The hype that big data will improve healthcare delivery is extraordinary. However, the reality of actually translating big data insights into meaningful healthcare improvements is far more limited. Substantial challenges exist. Variability in data standards and interoperability prevent efficient linkage of health data. Regulatory and privacy concerns regarding the widespread dissemination and use of health data remain. Healthcare data are largely observational, meaning that any relationships identified in analysis of healthcare data are subject to spurious correlations, bias, and unmeasured confounding. Even if the insights from big data analysis prove valid, optimal methods to integrate them effectively into healthcare delivery are unknown. Clearly, the conversion of big data hype to reality will require significant work. The hype to reality will require significant work.

So, assuming that one has not lost resolve in the face of such challenges, where to begin? A logical place is identifying the best data. Administrative data from medical billing codes, also known as claims data, are an attractive option. Because claims data are generated by virtually all healthcare systems, they provide a broader view of healthcare delivery than clinical registry data or abstracted medical chart reviews. In addition, claims data are standardized across healthcare systems, generally using the International Classification of Disease or the Systemized Nomenclature of Medicine terminology. As a result, claims data should, in theory, generate broad and generalizable insights into care delivery patterns and inform quality and value improvements. Unfortunately, claims data often fail short of this potential because they often lack sufficient clinical granularity to effectively characterize healthcare delivery. For example, billing codes can identify both a hospitalization for a coronary artery stent thrombosis and its preceding percutaneous coronary intervention procedure. However, they cannot distinguish the underlying causes behind these events, such as poor procedural technique or insufficient antiplatelet therapy. This lack of granularity has inspired comparisons of using claims data to determine the quality of healthcare to using jet fuel receipts to determine the quality of an airplane flight.

Information that a plane refueled at one airport on Monday and at another airport on Tuesday does not provide any specifics regarding the speed, safety, or comfort of the flight. Similarly, claims data may be ultimately limited in its ability to serve as an effective tool in driving improvements in healthcare quality and cost.

One area where the value of claims data can be tested is prevention of unnecessary hospital readmissions. Hospital readmissions have been a recent focus for healthcare improvement, largely because of the Hospital Readmissions Reduction Program (HRRP) established by the 2010 Affordable Care Act. The program created financial incentives for healthcare organizations to understand and reduce preventable hospital readmissions. Estimates for the proportion of readmissions that are preventable vary widely, between 5% and 79%. Regardless of the true number, early experience with the HRRP suggests that at least some readmissions are preventable. Analysis of Medicare claims data found that readmission rates for conditions targeted by the HRRP, which included acute myocardial infarction (AMI) and congestive heart failure, declined by nearly 4% between 2007 and 2015, with a rapid reduction occurring shortly after Affordable Care Act passage. To build on this initial improvement, effective identification of patients at risk of preventable readmission is needed. Prediction of overall hospital readmission has been accomplished with a variety of risk models, but they do not distinguish between preventable and nonpreventable readmissions. Given that hospitalizations generate medical billing claims that document the primary and secondary diagnoses causing the hospitalization, claims data may be well suited to identify preventable readmissions.

With this goal in mind, 3M Health Information Systems developed the Potentially Preventable Readmissions (PPR) software to identify preventable readmissions from claims data. The software uses a 3-step process to identify candidate preventable readmissions. First, the software excludes index admissions for specific conditions deemed unlikely to be followed by preventable readmissions, such as trauma, index admissions during which the patient leaves against medical advice, or elective admissions for nonacute care. Second, the software excludes readmissions after 30 days from index hospital discharge, consistent with the HRRP targeting readmissions occurring within 30 days after the index hospitalization. Third, the software determines if the readmission was preventable using a series of clinical rules. To achieve this, claims data for both the index admission and readmission were categorized by their All Patient Refined Diagnosis Related Groups.
(APR DRGs) designation. In total, 314 APR DRGs were identified. Using this data, all possible admission–readmission APR DRG combinations were categorized into pairs (ie, 314 multiplied by 314, resulting in 98,596 possible pairs). These pairs were then judged preventable or nonpreventable based on criteria determined by clinical panels. For example, surgical readmissions were generally considered not preventable, unless the readmission episode of care addressed a potential complication of surgery or a recurrence of the problem causing the initial hospitalization. Thus, a readmission for drainage of a postoperative wound after initial hospitalization for bowel resection would be considered preventable. Similarly, medical readmissions were considered preventable if the APR DRG pairs were for closely related conditions, for a readmission that could have resulted from inadequate care during the initial hospitalization, or for a readmission caused by a medical complication of treatment during the initial hospitalization. For example, an index admission for a hernia repair followed by a readmission for a urinary tract infection is considered preventable given that the urinary tract infection may have resulted from an indwelling urinary catheter used during surgery. The sophistication of these algorithms to determine potential preventability of readmissions is a major strength of the PPR software. However, its exclusive reliance on claims data does limit its ability to definitively determine whether a readmission is truly preventable. For instance, in the urinary tract infection example listed above, the software cannot distinguish between a potentially preventable iatrogenic catheter-associated infection and a urinary tract infection unrelated to the index admission. Nonetheless, the PPR software does represent a potentially useful approach for harnessing insights from claims data.

In an attempt to validate the PPR software and its use of claims data to identify preventable readmissions, Borzecki et al conducted a study, published in this issue of Circulation: Cardiovascular Quality and Outcomes, to measure the association between PPR-identified preventable AMI and congestive heart failure readmissions and high-quality process-of-care measures in the Veterans Affairs (VA) healthcare system. The authors hypothesized that there would be a relationship between higher rates of preventable readmissions and lower rates of high-quality process-of-care measures. The authors identified PPR-determined preventable readmissions occurring in the VA between 2005 and 2010. Next, they constructed, in conjunction with clinical experts, quality process-of-care measures in 4 domains that span the care continuum of the index hospitalization: (1) admission work-up, (2) in-hospital evaluation/treatment, (3) discharge readiness, and (4) postdischarge period. The measures were then catalogued and normalized to a numeric scale that ranged from 0 (lowest process-of-care performance) to 100 (highest process-of-care performance). Then, nurse abstractors reviewed a subset of AMI and heart failure readmission cases in the VA, with samples weighed to provide sufficient power to detect meaningful differences in process-of-care between PPR-determined preventable and nonpreventable readmissions. In both unadjusted and adjusted analyses, there was no statistically significant association between PPR-determined preventable readmissions and process-of-care measures. For AMI readmissions, overall quality scores for preventable readmissions were 61.6 and overall quality scores for nonpreventable readmissions were 60.4. For congestive heart failure, overall quality scores for preventable readmissions were 61.2 and overall quality scores for nonpreventable readmissions were 63.4.

So what lies behind these findings? Several possibilities exist. First, there are several threats to the internal validity of the study. It used a complicated method of assessing process-of-care measures. Although the authors went to great lengths to ensure that the measures had appropriate face validity, rigorous psychometric evaluation was not conducted. As a result, the measures may not have had sufficient correlation to actual quality care to detect an association with readmission. Similarly, the PPR method of identifying preventable readmissions is sophisticated, but hardly perfect. In the derivation of the PPR algorithm, the pairs of APR DRGs were subject to clinical review, but VA cases adjudicated by the PPR software for this study were not. Thus, misclassification of the type of readmission, particularly if it was evenly distributed by readmission type, could have biased the findings to support a null hypothesis. Second, the place and time of the study are potentially problematic. The study is conducted in a healthcare system, the VA, that does not generally bill outside insurers for its care. As a result, there is less incentive to properly code events such as hospitalization diagnoses, which could lead to misspecification of readmission type. In addition, the time period of the study—2005 to 2010—was before the passage of the Affordable Care Act and its HRRP, meaning that focus on AMI and congestive heart failure preventable readmissions was likely low. Furthermore, even after 2010, the VA was not subject to the HRRP incentives, so it is unclear that even a later study would demonstrate reasonable discrimination between preventable and nonpreventable readmissions. Finally, of course, the lack of association may actually demonstrate that there truly is no association. Although the hypothesis between preventable readmissions and quality of care is reasonable, the factors that potentially connect these concepts are multiple and complex. As a result, any correlation may be obscured by the broader context in which both readmissions and quality of care occur.

So now what? The answers to this question are largely dictated by the potential reasons listed for the negative findings of this study. Ultimately, reliance on claims data is likely a major methodological hurdle for the PPR or similar software, given its lack of sufficient granularity to accurately adjudicate preventability of readmission. Combining primary and secondary diagnostic billing codes, rather than relying solely on the primary diagnostic code, may provide more insight, but these types of algorithms will be much more complex—and potentially unwieldy—than the PPR algorithm. Furthermore, miscoding is even more likely among secondary diagnostic codes, opening the door for additional misclassification and bias. A potential path forward is integrating hospitalization claims data with other types of claims information, such as data on prescription refills claims. However, a better approach is coupling claims data with clinical data that contains sufficient detail about care delivery. Although this type of data has historically been more difficult to collect, the growth of electronic health records may allow
broader efforts to collect clinical data with fewer resources. Other sources of clinical data, such as patient-reported outcomes, can also assist efforts in identifying potential causes behind rehospitalization.

Negative studies such as these can be frustrating, but also instructive. This particular study reminds us that the broader reach of claims data comes at the cost of a lack of granularity. Integrating claims data with other sources of data, like prescription refills, patient-reported outcomes, and other data extracted from the electronic health records, may provide more granularity and potentially more ability to identify actionable targets for improving care. The study also reminds us that the chasm between the hype and reality of big data is gaping. Nonetheless, it does not necessarily suggest that efforts to span that chasm are doomed to failure. Rather, it serves as a sober reminder that these efforts will require much work. We are very much in the nascent stage of understanding if and how big data can support the promise of improved healthcare delivery.

Disclosures

None.

References


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