results or recent prescriptions, could enhance the patient-identification model.

Interoperability between EMRs is another issue. Six different EMR vendors feed data into the patient-care programs. Organization 5 is actively looking for vendors who can help consolidate EMR data streams.

Lessons Learned

- A hybrid analytical and clinical judgment approach helps overcome challenges with data lags and issues in model accuracy.
- The ROI of a care-management initiative needs to be examined holistically, not just by analyzing the ROI of the predictive model.
- A strict validation approach helps with making successful selection between risk models.

Organization 6

Background

Organization 6 is a 470-bed county medical center with a level 1 trauma center and serves 180,000 lives within its network of primary- and specialty-care clinics. About 55,000 patients are served under an alternative payment model; this number is expected to reach 100,000 by the end of 2017.

Organization 6 does not participate in the Medicare Shared Savings Program (MSSP) or Medicare Advantage. There are 2,500 patients under a commercial ACO arrangement. The organization is also a partner in a Medicaid ACO demonstration project focused on 11,000 adults. Organization 6 directly contracts with the state for 30,000 Medicaid

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patients covered by fee-for-service, managed-care, or special-needs plans. In 2016, most of the Medicaid-contracted populations are in total-cost-of-care contracts.

Initiatives

Organization 6 has developed multiple care-coordination programs based on the risk stratification of patients. Populations are stratified to determine where costs can be affected. The Medicare HCC model is applied to clinical data across the population as a basis for the risk-stratification model. Organization 6 is in the process of incorporating external ACO data to cover the absence of diagnosis codes that are unavailable internally. Currently, the state Medicaid program is using CDPS-Rx for managed-care contracts with health plans and Adjusted Clinical Groups (ACGs) for direct contracts with providers. ACG is also used to determine health home enrollment for Medicaid populations. It is also common for ACGs to be used for determining risk for commercial populations in the market.

Organization 6 chose HCCs in part because they are publically available; however, it is still examining commercial groupers such as ACGs. In an effort to account for complexity beyond medical diagnoses, the organization is conducting experimental modeling using sociodemographic factors. Third-party actuaries are using CDPS-Rx to measure changes in risk and revenue within or between populations. These models are not yet in operation in the EMR for care coordination.

The HCC model stratifies patients into extreme-, high-, rising-, and low-risk strata. Care coordination is focused on the extreme- and high-risk populations, many members of which are Medicaid recipients with multiple complex behavioral health and medical diagnoses. Primary-care and home health care staff generally manage the high-risk populations.

The lifestyle-overview survey developed by the state initially for high-risk pregnancy has been adapted to Organization 6's needs. The tool is administered to patients and the data are incorporated into the internal data warehouse. They are not yet collected, from all patients, which limits their usefulness. The organization uses various approaches to add social-determinant data. Its health network collects data on factors such as unstable housing, homelessness, and dependence on social services.

Organization 6 has some innovative models for creatively allocating resources to reduce cost for populations at risk. Paramedics are placed in homeless shelters to assist with triage. There is an “anytime access” clinic for patients to go to when they need medical care, as an alternative to the ED. In the ED, dentistry-pain-management, primary-care, substance-use, and care-coordination services are available. Despite the inability to share

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direct utilization data, a behavioral health and substance abuse indicator is shared to help identify patients with higher risk.

During its work on ED use, Organization 6 discovered that many ED high utilizers have a trusted relationship with their PCP but had urgent-care needs that were often not being met in a timely manner. Radar, a report within the organization's EMR, is used to discover whether a patient in a coordinated-care program has been in the ED and enables interventions to be immediately activated. The state has acknowledged Organization 6 for achieving major savings in Medicaid.

Challenges

The state Medicaid program uses multiple risk-adjustment models. Its health home program has enrollment criteria based on ACG risk adjustment for retrospective total-cost-of-care contracts, and uses a prospective payment model with health plans using the CDPS-Rx model. It is a challenge to determine the appropriate investment in a commercial risk-stratification model when there are multiple models used by the payers. In addition, payer-specific modifications to the standard models are often made.

The organization has another challenge with payer claims data. Most of the external utilization from payer claims data are not being incorporated into the internal data warehouse. The organization relies on payers to calculate risk scores across all providers for a given patient. Every payer has unique sets of data and different reporting systems, reports, formats, and measures. In addition, there is a prolonged lag time for Medicaid claims data. Finally, this state's Medicaid program prohibits the sharing of cost data, making it impossible to assess total cost of care.

Health-information exchange cannot inform real-time utilization in the marketplace because HIE is not in real time. Organization 6 built a homegrown system to incorporate inpatient, ED, and pharmaceutical data from outside the system, when available.

Future

The formation of an “administrative uniformity community,” a public-private partnership in which plans and providers agree on common data standards, represents an important first step to resolving issues about payer claims data. Initial tasks include developing standards for how enrollment data would be exchanged in the context of ACOs and a standard format for the exchange of claims data.

A task force is being convened to investigate a standardized set of sociodemographic data elements across Organization 6. Working with Epic in this effort, it is developing an unstable-housing indicator based on patient addresses and data from the homeless shelters in the area.

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Lessons Learned

- Real outcomes in quality and cost improvement can be achieved even if the predictive models are still evolving.
- It is important to proactively address the needs of the Medicaid population using different approaches and resources, regardless of direct reimbursement.
- Investing in payer relationships to help define data-sharing standards to coordinate care is worthwhile.

Organization 7

Background

Organization 7 is a 1,000-bed nonprofit teaching hospital that includes a children's hospital, a heart and vascular institute, and a neuroscience institute. In 2006, Organization 7 created a clinically integrated network with a physician compact, covering 400,000 lives in some level of risk contracting.

Organization 7 has served as a Medicare Shared Savings Program (MSSP) ACO for three years with 50,000 lives and contracts with a commercial insurer under a Medicare Advantage plan for about 5,000 lives. It also has two other commercial risk contracts, and 50,000 additional lives are covered under its self-funded employee health plan.

Individual-Patient Identification

A movement toward population health has been championed by the CEO and supported by the leadership team. A physician compact was developed between the Independent Practice Association (IPA) physicians and the hospital physicians. It forms the underpinnings for the trust and collaboration needed to execute population health initiatives.

Organization 7 has an ambulatory and inpatient care-management approach. The ambulatory groups use risk scores from The Advisory Board Company's Crimson product to identify patients for care management. The inpatient care managers use risk scores from the Cerner EMR to identify patients amenable to readmission reduction. If an inpatient care manager identifies a high-risk patient, an ambulatory-care manager is manually notified about the patient for close follow-up care postdischarge. Inpatient care managers document patient outreach in the Midas+ case-management software. Additionally, failed interventions are documented for root-cause analysis to determine appropriate interventions.

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Both ambulatory and inpatient care managers use high-, medium-, and low-risk-stratification levels. The high-patients correspond to the top 5% patients ranked by cost. The inpatient risk-identification tool uses data in the patient's EMR to assign a risk score for readmission. The risk score is posted in the EMR and is used to develop transition care plans. A health-information exchange incorporates lab results into the score.

Through a partnership with a commercial vendor, a remote-monitoring initiative is used to identify very complex patients. When high-risk patients transition home, they receive a tablet with blood pressure, weight, and oxygen-level monitoring options. Nurses regularly remotely review the data for changes in readings, which trigger patient outreach.

Population-Level Analytics

Organization 7 tests care-redesign initiatives, supported by the physician compact, at the local level. Care-management, ancillary-department, and administrative units represent 57 clinical program committees. The multidisciplinary nature of the initiatives encourages combined clinical and financial perspectives when redesigning care. The redesign committees use population-level analytics to define metrics and outcomes. One successful effort resulted in reducing the cost of implants. Currently, a cardiovascular project is assessing performance with respect to comparative databases, reporting, the use of registry information, clinical and financial outcomes, and infection rates.

Because of the local surplus of long-term-care acute hospitals (LTACHs), Organization 7 targets the postacute-care period. The organization developed a narrow preferred PAC provider network and set of requirements for including PAC providers. A homegrown information system is used to collect quality data from participating PAC providers as a condition for preferred status. Case managers access the facility-quality scores when updating patient disposition. If there is deterioration in quality scores for two consecutive quarters, the PAC provider is removed from the preferred network. Ambulatory-care managers are also required to be able to follow patients in the PAC facility as part of the preferred status agreement. This helps reinforce the plan of care initiated at the hospital at the PAC facility. The PAC provider is encouraged to enroll in the health-information exchange so that medical information can be seen at the PAC facility.

Organization 7 participates in several community-focused initiatives, managing 17 school-based clinics and several open-access dental clinics in underserved areas in the community.

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Outcomes

The employee health plan successfully cut employee health expenditures through a multitude of programs. The remote-monitoring program successfully reduced readmission rates. Organization 7 is actively expanding the remote-monitoring program to also include glucose monitoring. Finally, LTACH utilization for the Medicare population decreased by 50% after implementing the narrow preferred PAC provider network.

Challenges

Care managers use multiple systems for their workflow. The Crimson risk-identification system does not allow easy documentation and follow-up care tracking. Physicians participating in the clinically integrated network use a multitude of EMRs. The goal is to move to one platform for the ambulatory and inpatient care managers, to improve efficiency and effectiveness. Further work is needed to investigate high ER utilization and root cause for readmissions reduction. Readmission penalties, even though not financially impactful, were incurred this year.

Lessons Learned

- A narrow postacute-care provider network can result in enormous savings for a Medicare population.
- Remote patient monitoring improves real-time identification of readmission risk and reduces readmission rates.
- Manual workflow can be used to bridge the connection between ambulatory and inpatient care-management programs. However, systems and data consolidation offers the opportunity to further improve workflow efficiency and patient outcomes.

Organization 8

Background

Organization 8 is a 2,500-bed inner-city teaching hospital system known for treating diabetes and for geriatrics, nephrology, and neurology care. The organization's health system consists of 10 hospitals, has been participating in risk arrangements for more than 15 years, and has 500,000 lives in some type of risk arrangement. A very large care-management unit supports the care-management initiatives and serves as a payer contracting entity. Care managers, social workers, nurses, pharmacists, and psychologists help improve care. The majority of risk contracts are concentrated with Medicare and Medicaid patients, and there is a small number of commercial contracts.

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Individual-Patient Identification

The goal of the care-management initiative is to proactively reach out to high-risk patients to help manage issues that affect patients' quality of life, morbidity, and health care utilization. Organization 8 developed a structural predictive model based on 76 factors associated with high likelihood for increased utilization. The factors include diagnostic categories, behavioral health issues, substance abuse issues, and previous utilization. The model is used to differentiate high-risk from lower-risk groups for intensive care management.

The data model produces lists of patients with uncontrolled chronic illness and high future expected utilization. Following the delivery of these lists to the care-management unit, the care-manager lead distributes patients among the care managers, depending on case load, patient acuity, and care-manager expertise. The care managers establish short-term, medium-term, and long-term goals for individuals. They also track ED, hospital, and primary-care utilization. Once the patient is stabilized and their condition has improved, the patient graduates from care management.

Organization 8 is currently in the process of searching for commercial care-management software to improve this workflow. It has used a homegrown system but now requires more functionality. The information from the care-management unit currently does not integrate into the organization's Epic EMR. Being able to integrate that information is an important consideration in the search for new care-management software.

Population-Level Analytics

Organization 8 uses The Advisory Board Company Crimson™ Advantage product to monitor revenue leakage to other health systems. The level of ACO-network leakage (that is, the number of people leaving the ACO) depends on the subspecialty a patient needs, patient demographics, and patient neighborhood.

Analytics are used for the postacute-care (PAC) strategy to determine how to better partner with a select group of local SNFs for improved patient outcomes. Multiple criteria are used to choose the select group of SNFs, including their ability to provide patient data, their ability to handle certain clinical scenarios, how willing they are to be in contact about specific patients, and whether they accept patients on weekends. Cost was not a central consideration in developing the select SNF network.

Palliative care is a frontier issue for Organization 8. Publically reported mortality rates are lower than they are for other area institutions, and the reason for this is not completely understood. A variety of techniques are used to move the conversation with

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patients about advanced directives from the inpatient setting to the primary-care environment, instead of the inpatient setting.

Validation

The structural model is evaluated against different populations to test predictive power. An annual evaluation is performed to determine whether model coefficients need to be adjusted. The model is stable enough that an annual process is sufficient. False positives are handled through the care-management process. It is common to discover that the contact information is incorrect or that patients are not interested in participating despite the opportunity for them to benefit.

Advantages

Organization 8's managed-care operational efforts started decades ago when it recognized a need for an EMR and developed a homegrown system. The EMR is now in the process of being transitioned to Epic.

The organization has a very successful internally developed predictive analytics system. The early risk assumption prompted homegrown development. An experienced data analytics team developed a product called the Clinical Looking Glass that was able to mine the data in the clinical information system. The product has since been acquired and commercialized.

There are few concerns about EMR fragmentation across providers because the organization employs most of the doctors who participate in risk arrangement. Organization 8 enjoys a large pool of salaried physicians who are experienced in delivering care and participating in risk. There is a robust state HIE and a Regional Health Information Organization (RHIO). These data sources are used to gather patient information about ED and inpatient use. There are plenty of opportunities to use HIE data, despite the current preference for richer data extracted from the Organization 8 Epic EMR.

Challenges

Organization 8 is in the midst of changing its EMR to Epic. Unfortunately, Epic does not have a fully functional care-management product, and another solution is required. In general, the software market for care-management activities is underdeveloped relative to current requirements. One reason may be the health systems' historical preference to develop such solutions internally.

Nonresponders, or patients who do not cooperate with care instructions, represent a central challenge. Organization 8 continues to try to connect with these patients to include them in the care-management process. Some patients have changed phone

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numbers, declined participation, are not domiciled, or are non-responsive to outreach. These patients pose a challenge for medical management.

It is difficult to evaluate the ROI of the care-management intervention since a true comparison group does not exist. One potential solution is to use patients who are on the waiting list as a comparison group. A formal process of ROI evaluation has not been established yet, because the organization needs to focus the analytical resources on the care-management activities themselves.

Future

A newly implemented Epic EMR is adding ways to generate data that will flow into the internal enterprise data warehouse, including claims, clinical, and patient-satisfaction data. Organization 8 is optimistic that these data will help refine the predictive model in the future. Additionally, pharmacy fill data are now integrated into the data warehouse to supplement prescription data.

Semantic data lakes hold promise for allowing an architecture to be created to extract data definitions in an automated and efficient way. Due to the large volume of data generated, this approach is the next frontier for Organization 8. The system will be able to query itself to discover utilization patterns and inflection points over a longitudinal patient dataset. Care managers can intervene at an inflection point before the chronic condition takes the patient on a less favorable trajectory. Ideally, the patient's risk status would be predicted 6 months, 12 months, 18 months, and 2 years into the future so that providers can intervene with, delay, or prevent health care events. However, the patient-identification process will not be fully automated since relevant social data, such as housing, transportation issues, legal issues, and immigration status, still requires a labor-intensive initial-intake-form process.

Key Takeaways

- Begin with any predictive model and refine the model over time. Such models are essential to focusing limited resources on the correct patients. Developing an initial model does not take much effort.
- Social risks are highly important in managing patients. Data collection will likely remain manual.
- There is great opportunity to investigate existing processes and use technology to improve care-manager workflow.

High-Risk-Patient Identification

Strategies for Success

Organization 9

Background

Organization 9 is a 1,500-bed academic medical center composed of five hospitals treating a range of medical conditions including cardiac and vascular, cancer, musculoskeletal, and neurology and neurosurgery care for both children and adults. It combined with its physician multispecialty IPA to form a clinically integrated network (CIN) in 2012.

Through its CIN, Organization 9 manages 200,000 commercial and Medicare Advantage lives under various ACO-like shared-savings arrangements. About 20,000 employees and family members receive care in a self-funded employee-health-benefit plan. The organization participates in three bundles under the Bundled Payment for Care Improvement (BPCI) demonstration project.

Medicaid contracting through the state Delivery System Reform Incentive Payment (DSRIP) Program is under way, with 100,000 lives attributed with a goal of reducing utilization by 25% over the next five years through reduction in ER and inpatient utilization and by using risk-based contracting.

Initiatives

Organization 9 uses a population-health-management (PHM) platform to achieve its five pillars of success under their ACO arrangements: gaps-in-care closure, domestic-network management, out-of-network management, care management of patients in the top 5% of patients ranked by cost, and the recently added fifth pillar, managing high-cost pharmaceuticals, such as hepatitis C treatment.

The PHM platform consolidates payer claims, EMR, and HIE data to prospectively identify the top 5% of patients ranked by cost for care management. The list is first created by sorting the top-cost patients into descending order. Exclusions include patients with nonrecurring medical events or who are likely to hit the stop-loss threshold. Nonrecurring events include infertility treatment, pregnancies, and emergency procedures such as a ruptured appendix. A patient whose care costs reach the stop-loss threshold no longer counts toward aggregate shared savings. The high-cost-patient list is uploaded into the EMR so that internal care managers can determine how to manage the patient.

Other Initiatives

A discharge setting prediction tool developed by another health system and validated by Organization 9 is used to help prioritize patients identified under the BPCI program to measure intensity of need for postacute-care coordination. Clinical validation of the tool largely showed agreement with predicted discharge settings.

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Validation

Clinician validation of the patient lists from the PHM has found some discrepancies. For example, the model is generally overly sensitive, erring on the side of identifying too many patients as high-risk. An internal data warehouse is being used to validate the risk-scoring results.

Organization 9 reported frustration over its PHM solution because it can only select single conditions, and not comorbidities, for risk assessment. To test the impact of this situation and to understand which triggers resulted in high cost, high-cost patients identified as diabetics were analyzed over a 36-month period. The results for the five highest-cost diabetic patients all differed, and the costs were not predominantly driven by diabetes. One diabetic patient had multiple sclerosis that triggered the excess spending, and another had a very long SNF stay for an unrelated condition. This information helped highlight the fact that managing HbA1c alone does not control the total cost of diabetic patients.

Advantages

Compared with other health systems across the country, Organization 9 demonstrates disproportionately higher spending on specialty care but significantly lower spending on inpatient, ER, days and readmissions, which is encouraging to its care managers and providers.

Challenges

Issues surrounding ACO contract construction are a top concern for Organization 9. The confusing patient-attribution methodology used under commercial ACOs and DSRIP make it difficult to prospectively identify whether a patient should be managed. For example, patients who see one of their specialists could unexpectedly be attributed to an ACO. Fifty percent of patients who are attributed to one of their physicians do not receive any services at the organization. It is important to choose a PHM system that is flexible enough to handle state-specific attribution logic. Although payers provide a prospective-risk score for their attributed patients, retrospective risk-score adjustments is another area of great concern, since it could change the financial performance under the shared-savings arrangement.

Organization 9 acknowledges that the savings resulting from their shared-savings arrangements to date have, at most, covered the costs of the care coordinators plus a small fraction of the infrastructure cost. The ROI for predictive analytics alone is not yet compelling.

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Future

Organization 9 is continuing to improve the data sources that are feeding into their PHM and internal data mart, which houses data on a single subject. For example, an upcoming project to connect the HIE to the PHM will result in a more complete picture of patient risk. Additionally, it is engaging with its PHM to implement a cancer registry to better manage cancer patients since spending on cancer care makes up 45% of its total spending. The organization is transitioning to contracts that include upside and downside risk within the next three years.

Lessons Learned

- A thorough understanding of risk contracts helps identify process and system issues early on in order to optimize financial outcomes. For example, attribution logic is a fundamental piece of patient-outreach identification because scarce clinical resources should not be wasted on patients who are relatively healthy or not truly attributed to the organization.
- A strict validation process, especially when implementing a population health platform, is critical for the long-term success of initiatives guided by the tool.
- A combined internal and external data approach retains the flexibility to discover root-cause sources for high cost while operationalizing predictive models.

Organization 10

Background

Organization 10 is a nonprofit 500-bed teaching hospital, an integrated delivery network, with eight hospitals and 2,500 employed and community physicians. In addition, the system has a large CIN.

Organization 10 manages about 200,000 lives, with decades of experience in participating in risk, participating in fully capitated Medicare Advantage, shared risk with Medicare Advantage, as well as a Track-1 Medicare MSSP ACO. The organization manages a self-funded employee population that is fully at risk (that is, at very high risk) and has risk-sharing arrangements with all the large commercial payers in the region.

Programs of Care

The organization has a variety of initiatives in place to improve care and reduce cost. Each uses its own patient-identification approach, with reliance on both an automatic prediction tool and clinician judgment. In general, the organization does not focus primarily on predicting medical spending for determining which patients will likely

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benefit from each program; it uses a clinical- and sociodemographic-identification approach.

There is an initiative to control readmission risk. The 3M APR-DRG is used as a severity-of-illness (SOI) indicator to triage patients and get them the appropriate resources. If a patient is rated as the highest severity, then they are excluded from the standard readmission intervention since they are likely too far into the disease progression to benefit. Instead, they are assigned to complex-care management or palliative care for an aggressive readmission-risk-intervention program.

The readmission-risk program focuses on a follow-up phone call and risk evaluation within two days of discharge, including weekends. Depending on the patient's risk, they may qualify for a regular primary-care follow-up appointment or a priority clinic. The priority clinic offers a 60-minute appointment with a more comprehensive follow-up assessment and medication reconciliation. The program has resulted in readmission rates as low as 6–8%.

Organization 10 has a sophisticated outpatient complex-case-management program. The identification process begins with standards for all high-risk patients in which a medical assistant collects a Patient Health Questionnaire-2 (PHQ-2), performs a fall-risk assessment, and ensures that a completed state-mandated advanced-directive form is built into the EMR before the physician enters the room. In addition, patients are identified using clinical information sources to indicate multiple chronic conditions and/or polypharmacy. Then patients are identified using the Johns Hopkins ACG system, informed by the clinical parameters, to further select patients suitable for care management. A new program for palliative care is committed to offering patients the right palliative care, not just end-of-life care, with a goal of reduced inpatient, ED, and SNF utilization, inappropriate drug use, and better quality of life.

One of Organization 10's commercial risk products is a model program for strong payer-provider collaboration to better identify high-risk patients. Instead of relying on patients or providers for previsit planning, the care-coordination team has a weekly call with the payer. The organization sends the payer an appointment list on a daily basis for upcoming appointments. The payer then matches the appointment information to claims and other patient information to help identify the patients who should be targeted for increased resources. A weekly call is used to discuss the upcoming patients with psychosocial issues or other high care-coordination needs. The care coordinators notify the physician to gather more information on these patients. Additionally, care coordinators are sent to the physician's office to help with the burden of collecting the information and providing direct intervention.

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To close patient-care gaps, Organization 10 physicians have designed a high-patient-value alternative to the Medicare Annual Wellness Visit. During a 60-minute appointment, an advanced practice nurse (APN) collects information for a health-risk assessment, including psychosocial and clinical data. In addition to the value to patients of informing the clinicians, more accurately documenting diagnoses annually means that the risk-adjustment factor (RAF) will more closely match the actual risk of the population.

Advantages

Organization 10 has a large information services department and a rich history of homegrown solutions. For example, they developed an in-house EMR that was used for two decades before meaningful use regulations forced the move to a commercial EMR. The organization is working to integrate utilization risk models provided within the EMR. The EMR company employs data scientists who are developing ED-utilization predictive models. This work is preliminary and limited to data contained within the EMR at this time.

The hospital does have an enterprise data warehouse (EDW) that accepts payer claims data to supplement EMR data. Also, in addition to multiple commercial tools, flexible analytics tools such as Tableau and QlikView are used to perform custom analyses. Organization 10's EMR provides useful point-of-care tools to alert physicians to close gaps in care. However, these tools are limited because they can only alert users on the basis of the portion of data contained within the EMR. This is often only 50% of encounters due to heavy patient leakage.

Challenges

The main challenge is connecting all the clinical data sources across the CIN. Establishing a master patient identifier across disparate data sources is another daunting challenge. The organization's hospital and other providers have a 50% network leakage rate (that is, 50% of patients leave or utilize services outside the network every year), necessitating the use of payer claims data. The deficiency of information in the payer claims data about metrics such as BMI, blood pressure, and lab results limits the usefulness of those data. Organization 10 acknowledges the value of using socioeconomic data to identify patients who would benefit from care management. However, the burden of collecting these data currently falls on physicians' offices, where staff must collect the data manually.

Organization 10 states that it would be lightyears ahead in improving patient care if the issues of interoperability were solved for the 30-plus EMR systems in its CIN.

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Future

Organization 10 is hopeful that a commercial HIE and analytics platform will provide connectivity across the entire CIN to help guide patient care. The first step is to connect all hospitals to the state HIE. The second step is to connect all physicians to a private CIN-wide HIE.

The organization is preparing for the transition to the comprehensive care for joint replacement (CJR) program. It is currently not a bundled payment participant and is seeking third-party help with administering episodic payment.

Key Takeaways

- Each care initiative has a tailored patient-identification approach.
- A hybrid manual-automated approach is currently used to identify patients for initiatives, which slows progress.
- Partnering with payers for care coordination has yielded improvements in the identification of high-risk patients. However, the process is currently too manual to be expanded beyond a small population.

Organization 11

Background

Organization 11 is an ACO that provides a platform where independent physicians work together to improve care for Medicare fee-for-service beneficiaries and commercial patients. The organization has enrolled physicians from several IPAs, was developed by and for physicians, and is aligned with the patient-centered medical home (PCMH) efforts. Organization 11 participates in Track 1 of the MSSP, and it has more than three years of experience. The organization and its key partner manage more than 90,000 Medicare beneficiaries and 200,000 commercial members in ACO contracts.

Interventions

A patient-centered medical home model and its “team” concept of care are used to identify gaps in care and increase patient contact. Practices designate an ACO clinical coordinator(s) from their own staff. A per member per month (PMPM) care-coordination payment helps support the hiring of additional staff and cover upfront costs. The care-management fee is dependent on the quality score.

Quarterly, Organization 11 uses a risk-stratification model to identify rising-risk and high-risk patients. Physicians are responsible for the highest-risk patients and work closely with their clinical coordinators and specialist colleagues. The list of high-risk,

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vulnerable patients is limited to 10 patients per payer per physician within the practice; all high-risk patients are noted on the list, as well. The member's diagnosis and risk score is included in the report along with potential patient interventions including developing a customized patient-care plan, referring patients to case managers, using centers of excellence, and creating an advanced-care plan. ER-high-utilizer-patient lists are distributed to the ACO practices quarterly, and potential management interventions are also distributed.

Care managers support a program for hospital-readmission prevention involving a readmission-risk-assessment tool, and they can view patient care across multiple data and information sources, including access to Smart View (McKesson Risk Manager) containing patient diagnosis, medication lists, problem lists, recent ER visits, inpatient visits, and cost of care. To help coordinate care and educate patients about self-management, patients at high risk for readmission are aggressively followed by phone for 30 days.

The organization's software solutions include McKesson Population Manager (disease and patient registry) and Risk Manager (financials and analytics). The McKesson Performance Manager, an inpatient hospital system, is being combined with the ACO applications within McKesson Explorer to provide another level of analytics and reporting. The regional HIE is used to notify providers about patient hospitalizations in real time and provide access to utilization outside the organization's walls.

One of the main educational and support tools provided by Organization 11 is its weekly webinars, where physicians and their care teams are invited to learn population health topics and share their best practices. Topics include how to identify rising-risk patients, evidence-based care guidelines, feedback surveys, risk scoring, quality measures, group practice reporting option (GPRO) reporting, and how to use the patient registry to manage gaps in care.

Outcomes

Organization 11 has been very successful with both quality improvement and managing costs of care. A critical metric reveals that its primary-care providers have a 35% higher "primary-care visits per thousand" than the ACO MSSP national benchmark. This allows more opportunities for managing gaps in care and establishing strong physician-patient relationships. These relationships produce ACO costs of care 4–5% below CMS benchmarks each year.

Another critical lesson is that physicians need to engage in population management. Predictive-modeling tools, case management by phone, and advanced analytics are

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necessary, but the hard work is redesigning health care delivery between the physician and the patient.

Challenges

It is important to perform due diligence on all ACO vendors to see whether they can deliver results. Use KLAS or other comparison organizations and talk with other organizations that have used them.

The MSSP ACO attribution methodology is extremely challenging and results in a 20% annual churn (turnover) in attributed patients. Another challenge is 45% network leakage that needs to be managed because Medicare members are allowed to seek care on their own.

Commercial payers have many different formats for data exchange, and the usefulness of the information they provide is variable. The difficulty is standardizing the data to present to practices in ways that are meaningful and helps improve patient outcomes.

Key Takeaways

- Data and analytics are critical to the change process, but intelligence must be combined with passion to produce sustainable change in health care delivery.
- In designing any report, tool, or resource, start with the patient. Make sure “form follows function” and not the other way around.
- Organization 11 has effectively self-produced weekly webinars to educate physicians, their staffs, and care managers. These have been both useful and popular.

Organization 12

Background

Organization 12 is a physician-owned ACO established to improve patient experience and population health and to decrease cost. There are 400 physicians and 200 allied professionals and affiliates in the network and 100,000 attributed lives in Medicare Shared Savings Program (MSSP) ACO and commercial arrangements.

Initiatives

The physician-led model targets the lack of PCP access and consistent patient follow-up visits, improving referral management, reducing “familiar-faces” visits to the ED, and better managing postacute-care utilization.

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A combination of homegrown analytics and commercial solutions is used to support initiatives. Organization 12 selected the commercial tool created by Storan Technologies due to its ease of use and compliance with Medicare guidelines. Actionable physician performance reports are produced to show physicians their current performance and identify opportunity for improvement. For example, the tool shows doctors the financial impact of a high-dollar home-health visit and describes nursing-home risks. The organization identified one practice that closed on Fridays, resulting in a lack of PCP access and increased ED utilization. Internal ACO consultants deliver reports to the physician offices using face-to-face meetings rather than by mail or an online portal. An upcoming disease-management project includes diabetic patients with HbA1c > 9% and LDL > 100 mg/DL to increase adherence to medications and primary-care visits. Early reports show that chronic patients are not being seen enough in their patient-centered medical home (PCMH).

Storan uses a classification for ED cases involving two or more ED visits in the past 12 months. Physicians can input data on root causes of unexpected utilization, their awareness of the patient's after-hours-care use, their knowledge of the patient, and the patient's short- and long-term-care plans, access to medications, and mental health conditions. The real-time ED notification provided through a state HIE is indispensable for controlling excess ED utilization.

In-house Structured Query Language (SQL) programmers are used for customized reporting. Information is loaded into the GPRO and exported in XML format for analysis. Organization 12 has found that an iterative approach, starting with claims data and then adding more advanced data sources, is best.

The network of primary-care practices is on 20 distinct EMRs. However, 80% of practices are on only five EMR systems—eClinical Works, Practice Partners, Practice Fusion, Care360, and Greenway and Vitera. The biggest challenge Organization 12 has found is not which EMR is in a practice but ensuring that physicians make full use of the EMR to support quality. One way that ACOs can fail is to try to connect all the EMRs in the beginning.

Outcomes

Organization 12's ACO has achieved MSSP savings for two years in a row. It describes high patient satisfaction and quality scores. Attributed lives have grown dramatically, from 37,000 to 60,000 lives. The success of MSSP has attracted commercial payers interested in contracting. Better predictive modeling would be useful, but the financial outcomes were achieved by first addressing the most critical administrative-process issues.

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Advantages

Using simple methods for identifying patients for care management creates an easier and less expensive process than using more complex methods. Organization 12 is comfortable with using its current model combined with Storán Technologies to produce actionable plans.

Challenges

There are concerns about the attribution process. The ACO is graded based on former patients rather than on current patients because of the retrospective-attribution rules.

Key Takeaways

- Some ACOs fail because they buy a large, expensive system at the beginning instead of taking an iterative approach to predictive modeling.
- Data are not as exciting as anecdotal information but are much more useful. ACOs can be misdirected by anecdotal stories and assumptions.
- Administrators cannot monitor what they cannot measure.
- High-performing physician ACOs should be recognized and rewarded for their efforts.

Organization 13

Background

Organization 13 is a nonprofit health care system that includes community and specialty hospitals, a managed-care organization, a physician network, community health centers, home care, and other health-related entities.

Organization 13 has been a Medicare Pioneer ACO since 2012. There are long-standing contracts with HMO, point-of-service, and PPO health plans, including the Alternative Quality Contract executed over a decade ago. Organization 13 serves a large low-income and Medicaid population in a risk arrangement. About 60% of patients seen within the primary-care practices are in a risk arrangement.

Individual-Patient Identification

The organization developed several analytic tools internally for the long-standing risk contracts to better understand cost, trends in utilization patterns, and potential interventions. These tools are based on claims data from commercial and public payers.

The organization participated in a high-cost Medicare demonstration project that was the precursor to the Medicare ACO. The demonstration project involved a nurse care

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manager who worked closely with a primary-care physician to manage high-cost patients. The success led to their interest in becoming a Medicare Pioneer ACO.

Unlike the demonstration project, in which all patients were high-risk, the Medicare ACO contains a mix of patient risks. To use the same collaborative nurse-care-management model in the primary-care practices, a patient-risk-identification model was needed. A hybrid model was developed to identify patients appropriate for care management. Organization 13 uses administrative claims data to identify a pool of patients with multiple chronic conditions and potentially suboptimal utilization patterns. Primary-care practices then review the list of potential high-risk patients and identify those who are appropriate for care management. Primary-care providers may also refer additional or new patients at any time.

The risk-identification model is designed to identify patients who have a longitudinal need for care management, such as those patients with multiple chronic conditions. Accidental or acute high-cost events are excluded from the model because they are not manageable events, and cost generally declines over time. Lists of potentially high-risk patients err on the side of overselecting patients. The subsequent removal rate is about 40–50%. The patients are removed for various reasons, including administrative removal for patients no longer attributed to the practice. Administrative removals occur before delivering the list to the physician. The clinician is asked to make two determinations: 1) whether the patient is actually high risk and 2) if they are, whether they would benefit from the primary-care-based care-management program. Lists of potential high-risk patients include information on why a patient was identified, such as the patient's chronic illnesses, which utilization areas were triggered, or set off, and the patient's prospective-risk score.

The claims data tell only part of the story. Sociodemographic elements can affect patient risk and the ability of patients to manage their care. For example, a very sick patient who is wealthy and well-resourced may not need a care manager. There are also patients who are very ill but have plenty of specialty support, such as cancer patients. Organization 13 is in the process of implementing the Epic EMR and has begun to systematically collect sociodemographic information.

The hybrid patient-identification process was developed to help give nurse care managers and primary-care physicians a degree of control over the selection and management of their patients. Clinical judgment supplements the model, given the lag in claims data. The considerable autonomy provided allows care managers to triage a patient based on the patient's intensifying or resolving needs and the urgency of intervention. The hybrid

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model has been reviewed and improved in the past and will continue to evolve as new data become available.

Population-Level Analytics

The evaluation of care-management initiatives is very important for designing and tweaking initiatives. However, there are analytical complexities such as regression to the mean—for example, patients who get better on their own after an acute event. Other complexities include allowing enough time for the effects of the program to occur before it is evaluated. Ideally, a randomized-control group would be used to estimate the savings resulting from an initiative. A proxy-control group is composed of those patients who refused to participate in the program.

A multitude of patient comparison groups is used for assessing an intervention. All patients, high-risk patients identified by the algorithm, and patients who refuse intervention are used as comparison groups. The organization notes that patients who refuse interventions may improve on their own but rarely sustain improvement.

Advantages

Although they are lagged, claims data received provide a broad picture of the services received both inside and outside Organization 13. The geographic area is saturated with both community and academic hospitals. Ambulances can take patients to any number of hospitals, so it is important to use claims data to see the patients' full profile of care.

Challenges

HIE data have been explored as a way to provide a complete patient picture in a more real-time fashion, but there are issues with the data definitions and integrity. For example, GE Healthcare's EMR is highly customizable, and despite all community practice data being centralized in the HIE, a huge effort is required to standardize the data fields across different EMR versions. Additionally, data are unstructured and text-based, which means they are more labor-intensive to analyze than structured data. Since the system is paying for care-management resources, fair and equitable allocation of care managers across primary-care practices is a key objective that could not be supported based solely on HIE data. It is crucial not to disadvantage a practice just because its clinical data are not as easily integrated as another practice's data.

The challenge with Medicare beneficiaries is maintaining relationships with existing patients as their acuity increases. Since they are elderly, have multiple chronic illnesses, or have a pattern of going to the ED or having multiple hospitalizations and seeing many doctors, they likely need more support to manage their illness than people who are not on

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Medicare. The concern with chronic-disease management is less about primary-care practices being unaware of patients and more about coordination across sites of care.

Future

It is unlikely that a completely claims-data approach will be used for patient assignment to care-management programs. Organization 13 believes that it is important to keep the clinicians involved, and allow them to override the prepared list if they believe that one of their patients has an overwhelming need.

As part of the move to the Epic EMR, newer clinical data sources, such as problem lists, lab data, family history, and sociodemographic information, may provide faster risk identification, but it is currently limited to the data within Epic. Additionally, Organization 13 is hopeful that quarterly patient identification can be achieved more often through delivering lists directly to PCPs embedded within the EMR.

Another opportunity is to better match the level of risk to the level of professional resource. For some patients, community health workers and social workers can make an impact, and a nurse care manager is not needed. An assessment is used to determine who the best single point of contact is for the patient.

Key Takeaways

- A hybrid algorithmic and clinical approach to patient identification for primary-care-practice-based-care management helps
 - Encourage physician ownership
 - Incorporate nonelectronic data such as sociodemographic factors
 - Overcome lagged-data issues by making predictions earlier
 - Use a clinical sense of urgency to schedule high-priority patients for limited appointment spots
- A robust evaluation process along with iterative testing helps improve the chances that a care-management initiative will be successful.
- There are other analytical questions beyond how to target the right patients, such as how to match patients to the right care-management resource and how to determine the right time for stopping care or graduating patients.

Organization 14

Background

Organization 14 is a 600-bed teaching hospital, world renowned in cardiovascular medicine and surgery, organ transplantation, neurology, neurosurgery, and cancer diagnosis and treatment.

High-Risk-Patient Identification

Strategies for Success

Thus far, the organization has taken a gradual approach to risk-based contracting. Most commercial payers and contracts are fee for service. There is a 40% commercial-payer mix. Organization 14 participates in a commercial fee-for-service plan with quality-performance objectives. There are also direct-to-employer contracts with cost-control expectations, and some employers have Organization 14 health clinics onsite.

Organization 14 has been engaged in a university- and hospital-employee ACO model. A Medicare Advantage plan is now offered as well. Although Organization 14 is not a participant in BPCI, one of the hospitals is in the Comprehensive Care for Joint Replacement (CJR) program.

Initiatives

Organization 14 is pursuing a homegrown approach to managing risk under alternative payment models. It is designing episode-based clinical pathways for several medical and surgical bundles. Direct-cost, quality-measures, and risk-stratification models are being custom designed. The entire process is physician led. At this time, physicians are not provided with monetary incentives but are motivated by learning and the opportunity to publish results.

As episodes of care are expanded, considerations are made about which interventions are needed in person and which could be delivered digitally. Alternative modalities such as phone and video are being explored to understand how to best scale visits. The organization believes that both panel size and doctor efficiency can be optimized through the use of digital health.

Analytics Use

A commercial population-health-management vendor platform is not currently being used but will be in the future. Desired traits include:

- Identification of coding opportunities because severity is not being captured adequately
- Care-management functionality that has registry and recall function so it is clear which patients to reach out to and which patients lag in preventive care
- The flexibility to define custom metrics
- Risk stratification
- Integration and overlap in the EMR for all these requirements

A central enterprise data warehouse captures only the care at Organization 14 facilities. It is used to capture clinical data from the EMR for designing pathways. An internal clinical integration team is developing algorithms for patient stratification by disease.

Commercial tools are not used beyond 3M's APR severity-of-illness score (SOI) or

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Charlson or Elixhauser scoring methods for chronic conditions. The use of hierarchical condition categories, or HCCs, is being investigated but has not been widely implemented.

Risk modeling during an acute episode is used to model patients at risk for sepsis and death. Composite triggers were identified and built into the EMR at point-of-care to fire alerts directed toward physicians. A project for identifying cost outliers and repeating this process for other conditions is under way. Various acute-care surveillance models have been developed but are not yet implemented in the registry or EMR.

Challenges

Alternative payment models designed by CMS or insurance companies present multiple challenges for Organization 14. The cost of necessary specialists and standby physicians are not incorporated into the proposed payment models. Organization 14 does not own postacute-care services, which requires other forms of relationships for managing care and costs with facilities separate from the organization. Finally, standard risk-stratification methods do not adequately compensate for the complex cases managed at this organization.

Lessons Learned

- Physicians can be motivated by learning and scientific achievement and research to take ownership and develop innovative episode-based payment models and quality measures.
- Digital health may be a promising way to redesign care and reduce the cost to patients, recover physician time, and increase value.
- Organizations in heavy fee-for-service markets may lag behind in implementing risk-based models yet also have the opportunity to develop innovative ways to manage cost and care.

Organization 15

Background

Organization 15 is a partner in more than one ACO in several large states and focuses on the Medicare population. The organization's ACOs are primarily physician-led and of medium size.

Individual-Patient Identification

Organization 15 primarily uses a homegrown approach to predictive-risk modeling for assigning patients to care coordination. A predictive model was developed internally to

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help with assigning daily work lists to care coordinators. In addition, a modified version of a commercial platform for population health management is licensed for optional use by the participating ACOs. Organization 15 has a growing relationship with an analytics service vendor to periodically analyze, through machine learning and advanced analytical techniques, anomalies observed in the data.

The internally developed mathematical risk model weights each type of admission the same. It assigns a score from 1 to 100 by using linear regression informed by the past number of admissions and emergency room visits. A cutoff score is established as a high-risk threshold for patients requiring care-coordinator attention. Due to care-coordinator constraints, the rising-risk patients, who are not considered among the highest risk, do not receive focused care management.

Instead of identifying high-cost patients, Organization 15's overarching goal is to identify those cases in which management makes a difference. A **practical, focused** approach is taken to narrowly identify high-impact diagnoses and DRGs. The focus is on high-cost conditions, such as chronic kidney disease, that have a predictable progression. There is an additional focus on DRGs based primarily on symptoms, such as syncope, chest pain, and nausea with vomiting, which are imprecisely defined. Patients with these DRGs are more likely to be readmitted since the root cause for admission was not found.

The internal risk model was developed through their data warehouse. The data warehouse loads claim line feed files, ADT events, and lab feeds. Paid claims data are refreshed monthly for the ACO. The risk model is not integrated with the individual physician practice EMRs. Instead, prioritized lists are electronically loaded into an internal case-management system with minimal functionality. Care coordinators can perform outreach and schedule patient interventions from the case-management system.

Organization 15 believes that it is important to focus on what will be done after the patient is identified, who will intervene, and how that person will be held accountable. Every patient identified by either the mathematical model or through expert determination is subject to the same multistep care-coordination process. Care coordinators are trained in motivational interviewing to achieve desired behavior change.

Validation

Model validation through identifying false positives and false negatives is not formally performed. The intervention process itself partially corrects for a high false-positive rate. After the patient is contacted, the first step in the care-coordination process is to use care-coordinator judgment to determine whether outreach will be impactful. If the care coordinator determines that it will not, the outreach ends, saving resources for patients who will most benefit.

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Outcomes

Organization 15's ACOs collected savings at a rate higher than the nationally expected rate. The organization attributes little of the success to the risk-identification model. Instead, practical issues such as attribution management, annual-wellness-exam compliance, and risk-score accuracy and use seemed to impact ACO financial performance the most.

Future

Despite the current focus on model application and clinical execution instead of model accuracy, Organization 15 does believe there is value in increasing model accuracy for future efforts.

There is an initiative to increase social-worker resources available for care-coordination referral. Social workers can be used to best support patients with resolving social barriers, and then later, they can focus on important clinical goals.

Lessons Learned

- An approach combining algorithmic and expert judgment is used to select patients for care coordination. Currently, only the highest-risk patients are selected for care coordination.
- There is a focus on the application of a balance between the focus on the risk model and the commitment to help build meaningful relationships with patients to make a difference in their lives.
- An overly sensitive patient-identification model can be corrected during the initial stage of the care-management patient-outreach process.

Organization 16

Background

Organization 16 is a 1,000 bed teaching hospital and a clinically integrated network, currently focused on episode-based payment models. It is participating in multiple-care episodes for 80,000 to 100,000 covered lives. There are mandated episodes of care in Organization 16's state's Medicaid program, and they participate in BPCI. They are also engaged with commercial payers for several pay-for-performance (P4P) contracts.

Population-Level Analytics

Organization 16 has limited resources, and instead of tackling every opportunity for care and performance improvement, it is focused on the biggest opportunities. It uses a risk model to identify populations that should be targeted. To help with patient identification

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for population health initiatives, such as chronic care management, it uses commercial tools. An integrated clinical, financial, analytics, and quality team collaborated to develop a homegrown population-prioritization tool. The tool uses a mix of quality and cost measures. The goal is to improve and reduce the cost of care regardless of payer.

The prioritization tool is designed to allocate limited resources to the populations and clinical areas in which the resources will have the highest impact. It can be used for other applications, too, such as benchmarking, assisting with payer contracting, and pricing bundles. There have been several iterations of the tool to date.

The foundation of the prioritization tool is the definition of bundles and their DRG mapping. It is expected that the CMS and state episode definitions will vary somewhat. Alterations can be made to map between the two. Additionally, proactive contracting with commercial payers is under way.

When the bundles are identified, a scoring framework divides the patients into six categories. An internal decision-support system, fueled by cost-accounting data, incorporates internal hospital costs into the model. Detailed charge-level information, as well as non-charge-based supplies and drugs, are used to feed the analysis. The variable direct cost of care is related to controllable direct cost, such as physicians' ordering patterns and the efficiency of delivering services. Case-mix-adjusted coefficient of variation is used as a measure of variation within and across populations. A high degree of variation indicates that there is an opportunity to investigate the source of variation and whether it is modifiable.

Aggregated Medicare claims data are used to estimate the percent inpatient spend for a given bundle. Claims data are used to understand how much of the episode is attributed to the acute encounter and is controllable. A 10-point scoring scale is assigned to each episode in each category along with category weights. For example, the highest weight is applied to the Medicaid cost category since it is a mandatory bundle. All scores are then extrapolated for each episode, and episodes are sorted. The ranking is presented to an executive committee and clinical audiences.

Care Redesign

After population risk has been assessed, analyses are done to determine root causes for variation in care. Physicians are engaged in care-plan development.

Improvement to rates of making follow-up phone calls was first tested using a single nurse outside the clinic. The nurse allowed 45 minutes to prepare for the call and another 30 to 35 minutes for the call. For comparison purposes, a phone-call process was tested with a clinic nurse who knew the patient she was calling prior to the call. Preparation for

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the phone call took only 10 minutes, and the patients reported that they appreciated knowing the nurse who was calling; care gaps were closed more rapidly than when there was no call or when the call was made by a nurse who did not know the patient. Recognizing that what works in one location may not work in another, the testing process is revisited for each new location.

There has been an effort to reduce heart-failure readmission over more than five years. Incorporating social determinants into planning interventions is a challenge, but Organization 16 is exploring the use of this information to focus its interventions.

Challenges

Providers at other hospitals may be assigned patients in the Medicaid perinatal bundle, but those patients may seek care at the Organization 16 medical group. The medical group must then work with those hospitals to achieve the high-quality care at the right cost. Much care is provided outside the direct control of the hospital, without available patient-level data. Bundles with cost concentrated heavily in SNF, rehab, and home health are less easily controllable.

There are multiple challenges with payers. Medicaid has not yet identified all episode definitions. The postacute portion of the episode is a struggle due to payer data availability and lag.

Organization 16's medical center uses a homegrown EMR and is in the process of planning for an Epic EMR implementation. It is also implementing an HIE across the network to bridge the gap.

Finally, the modeling work is being done as the cost-accounting system is being transitioned, causing operational challenges for the model.

Future

The prioritization tool will be refreshed on a monthly basis to help support more frequent goal-setting. Hospital internal data sources that can serve as a proxy for postacute cost will continue to be explored.

Lessons Learned

- An episode-of-care prioritization tool is used to rank population-level opportunity for different bundle configurations.
- In addition to internal cost modeling, qualitative considerations, such as physician input, are used to rank bundle risks.
- Once an opportunity is identified, testing is critical to the correct implementation of an intervention.

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Organization 17

Background

Organization 17 is an integrated system that operates 1,000 acute-care, rehabilitation, and psychiatric-care beds; outpatient services; and community health centers, with 2,500 employed physicians including 158 primary-care physicians.

They participate in the Medicare Shared Savings Program (MSSP) through a regional ACO. Organization 17 participates as a track one MSSP ACO and just completed its first performance year. Of the more than 30,000 lives in the ACO, almost half are attributed to Organization 17. It will enter into Medicare Advantage in 2016.

Individual-Patient Identification

Organization 17 implemented care-navigator and care-gap-closure programs and annual wellness visits. Each provider member of the ACO is responsible for local implementation of care-improvement programs, even though some tools are provided to all ACO providers. One example is a highly customized version of the Lightbeam web-based, population-health-management platform. A data-visualization layer allows participating providers to investigate ACO-wide financial and utilization-trend benchmarks to identify areas for improvement.

A combined risk-stratification approach through Lightbeam, a school of public health science, and Epic Healthy Planet is being used to identify individual patients for care navigation. The combined approach is used because a single perfect tool has not yet been found. Through the ACO, Lightbeam provides Johns Hopkins ACG risk scores based on CMS claims data and impactability scores. The risk score is mainly a cost multiplier. EMR data have not yet been connected to the solution to drive the impactability score or validate quality measures. The John's Hopkins impactability score will help RN, CNA, and pharmacists identify which patients need their care and whether the foci are clinical, social, or pharmaceutical. Impactability is an important objective for modeling and is partially driven by social-determinant data. The Centers for Disease Control and Prevention has shown that zip code is more indicative of health care utilization than disease state, which is especially true for dual-eligible and other high-risk patient cohorts. Organization 17 engages in a community partnership for resources such as transportation and housing. It is exploring new sources of data such as credit scores, Charlson comorbidity score, and out-of-network score on the Lightbeam patient list, as well.

Organization 17 has a division of public health science that has worked together with clinicians, data scientists, and statisticians. Its projects will help to better use the claims data aggregated within the EMR to improve the risk segmentation and identification of

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patients who could be affected. The research-data-science team plans to import claims data to produce a risk score that can be used to numerically segment the data based on clinical, lab, utilization, and comorbidities. Cost and network utilization would be incorporated as well. The thresholds for different risk strata have not yet been determined.

Staff from population health, IT, and analytics are collaborating on building an internal data warehouse. They are building a data lake and repository to store EMR and payer data for identifying patients. Additionally, the internal data warehouse will be used to monitor and evaluate programs in real time. Senior leadership agreed to capitalize on the clinical research assets available to them as an academic institution. The advantage to using a homegrown data warehouse is that researchers can drill down to the lowest level of the data to find root causes. This information is used to objectively inform care redesign.

High-risk patients are ultimately determined by each practice. A practice report with the ACG and Epic's Healthy Planet score is delivered to the care team to guide patient outreach. The risk score is based on certain conditions, such as living alone, transportation issues, and ED and IP utilization. A registered nurse navigator and their team use the data to meet with the provider team to confirm the opportunity. The data are instrumental but must be used in tandem with provider expertise. Identifying provider champions who can devote their time is crucial to program success. No provider-level incentives are awarded for this activity since they are still reimbursed using a relative value unit (RVU) compensation model.

A transitional-care-management program began with the CMS Community-based Care Transition Demonstration Program. Organization 17 partnered with Blue Cross Blue Shield (BCBS) to target high-readmission-risk patients for a home visit and PCP follow-up visit within a 7–14-day window. One staff member searched reports daily and manually triaged patients to the correct team.

Organization 17 now has a readmissions-reduction program using an algorithm that takes into account more than three IP or ED visits in the past 6 to 12 months. Many patients are ESRD and dual-eligibles who are in the ACO's top-tier risk score. Currently, inpatients are monitored daily. If the patient belongs to the ACO, they will be seen by a physician during hospital rounds, contacted by a nurse or social worker before discharge, and have a follow-up PCP appointment scheduled between 7 and 14 days from discharge.

Population-Level Analytics

There is a strategic care-improvement initiative across all quality metrics, including the GPRO, Healthcare Effectiveness Data and Information Set (HEDIS), and Medicare

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Advantage Star Ratings. The Epic registries are used to drive aggregate identification. This ensures that primary-care providers have a standard workflow when a pharmacy or education consult is needed. Quarterly ACO reports are built by combining data in Healthy Planet registries. Eight to 10 chronic-disease registries are being used to help drive workflows and automate ordering within Epic for the Organization 17 providers within the regional ACO.

Pilot models are being designed to tackle high-risk patients. Reductions in ED and inpatient admissions are sought by identifying patients with major behavioral health, cognitive, or substance abuse that affects their ability to adhere to the care plan. Another high-risk population identified through the pilot process is the one requiring end-of-life care. Patients are often not converting to palliative or hospice care and continue to be high utilizers of acute services.

A successful postacute-care initiative including a preferred network of five SNFs began two years ago. One SNF excels at high-risk patient care and for dually eligible patients. The success is attributed to a strong relationship between medical directors at the SNF and at Organization 17. The SNF installed a subacute unit containing 8 to 10 beds that medical staff from Organization 17 can use to reduce readmissions and also for provider training purposes. Data sharing with SNFs is still a struggle. Another postacute-care improvement initiative is through a Gentiva home-health joint venture. Again, the medical director has a strong relationship with Organization 17 staff. Workflows and care models for COPD and CHF disease states were implemented so that higher-acuity patients can be managed successfully.

Model Validation

It is early in the process to evaluate whether the impactability score is consistent with the patients who actually benefitted from care management. The internal data-science team will be used to incorporate more evaluation on the implementation side and outcome evaluation for interventions in hopes of improving quality metrics and reducing utilization.

Challenges

There are consistent care-navigation and care-gap-closure models across the regional ACO, but the Epic registry is not centralized. Each provider adapts the programs to their own EMR and process. The Epic registry is limited to the patients who are being managed within the primary-care network.

Automation is still a challenge. The IT team is currently trying to automate ACO reports. Currently, there is a manual process to run the reports in Lightbeam and send them to

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each practice's navigation team. The ultimate goal is to have more reporting embedded in the Epic EMR through Healthy Planet so that the navigation team can identify high-risk patients directly from the EMR.

The Lightbeam tool generally meets requirements. There were issues with defining MSSP retrospective-attribution rules. Also, the tool does not allow detailed drill-down to discover the root cause of why patients are high utilizers, which could inform care redesign.

Key Takeaways

- Academic medical centers can use their own academic data-science and statistical resources to help build models.
- A combination risk-stratification approach is refined by using clinician input.
- Attribution should not be overlooked because of the importance of knowing who is actually managing patients. Attribution management is a more complicated process than widely believed.
- When initiating your ACO, should start simple with using data. Care improvement is an iterative process. There needs to be a way to risk stratify patients so that PCPs can use it as a starting point for conversation about engaging patients, but it does not need to be perfect.

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SUMMARY OF SELECTED RESOURCES

Introduction

Background

The Patient Protection and Affordable Care Act (ACA) includes numerous provisions that encourage or require health care providers to implement or expand a variety of value-based care initiatives. The ACA created the Hospital Value-Based Purchasing Program, which ties payment to quality; the Medicare Shared Savings Program (MSSP), the largest Medicare accountable care organization (ACO) program; and the Center for Medicare and Medicaid Innovation, which tests the impact of new delivery and payment models on expenditures and clinical outcomes. These alternative payment models shift financial risk from payers to providers by rewarding those who achieve quality and cost thresholds and penalizing those who fail to do so.

Across all models, the identification, stratification, and management of high-risk patients is central to improving quality and cost outcomes. One solution believed to improve risk management for providers transitioning to value-based payment is to use predictive modeling to proactively identify patients who are at highest risk of poor health outcomes and will benefit most from intervention. The patient-identification process may include both the use of predictive modeling and manual, clinical selection of patients through a health provider or family referral.

It is well established that a small percentage of the population accounts for a disproportionate amount of total health care spending. In a 2015 study of the Veterans Administration (VA) health system, when patients were ranked by cost, the top 5% highest-cost patients accounted for 47% of total costs (Zulman et al. 2015). National civilian statistics are similar (Conwell and Cohen 2002). About two-thirds of these patients not only had multiple comorbid conditions, but at least three body systems were affected. Multimorbidity is associated with greater outpatient and inpatient utilization (use of services); in fact, people in the top 5% in terms of cost spent more than 17 times as much per person as those in the bottom 50%. Health care costs in the top-5% population are generally concentrated in a single year, but a significant percentage of those costs do tend to persist over a two-year period.

Common strategies for managing high-cost patients and high-risk events include interventions such as complex-care management, specialized clinics that manage multiple conditions simultaneously, enhanced palliative care, behavioral and social interventions, and deployment of multidisciplinary teams. All of these begin with a strategy to identify high-risk patients before substantial preventable or avoidable costs have been incurred and health status declines. Predicting patients' risk of adverse clinical outcomes and high

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care costs requires the systematic use of key information. With such information, risk identification and stratification tools can help identify high-risk patients and enable providers to match them with the most appropriate level of intervention. Key information is based on what you want to predict and may include past utilization of services, number and types of diagnoses, demographics, medications, and factors regarding patients' functional and psychosocial status. Predictive models can predict events such as unplanned admissions and readmissions, mortality, cost, and postacute admission.

This report focuses on risk-identification tools, not on the resulting interventions. Yet, complex-care management is such a common and promising intervention that we believe a summary of four key resources is important.

1. The Advisory Board Company states that “to prepare for high-risk care management, organizations must first coordinate existing resources and outline a process to identify high-risk patients. With a clear picture of system resources, organizations can identify targeted groups of patients for care management support” (Advisory Board Company 2012).
2. In the California Healthcare Foundation (CHCF) 2015 report *Finding a Match: How Successful Complex Care Programs Identify Patients* (Hong et al. 2015) describe how providers and health-plan partners can identify high-risk patients using predictive-risk tools and claims data, adding clinical input, functional status, patient activation, and social support to refine the list of patients. Off-the-shelf claims-based tools can produce a prospective-risk score based on a combination of demographics, utilization, diagnoses, medications, comorbidities, and previous costs. These tools provide objective methods but are not perfect predictors of future utilization and cost. Hong et al. recommend adding a secondary level of review of identified patients using inputs such as clinical review (for example, care-team chart reviews and clinical assessment); direct referrals from primary care providers (PCPs), disease case managers, or health plans; and identification of high-risk patients during care transitions. Using multiple methods to identify high-risk patients may increase the predictive value of the model (thus yielding a score that corresponds to a patient's likelihood of having an adverse event). A table that summarizes the primary models for patient identification can be found on pages 2–3 of this resource.

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3. A complex-care-management toolkit developed by Giovanna Giuliani and colleagues at CHCF in 2012 described a series of critical questions for providers to determine the rationale for using a predictive-risk model, such as:
 - What is the business case behind improving care for high-risk patients? For example, do you accept full risk for patients, or are there management fees or shared-savings dollars available?
 - Is the organizational leadership engaged, as evidenced by the commitment of financial and staff resources?
 - Can you clearly identify your target population? What data do you have that can help you identify and stratify your high-risk population, such as utilization, diagnoses, pharmacy data?
 - Can the organization articulate the purpose of a complex-care program and how the program would help physicians and patients?
 - Are the necessary organizations aligned, such as payers, hospitals, and specialists? Do you have what you need from these partners, such as data or a process for data transfer?
 - Do you have a data-measurement plan in place to measure effectiveness of the program?
4. In the Commonwealth 2014 issue brief “Caring for High-Need, High-Cost Patients: What Makes for a Successful Care Management Program?” Hong et al. (2014) address the characteristics of an effective care-management program as the companion question to the optimal patient-identification approach.

This section of the report focuses on the patient-identification strategies that can determine care-management models and resource use. It provides an overview of common risk-stratification tools, how the health care industry uses them to predict and prevent avoidable clinical events, and describes their many limitations. Overall conclusions from this section include:

- Existing predictive tools have limitations.
- The more variables included in a risk-stratification approach, the better its predictive ability.
- Obtaining input from clinicians and health-assessment surveys enhances the effectiveness of predictive tools.
- There are many gaps between the current reality of predictive-tool integration with electronic medical record (EMR) data and the clinical and operational demands of alternative payment programs.

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Methods

Objective

The objective of this study is to better understand the role of predictive modeling in the patient-identification process. The recent literature on the use of predictive models in a provider-led care-management context is reviewed. The focus of this review is the practical considerations encountered when implementing and using predictive modeling for patient identification. This review summarizes key findings in each of the following areas:

- Technical Background
- Model Problem Statement
- Necessity for Using Predictive Models
- Modeling Strategies
- Model Implementation
- Model Evaluation

Researchers for This Section

Andrew M. Webster and Nicholas Patnode, an actuarial student at the University of Wisconsin, served as the primary authors.

Search Strategy

A scientific literature search was performed using PubMed and Google Scholar. In addition, key journals were reviewed systematically to search for relevant articles. Finally, articles that cited relevant papers were reviewed, as well as bibliographies of key articles. Several keywords appear in the literature referring to the activity of high-risk patient identification and appropriateness for care-management intervention. An identification keyword from the first column of Table 10 was combined with a program keyword from the second column to form a full search term. For example, the search combination “patient identification” and “care coordination” was used to search for relevant articles. The combination of four identification keyword choices with three program keyword choices resulted in 12 keyword combinations.

Table 10. Search Keywords Used

Identification Keywords	Program Keywords
Patient Identification	Care Coordination
Case-finding	Care Management
Risk Stratification	Case Management
High-risk	

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Article Inclusion/Exclusion Criteria

We confined our search to articles published between 2010 and 2015 and specifically focused on peer-reviewed journal sources. We targeted articles of interest to health care providers instead of those based on the perspectives of insurers or managed-care organizations. Furthermore, we focused on patient-identification methods aimed at populations rather than at patients with specific conditions. We did not review articles focused on the administrative aspects of risk adjustment or provider performance measurement. Finally, although we acknowledge that there is active patient-identification research in other countries, such as Britain, Canada, Germany, and Israel, we primarily reviewed articles within the context of the U.S. health care system in light of the unique attributes that characterize different countries' health care delivery systems.

Summary of Findings and Discussion

Technical Background

The literature review relies on concepts from statistics to define predictive models. Models come in two varieties. Models that predict a continuous outcome are called *regression* models, whereas models that predict a discrete outcome are called *classification* models. A model that uses past data to predict a future outcome is called a *predictive* model. In contrast, a model that uses past data to determine a relationship with a past outcome is a *retrospective* or *concurrent* model. Retrospective models usually exhibit higher model accuracy than predictive models.

A common measure of regression model accuracy is *R-squared*, or R^2 , a quantitative goodness-of-fit method that works particularly well for comparing linear regression models. *Model sensitivity* is the ability of the model to accurately predict true outcomes. *Model specificity* is the ability of the model to accurately predict false outcomes. A common measure of *classification model accuracy* is the C-statistic, or the tradeoff between model sensitivity and specificity. Classification models with a high C-statistic accurately predict an outcome without introducing false negatives. In health care, classification models with high sensitivity are often used because it is more costly to misidentify a high-risk patient as low risk than it is to misidentify a low-risk patient as high risk.

Model Problem Statement

Predictive modeling in the medical field serves many purposes, and it is often used to inform risk adjustment, actuarial science, and high-risk patient identification for care-management programs (Iezzoni 2012). *Risk adjustment*, or severity adjustment, can be broadly defined as accounting for patient-related factors prior to examining care

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outcomes (Iezzoni 2012). Risk adjustment is primarily used to enable the comparison of different populations by controlling for patient-specific factors. In Medicare Advantage and public-exchange insurance plans, risk adjustment is used for making equitable financial transfer of funds to adjust for differences among populations.

Actuaries primarily use predictive modeling to prospectively set insurance premium rates. By projecting population costs and utilization, actuaries can calculate premiums that allow insurers to cover the cost of care and produce a profit. Patient identification for care management refers to the initial and ongoing individual selection of patients who are highly likely to access high-intensity care and who may be highly likely to need and benefit from care management. Patients with high levels of care costs and utilization are generally the ones most in need of care coordination (Peikes et al. 2012). High-risk patient identification helps establish the need for care-management intervention to prevent, slow, or stop disease progression.

However, there are clinical and social metrics beyond utilization that should be used to identify need, such as predisposing, enabling, and clinical-need factors (Haime et al. 2014).

- *Predisposing factors* refers to the patient predisposition to use services. Some factors include health literacy and navigation of the health care system and services, physical vulnerability, and patients' insight into their health.
- *Enabling factors* are those that enable (or, if lacking, impede) health care use, including social or home environment, patient coping skills, and patient financial resources.
- *Clinical-need factors* are those related directly to the condition-specific risks that must be managed, such as disease severity, comorbidity, and control of disease.

Other considerations include whether the intervention is likely to benefit the patient, whether cost is avoidable, and whether the patient is willing to participate and adhere to the care plan (Johnson et al. 2015; Peikes et al. 2012). Four essential requirement areas for effective patient identification appear in the Patient Identification Framework shown in Table 11 (based on Haime et al. 2014, Johnson et al. 2015, Lewis 2010, and Peikes et al. 2012). Patients who qualify in all four areas are likely to benefit most from care-management intervention. Ideally, a predictive model would be able to incorporate all areas of the Patient Identification Framework during initial risk identification, but most current models require manual review to incorporate all areas.

Table 11. The Patient Identification Framework

I. Intervention Alignment and Action (Johnson et al. 2015) <i>Is the program clinically and socioculturally designed to help the identified patient?</i>
II. High Risk of Cost Utilization (Peikes et al. 2012) <i>Will intervention with the identified patient result in a financial outcome that justifies the cost of the intervention?</i>
III. Patient Need (Haime et al. 2014) <i>Does the identified patient display the clinical and social need for intervention? Predisposing factors, lack of enablement, and clinical need should be considered.</i>
IV. Patient Engagement (Lewis 2010) <i>Will the patient enroll and actively participate in the program as long as needed to demonstrate optimal outcomes?</i>

Necessity for Using Predictive Models

Many integrated delivery systems, health insurers, and other health care organizations use predictive modeling for a variety of purposes (Wharam et al. 2012). The Medicare Coordinated Care Demonstration was an initiative under which providers tested care-coordination strategies in an effort to improve quality of care while lowering costs. Successful programs targeted resources toward high utilizers to reduce hospitalizations and spending (Liaw et al. 2015). One such provider, the Washington University School of Medicine in St. Louis, achieved an 11.7% reduction in hospitalizations and a 9.6% reduction in Medicare Part A and B spending (Peikes et al. 2012).

Modeling Strategies—Applicable Population

As described above, there is a variety of care-management activities, including case, or care, management, complex-case-management, transitional case management, chronic-disease management, and population health management (Berry et al. 2013). Program objectives dictate the necessary data and the predictive model for identifying patients. The literature reveals a corresponding variety of modeling objectives and approaches.

Models can be classified into three types (Table 12):

- populationwide
- event-based
- disease-specific

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Each approach has its own advantages and disadvantages (Hong et al. 2014). Populationwide models are applied to the entire population at once and offer the most comprehensive expenditure information. Disadvantages include having to integrate standard psychosocial factors and collecting data across many health care services. Meanwhile, event-based models target a patient during a time of need but are not used to predict or avoid triggering events. Disease-specific models are easier to address clinically, but may not accommodate the comorbidity or utilization patterns of high-risk or high-cost patients. For example, a congestive heart failure patient who is well controlled may not be at high risk in the near future, even though they have a high-risk chronic condition punctuated by acute costly events.

Table 12. Types of Predictive Models

Type of Model	Definition	Examples
Populationwide	Applies generally to the entire population of interest	Top X% of Next Year's Expenditure*
Event-Based	Applies to a population after a specific event trigger, such as a hospital admission	All-Cause Readmissions, Inpatient Length-of-Stay
Disease-Specific	Only applies to patients with a specific disease or condition	All congestive heart failure (CHF) patients

*X% is commonly 5% or 10%, depending on available care-management resources and level of risk.

We reviewed models that predict which patients will generate the top 10% of cost for the next year by using a variety of predictive variables (Boscardin et al. 2015; Fleishman and Cohen 2010; Shen et al. 2014). Systematic review articles for event-based models, such as readmission-prediction models (Peikes et al. 2012) and length-of-stay management (Stam 2010), were available in the literature.

Modeling Strategies

Raw Data

Risk-adjustment models based on administrative billing data can initially be used when constructing a patient-identification model (Haas et al. 2013; Johnson et al. 2015). However, claims and demographics-based predictive models have a high degree of unexplained variation as measured by R^2 values, suggesting that other factors may

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improve the ability to predict cost and utilization (Haas et al. 2013; Haime et al. 2014; Shen et al. 2014). Claims-only models also have the disadvantage of including both avoidable and unavoidable costs, whereas care-management programs primarily target avoidable cost (Johnson et al. 2015). For example, random-accident claims are unavoidable costs that need to be removed from claims data during preprocessing.

Table 13 describes the types and sources of data used for modeling. Adding patient characteristics, such as functional status, sociodemographic factors, and psychosocial indicators, has been shown to improve predictive accuracy (Barnett et al. 2015; Boscardin et al. 2015; Fleishman and Cohen 2010; Stam 2010). Predictive accuracy increased moderately in a study comparing diagnosis-only models with models based on diagnosis and the Short Form 36 (SF-36) Health Survey (Stam 2010). However, the model containing only the SF-36 underperformed the diagnosis-only model.

Table 13. Raw-Data Types and Sources

Type of Data	Sources
Patient demographics	Payer claims, electronic medical record (EMR)
Diagnoses	Payer claims, problem lists, EMR, self-reported data
Clinical measurements	EMR readings, health-risk appraisal (HRA), external lab data
Historical cost and utilization	Payer claims, EMR
Functional	EMR, OECD limitations, nursing assessment
Socioeconomic and psychosocial	Patient questionnaires (SF-2, SF-36, PHQ-2)

In addition to improving predictive accuracy, sociodemographic and psychosocial factors help improve identification of patients who have inadequate social support to manage their own care and who may benefit most from care-management resources (Peikes et al. 2012). For example, Gundersen Health used a simple scoring method based on diagnoses and psychosocial-risk factors to achieve significant decreases in unplanned hospitalization and emergency department (ED) use (Berry et al. 2013).

Modeling Methodology

Ordinary least squares regression was the typical modeling method used when the outcome of interest was absolute cost (Lu et al. 2015; Stam 2010). When the outcome of

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interest was a binary indicator, such as readmission or patient rank in an upper percentile of next year's cost, a logistic modeling method was typically used (Boscardin et al. 2015; Fleishman and Cohen 2010; Kansagara et al. 2011; Lu et al. 2015). There were large disparities between predictive-model performance based on the modeling methods used (Kansagara et al. 2011; Lu et al. 2015). Advanced predictive modeling methodologies were explored to measure the increase in predictive accuracy. For example, data-mining techniques, such as decision trees, outperformed other modeling techniques to predict the top 5% high-cost patients (Shenas et al. 2014).

Hybrid Approaches

Predictive modeling is necessary but not sufficient for successfully identifying patients for interventions such as care management (Bellis et al. 2010). Patient-identification approaches that include predictive modeling supplemented with clinical judgment are highly successful (Annis et al. 2015; Haime et al. 2014; Johnson et al. 2015). One way to incorporate clinical judgment input is by offering full transparency to front-line clinical personnel who are using the model. The personnel can then identify areas where the model is incorrect to inform future iterations of the model. Another method is to incorporate post hoc clinical judgment into predictive-model results during the patient-identification process (Annis et al. 2015; Haime et al. 2014). Interventions that best strengthened patient-identification capabilities included strong alignment between patient-risk tiers and level of clinical intervention (Johnson et al. 2015), enhanced provider ownership (Haime et al. 2014), and the incorporation of data elements that are difficult to collect automatically (Annis et al. 2015). For example, personal knowledge of patients and their social risks, patient-reported health-assessment information, and information from disease-specific programs have been used to identify potential patients, yet these data elements were not easily collected electronically (Annis et al. 2015).

Model Implementation

A general modeling workflow framework, called the Actuarial Control Cycle, is shown in Figure 2 (Bellis et al. 2010). The predictive modeling lifecycle is broken into three components: 1) define the problem, 2) design a solution, and 3) monitor results. External forces, such as health care regulatory change, insurer or provider market changes, changes in medical technology, and/or shifts in underlying population illness burden continuously change model requirements. Thus, an iterative approach is required to continuously react to external changes and improve the predictive model used for risk identification.

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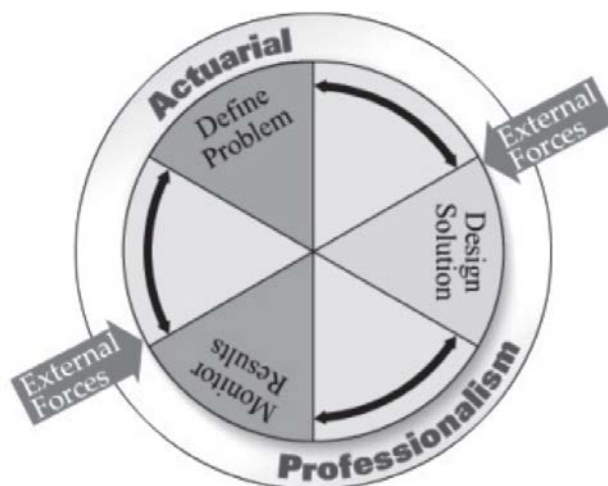


Figure 2. The Actuarial Control Cycle.

A specific eight-step iterative modeling workflow framework for patient-risk identification appears in Table 14 (Johnson et al. 2015). The cyclical framework can be applied to successfully implement a predictive modeling approach for patient identification. A multidisciplinary team with expertise in a variety of areas is needed during the development, implementation, and evaluation phases.

Table 14. Example of an Iterative Modeling Workflow Framework

Step	Task
1	Assemble multidisciplinary team
2	Choose accountable population
3	Develop risk-stratification rules to define population segments (risks or tiers)
4	Evaluate financial stratification and clinical coherence of tiers
5	Develop care models for use within tiers
6	Identify individuals who are good candidates for a care model
7	Develop associated workflows
8	Develop performance monitoring and evaluation

Source: Johnson et al. 2015.

The two previous modeling workflow frameworks (that is, the general and iterative ones) demonstrate that model refinement occurs continuously as external forces cause change. Multiple models' performances can be tested concurrently in parallel to practically

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determine which is most useful for the application at hand. A study measuring the predictive accuracy for six commonly used predictive-risk models demonstrated that all had comparable predictive accuracy (Haas et al. 2013; Shen et al. 2014). Other considerations, such as ease of implementation, can be used to decide which model to choose. Two models showed that a simple approach to risk identification could be effective (Boscardin et al. 2015; Fleishman and Cohen 2010). For example, a simple count of chronic conditions can be used to predict patients in the top 10% high cost with reasonable accuracy (Fleishman and Cohen 2010). A simple model involving self-reported health status, patient demographics, and past health utilization is also effective in predicting which patients will be in the top 10% of cost (Boscardin et al. 2015). These models reduce the administrative complexity of implementing a diagnosis-based predictive model.

Model Evaluation

Predictive-model accuracy can be evaluated directly through statistical techniques. While a predictive model's accuracy is central to model evaluation, there are additional desired qualities that assess the effectiveness of the patient-identification process. These include clinical coherence, transparency, and stability (Johnson et al. 2015). Clinical coherence refers to the model's ability to match patients to the aligned interventions. It is important to design a model that has clinical coherence so that clinical personnel can trust the model and perform the appropriate intervention (Berry et al. 2013). Transparency refers to the degree to which the front-line clinical personnel have access to the model rules and the reasoning behind modeling results. Transparency is important so that front-line clinical personnel have input into the modeling process (Arce et al. 2014) and (Hodgman 2008) and can provide valuable feedback for iterative model refinement (Johnson et al. 2015). Stability is a measure of how sensitive the model is to changes in the underlying data. For example, at Denver Health, indicators of highly elevated lab results were added to the predictive model and then ultimately removed. This was because each model refresh caused a massive change in patient assignments when lab results returned to normal (Johnson et al. 2015). Table 15 summarizes desired qualities of models.

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Table 15. Desired Qualities of Predictive Models

Quality Measure	Definition	Purpose
Predictive Accuracy	Usually statistically defined. Examples are R^2 , C-statistic, and prediction error.	Intervene before the avoidable utilization occurs.
Clinical Coherence	Degree of correspondence between model result and aligned intervention.	Achieve model results that guide clinical action.
Transparency	Access to the model's rules and reasoning behind results.	<ul style="list-style-type: none"> • Involve and engage clinicians. • Enrich the model with clinical insight.
Stability	Level of model sensitivity to changes in the underlying data.	Avoid having patient assignment or reassignment be subject to random variation.

Conclusion and Recommendations

After reviewing practical considerations regarding the application of predictive modeling to patient identification for care management, four key recommendations were identified and appear below.

1. An interdisciplinary team and an iterative approach are required.
2. Having a simple model for identifying risk is better than not having a model.
3. Predictive modeling is necessary but not sufficient; clinical judgment is also required.
4. Models can be evaluated directly through model-evaluation criteria or indirectly through measuring the care-management outcomes.

Predictive modeling is an active area of research with great potential to improve health system patient risk management.

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Peikes D et al. how changes in Washington University's Medicare Coordinated Care Demonstration Pilot ultimately achieved savings. *Health Affairs* 31.6 (2012):1216-1226.

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Reviewed Articles in Structured Abstract Format

The summary information below was used to create structured abstracts for the 16 featured articles (Table 16).

1. Formal citation including author(s), year, title, journal, volume, pages
2. Subject/Category
3. Purpose of Article
4. Number of references
5. Perspective of authors
6. Data
7. Methods
8. Results
9. Limitations
10. Conclusions

Number of Articles

Sixteen articles were selected and are summarized for convenient review.

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Table 16. Peer-Reviewed Journals and Non–Peer-Reviewed Publications

Primary Author	Article Title	Year
Annis, Ann M.	Comparison of Provider- and Plan-Based Targeting Strategies for Disease Management	2015
Arce, Regina Sauto	A Qualitative Study on Clinicians' Perceptions About the Implementation of a Population Risk Stratification Tool in Primary Care Practice of the Basque Health Service	2014
Barnett, Michael L.	Patient Characteristics and Differences in Hospital Readmission Rates	2015
Berry, Leonard L.	Care Coordination for Patients with Complex Health Profiles in Inpatient and Outpatient Settings	2013
Boscardin, Christy K.	Predicting Cost of Care using Self-Reported Health Status Data	2015
Fleishman, John A	Using Information on Clinical Conditions to Predict High-Cost Patients	2010
Haas, Lindsey R.	Risk-Stratification Methods for Identifying Patients for Care Coordination	2013
Haime, Vivian	Clinician Considerations when Selecting High-Risk Patients for Care Management	2014
Hong, Clemens S.*	Caring for High-Need, High-Cost Patients: What Makes for a Successful Care Management Program?	2014
Johnson, Tracy L.	Augmenting Predictive Modeling Tools with Clinical Insights for Care Coordination Program Design and Implementation	2015
Kansagara, Devan	Risk Prediction Models for Hospital Readmission: a Systematic Review	2011
Lewis, Geraint H.	Impactability Models: Identifying the Subgroup of High-Risk Patients most Amenable to Hospital-Avoidance Programs.	2010
Lu, Mingshan	Systematic Review of Risk Adjustment Models of Hospital Length of Stay (LOS)	2015
Peikes, Deborah	How Changes in Washington University's Medicare Coordinated Care Demonstration Pilot Ultimately Achieved Savings	2012
Shenas, Seyed Abdolmotalleb Izad	Identifying high-cost patients using data mining techniques and a small set of non-trivial attributes	2014
Stam, Pieter	Diagnostic, Pharmacy-Based, and Self-Reported Health Measures in Risk Equalization Models	2010

*Not a peer-reviewed publication.

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Annis, Ann M., et al. Comparison of provider- and plan-based targeting strategies for disease management. *The American Journal of Managed Care* 21.5 (2015):344-51.

Subject/Category: Provider versus Payer Perspectives

Purpose of Article

To compare and contrast the patient-targeting approach and engagement results of providers and payers.

Number of References: 25

Perspective

Authors were affiliated with health systems including University of Michigan and University of Colorado Denver. The study was funded by the Agency for Healthcare Research and Quality. Five different provider organizations participated. One payer, Blue Cross Blue Shield of Michigan, participated.

Data

The health plans in this study used claims-based data for targeting patients. The provider organizations used varied data for this. One provider organization used health-risk-assessment data to compute a standardized risk score across patients for targeting. Most providers based targeting on clinical and relational knowledge of the patient. Poorly controlled lab values, psychosocial issues such as lack of family support or resources, and patient motivation were commonly used.

Methods

The health plan used the commercially available Optum Impact Intelligence claims-based algorithm to create a patient-outreach list. Health-plan nurses performed phone outreach and sent letters to patients for enrollment in care management. Provider-organization care-management programs and targeting strategies were variable. One provider organization used participation screening to prevent the care manager from reaching out to patients who did not tend to participate in care management. Another provider organization used only a risk assessment to offer care management to moderate-risk and high-risk patients.

Results

Provider organizations targeted more patients than the health plan did. The different targeting methods resulted in only a 7% targeted-patient overlap between the health plan

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and the provider. Patient engagement in the provider-driven care management was consistently higher across the practices than it was in the health-plan disease-management program. The provider organization that used only a risk assessment to offer care management had the highest number of engaged targeted patients of all the providers.

Physician-led care management increases patient engagement as measured by having one care-manager interaction versus payer-driven programs. Not all physicians are willing to consistently offer this service to patients. When patients did engage, providers had the advantage of knowing clinical metrics, such as weight and blood pressure, personal situation, and health care preferences. Clinical data helped overcome misclassification error encountered in claims data. Providers were also able to identify problems earlier than payers because providers were involved in the primary care of the patients.

The average risk score across patients in the provider programs was lower than for the health-plan program. This was likely related to targeting patients earlier in their disease progression or patients whose overwhelming health issues excluded them from the targeted population.

The health-plan program had the advantage of knowing utilization and cost of services provided outside the primary care office.

Limitations

The study only included patients from one commercial payer, Blue Cross Blue Shield of Michigan, whose experience may not be able to be extrapolated to other insurers. The definitions of targeting and engagement were restricted to care-manager interventions and excluded similar activities performed by primary care physicians or specialists. The study is not a randomized controlled trial, and there may be important comparison differences between groups studied. Finally, data difficulties did not allow for the comparison of the care-management programs because of the inability to evaluate patient-reported outcomes, effectiveness, or duration.

Conclusions

Identification of patients most likely to benefit from and participate in care management may be facilitated by a combination of predictive modeling and selection of patients by primary care providers (PCPs). More investigation is required to determine the optimal approach.

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Arce, Regina Sauto, et al. A Qualitative Study on Clinicians' Perceptions About the Implementation of a Population Risk Stratification Tool in Primary Care Practice of the Basque Health Service. *BMC Family Practice* 15.1 (2014): 150.

Subject/Category: Model Implementation

Purpose of Article

Risk stratification is the process of separating the population into high-risk, low-risk, and rising-risk groups. A Population Risk Stratification (PRS) tool has been developed and was introduced to the public by Basque Health Service. The purpose of this study is to examine the tool's implementation process by potential users (primary-care clinicians, doctors, nurses) and elements that would act as barriers or facilitators in the implementation of PRS in daily practice.

Number of References: 20

Perspective

Not available.

Data

Twelve doctors (general practitioners) and 11 nurses (primary care) were interviewed in a focus group. They were organized into three separate groups: the Doctors' Group, the Nurses' Group, and a mixed group containing primary-care nurses and general practitioners. Two researchers were present during the 90-minute discussion, one acting as a facilitator and the other as an observer. Managers decided which clinicians would participate in the focus groups.

Methods

The researchers used a qualitative method through focus groups to achieve their objectives. They used a statistical sampling method to assign participants to groups and the knowledge-translation model to identify criteria. After the group discussions, a thematic analysis was conducted using NVivo, data-analysis software that identified patterns in the data and classified these patterns by theme.

Results

The researchers divided their results into four different categories. The first focused on "elements related to the clinician's characteristics as a potential tool adopter." They found that clinicians with a higher degree of awareness of and alignment with a population health management approach expressed a more positive perception of PRS. Although they found PRS of potential use, clinicians found that implementing it was

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challenging because it did not sufficiently reflect the realities of their everyday practice. They admitted that there would need to be a large organizational change toward a population health approach for PRS to be a part of daily practice. Clinicians' professional resistance to change was an additional barrier. Having prior knowledge of the PRS tool helped facilitate a more positive perception.

The second category was “elements related to the clinician’s perception of the practice setting.” The overwhelming clinical demand on individual physicians prevented them from taking a proactive role in a population health management approach. Patient dependency on the health care system and resistance to change was another barrier. Lack of coherence between population health activities and the managers’ evaluation of physicians was another issue. For example, individual patients who were well controlled did not need follow-up appointments, but physicians needed to schedule them to be evaluated as the performant. Finally, competition for clinicians’ time and effort in a change-saturated environment was another concern.

The third category was “elements related to the perceived characteristics of the PRS tool.” The reliability of the PRS tool was questioned in light of its use of the International Classification of Diseases (ICD), lack of social data, and development in a foreign health care system. The desirability of the PRS tool was questioned because clinicians found it difficult to see advantages compared with pre-existing tools, were concerned about the risks of prioritizing patients, and were uneasy about the quality and amount of evidence about stratification-based interventions.

Lastly, the fourth category was “elements related to the implementation strategy used by the tool’s promoter, as experienced by clinicians.” The clinicians believed that involvement at the outset when the tool was still being created would generate more engagement. This early involvement would allow the tool to be tailored more to the individual practice’s needs. Also, the availability of a development-team contact person to answer clinicians’ questions was essential. Additional factors that increased clinician buy-in included more information clarifying the uses and objectives of the tool in practice, specific strategies to improve clinical practice, and steps to achieve better population health outcomes. Gradual introduction, clear demonstrations of benefits, and close collaboration between clinicians and managers were believed to contribute to increased confidence in the tool.

Limitations

Physician managers decided which clinicians would participate in focus groups, thus introducing a selection bias.

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Conclusions

Clinicians' values, attitudes, and beliefs about a population health management approach determined their willingness to use a PRS tool. An increased understanding of the approach contributed to a greater understanding of its purpose and benefits. The gap between the values of the PRS tool and its application in daily clinical practice needs to be bridged. Resistance to change, workload, work assignment, roles (such as doctor or nurse), and professional performance-assessment strategies all prevented clinicians from adopting proactive attitudes toward implementation. The clinicians also expressed the need for the information to be up-to-date so there is no delay in implementing necessary actions. Presenting evidence that supports the tool's ease of use and its ethical implications may improve reception.

The researchers note that it is essential for clinicians to be involved in the early phases of the design and implementation of the PRS tool so that they can see the relevance to their practice. Clinicians should be given clear information about the tool, its usefulness, and corresponding implementation objectives. Overall, the implementation of a larger population health approach is necessary for the tool's success. This may require additional organizational resources, such as time redistribution, education, and role reassignment. In light of the risks of changing clinicians' busy daily practices, the usefulness and relevance of the PRS tool should be rigorously communicated to clinicians from the earliest opportunity.

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Barnett, Michael L., John Hsu, and J. Michael McWilliams. Patient characteristics and differences in hospital readmission rates. *JAMA Internal Medicine* 2015;175(11):1803-1812. doi:10.1001/jamainternmed.2015.4660. Published online Sept. 14, 2015.

Subject/Category: Readmission Models/Non-traditional Modeling Data

Purpose of Article

The authors sought to assess the extent to which a comprehensive set of patient characteristics account for differences in hospital-readmission rates. Recognizing the Centers for Medicare and Medicaid Services' (CMS) commitment to reducing avoidable readmissions, the authors examined how CMS should adjust not only for a patient's age, sex, discharge diagnosis, and diagnoses present, but also for other clinical and social characteristics that might make patients more likely to be readmitted. The goal of the research was to adjust readmission rates such that hospitals are only penalized for using

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their resources inefficiently, not for serving patients with social or clinical characteristics that increase their risk for readmission. This study focused on identifying the patient characteristics that make readmission more probable, as well as the distribution of characteristics among hospitals and the impact of these characteristics on readmission penalties.

Number of References: 42

Perspective

Michael Barnett, MD, is a graduate of Harvard Medical School and a researcher and general medicine fellow in the Department of Health Care Policy at Harvard. John Hsu, MD, MBA, MSCE, is the director of the Program for Clinical Economics and Policy Analysis within the Mongan Institute for Health Policy at Harvard Medical School. J. Michael McWilliams, MD, PhD, is an associate professor of health care policy and medicine at Harvard Medical School and received his MD from Harvard Medical School and his PhD in Health Policy from Harvard University.

Data

This study was conducted in three steps. The authors used data from the Health and Retirement Study (HRS) and linked Medicare claims. The data from the HRS are nationally representative data of the U.S. population. The first step of the study was to find social and clinical patient characteristics not included in current CMS adjustments that were potential predictors of all-cause 30-day readmission. Data were collected from patients from 2000 to 2012, including individuals who were eligible for Medicare and their Medicare claim and enrollment files. In the second step, the authors compared the distribution of the characteristics obtained in the first step for hospitals with high and low readmission rates. They used publicly reported HRS data from 2009 to 2012. Using the same data in the final step, they compared the differences in the probability of readmission between participants admitted to hospitals with high and low readmission rates, further segmenting and comparing the differences before and after the adjustment for the additional patient characteristics. They defined *index admissions* as all admissions to nonfederal acute-care hospitals (short-term visit for severe injury) without transfer to another acute-care facility, excluding readmissions and discharge against medical advice. When gathering the clinical and social characteristics from the HRS surveys, the authors selected 24 variables that could potentially predict readmission.

Methods

When analyzing the 2000–2012 data, the authors compared the proportion of admissions followed by readmission for each patient characteristic. They predicted 30-day

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readmission using a logistic regression model. They tested the variables by adding each variable individually to the model and seeing how it affected the probability of readmission. In addition, the authors included indicators for the quintile of the hospital's publicly reported readmission rate. Through sensitivity analysis, they showed that the characteristic had to be proportionally similar across quintiles to be considered a good predictor of readmission. After conducting this second step, they initiated the third step by "including indicators for the admitting hospital's quintile in a logistic model of readmission" in an effort to measure the difference in the probability of readmission between participants included in hospital-wide readmission rates.

Results

In the 2000–2012 sample, 22 of the 29 characteristics measured were significantly predictive of readmission after CMS standard adjustments ($P < .04$). Importantly, in the 2009–2012 sample, "the characteristics of participants with index admissions to hospitals in the highest quintile of publicly reported readmission rates differed substantially" from those in the lowest quintile. Seventeen of the 22 significantly predictive characteristics were distributed differently between the higher and lower quintiles of readmission rates. "Almost all of these differences (16/17) indicated that participants admitted to hospitals in the highest quintile of readmission rates were more likely to have characteristics associated with a higher probability of readmission." In the third step of the study, "the effects of successive adjustments for patient characteristics on the difference in the probability of readmission between participants admitted to hospitals in the highest versus lowest quintile of readmission rates" were measured. The authors found significant results, with the probability percentage points decreasing "from 5.86 percentage points without any adjustment to 4.41 percentage points after standard CMS adjustments, to 3.50 percentage points after adjustment for additional variables from Medicare enrollment and claims data, to 2.29 percentage points after additional adjustment for variables from HRS surveys. . . . The fully adjusted difference constituted a 61% reduction relative to the unadjusted difference and a 48% reduction relative to the difference adjusted for variables already used by the CMS for risk adjustment of readmission rates, or an absolute reduction of –2.12 percentage points." This difference means that there was less variation between being readmitted to a hospital on the higher end versus the lower end of the quintiles. The lower the difference in the percentage points, the higher the probability that the reason readmission exceeds the standard, expected readmission-rate percentage is inadequate care and not patient characteristics. For other multilevel models, "a substantial reduction in between-hospital variation in readmission rates after adjustment for more patient characteristics" was verified. All data were verified using sensitivity analysis. No data were found that altered the conclusions.

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Limitations

Linked survey data were missing and prior survey data were substituted, but only 1.5% of admissions were excluded. The HRS sample limited the precision of estimating the differences between quintiles in the probability of readmission.

Conclusions

The authors state that their findings suggest, “Medicare is penalizing hospitals to a large extent based on the patients they serve.” They found that many patient characteristics that are not being included in the current “risk adjustment of hospital-readmission rates were significantly predictive of readmission and more prevalent at hospitals with higher publicly reported readmission rates” compared with hospitals with lower readmission rates. The differences in patient characteristics between hospitals may significantly contribute to the penalties hospitals with high readmission rates have to pay. The authors suggest that this imbalanced distribution of patient characteristics among the most extreme quintiles is beyond hospitals’ influence. The authors question whether financial penalties imposed on hospitals with high readmissions rates is a result of poor care or of caring for patients with a higher probability of readmission.

These significant differences suggest that the Medicare Hospital Readmission Reduction Program (HRRP) imposes substantially greater costs on hospitals disproportionately serving patients more likely to be readmitted. “Hospitals serving healthier, more socially advantaged patients may not have to devote any resources to achieving a penalty-free readmission rate, whereas hospitals serving sicker, more socially disadvantaged patients may have to devote considerable resources to avoid a penalty. By selectively increasing costs or lowering revenue for hospitals serving patients at a greater risk of readmission, the HRRP therefore threatens to deplete hospital resources available to improve overall quality for populations at high risk of poor outcomes.” The authors propose legislation to adjust “readmission rates and other quality measures for patients’ socioeconomic status and more health-related variables.” The authors advocate for a system that uses alternative payment models “to preserve strong incentives to lower readmissions without unfairly penalizing hospitals based on the populations they serve and consequently risking deterioration in quality for patients at a high risk of readmission.”

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Berry, Leonard L., et al. Care Coordination for patients with complex health profiles in inpatient and outpatient settings. *Mayo Clinic Proceedings* 88.2 (2013): 184-94.

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Subject/Category: Non-traditional Data, Workflow

Purpose of Article

To describe the Gundersen, Wisc., approach to assigning patients to the care-coordination program and to report the favorable outcomes achieved.

Number of References: 34

Perspective

The authors are researchers at the Texas A&M University and clinicians at Gundersen Health in Wisconsin.

Data

Assignment to care coordination were primarily based on data gathered by care coordinators through personal interviews and EMR data.

Methods

The CMS demonstration project showed that Medicare savings were most likely to come from managing the patients who are most prone to being hospitalized. Gundersen Health developed specific criteria for identifying the patients who would benefit most from coordinated care. All staff used a single, systemwide EMR to enter an EMR-based care-coordination referral. Additionally, external agencies, patients, and families could make a care-coordination referral by telephone. Referral reasons included multiple diseases, use of multiple health care professionals, medication management issues, multiple inpatient admissions, multiple urgent-care and/or emergency department visits, lack of social support, financial limitations, and cognitive deficits.

A point-based tiering tool was used to assess the appropriateness of referrals to care coordination to avoid potential bias created by care coordinators who weight aspects of complexity differently. The tiering tool had components for medical complexity and psychosocial factors.

The medical-complexity component was modeled after the Johns Hopkins Care Coordination Tier Assignment Tool, Version 1.0 Health Care. A point was assigned for each chronic and severe medical condition requiring care-team management. Conditions included cardiovascular, malignancies, renal, and hematologic diseases, among others.

Psychosocial components were included because health care services and adherence to care were affected by lack of social support, mental health, and substance abuse. The psychosocial assessment was defined by the National Committee for Quality Assurance

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guidelines. Answers to certain questions automatically triggered the involvement of a social worker in addition to the care coordinator.

Tiering was performed based on the total score on both tool components. Patients attributed to tier 1 were not enrolled in care coordination, while Tier 3 patients were. Tier 2 patients were manually reviewed, meaning that a care coordinator decided whether to enroll the patient in the care-coordination program.

Once a patient was enrolled, care coordinators used the EMR and personal interviews to further understand the patient's support system, self-management capability, and current complexity of care. The patient was then assigned to active or monitoring status within the program on the basis of the patient's need for care-management resources and acute events such as a hospital admission. Care-coordinator scheduling and patient information, including clinic appointments, hospital admissions, and urgent-care and emergency department visits, is embedded within the EMR. "The EMR is also formatted to enable a patient's various health care practitioners to view the care coordinator's notes in a single tab, thereby aiding the practitioners in comprehending the patient's 'whole' story efficiently."

Results

Unplanned charges included those incurred for unscheduled hospital admissions and emergency department interventions. On the basis of 373 patients continuously enrolled in the care-coordination program for two years, there was a decrease in unplanned charges of 51% after year one and of 64% at the end of year two. Furthermore, hospitalizations decreased by more than half over the two-year span. Length of stay decreased, on average, by 39% at one year and 46% after two years. Forty percent of physicians stated that care coordination saved them at least 30 minutes per patient per month. Patient-satisfaction surveys showed that patients who received care coordination had high satisfaction with their ability to better manage their own health.

Limitations

The study was limited to a single institution. Also, there are challenges with attributing the decline in unscheduled hospital admissions to the care-coordination program because the outcomes were not adjusted for confounding variables. .

Conclusions

A rigorous tiering protocol helps select appropriate candidates for care coordination. It is crucial to include psychosocial factors as well as medical criteria. Further investigation is under way to determine whether predictive modeling can enhance care-management outcomes.

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Boscardin, Christy K., et al. Predicting cost of care using self-reported health status data. *BMC Health Services Research* 15.1 (2015):1.

Subject/Category: Non-traditional Data, Total Cost of Care Models

Purpose of Article

The authors studied the effect of self-reported employee–health-status data on the performance of data-based models to identify individuals at risk for high future health care costs and to develop a model that could predict which subgroups of people are at greatest risk for generating high health care costs.

Number of References: 29

Perspective

Not available.

Data

Studies done thus far using only administrative data have primarily used Medicare and Veterans Affairs (VA) data, which reduces generalizability. The authors of this study used data from commercially insured patients. Specifically, they examined biometric and self-reported health status data (HRQ) from 8,917 Safeway employees insured by Safeway Health during 2008 and 2009.

Methods

The authors used a retrospective cohort study design to identify patients with high future costs in 2009. They developed two models: one included patients that generated high costs in 2008, and the other excluded these patients in order to identify predictors for becoming a “new” high-cost patient. One of the outcomes included the expenditure on high utilizers for health services in 2009 (*high utilizers* was defined as being in the top 10% of the study population for the subsequent year’s expenditure distribution). The authors established three categories of predictor variables: health-services use (past hospital and emergency department [ED] utilization, BMI), sociodemographic factors, and self-reported health status from 2008. The authors used three separate multivariable logistic regression models. The initial model used health-services claims, the second model incorporated sociodemographic factors, and the final model added self-reported health status data. Authors assessed the predictive power of each multivariable logistic regression. To isolate variables that could predict members who would be newly high-

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cost in 2009, they compared the model excluding previous-year high-cost members with the one that included previous-year high-cost members. They evaluated goodness of fit using the Homer-Lemeshow chi-square test and model discrimination by the C-statistic.

Results

The authors determined that the factors associated with being high cost in the final adjusted model were female gender, increasing age, self-reported depression, chronic pain, diabetes, high blood pressure, above-average BMI, one or more ED visits in 2008, and one or more hospitalizations in 2008. The C-statistic for this model was 0.70. When the authors compared the broad model that included the whole study population with the narrower model that included only people who had not previously been high cost, there were a few differences. The narrower model for newly high-cost individuals included all the characteristics for being high cost, with differences for one or more ED visits in 2008 and above-average BMI. The narrower model with variables of having one or more ED visits in 2008 and of above-average BMI had wider confidence intervals (CIs) and larger *p*-values compared with the model that included previous high-cost members. The C-statistic for this model was 0.65.

Limitations

Given the use of self-reported data, potential errors in omission and response bias exist. Also the authors' data were based on a single commercial plan. This fact might impede generalization across other employer plans with different patient populations.

Conclusions

This study examined the relative value of self-reported-status data in predictive modeling for high-cost, commercially insured individuals. The authors found that the self-reported data were of key significance to the final predictive model. These findings are consistent with findings using Medicare data. The authors note that a reason for a lower C-statistic in the study may have been a lack of diagnoses data in the model. However, adding these data may be costly, and the authors provide a simpler algorithm of nine factors that could be a less costly alternative to the Diagnostic Cost Group (DCG) model. DCG models use demographic and diagnostic information to determine risk scores. The authors note that the usefulness of self-reported health data reaches beyond predictive power. Those data can also help provide valuable information that could facilitate the development an adoption of interventions at the individual-patient level. Having one or more ED visits was a very significant predictor in the narrower model. However, the lack of significance of hospitalization as a predictor in the narrower model can most likely "be attributed to the exclusion of past high utilizers."

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The significance and predictive value of the self-reported health status data mean that payers can target new potential-high-cost groups that are usually missed. The authors note that “reducing ED revisits by tracking frequent ED patients, contacting primary care provider[s] while the patient is in the ED and focusing on better communication, proactive transitions and collaboration between ED and primary care providers can all help to reduce utilization of services in the future.” The authors note that their models may provide an effective alternative to DCG models. They also note that self-reported health status data are important for identifying high-risk, high-cost patients and for developing interventions to improve care.

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Fleishman, John A., and Joel W. Cohen. Using information on clinical conditions to predict high-cost patients. *Health Services Research* 45.2 (2010):532-552.

Subject/Category: Need for Predictive Models, Types of Models

Number of References: 42

Purpose of Article

The purpose of the article is to differentiate various models’ ability to predict whether an individual will incur high medical expenditures (defined as being in the top 10% of the expenditure distribution). Most expenditure-prediction models take into account data from medical records, claims databases, and demographic information. The DCG system groups diagnosis codes from the International Classification of Diseases, Revision 9 (ICD-9) to predict health care expenditures. A simple count of prevalent chronic conditions has been suggested as a simple alternative to using other factors in predictive models. In this study, the authors compared the impact on the predictive power of models of the simpler alternative and DCG risk scores. The authors aimed to “systematically compare the performance of different risk adjusters when predicting high-cost cases.”

Perspective

The article is coauthored by two members of the Agency for Healthcare Research and Quality (AHRQ). Cohen is the Director of the Division of Social and Economic Research in the Center for Financing, Access, and Cost Trends at the AHRQ. He also holds an MA and PhD from the University of Chicago’s School of Social Service Administration. Fleishman has a PhD in Sociology from the University of Wisconsin–Madison.

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Data

The authors used nationally representative data from the Medical Expenditure Panel Survey (MEPS) sponsored by the AHRQ to compare the expenditure models (Table 17). MEPS gathers data on health care utilization, insurance coverage, medical conditions, and expenditures. The MEPS survey used in this study includes an overlapping group design. The authors measured eight panels (one panel, two years in length, every calendar year), initiated from 1996 to 2003. In each panel, data were gathered on expenditures from the two separate calendar years: Year 1 and Year 2.

Methods

Using different combinations of risk factors, the authors developed predictive models. They focused on “the prospective risk score generated by the DCG algorithm, the indicators of prevalent chronic conditions, and a simple count of chronic conditions.” They also examined “the extent to which patient-reported health status information [specifically, the SF-12, a 12-question survey that measures functional and overall health of a patient from the patient’s point of view] improves the performance of expenditure prediction models.” Using these variables, they developed different models, including a standard model that used gender, age categories, insurance, and panel indicators. Other models included combinations of indicators for the 10 most prevalent, or “key,” chronic conditions, indicators for the number of chronic conditions, SF-12 information, and the DCG risk score. In addition, functional health status and perceived health variables were added to the models with the highest C-statistic values. Models were numbered 1–10, with Model 1 being the baseline model.

The authors used Year 1 logistic regression models (based on the factors incorporated into each model) to predict which individuals would be in the top 10% of Year 2 expenditures. They measured the accuracy of these models by comparing the models’ prediction with actual data from Year 2. The data from calendar years in Panels 1-4 were used to establish goodness-of-fit indicators and develop the logistic models. Data from calendar years in Panels 5-8 were used to validate the models. When assessing the models, the authors used the Hosmer-Lemeshow statistic, the pseudo R^2 statistic, the Pearson correlation, the Bayesian Information Criterion (BIC), and the C-statistic.

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Table 17. Medical Expenditure Panel Survey (MEPS) Panels Used in the Study

Panel	1996	1997	1998	1999	2000	2001	2002	2003	2004
Panel 1	Year 1	Year 2							
Panel 2		Year 1	Year 2						
Panel 3			Year 1	Year 2					
Panel 4				Year 1	Year 2				
Panel 5					Year 1	Year 2			
Panel 6						Year 1	Year 2		
Panel 7							Year 1	Year 2	
Panel 8								Year 1	Year 2

Results

With similar demographic and clinical characteristics, Panels 1 to 4 and 5 to 8 also showed similar values in mean expenditure (\$2,662 and \$2,770, respectively). Only 1.6% of those with no chronic conditions in Year 1 were in the top decile for Year 2. Of people with six or more chronic conditions, 50% had high Year 2 costs: “The prospective DCG risk score was also strongly related both to the probability of being in the top 10% and to mean expenditures in the subsequent year.”

In addition to the standard model of age, gender, insurance, and panel, Model 6 included the number of chronic conditions and DCG categories. In addition to the standard model, Model 9 included the number of chronic conditions, DCG categories, and perceived health and functioning. Models 6 and 9 were the most accurate models and had the most predictive power. In the validation, Model 6 had a high C-statistic of 0.854 and a low BIC of –10,051. In the validation, Model 9 had a high C-statistic of 0.857 and a low BIC of –10,187.

In addition to the standard model, Model 7 included the number of chronic conditions and key condition indicators. Model 10 included the number of chronic conditions, key condition indicators, and perceived health and functioning. Of the models that did not include DCG categories, Models 7 and 10 were the most accurate. In the validation, Model 7 had a competitive C-statistic of 0.837 and a BIC of –9,895, and Model 10 had a C-statistic of 0.842 and a BIC of –9,119. These results were competitive with the models containing DCG categories. When the data were tested using the upper 5% as a cutoff, the results were consistent.

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Limitations

Data on clinical conditions came from interviews with respondents who had not been medically trained, not from medical records or claims databases. The study had a potential for error and omission due to potential DCG misclassification. It is possible that the predictive power of the DCG risk score and the count of chronic conditions would have been stronger if the data had been improved.

Conclusions

All models used in this study outperformed the standard model. The DCG risk score was the most valued tool because it provided greatest improvement in prediction. In addition, counts of the number of chronic conditions and indicators of poor health status and functioning also carried great weight. The authors concluded, “The number of chronic conditions also significantly predicted high-cost cases, controlling for DCG score category. A simple count of the number of chronic conditions is useful in predicting future high-cost cases and may be sensitive to information on severity of conditions that the DCG score is not picking up.” When the DCG score was excluded, the separate indicators of prevalent diagnoses were significant. However, when the DCG score was included, separate indicators did not contribute significantly. Models 7 and 10 (without the DCG categories) did not perform as well as Models 6 and 9 (with DCG categories), but were competitive.

This leads to the question: does the improved predictive power compensate for the cost and complexity of using the DCG score? It was concluded that self-rated health measures and functional limitations provided “some additional predictive power” but “less than DCG scores and chronic condition counts.” The general conclusion of the authors was that an unweighted count of the number of chronic conditions warrants consideration in the development of expenditure-prediction models. In addition, combining a variety of measures is much more effective and informative than basing a model on a single measure.

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Haas, Lindsey R., et al. “Risk-Stratification Methods for Identifying Patients for Care Coordination.” *The American Journal of Managed Care* 19.9 (2013): 725-732.

Subject/Category: Model Benchmarking

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Purpose of Article

To benchmark multiple methods of risk identification for care coordination across several clinically and financially meaningful metrics.

Number of References: 32

Perspective

The authors are health care policy researchers and practicing physicians at the Mayo Clinic in Rochester, Minnesota.

Data

Mayo Clinic Rochester electronic medical record (EMR) administrative billing data across inpatient and outpatient settings were used. Data captured all primary-care patients age 18 and older who were empaneled to the Employee and Community Health practice at Mayo Clinic Rochester. Demographic variables such as age, sex, marital status, and insurance status were collected. Diagnostic codes, utilization, and cost were extracted from institutional billing data from 2009 (base year) to predict 2010 utilization and cost. Diagnoses were derived from hospitalizations, emergency department (ED) visits, and primary and specialty-care evaluation and management visits. Private insurance accounted for 63.1% of the population, and 21.8% had Medicare and/or Medicaid coverage.

Methods

Six risk-adjustment methods were evaluated for identifying high-utilization cases. Adjusted Clinical Groups (ACG), Minnesota Tiering (MN Tiering), Hierarchical Condition Categories (CMS-HCCs), Elder Risk Assessment (ERA) Index, Chronic Condition Count (CCC), Charlson Comorbidity Index, and a hybrid approach were considered. Minnesota Tiering groups patients into complexity tiers on the basis of the major condition categories. ERA Index uses age, sex, number of hospital days in the prior two years, marital status, and selected diagnoses to assign a score. The hybrid model combined Minnesota Tiering and ERA scores.

SAS software, version 9.1 was used to evaluate the risk scores. A logistic regression was used to predict outcomes. Multiple outcomes were measured in the prediction year: inpatient hospitalization, ED visits not resulting in hospitalization, any readmission within 30 days of an initial hospitalization, and being in the top 10% high-cost users. The 10% threshold was chosen because the top 10% of users consume almost 70% of total cost. Patients at the 10% threshold are less influenced by catastrophic conditions and are

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potentially more amenable to the effects of care coordination than those at a higher thresholds.

Results

The ACG model outperformed all models in predicting hospitalizations, ED visits, 30-day readmissions, and top-10% high-cost users. The CMS-HCC model performed the worst across all four outcomes. The CMS-HCC method underpredicted high cost, whereas the ERA Index overpredicted cost for patients in the top decile.

There was at least 40% patient overlap for top-decile patients across all models. Due to this overlap, any of the identified risk-screening methods demonstrate comparable predictive ability. As a result, providers could base model selection on ease of implementation or other preferences. None of the models explained more than half of the variability in outcomes. This suggests that there are other factors that could be used to better identify patients who should be managed to reduce hospitalization and cost.

Limitations

The provider dataset only included patients treated at Mayo Clinic and omitted any care received outside the system. The billing data used were prone to miscoding or missing information. Finally, the population was concentrated in one racially homogenous county. The fact that the patient population was largely composed of children and adults less than 64 years old placed the risk-identification methods for elderly people, such as CMS-HCC and ERA Index, at a disadvantage.

Conclusions

Multiple considerations can be used to select a predictive model for patient identification in care coordination. All models used in the study were highly consistent with each other, and using any model resulted in improved care-coordination efforts by focusing on the highest-risk, highest-utilizing patients.

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Haime, Vivian, et al. Clinician considerations when selecting high-risk patients for care management. *The American Journal of Managed Care* 21.10 (2014):e576-82.

Subject/Category: Hybrid Approach

Purpose of Article

The authors discuss the possibility of using a hybrid approach to identify patients for care-management programs (CMPs) through an interview with a primary-care provider

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(PCP) in conjunction with claims-based and risk-prediction models. The purpose of the article was to summarize the criteria that PCPs and their nurse care managers (CMs) consider during their interviews to determine which high-risk patients should be targeted for CMPs. This identification is important because these essential characteristics cannot be included in quantitative risk modeling. Specifically, in an effort to identify patients most appropriate for care-based management, the authors evaluated clinicians' recommendations about patient characteristics that may or may not be included in clinical and billing data and the patient's existing linkages to other providers.

Number of References: 22

Perspective

Not available.

Data

Data were collected through a convenience sample by a physician researcher and a project manager through interviews with 20 PCP and CM dyads from an integrated health care system in Massachusetts. The Anderson Model of Health Services Utilization was used to organize the interview responses into predisposing factors, enabling factors, and need factors. The responses were coded using NVivo version 9, QSR International software. The data were sorted by factor category into major and minor factors present in at least 20% of the interviews.

Methods

In determining patients most qualified for the CMP, "a primary care-based, nurse-led longitudinal care program designed to help high-risk patients better manage their health and healthcare utilization," a claims-based algorithm was first generated using Optum™ Impact Pro® version 6.0 software. The algorithm identified patients who had combinations of chronic conditions and health care utilization that would usually make them high-risk patients. PCPs then categorized patients' risk. Patients who were not deemed high-risk by the PCP or who already had adequate care available were not considered appropriate for CMP. This study focused on determining which patient characteristics were considered in selecting patients for the CMP through phone and in-person interviews with PCPs.

Results

Important factors in patients' predisposition to use services included health literacy and navigating the health care system and services, physical vulnerability, and patients' insight about their health. Health literacy/navigation was a major factor (85% importance) that predicted comprehension of medical instructions, ability to navigate the

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health care system, and patient self-efficacy. Physical vulnerability was also a major factor (60% importance), which included advanced age, risk of falling, and fragility of candidates. Patients' insight about their health was a major factor (55%) in self-management. Patients with low awareness may be challenging to engage and affect through CMPs. The characteristics that impeded or enabled health care use were social/home environment, coping skills/anxiety, and financial resources. Absence of support and existence of home/social issues were each qualifiers for CMP selection. Social/home environment was a major factor (100%). Coping skills/anxiety was a major factor (65%) that selected patients with underlying mild psychological conditions. Financial resources or inability to pay for medication expenses was considered a minor characteristic (35%). Disease characteristics, another major factor (100%), included diagnoses, disease severity, control of disease, and complexity of chronic conditions. Other important characteristics included whether or not the patient was already connected to specialist physicians and specialty clinics, private CMs, or institutional care providers that could already meet the patient's needs (instead of a CMP).

Limitations

This study relied on a convenience sample of PCPs who were already familiar with and engaged in the CMP and, therefore, may constitute overrepresentation. Because this was a quality improvement activity, a more rigorous and multisite design may be more generalizable and effective in determining the costs and benefits of clinician review of algorithm-generated patient lists.

Conclusions

Clinicians consider a variety of predisposing, enabling, and need factors in their determination of a patient's qualification for a CMP. These factors are not usually contained in clinical and billing data and are unavailable for case finding. This study provides evidence that a hybrid approach to identifying patients who qualify for a CMP may be beneficial because it considers important factors not captured by claims or by algorithms based on medical records. By using a PCP interview, patients can be identified who are less likely to benefit from care management either because their utilization is not preventable or they are unwilling or unable to participate. However, biases may be introduced because physicians and practices vary in their threshold for CMP referral or how they weigh specific criteria. The hybrid approach provides a more complete view of patients in determining whether a CMP would be beneficial. Identifying appropriate patients for CMPs is essential to improve health care efficiency and value. Through the hybrid approach, characteristics can be identified to more accurately determine if a CMP would complement or complicate a patient's experience in the health care system.

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Hong, Clemens S., Siegel, Allison L., Ferris, Timothy G. Caring for High-Need, High-Cost Patients: What Makes for a Successful Care Management Program? *Commonwealth Fund* 19 (2014):1764.

Subject/Category: Implementation, Types of Models

Purpose of Article

Complex-case-management (CCM) is a program in which specially trained, multidisciplinary teams coordinate closely with primary-care teams to meet the needs of patients with multiple chronic conditions or advanced illness. Even though CCM holds promise for increasing quality and reducing cost for patients, implementation strategies and execution are varied. The article outlines implementation strategies and best practices to guide health care providers, administrators, health system leaders, and payers.

Number of References: 16

Perspective

Hong is a practicing primary-care general internist and health-services researcher at Massachusetts General Hospital. Siegel holds a master's degree in public health and has implemented the redesign of population-health-management practice with clinical teams. Ferris is a practicing general internist and pediatrician, medical director of the Massachusetts General Physicians Organization, and vice president of Population Health Management at Partners HealthCare.

Data

Qualitative CCM program information was collected through semistructured interviews. CCM program outcomes were gathered from research studies and informational interviews.

Methods

Site selection was done using review of peer-reviewed and grey literature and snowball sampling (a sampling technique where current subjects recruit the next subjects from their known acquaintances), with recommendations from an eight-member expert steering committee. Semistructured key-informant interviews were used to gather CCM program details. Eighteen respondents completed the interviews.

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Results

CCM programs identified patients who were at highest risk for poor outcomes and who would benefit from the care-management interventions. This required “alignment between selected populations, interventions, and desired outcomes.” A combined quantitative and qualitative approach appeared to work best. Quantitative approaches used risk-prediction software, chronic-disease criteria, or utilization thresholds. Qualitative approaches used patient or provider referrals and assessments. “In this hybrid approach, providers must clearly understand the program goals and available care-management interventions to select the right patients.” Acute-care events, such as emergency department visits and hospitalizations, helped “target opportunities to reduce costs and facilitate patient engagement.”

Six types of patient-selection approaches were identified, along with their advantages and disadvantages:

- Quantitative risk-prediction tools had the advantages of being validated and able to provide the most comprehensive information on expenditure. These tools have the disadvantage of not being able to incorporate psychosocial complexity, and results are dependent on data quality.
- Acute-care-utilization-focused approaches identify patients at a time of high need but do not identify patients before the need arises.
- High-risk-condition or medication-focused models provide clear implementation and are easier for physicians to address but may not adequately identify patients at high risk for utilization/costs.
- Health risk assessment is able to combine quantitative and qualitative data sources, but it is resource-intensive.
- Referral by physician or staff or patient self-referral allows physicians and patients to have more control over who is managed. Patients who are challenging may not necessarily be the high-risk patients. Patients who self-refer may exclude vulnerable patients who are not as activated.
- A hybrid quantitative and qualitative approach allows for predicting high risk of cost/utilization and high patient need and responsiveness. Implementation of a hybrid approach can be more complex than the other five types of approach identified.

Limitations

This is a qualitative, non-peer-reviewed article. There were no study limitations given the approach taken. The snowball interview method helped find a more representative sample of the population to interview.

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Conclusions

Multiple patient-selection approaches for complex-case-management were observed across interviewees. Each approach has advantages and disadvantages. The hybrid model strikes a good balance between quantitative and qualitative approaches.

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Johnson, Tracy L., et al. Augmenting predictive modeling tools with clinical insights for care coordination program design and implementation.” *eGEMs (Generating Evidence & Methods to improve patient outcomes)* 3.1 (2015):14.

Subject/Category: Hybrid Approach, Model Development Cycle

Purpose of Article

An algorithm for assigning patients to different care-coordination tiers was developed over four iterations. The process illustrates how an algorithm using purely financial predictive modeling and clinical judgment can be integrated “to implement a clinically actionable” risk stratification of patients. Clinical coherence, transparency, accuracy, and stability of assignment were all desired characteristics of the final algorithm.

Number of References: 22

Perspective

The authors are doctors and pharmacists at Denver Health. Models were additionally developed by a health policy expert with doctoral-level public health training and an IT business analyst. Denver Health developed the algorithm to support the 21st Century Care project, supported by a \$19.8 million grant from the Center for Medicare and Medicaid Innovation (CMMI) to implement population health in primary care. Specifically, Denver Health participates in the Patient Centered Medical Home (PCMH) and the Chronic Care Model for Colorado Medicaid recipients.

Data

The predictive modeling used data internal to Denver Health. Billing data, utilization of services, and lab results were incorporated into the final model.

Methods

A framework for optimizing population segmentation and patient identification was developed. It is an iterative process. The steps include 1) assemble a multidisciplinary team, 2) choose an accountable population, 3) develop risk-stratification rules to define

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population segments (in terms of risks/tiers), 4) evaluate the financial stratification and clinical coherence of tiers, 5) develop care models for use within tiers, 6) identify individuals who are good candidates for a care model, 7) develop associated workflows, and 8) develop performance monitoring and evaluation.

An initial method of risk stratification started with the Chronic Illness and Disability Payment System (CDPS). Model developers calculated a numeric risk score that expressed individual risk in relation to average risk and to tiers defined by threshold range. Tier sizes were predetermined according to the estimated clinical resource capacity for that tier's intervention.

Version 1.0 of the algorithm still used CDPS risk-score thresholds to assign patients to tiers. Clinical rules developed from literature and clinical experience were used to promote certain individuals to higher tiers. The top tier, or super-utilizing, adults were defined by multiple recent hospitalizations. Lab results indicating uncontrolled diabetes or hypertension were included in the model.

The version 2.0 algorithm replaced the CDPS with 3M's Clinical Risk Groups (CRGs) because of its clinical accessibility. A validation process examined mean facility charges for each cohort during the year post-identification. Tier-demotion rules were developed to account for clinical actionability. For example, patients hospitalized for catastrophic events and those undergoing chemotherapy were assigned to lower tiers because they were less amenable to intervention. Additionally, clinical rules were added to promote tier 1 women with a history of adverse birth outcomes to tier 2 and to promote tier 2 adults with recent utilization to tier 3. The lab-value rules were removed in tier assignment.

The version 3.0 algorithm was developed to improve identification of high-opportunity individuals and to better align tiers with clinical interventions. For example, a clinical-pharmacy intervention prompted an investigation into a three-year retrospective study of CRGs that stable or increasing utilization and costs. Clinicians were given an IT tool to drill down to the individual-patient level to determine which CRGs should map to tier 3.

Results

The CDPS risk-adjustment model was originally developed for payment and was not perfectly suited to risk stratification for care coordination. Chart review revealed lists of patients with the same risk score who were clinically heterogeneous. The model predicted health care expenditure according to prevailing practice patterns, including both necessary and potentially avoidable service use. The need for parsing avoidable from unavoidable utilization through clinical input was established. For example, patients on dialysis or active chemotherapy had utilization patterns that were insensitive to change.

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The version 1.0 model had greater clinical significance than previous versions, but this came at the expense of reduced financial distinction between tiers. Stability became an issue when tier 3 was tied to lab values; the model was too sensitive to changes in lab values. It was concluded that the chronic-disease-control status works to prompt clinical activities within a tier but is too unstable to define the tier itself.

The version 2.0 model improved financial performance and was better accepted by clinical teams. The descriptive classification groups were more transparent and clinically relevant than numerical risk scores. CRG status 7, the highest tier for patients with multiple chronic conditions, had been assigned tier 4. This had the clinical advantage of identifying high-risk individuals before a super-utilizing episode, but it degraded the financial performance of the model.

Financial results of the version 3.0 model are not currently available. Version 3.0 clinical validation is being performed by front-line clinical teams through use of the CRG IT drill-down tool. The need to incorporate social-determinant data was identified.

Limitations

The study was restricted to the adult Medicaid population.

Conclusions

Interdisciplinary internal development of an algorithm requires common language and mutual understanding. Time and leadership are required to achieve results. Predictive-modeling tools are necessary but not sufficient to identify populations and individual patients appropriate for enhanced-care-team services. A CRG IT drill-down tool was used to facilitate the collection of clinical input for tailoring the predictive model.

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Kansagara, Devan, et al. Risk prediction models for hospital readmission: A systematic review. *JAMA* 306.15 (2011):1688-1698.

Subject/Category: Event-Based Models

Purpose of Article

The authors evaluated different readmission-risk-prediction models and discussed their performance and appropriateness for clinical and administrative use. The models could be used to reduce readmission rates either through providing early warnings to health systems and triggering a transitional-care intervention or through validating risk-adjustment methods to increase the accuracy of the standardized readmission rates used

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by the Centers for Medicare and Medicaid Services (CMS) as a metric for hospital-quality performance.

Number of References: 63

Perspective

Not available.

Data

The authors used data from various databases (Ovid MEDLINE, CINAHL, and Cochrane Library) to search for articles about readmission-risk-prediction models in populations. They used a dual independent approach to assess the articles for eligibility, having two reviewers read each article and assess them using eligibility criteria. Of the 7,785 citations obtained, the authors narrowed down the field to 30. From each of these studies, “population characteristics, number of patients in the derivation and validation cohorts, timeframe of readmission outcome, readmission rate, range of readmission rates according to predicted risk, and model discrimination” were abstracted. The authors further classified the models as using real-time or retrospective data. Real-time data were available upon the index (initial) hospital admission and were useful for transitional-care intervention. Retrospective data were not available early in the hospitalization but would be useful in the CMS quality-measurement model.

Methods

The authors compared the models using a C-statistic; a value of 0.70 and above indicates acceptable discriminative ability. They also used model calibration: the degree to which predicted rates are similar to those in the population. The authors qualitatively synthesized the results, “focusing on model discrimination, the populations in which the model has been tested, practical aspects of model implementation, and the types of variables included in each model.”

Results

The authors first examined the studies with retrospective administrative data. Of the 14 models studied, only 3 had C-statistics of 0.70 or higher and were all from populations in Europe and Australia. The nine U.S. studies had poor discriminative ability (0.55–0.65). The other models were too specific and had limited generalizability. For the three studies with real-time administrative data, only one model had a C-statistic above 0.70. Of the nine models that included primary data collection, the best-performing models used administrative data on comorbidity and prior use of medical services along with functional-status data from the Medicare Beneficiaries Survey. Overall, most studies used medical comorbidity data and included variables for prior use of medical services.

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Sociodemographic variables were included by most studies but were not deemed effective enough to be a part of the final model. The authors state that the studies found that models based on sociodemographic factors were more predictive than comorbidity-based models, and functional status from survey data slightly improved model performance.

Limitations

Because data from studies outside the United States were included, the applicability of this study's findings to the U.S. health system may be limited. Even though a dual independent approach was used for data processing, subjectivity still remained. Few studies compared models within the same population directly, so the C-statistic "should not be used to directly compare models across different populations."

Conclusions

The purpose of these models includes both hospital comparison and identification of conditions appropriate for transitional-care intervention. The authors concluded that a majority of readmission models have poor predictive ability. As the authors state, "Readmission risk prediction remains a poorly understood and complex endeavor." Although factors at the hospital and health system levels could be used in the models, it would be inappropriate to include these factors because there is no standard of comparison for quality of care. The poor performance of standardized models raises concerns about the ability to fairly compare performance of hospitals using standardized risk. The authors found that while the overall performance of the models was poor, a few exceptions suggest that using social and functional variables may improve overall performance. Factors obtained through medical record review or patient reports might be valuable as well. The authors suggest that certain models may succeed in specific populations because patient-level factors associated with readmission risk differ according to the population studied. The authors suggest that in future studies, relative contributions of different types of data could be weighed to determine the optimal impact for the specific population.

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Lewis, Geraint H. Impactability models: identifying the subgroup of high-risk patients most amenable to hospital-avoidance programs. *Milbank Quarterly* 88.2 (2010):240-55

Subject/Category: Patient Identification Framework

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Purpose of Article

To describe “impactability models,” developed to identify at-risk patients likely to benefit from preventive care.

Number of References: 31

Perspective

The author is a health care–policy researcher supported by the Commonwealth Fund.

Data

Qualitative data from interviews with predictive-modeling vendors, universities, physicians, actuaries, consultants, and others were used in this study.

Methods

Semistructured interviews were performed with stakeholders who build, use, and appraise predictive models. Open-ended questions were asked, including about how predictive modeling is currently being used, issues relating to the data used to build and run predictive models, the outcomes predicted by the models, how predictions are used, and likely new developments in the field.

Results

It is important to target high-risk patients or patients who are likely to be at high risk of a particular outcome. There is opportunity to improve intervention efforts by also determining whether or not the patient will be amenable to intervention. “Impactability models” are tools designed to systematically identify the subset of at-risk enrollees for whom preventive care is expected to be successful.

There are three types of impactability models: 1) those that give priority to patients most amenable to care, 2) those that exclude patients unlikely to respond to care management, and 3) those that tailor preventive care to individual-patient characteristics.

1. The most common impactability model is one that gives priority to patients most amenable to care, based on the “actionability” of their disease and treatments. One form of prioritization model excludes patients who are extremely high-risk because that risk level may be a sign of unmanageability. Such patients could die before they can be contacted about care management. A diagnosis-specific prioritization model gives priority to patients with diagnoses that are most amenable to intervention based on ambulatory-care-sensitive (ACS) condition. These are diagnoses for which prompt, high-quality primary or outpatient care can reduce the risk of hospitalization. Closing gaps in

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care is a prioritization model focused on patients who may be nonadherent to their care plan or unable to access needed care.

2. Exclusion impactability models concentrate resources on those patients who are most likely to fully participate in the program. These models could exclude certain conditions such as mental health diagnoses or social factors that prevent full engagement in care management. The patient-activation measure is a prospective score that predicts the chance that patients will engage in care management. Finally, some model the likelihood of disenrollment of the patient in the program to see whether they should be assigned to care management or may require additional resources.

3. The least common impactability modeling involves predicted receptivity. This type of model forecasts the approach most likely to work for a given patient. Patients whose predicted risks of hospitalization are similar may respond differently to the same intervention. Demographic, diagnostic, neighborhood, and other data are used to characterize the best ways to increase receptivity. One method predicts the optimal type of communication channel and time of day to invite patients to enroll in care management. Another method tailors the actual care to the patient according to their readiness to change their unhealthy behavior.

Limitations

There are challenges with isolating a control group used to measure nonimpactability. Data mining, quasiexperimental methods, and data analysis offered practical approaches for developing impactability models. The interviewers had mixed responses about whether extremely high-risk patients should be offered preventive care that necessitated further investigation before drawing conclusions. Finally, gaps-in-care measurement may select for nonadherent patients unlikely to comply with care-management programs, despite being identified as high-impact.

Conclusions

There are other applications of predictive modeling beyond identifying high-risk patients that can increase the efficiency of care interventions. These “impactability” models help isolate the patients who are most likely to benefit, those who will actively participate, and the best ways to communicate with and engage the patient. Predictive models can identify patients according to objective criteria rather than physician attentiveness or patient wishes, and these criteria include socioeconomic variables to equitably allocate resources.

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Lu, Mingshan, et al. Systematic review of risk adjustment models of hospital length of stay (LOS). *Medical Care* 53.4 (2015):355-365.

Subject/Category: Event-Based Models

Purpose of Article

Hospital length of stay (LOS) is a key indicator of hospital resource use and efficiency. As a result, risk-adjustment models are needed to analyze hospital LOS, but it is unclear which risk adjustors best control for patient severity and the predictive power. Most literature has focused on predicting hospital spending and not on LOS directly. The authors provided a review of risk-adjustment models for LOS derived from a systematic search of studies from a variety of databases.

Number of References: 79

Perspective

Not available.

Data

The authors reviewed a variety of databases, including MEDLINE, EMBASE, Cochrane, PubMed, and EconLit, searching for studies that were relevant to LOS and risk-assessment models. They started out with 3,793 abstracts and selected the ones that measured LOS as an outcome, were original research, and used data from nonexperimental hospital settings to test the performance of risk-adjustment models. They excluded studies that used disease-specific risk-adjustment models. This narrowed the focus to 37 studies.

Methods

Investigators independently reviewed the abstracts of these 37 studies. They focused on two types of risk adjustors for patient characteristics: “those that adjust for disease type based on diagnostic information (i.e. disease groupers) or patient case mix (i.e. disease severity/morbidity indexes).” The data were synthesized first by summarizing the risk adjustors used in studies by name, type, and test population; next by patient group (either general or disease-specific); and lastly, within each patient group in which the authors “presented the study population and data source including sample size, statistical method, model specification, and model performance.”

Results

To predict LOS, disease groupers, disease morbidity/severity indexes, and their test populations were used. Disease groupers, or diagnosis-related groups (DRGs), classify

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inpatients by main diagnosis and can be formed from tools such as the International Classification of Diseases, Revision 9 (ICD-9). Twenty-two studies used disease groupers and were tested for predictive power. For disease severity/comorbidity indexes, the Charlson Index (CI) was most commonly used. For LOS risk-adjustment models, the 37 studies were separated into two groups: those that analyzed general inpatient populations (8 studies) and those that analyzed LOS for inpatient populations with specific diseases (29). The studies used hospitalization data. The statistical methods included ordinary least squares (OLS), generalized linear regression models, hierarchical regression models, and data-mining models. Most of the studies (78%) used OLS. Very few of the studies included only one risk adjustor, and many tested various model specifications. Age and sex were commonly included, and the most common adopted model specifications were sociodemographic controls, groupers, and disease severity/comorbidity indexes. Most of the models were measured using R^2 . Models that only used demographic factors performed poorly, while models that performed well included “one or more disease groupers and/or disease/comorbidity indexes.”

Limitations

The authors noted that the studies used different data, which consequently made it difficult to accurately compare model performance. The authors only used English language studies that used disease groupers and disease severity/comorbidity indexes.

Conclusions

The authors determined through this study that few models have been developed for LOS. OLS regression remains a popular method for predicting LOS with reasonable performance. There is large variation in performance across different risk-adjustment models. Some models explain less than 1% of LOS, while others explain as much as 63%. The variations depend on the model specifications and risk adjustors used. The authors noted that while they could not recommend risk adjustors, the models that included “other clinical controls” in addition to age, sex, DRGs, and CI variables performed well. They ultimately concluded that models with a variety of LOS risk adjustors performed better in their ability to predict variance in LOS.

The authors noted that a wide range of determinants other than patient characteristics affect LOS, such as hospital, clinical caregiver, and social/family environment characteristics. Since most studies focus on patient characteristics, it is unknown what effect the other characteristics could have in explaining variation in LOS. The authors also noted the evaluation using R^2 could discriminate against nonlinear models, which might result in misrepresentation. The applications of these risk-adjustment models are complicated because penalties for poor performance could reduce resources and result in a decrease of the quality of patient care. The authors conclude that LOS risk-adjustment

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models are limited in predictive power and more research is needed into incorporated characteristics, accurate standardization, and evaluative statistical methods to improve prediction of LOS.

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Peikes, Deborah, et al. How Changes in Washington University's Medicare Coordinated Care Demonstration Pilot ultimately achieved savings. *Health Affairs* 31.6 (2012):1216-1226.

Subject/Category: Need for Predictive Models, Non-Traditional Data Sources

Purpose of Article

To identify the features of a successful care-management program by comparing hospitalization and cost impact before and after the redesign of the program.

Number of References: 26

Perspective

Researchers from Mathematica Policy Research and The Washington University School of Medicine in St. Louis performed the evaluation of the redesign of a care-management program for Medicare fee-for-service beneficiaries as part of the Medicare coordinated-care demonstration.

Data

Before the redesign, professional claims data were used for predictive modeling. After redesign, past and present inpatient hospitalization data were used.

Methods

Before the redesign, patients were prospectively identified through a predictive-modeling approach and through direct referral from health care providers. The predictive modeling approach used the care-management-outsourcing company StatusOne (now Healthways). The predictive model was evaluated monthly to identify patients who were likely to become clinically unstable and require hospitalization in the subsequent 12 months. Dedicated recruitment staff explained the program to eligible beneficiaries. Twenty percent of those beneficiaries who accepted were randomly assigned to a care-management group or a usual-care group that did not receive care-management services.

Before the redesign, patients were stratified into five levels of risk based on acuity, disease, physical, social, psychological, and financial status components and on the

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ability to self-advocate. The care manager evaluated subjective criteria, such as the level of health literacy. Objective data, such as whether the patient was discharged from the hospital in the past six months, were determined using hospital data. The Patient Health Questionnaire 2 (PHQ-2) was used to evaluate depression risk. After the redesign, during each patient contact, the acuity assessment combined with the PHQ-2 was administered more systematically than before the redesign.

Results

Before the redesign, hospital admissions were 2.6% less frequent for the care-management group than for the usual-care group. After the redesign, the care-management group had 11.7% fewer hospitalizations annually than the usual-care group. The impact of care management on the reduction of hospitalizations was significantly higher after program redesign.

Before the redesign, there was a 12.3% annual Medicare Parts A and B spending increase, including care-management fees. After program redesign, total spending decreased 2.9% annually for the care-management group compared with the usual-care group. The high-risk care-management enrollees who had two or more hospitalizations in the two years before enrollment showed a 9.6% reduction in total annual spending compared with the high-risk usual-care group.

After the redesign, medical and psychosocial needs that were previously undetected because staff communicated with patients only by telephone were detected, and care managers increased the acuity scoring for many patients, revised patients' care plans, and contacted patients more often. The program could be administered even more effectively by just focusing on the highest-risk patients. Of the highest-risk patients, or 55% of enrollees who had two or more hospitalizations in the previous two years, the ones in the care-management group had a 2.5 times higher hospitalization rate than those in the usual-care group. Program effects for the higher-risk group included a 17% reduction in hospitalizations per beneficiary per year.

Limitations

Besides changing how patients were identified, there were redesigns in other areas that could have contributed to the difference in hospitalization rates, including staffing changes, stronger transitional care, and more comprehensive medication management. Another limitation is that only Medicare fee-for-service beneficiaries were included.

Conclusions

A focused effort on the highest-risk patients reduces hospitalization and costs. Getting information relevant to risk when a patient is admitted to the hospital is key. It allows

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lower-level care-manager assistants to maintain contact with low-risk patients while nurses focus their attention on the highest-risk patients.

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Shenas, Seyed Abdolmotaleb Izad, et al. Identifying high-cost patients using data mining techniques and a small set of non-trivial attributes. *Computers in Biology and Medicine* 53 (2014):9-18.

Subject/Category: Alternative Modeling Methods

Purpose of Article

The goal was to compare the ability of different predictive models to estimate high-cost patients in the general population in the United States. In an effort to proactively estimate health care costs, the authors also looked for nontrivial attributes that could predict high- and low-cost patients. Such factors can be identified before the event, as opposed to trivial factors, which can only be identified after it (such as diagnostic disease category or visit counts).

Number of References: 31

Perspective

Not available.

Data

Data were from the Medical Expenditure Panel Survey (MEPS), including 19,875 records and 1,600–1,800 attributes. Through extensive review of all attributes and insight from the academic literature review, 66 attributes were chosen for the study.

Methods

The authors used a bottom-up data-mining approach, including machine learning, information retrieval, and statistical analysis, to place individuals into specific classes. They studied this process to understand the best predictive-modeling strategies for specific tasks, and they built and tested models using a three-step process. First, they extracted data, selected attributes, and prepared data for decision-tree or neural-network modeling. Next, models were built, trained, and run based on the data. Then, models were evaluated using different measures of model quality. Evaluation criteria included sensitivity (ability to identify true positives), specificity (ability to identify true negatives), and correctness accuracy (degree of closeness of the prediction to the actual

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values). The authors also used the geometric mean, or G-mean, which is the square root of the product of sensitivity and specificity. They also reported an area under-the-curve (AUC) measure. Both G-mean and AUC measures overcome biases toward correctness accuracy caused by the small proportion of true positives.

Identifying easy-to-survey attributes indicative of high-cost patients could be effective in reducing costs because it could lead to proactive measures that could lower costs by changing care delivery. The authors used a secondary-attribute-reduction process to narrow the 66 attributes to 39 by removing attributes that had many missing values or a high degree of correlation with other attributes. The authors intended to organize the target attributes into a binary format, identifying high-cost and low-cost instances using true and false measures. When developing the models, the authors used current-year expenditures as an input variable and attempted to measure the current and predict the next year's total expenditures. They defined "high-cost" as those in the top 5% of expenditures. The authors built two different types of models: decision tree and neural network. The decision tree (DT) measures information gain at the splitting node to classify data through leaf assignment. The neural network (NN) is a nonlinear model that adjusts the weight of internal connections through an iterative process. The authors built C5.0 and CHAID decision trees with the IBM SPSS Modeler software package. They evaluated the performance of the models using accuracy and AUC, and they used the CHAID classifier to find the set of predictive attributes.

Results

The findings in Table 18 show that the modeling and evaluation methods were of great importance. The authors determined that the C5.0 DT had the highest accuracy rates (93.7%), compared with the CHAID (86.3%) and the NN (76.2%). The AUC showed the NN performing the best at 95.6%, with the C5.0 at 81.6% and the CHAID at 94.6%. Because the NN performs best with continuous values and it takes a long time to converge when the number of input attributes is high (39), the authors decided it was not useful. Because the C5.0 generated a higher rate of false negatives and the CHAID had a higher sensitivity, the CHAID model was used.

The authors used the CHAID classifier to predict the top 5% of expenditures throughout the study. To rank the top 37 attributes, they used CHAID classifiers and evaluation methods (AUC, accuracy, G-mean) to selectively add the other attributes to the demographic attributes. The attribute list was further narrowed down to a list of 10 that held the same predictive value as the set of 37. To create a smaller, usable list of factors that were nontrivial, the authors eliminated trivial factors, which led to five final factors. The model the authors used measured the top 5% of total expenditures in the current year based on five nontrivial predictors: "individual's overall health perception, age, history of

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blood cholesterol check, history of physical/sensory/mental limitations, and history of colonic prevention measures.” This model performed acceptably well in predicting the top 5% of expenditures in the next year, with an accuracy of 75%, G-mean of 76%, and AUC of 0.812. This compared with the 10-factor model with an accuracy of 89%, G-mean of 85%, and AUC of 0.942.

Table 18. Comparison of Different Modeling and Evaluation Methods

Model	Notes	Accuracy Rate	Geometric Mean	AUC
C5.0	Not investigated further due to high number of false negatives	93.7%	73%	0.816
NN	Not investigated further due to long model calibration times	76.2%	86%	0.956
CHAID-39 (39 predictors)	Model chosen for further variable selection	86.3%	88%	0.946
CHAID-10 (10 predictors)	Reduced variables from CHAID-39 model	89%	85%	0.942
CHAID-5 (5 predictors)	Reduced variables from CHAID-5 model	75%	76%	0.812

Limitations

The authors used the MEPS database, a unique dataset “that stores data for the noninstitutionalized US population according to the sources of payments and services that incurred the costs.” The usefulness of the MEPS database could be limited given the categorical nature of the data it stores. Strong data-mining algorithms work better with continuous data.)

Conclusions

The authors concluded that the DT models outperformed the NN models and the CHAID algorithm performed best for predictive modeling purposes. They also concluded that using information from a set of five nontrivial variables (individual’s overall health perception, age, history of blood cholesterol checks, history of physical/sensory/mental limitations, and history of colonic prevention measures) could provide proactive insight into health care spending, which identifying patients after they have incurred costs does

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not. These findings could lead to proactive disease-management programs in which interventions with high-cost groups could be used to limit spending. Easily administered surveys using the five nontrivial variables could be developed to identify high-cost groups. The findings could lead to the better allocation of resources to high-risk groups and improved budgeting by health care planners.

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Stam, Pieter, van Vliet, René, van de Ven, Wynand. Diagnostic, pharmacy-based, and self-reported health measures in risk equalization models. *Medical Care* (48) (2010):448–457.

Subject/Category: Total Cost of Care Models, Non-Traditional Data Sources

Number of References: 42

Perspective

The three authors are associated with the Institute of Health Policy and Management, Erasmus University Rotterdam, Rotterdam, The Netherlands. One author is a consultant for SiRM–Strategies in Regulated Markets, a consulting and business services firm.

Purpose of Article

The purpose of the article is to determine the predictive power of all types of self-reported health measures for prospective modeling of health care expenditures in a general population of enrollees in the adult Dutch sickness fund.

Data

The study considered enrollees in the Dutch sickness fund who had 2002 annual family wages below €30,700. Enrollees were at least 16 years old and overrepresent people with poor health status. Enrollees were continuously enrolled from 2001 through 2002 through a single carrier, Agis Health Insurance. All enrollees had the same coverage without any out-of-pocket cost.

The study used administrative-expenditure data from 1997 through 2002. Expenditure data for pharmacy-based cost groups (PCGs) and diagnosis-based cost groups (DCGs) were determined for 2001 based on hospitalization data. PCGs are DCGs are used in risk adjustment, as defined by the Dutch risk-equalization system.

Health-survey data were collected in the last quarter of 2001. Self-reported data consisted of 8 measures of general health status as defined by the SF-36 questionnaire, 3 measures

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of functional status as defined by OECD limitations, and 20 select long-term chronic conditions.

Methods

Five models were constructed: an age/gender model, one consisting of only PCGs/DCGs, one with only self-reported data, one with PCGs/DCGs combined with the SF-36 data, and one with all administrative and self-reported data. Ordinary least squares approximation was used to predict 2002 expenditures for each combination of explanatory variables derived from 2001 data. Total, inpatient-only, and outpatient-only expenditures were separately predicted.

A split-sample approach was used to train the model on half of the data and evaluate model accuracy on the other half to avoid overfitting the model and to more accurately estimate out-of-sample prediction error. Adjusted R^2 and mean absolute prediction error (MAPE) for both the entire sample and the test sample were used to measure error.

Expected over- and undercompensation and model accuracy were evaluated within select subgroups of the population using six subgrouping methods: by number of years in the top quartile of expenditures, number of years with hospitalizations, unhealthy general health status, lowest functional status, selected self-reported chronic conditions, and insurance-coverage switching.

Results

R^2 for the age-gender model, the PCG-DCG model, and the full model were 3.2%, 17.9%, and 19.6%, respectively.

The full-model R^2 for inpatient expenditures was 2.6%, and for outpatient expenditures, it was 32.4%. R^2 for the entire sample was comparable to test data R^2 for total and outpatient expenditures and, due to outliers, about twice as much for inpatient expenditures.

For the unhealthy subgroup, the model with only self-reported measures performed better than the only PCG/DCG model, with some exceptions. The predictive power of the SF-36 data “dominates for subgroups defined by general health and functional status, whereas it is about equal for people who reported chronic conditions.”

Models using self-reported data for enrollees who switched insurance coverage during the five-year measurement period or enrollees without any top-quartile expenditures performed better than the PCG/DCG-only model did.

The PCG/DCG model performed better than the self-reported-data-only model for subgroups of people with more than one year of hospitalizations and of people who

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switched insurance. The additional predictive power of self-reported health measures declines with number of years of hospitalizations.

Limitations

Models were constructed with risk equalization as the primary application. This limits the use of indirect measures of health status such as sociodemographic and socioeconomic status. Additionally, measures based on mortality and previous expenditures were excluded because their use comes at the risk of unintended behavioral interventions by providers or insurers.

Expenditures include dental care and prescriptions outside the hospital. Current provider risk arrangements in the United States exclude those services from total expenses. Lack of out-of-pocket expenses may cause patients' utilization patterns to be different from those of patients who have U.S. insurance plans with out-of-pocket expenses.

Conclusions

Self-reported health measures were shown to provide an independent contribution to the prediction of individual expenditures. Self-reported health-measure collection has advantages and disadvantages over administrative data, and it has the potential to improve equalization payments for every individual in the total population.

ASSESSING SYSTEM SOLUTIONS

Introduction

The identification of high-risk patients and the execution of care-management programs require a coordinated multidisciplinary approach that leverages clinical, financial, operational, and information technology (IT) resources. Because of limited time and expertise, many providers have sought solutions offered by an emerging population-health-management (PHM) software market. The market is in its infancy and is rapidly changing as regulatory reform and market effects alter the landscape. As a result, providers must proceed with caution when identifying the optimal PHM tool. The selection of the final tool, whether developed internally or externally, must be based on the purpose of the tool and be aligned with the level of engagement in value-based payment programs within the institution.

This report provides guidance in identifying and assessing the relevant components of a PHM solution for risk assessment (see Table 19). This report also provides guidance for a request-for-proposal (RFP) process, and help with the evaluation of your institution's current ability to manage population health data.

Key Content and Functional Areas to Consider

This section addresses six key content and functional areas to consider for both risk model implementation and ongoing program monitoring: **data management, descriptive analytics, predictive analytics, provider action, patient involvement, and overall project management**. The first three sections are heavily focused on data and data use, whereas the last three sections cover workflows and implementation tactics.

Please note: The following content areas address a series of current requirements, the importance of which may shift as new reimbursement models emerge.

Data Management

Data management is an essential component for PHM software. Such software needs to be able to effectively import, integrate, and aggregate data from multiple sources while providing an underlying structure to organize and map such data. These functions are critical because raw data are the main ingredients for predictive models that guide care-management workflows. Challenges for management of raw data emerge as a result of new data sources, fluid data definitions, data-integrity and completeness issues, and practical barriers to data acquisition. Further, the sources that provide data that can be useful for population health management are continually increasing in the variety, volume, velocity, and variability of information that can be made available. If there are data-integrity issues, then all downstream activities, such as descriptive and predictive

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analytics, will suffer. Data management is one of the most time- and resource-intensive aspects of implementation. The movement toward complex-care management reinforces the need for data management best practices and for further investment in this key operational area.

The following items are the key components in raw-data management:

Imports Payer Data Sources – The ability to import payer data sources is often a necessity for care-management activities. Although there are quality and timing challenges with payer eligibility and claims data, this data source often forms the broad data foundation across the health care continuum that is needed to support initial selection and longitudinal tracking of patients and their care. Seamless and meaningful integration between external payer data and electronic medical records (EMRs) and PHM continues to be a challenge.

Imports Clinical Data Sources – In contrast to payer data sources, clinical data sources largely encompass admission, discharge and transfer (ADT) feeds, problem and medication lists, lab and imaging results, registry identification, and other fields collected during clinical assessment and patient documentation.

Integrates Payer and Clinical Data Sources – Because value-based reimbursement models are clinically and financially integrated, the data foundation for PHM activities demands a sophisticated level of meaningful integration between payer and clinical data. For example, clinically derived identification rules for diabetes patients can be combined with financially derived rules to capture the accurate number of diabetic patients. Combining HbA1c test results and problem-list diagnosis criteria with previous coded-claim diabetes diagnoses and relevant pharmacy-claim history will identify most diabetic patients.

Aggregates Data across Multiple EMRs and Insurers – Health systems are often affiliated with a variety of provider organizations, which can lead to the use of multiple EMR systems across the health system. Aggregating data across multiple clinical information systems requires a solution to be flexible enough to import multiple different data definitions. In effect, the software may need to act as a private health-information exchange (HIE) to connect disparate sources of clinical information. Similarly, providers are now engaging with multiple contract configurations and insurers in risk contracting, each with varying data-sharing capabilities and data formats. Aggregation across multiple information systems is less important if the provider relies on public, state, or regional HIEs or has a separate HIE solution. Similarly, a robust All-Payer Claims Database (APCD) that aggregates

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and standardizes data across multiple payers would also lower the value of this dimension.

Imports Nontraditional Data Sources – New data sources are appearing as health care and other industries become increasingly digitized. Research into which data sources will provide the highest value for care management is ongoing. Examples of nontraditional data sources include remote patient monitoring and patient-reported surveys. A high-quality data management tool will electronically integrate such nontraditional data so that the data are reportable or usable in predictive models, similar to traditional data elements.

Ease and Length-of-Time Mapping Data – One of the most challenging aspects of implementing an internal data warehouse, or PHM platform, is defining a data relationship model and structuring data elements from multiple data sources within the data model. For example, mapping claim-denial codes to readable denial-code descriptions takes considerable effort since denial-code descriptions change. This example illustrates the importance of processes such as “data binding,” which links data elements and data definitions such that updates occur synchronously. Data binding includes several activities that ultimately allow for meaningful analysis; data can be bound to definitions or to rules in the form of algorithms. Some commercially available solutions herald a “late binding” approach to allow for greater flexibility and to reduce the amount of upfront effort expended to implement the solution.

Data-Mapping Flexibility – Data definitions constantly change due to shifting regulatory, clinical, and business requirements. Data-variability issues can cause data sources to change over time. Any solution would need to have flexible mapping capabilities that can keep pace with ongoing changes in the market.

Data Quality Assurance – Descriptive and predictive analytics are only as reliable as the underlying raw data. A proactive approach involving continuously applying robust data-validation checks needs to be adopted to monitor issues with the data before they become problems.

Data-Refresh Frequency and Lag – For early identification of developing health risks, the goal is to have real-time or near-real-time data refresh. The reality is that most analytics remain batch processed. The frequency at which certain types of administrative data, such as paid claims data, can be refreshed is naturally limited since claims are processed daily. Clinical information, such as admission, discharge, and transfer (ADT) messages, can be triggered immediately when the event occurs. In addition to natural limitations from the data sources, there is usually a processing lag

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with the system to generate reports or predictive-model results. Some vendors can take weeks to prepare analytics each time the data are refreshed.

Descriptive Analytics

The second phase of an operational implementation involves using historical data to set baselines, establish patterns, and build reports. Powerful descriptive analytics allows the provider not only to report on past data but also to drill down to subsets of data to investigate root causes for observed outcomes. Internal data-warehouse solutions usually excel in descriptive analytics but may not be configured to support care-management initiatives.

Reporting Interface and Data Visualization – Various stakeholders in the multidisciplinary team, including clinical and financial experts, use the reports. It is essential that an easy-to-read reporting display is available so users can quickly understand summary findings to support their daily workflow. Some products allow users to include visual elements in reports that provide insight into the data.

Overall Reporting Capability – Powerful reports use data elements from a variety of sources and allow complex logic and calculations. Any solution must have the ability to mine the data and create robust and meaningful reports.

Reporting Flexibility – Having the flexibility to alter, or tailor, reports is a key function as you continue to develop your expertise in PHM. While altering reports may be feasible within an internal solution, it may be more challenging for a vendor solution.

Ease of Defining Reports – Internal data warehouse solutions require a team of skilled report builders to define and deliver user-friendly reports. Vendor solutions make this process easier by beginning with prebuilt reports that speed adoption. Some solutions offer a user-friendly interface to update reports, whereas others require special training to customize reports.

Drill-Down Capability – Health care data appear at various levels of granularity, from the detailed patient level to the grouped cohort and population levels. The end user needs to be able to use data at all levels of aggregation in order to quickly spot trends and perform deep drill-down investigations. Some vendor solutions allow full drill-down capabilities, whereas others offer no drill-down for certain reports, limit the fields available during drill-down, or impose restrictions on the number of rows of data displayed during drill-down.

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Report Sharing and Repositories – The development of a provider network can entail technical difficulties and resources constraints. A forum for sharing reports or a repository for sharing across a network can enable resolution of common issues and can speed up implementation. Some vendors provide this option.

Benchmarking Capability – External benchmarks help providers understand how they compare with other providers or populations in the same or across different markets. Benchmarks often need to be purchased from data-product companies or consultancies. Some vendor solutions provide commercially available benchmarks through partnerships or develop their own benchmarks by pooling customer data.

Query Performance and Scalability – Query performance and scalability is a crucial topic because the burden placed on existing data infrastructures is magnified with high volume, variety, and velocity of data. Both internal data warehouses and vendor solutions must articulate whether they build a foundation using traditional data-storage techniques or follow the movement seen outside the health care industry toward distributed architectures, such as Apache™ Hadoop®. Distributed architectures have allowed outside industries to efficiently query terabyte- and petabyte-size datasets. Additionally, many vendors are building their solution by using cloud hosting, which holds the promise for an indefinitely scalable infrastructure. This is in contrast to traditional provider data warehouses hosted onsite. It is unclear how important these newer technologies are for the current types and volume of data encountered in PHM. As PHM data become larger and more complex, opportunities will expand for improved scalability through these technologies. It's important to ask vendors detailed questions about their architecture, current system limitations, and average query-processing times. Internal solutions also require diligent performance measurement to discover query-processing bottlenecks and to avoid business disruption.

Predictive Analytics

The final data-focused section of the outline lists considerations within predictive analytics. These are mathematical or computational models that use data sources to predict outcomes before they occur. The most common predictive models required for PHM are the ones that identify high-risk patients. However, the following are additional modeling capabilities that could be included in an electronic platform.

Clinically Focused Predictive Models – Many solutions import clinical data and offer clinically based reporting, but only some take full advantage of the clinical data available to predict which patients should be managed. Examples of clinically focused predictive models include the Charlson comorbidity index and readmission-

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prediction models. The incorporation of clinical data into predictive models can better flag patients who otherwise may have been ignored by applying only administrative data sources to a predictive model. Clinically focused predictive models are beginning to be available in EMRs but are generally limited to the data contained within the EMR.

Financially Focused Predictive Models – A variety of financial modeling activities include prediction of high-cost patients and estimation of the expected value of risk-based contracts under different conditions. Financial-decision-support systems are typically used to model internal costs, but some PHM platforms incorporate internal cost data as well.

External Model Interoperability – The use of predictive models from sources other than the PHM platform is often necessary. Third-party predictive models and provider-developed predictive models are examples of external models that can be incorporated into the PHM platform. The importance of the interoperability dimension depends on whether or not models are internally developed at the provider organization. Another example of a necessary external model is when the provider has identified a unique population, such as within pediatrics or within long-term care, and standard predictive models do not apply.

Proprietary Predictive-Model Development – Some PHM platforms may include proprietary predictive models in their solution. It's important to understand which models are included and whether your institution has the internal capability and data to use them.

Transparency and Interpretability of Model Results – The result of standard predictive models is often a single risk score. It's crucial that the underlying logic within the predictive model is transparent to the provider. Clear documentation describing statistically significant factors used by the model, model weights and methodology, and model limitations is necessary for full transparency. The model developer needs to provide the definitions and guidelines that allow users to clearly interpret the model results.

Provider Action

This section describes product features that facilitate day-to-day care-manager tasks where automation is the main goal. Tools for improving care-manager workflow are imperative for daily care-management operations. Ideally, the PHM platform satisfies all the following dimensions so providers have the choice to implement a single solution powerful enough to support all care-management activities. However not all providers

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integrate the care-management activities into the PHM platform. The relevance of this section will depend on how you plan to handle care management overall. To effectively manage your patient population, the following capabilities should, ideally, be supported.

Patient-Registry Functionality – Patient registries are the foundation for the identification of subpopulations of patients. Registry functionality both assists with care-management workflows and supports data reporting. Most vendor solutions include a patient registry; however, the ease of registry configuration varies.

Quality of the User Interface – A simple and easy-to-understand user interface improves care-manager satisfaction, reduces the risk of error, and streamlines end-user training. Graphical displays, web-based controls, and patient summaries help maximize the value of what’s being displayed so that care managers can access critical information when they’re engaging patients.

Workflow Efficiency – Workflow efficiency within the PHM platform refers to the amount of clicking and navigating required to complete a task. Careful definition of care-manager workflow and software demonstrations involving realistic scenarios help potential buyers gauge how much effort is involved to complete workflows. Complex and difficult workflows can defeat the purpose of using software to improve efficiency.

Patient-List Generation – Care managers begin their workflow with a customized patient list. It’s important to understand how patient lists are generated and can be augmented throughout the workflow. Central considerations include knowing whether or not care managers can manually add or remove patients, what information is displayed about the patient, and how care managers may interact with patient lists.

Notification, Alerts, and Reminders – Care managers are required to interact with many patients at any given time. It can be a challenge in some systems to have multiple records open simultaneously. Automated notification for patient follow-up activities or outreach based on whether or not a patient is meeting their goals is a critical functionality and should be included in the baseline system.

Gaps-in-Care Identification – Gaps in care are discrepancies between evidence-based clinical guidelines and actual care or quality measures and outcomes. Care managers must use the PHM tool to identify care gaps and suggested interventions. The PHM platform should contain standard care-gap rules right out of the box. The care manager then documents planned interventions, as well as reasons for the inability to close specific gaps.

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Care Planning and Goal Tracking – Chronic-disease management requires a long-term care plan and periodic assessments to determine whether patients are meeting the goals defined within the care plan. The care plans should be sharable across the care teams and clinical information systems.

Workflow Configurability – Workflow configurability refers to the process and speed with which changes can be made to elements of the workflow. Some vendors allow system administrators to alter care-manager workspace layout or customize alerts for individual care managers. Other systems do not offer this flexibility.

Automated Patient Communication – In order to increase staff efficiency, a PHM platform should have the ability to automate patient communication, such as being able to contact patients to remind them of appointments or to schedule an appointment. Important considerations include which types of outreach can be automated and how patients should be contacted.

Automated Ordering – Some solutions can automatically create standard orders based on care-manager criteria. This means more time can be spent with patients and less time on manual entry for groups of similar orders.

Assessment and Documentation – The ability to prepopulate data fields and other templates can enhance the efficiency of the care-management team and, thus, streamline the documentation process.

EMR Integration – If the PHM platform is the primary system care managers use to perform their work, important information needs to be generated to export into the EMR. This may include automated patient orders, electronic patient communications, care-manager notes, and registry updates. Although it's vital that the EMR and the PHM platform are synchronized with the most current information, the ability to do that is not widespread yet.

Patient Involvement

Vendors are not only experimenting with improvements to care-manager workflows through the use of technology, they're also using technology to better involve the patient in care-management activities.

PHM platforms can offer a patient portal that allows patients to access their data and engage in care management. The following are elements that can be included in a patient portal. This functionality may also be available in other provider portals available to

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patients both within and outside your institution. In general, a patient portal is only meaningful if the patient is able to access their clinical information in real time.

Patient Portal and Personal Health Record – A patient portal containing patient-specific data and patient activities is included in some vendor solutions. It can take the form of a web-based or mobile application. Some applications include a personal health record that allows the patient to enter and manage their own health data.

Patient-Facing Clinical Data – The patient portal can contain general education materials and specific patient information, and it may allow patient-reported data. A patient portal is most meaningful if the patient is able to access their clinical information within the context of real-time care needs.

Educational and Coaching Content – Patient portals may contain educational or motivational content in written or video form. These can help supplement patient education provided by the team and care managers.

Multimodal Patient Communication – The various modes of patient communication include mailings, phone calls, emails, texts, video visits, and secure patient portal messaging. Some vendors offer one or more of these modes of communication to reach the patient, using the patient's preferred means of communication.

Patient Portal Integration – This is the ability to incorporate patient-entered data or patient portal access data into the rest of the PHM platform. Few solutions currently support this integration in a meaningful way.

Overall Project Management

The following general aspects should be considered when you're installing and maintaining a software product and when you're assessing internal IT solutions yourself.

System Reliability – System downtimes compromise the effectiveness of even the most innovative products. System and software update stability is a fundamental need, but issues arise for all systems periodically. It's important to ask vendors about the internal quality assurance processes used when they release changes to existing features and when they introduce new features. Business downtime procedures need to be established and followed when inevitable system downtime does occur.

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Comprehensiveness – Many disparate features are required of comprehensive PHM platforms or internal IT solutions. Comprehensive PHM solutions offer broad functionality and address every stakeholder in the care-management process. The level of comprehensiveness you require will be driven by how your institution plans to use the PHM platform.

Contracting and Cost – Vendors can range in their suite of offerings, pricing schedule, and contract flexibility. Be sure to identify what level of risk your institution is willing to bear and what approach is fiscally appropriate.

Experience and Subject-Matter Expertise – Many vendors hire population health subject-matter experts to help with system design and implementation. Providers who are new to PHM should consider the importance of using subject-matter experts to help guide the software installation process and optimize the system. Be mindful that you may have to pay an additional charge for this expertise.

System Training – Because PHM platforms are new for everyone, care managers, analysts, and users will need thorough training to learn how to properly use the system. The training can be supplemented with in-house training and documentation.

Customizability – Software products must usually be customized to meet all customers' needs. PHM platform vendors vary in their willingness to listen to customer feedback and incorporate changes in future releases. Therefore, it's important to investigate vendors' willingness to make modifications to the out-of-the-box configuration and the potential cost associated with those modifications.

Customer Support and Responsiveness – A service-level agreement specifies mutually agreed upon customer expectations for system support and timelines for resolving issues. A sample service-level agreement should be requested during the vendor-procurement process. Vendors that are proactive in this area notify customers about system issues and do not hesitate to escalate urgent issues. Similarly, internal IT solutions should maintain a service-level agreement with key stakeholders within the organization.

Upgrade Process – Software products are constantly evolving. The vendor and your organization should establish a tradeoff between the need for the system to evolve and the burden of frequent updates. Additionally, upgrades should have a vendor-testing process and not cause existing functionality to break. Thorough upgrade documentation and procedures are mandatory.

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Regulatory Updates and Compliance – Because PHM is subject to frequent regulatory change, some vendors designate a team of personnel to proactively monitor regulatory change and inform the software developers. This service makes it easier for customers to remain compliant with current regulations. Similarly, internal IT departments should have a process in place to remain informed about regulatory change and generate IT change requests when sufficient regulatory guidance is available.

System Adaptation and Evolution – Some vendors exhibit a strong vision for their solution and how it will evolve to support changing reimbursement models and care-management initiatives. Other vendors do not have an effective process in place to gather customer feedback for future development. Usually, internal IT departments excel at adaptation because unlimited customizations can be made to internal solutions. However, hurdles to internal development include inadequate access to IT staff, competing project priorities, and cost.

Implementation Process – PHM requires strong change-management skills. Vendors provide implementation resources to ensure that the change to a PHM platform is successful. There is usually a commitment that implementation staff will be onsite with the customer to triage issues and ensure a smooth transition. It's important to meet implementation staff in person during the RFP process to assess whether or not the vendor team has sufficient experience, can access internal vendor resources, and is in touch with customer need.

Request-for-Proposal Process

A proper PHM-vendor request for proposal (RFP) contains more than a checklist of required dimensions. The previously outlined elements provide a foundation for an objective evaluation of commercially available software products during the procurement process. They can also help you develop focused questions to guide initial vendor discussions. The most important questions to ask during the RFP process are, arguably, open-ended ones. The following section identifies examples of relevant questions to consider including in an RFP process or interview session. The questions are organized by the following topic areas: overall solution, company, and functionality.

This guide contains a series of current requirements, the importance of which may shift as new reimbursement models emerge. The authors do not guarantee that the items will remain relevant as PHM activities evolve.

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Overall Solution

1. ***Solution Breadth*** – Are all patients and conditions covered? Are all components of system functionality included? Does the vendor offer services to complement the software?
2. ***Ease of Use*** – Do queries take a long time to run? Is it difficult to map data? Is it difficult to write reports? Are care-manager workflows efficient? Are care managers forced to do their work in two systems, or can they perform everything in the PHM system?
3. ***Flexibility*** – Is the data model modifiable or rigid? Can data mappings be altered? Is the user able to customize reports? Can the care-manager workflows be customized? Does the vendor incorporate customer feedback in upgrades? Is the vendor responsive and timely about programming customizations?
4. ***Understanding and Simplicity*** – Is the user interface clear and simple? Are reports easy to understand? Are results of predictive models interpretable? Are there user views that can deliver a lot of information at a glance? Are data and definitions clear and easy to understand?

Company

5. ***Contracting*** – Are there contracting terms that are favorable or unfavorable? Are there conditions for buying the product?
6. ***Customer Satisfaction*** – Is the system reliable? Does the vendor provide timely support? Is the implementation process smooth? Does the vendor provide training?

Functionality

7. ***Provider and Payer Integration*** – Are customers able to meaningfully import claims and clinical data?
8. ***Nontraditional Data Sources*** – Is the vendor moving beyond claims and standard clinical data to incorporate elements such as social determinants or remote patient monitoring? Are there other data sources that can be imported and used within the system? Are there custom data fields available for reporting?
9. ***Reporting and Descriptive Analytics*** – Does the vendor have prebuilt reports, regulatory reporting capabilities, or ad hoc reporting capabilities? Is there access to both administrative and clinical reports? Can the customer perform data-visualization activities?

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10. **Predictive Analytics** – Does the system include standard groupers and risk scores? Does the vendor provide an internal risk score? Are there clinical and financial predictive models? Can a model be truly predictive due to lagged-data sources? Is there the ability to integrate with third-party risk models?

11. **Provider Action** – Are there tools for care managers to manage patient lists, document their notes, track patient goals and initiatives, and write and revise care plans? Does the solution forward integrate with commonly encountered EMRs?

12. **Patient Involvement** – Are patient-outreach tools included? Can patients view their information on a portal? Are there educational and coaching resources? Is a variety of modes of communication with patients supported?

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Table 19. Elements to Consider When Evaluating Population-Health-Management Software

Data Management	Descriptive Analytics	Predictive Analytics	Provider Action	Patient Involvement	Project Management
Imports Payer Data Sources	Reporting Interface and Data Visualization	Clinically Focused Predictive Models	Patient-Registry Functionality	Patient Portal and Personal Health Record	System Reliability
Imports Clinical Data Sources	Overall Reporting Capability	Financially Focused Predictive Models	Quality of User Interface	Patient-Facing Clinical Data	Comprehensiveness
Integrates Payer and Clinical Data Sources	Reporting Flexibility	External Model Interoperability	Workflow Efficiency	Educational and Coaching Content	Contracting and Cost
Aggregates Data Across Multiple EMRs and Insurers	Ease of Defining Reports	Proprietary Predictive-Model Development	Patient-List Generation	Multimodal Patient Communication	Experience and Subject-Matter Expertise
Imports Nontraditional Data Sources	Drill-Down Capability	Transparency and Interpretability of Model Results	Notification, Alerts, and Reminders	Patient Portal Integration	System Training
Date-Mapping Ease and Length of Time	Reporting Sharing and Repositories		Gaps-in-Care Identification		Customizability
Data-Mapping Flexibility*	Benchmarking Capability		Care Planning and Goal Tracking		Customer Support and Responsiveness
Data Quality Assurance*	Query Performance and Scalability		Workflow Configurability		Upgrade Process
Data-Refresh Frequency and Lag*			Automated Patient Communication		Regulatory Updates and Compliance
			Automated Ordering		System Adaptation and Evolution
			Assessment and Documentation		Implementation Process
			EMR Integration*		

* These items are not entirely within the vendor's control.



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