VIEWPOINT

INNOVATIONS IN HEALTH CARE DELIVERY

Integrating Predictive Analytics Into High-Value Care
The Dawn of Precision Delivery

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United States health care costs are twice as high as spending in most industrialized countries. One key opportunity for health systems to improve value is by limiting overuse of costly resources, in part by focusing these resources toward high-risk patient groups.[1] Some health systems have been using retrospective claims data or other approaches, like the Framingham risk model, to identify high-risk individuals. However, most systems today are doing little in the way of risk stratification, and physicians often find it difficult to apply these characterizations of risk to the care of an individual patient.

Electronic health records (EHRs) have held the promise of allowing clinicians and health systems to determine an individual's real-time risk of a clinical event through predictive analytics. The use of EHRs is becoming ubiquitous in the United States. This sea change can be linked with advances in big data techniques and computerized decision support to transform health care delivery. Just as "precision medicine" is generally linked to the concept of using genetic and genomic data to personalize treatments, "precision delivery" involves using an individual's electronic health data to predict risk and personalize care to substantially improve value. In this Viewpoint, we make the case for precision delivery by describing how some health systems are beginning to successfully implement analytics into practice and discussing future directions for using predictive analytics to improve value.

Lessons From Other Fields

Other industries have successfully used predictive analytics to tailor service delivery in real time. Familiar examples include Amazon's product recommendation system for online shopping based on an individual's prior purchases, and American Airlines' ticket pricing system based on prior customer purchasing trends. Sports teams like the Oakland Athletics have relied heavily on analytics to select player rosters, outperforming expectations despite having a much smaller payroll than other teams. These organizations use large amounts of data and sophisticated machine learning algorithms to meet consumer and organizational needs.

In health care, predictive analytics offers an automated means to forecast future health outcomes for individuals or populations based on algorithms derived from historical patient data. Some smartphone apps have successfully applied predictive analytics to influence health care: Ginger.io, for example, uses analytics based on cell phone data to identify patients at risk for depression crises, cueing physicians and caregivers to intervene.[2] As more electronic health data become available, some health systems have begun to develop predictive models around clinical issues, such as acute intensive care unit decompensation and hospital readmissions.[1]

As organizations like Amazon and American Airlines have shown, however, development of these models is only a first step. Few health systems currently use predictive analytics at scale to influence health care delivery. Health systems must identify strategies to implement predictive risk algorithms into clinical practice.

Using Predictive Analytics to Focus Intensity of Services Across the Care Continuum

Acute Care

Antibiotic overuse predisposes patients to adverse events and resistant infections, the treatment of which results in significant health care costs in the United States. Kaiser Permanente of Northern California (KPNC), an integrated health service organization, has used predictive analytics to reduce antibiotic overuse in neonates. KPNC used maternal health data from more than 600 000 live births to determine the probability of early-onset neonatal sepsis in nonpremature infants prior to birth. These data were integrated with objective clinical data from the newborn at birth to assess the probability of sepsis by categorizing newborns as at low, medium, or high risk of sepsis. KPNC obstetricians and neonatologists then used this score to determine whether to administer antibiotics.[3] After implementation of this algorithm, use of systemic antibiotics in the neonatal period among newborns of 34 weeks or more gestation was estimated to decrease by 33% to 60%, and up to an estimated 250 000 newborns nationally could potentially be spared antibiotics at birth annually.[3]

Postdischarge Care

Hospital readmissions represent an important driver of spending, with all-cause 30-day readmissions costing the US health system more than $41 billion annually, and thus are a major quality indicator for health systems.[4] Parkland Health and Hospital System used an algorithm based on 29 clinical, social, behavioral, and utilization factors available within 24 hours of admission to predict risk of readmission for patients with heart failure.[5] In a prospective study, 228 patients with heart failure deemed at high risk of 30-day readmission received targeted evidence-based interventions including (1) detailed patient education by a multidisciplinary team including a pharmacist, nutritionist, and case manager; (2) follow-up telephone calls within 48 hours to ensure medication adherence; (3) outpatient heart failure specialist appointments within 7 days; and (4) a primary care appointment scheduled according to the urgency of noncardiac issues. Compared with

834 patients enrolled in the study prior to intervention, there was a 26% relative reduction in risk-adjusted odds of readmission among 913 patients with heart failure enrolled in the postintervention period (26% vs 21% 30-day readmission rates).[5]

Serious Illness

The Veterans Health Administration (VHA) applied analytics to improve quality of care for serious illness by creating its Corporate Data Warehouse (CDW), a repository for patient-level data aggregated from across the VHA, in 2006.[6] The CDW was used to calculate risk scores predicting hospitalization and death for VHA's primary care population, based on variables including demographics, vital signs, laboratory results, and prior utilization. Accessed 3000 to 4000 times monthly by more than 1200 clinicians, these scores are widely used in practice. Nurse care managers used these scores to guide services, including end-of-life and palliative care, delivered by multidisciplinary patient-aligned care teams (PACTs) to high-risk individuals. Compared with 87 practices with the lowest implementation of PACTs, the 77 practices with highest PACT implementation demonstrated a 17% reduction in hospitalizations (4.42 vs 3.68 quarterly admissions per 1000 veterans) for ambulatory care–sensitive conditions and a 27% reduction in emergency department visits (188 vs 245 visits per 1000 patients) over a 7-month period.[7]

Future Directions

These organizations are examples of health systems that apply predictive analytics to improve value for high-risk patient groups. Under accountable care, successful organizations will use a broad array of tools to predict important outcomes, including to identify patients likely to require expensive care, be readmitted, or experience a specific type of adverse event.[1] However, just as important as prediction is how the predictions are integrated with clinical systems to help physicians and other health care professionals make decisions and track real-time quality.

Organizations that aim for precision delivery of care will need several key pieces of infrastructure. First, they will need an integrated EHR infrastructure and access to long-term data, like the VHA CDW, on which to base predictive algorithms. Second, they will need robust, responsive tools to address suggestions and improve clinicians' workflow within clinical systems. Third, outputs of the algorithms will need to be actionable and prompt prespecified, evidence-based activities, similar to the KPNC antibiotic guidelines. Fourth, predictive algorithms will need to be flexible enough to quickly adjust for real-time patient data, as the Parkland readmission model does. Such iteration allows for flexible "dosing" of services across the continuum of care, with intensity geared up and down as the need requires.

Some health professionals have raised concerns about the application of predictive analytics, not the least of which is the perceived diminution of the role of the physician in managing clinical uncertainty.[8] Other concerns include protection of patient privacy, diminishment of patient preferences, and inadequate medical training.[9] Health professionals had similar hesitations more than a decade ago when considering implementing EHRs. However, algorithms routinely outperform practitioners' clinical intuition without decision support. Algorithms also may enhance the quality of interaction between physicians and patients—for example, machine learning algorithms based on retrospective data can provide survival projections that may help inform discussions regarding end-of-life care for patients with advanced cancer. However, physicians will still need to exercise clinical judgment, and with appropriate training can combine new insights learned from predictive analytics alongside patient preferences to make higher-value treatment decisions.

The time for precision delivery is now. With the advent of accountable care, the health care organizations that succeed will be those that deliver high value. Perhaps the most important step to improving value will be implementing clinical analytics in routine care. Organizations that adapt by integrating these tools may do better both clinically and financially going forward.

ARTICLE INFORMATION

Conflict of Interest Disclosures: All authors have completed and submitted the ICMJE Form for Disclosure of Potential Conflicts of Interest. Dr Bates reported receiving equity from Intensix, which makes software to support clinical decision-making in intensive care; being named as coinventor on patent No. 6029138 held by Brigham and Women's Hospital on the use of decision support software for medical management, licensed to the Medicalis Corporation, and holding a minority equity position in Medicalis, which develops web-based decision support for radiology test ordering; serving on the clinical advisory board for Zynx Inc, which develops evidence-based algorithms; consulting for EarlySense, which makes patient safety monitoring systems; receiving equity and cash compensation from QPID Inc, a company focused on intelligence systems for electronic health records; receiving cash compensation from CDI (Negev) Ltd, which is a not-for-profit incubator for health IT startups; receiving equity from Enelgy, which makes software to support evidence-based clinical decisions, from Ethosmart, which makes software to help patients with chronic diseases, and from MDClone, which takes clinical data and produces deidentified versions of it. No other authors reported disclosures.

Funding/Support: Dr Kakad is funded by The Commonwealth Fund and the Research Council of Norway under the Norwegian Harkness Fellowship in Health Care Policy and Practice.

Role of the Funder/Sponsor: The funders had no role in neither design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; nor decision to submit the manuscript for publication.

Disclaimer: The authors have no commercial or financial ties to any of the organizations or companies mentioned in this manuscript.

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