Agreement of Medicaid claims and electronic health records for assessing preventive care quality among adults

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ABSTRACT

To compare the agreement of electronic health record (EHR) data versus Medicaid claims data in documenting adult preventive care. Insurance claims are commonly used to measure care quality. EHR data could serve this purpose, but little information exists about how this source compares in service documentation. For 13 101 Medicaid-insured adult patients attending 43 Oregon community health centers, we compared documentation of 11 preventive services, based on EHR versus Medicaid claims data. Documentation was comparable for most services. Agreement was highest for influenza vaccination ($\kappa = 0.77$; 95% CI 0.75 to 0.79), cholesterol screening ($\kappa = 0.80$; 95% CI 0.79 to 0.81), and cervical cancer screening ($\kappa = 0.71$; 95% CI 0.70 to 0.73), and lowest on services commonly referred out of primary care clinics and those that usually do not generate claims. EHRs show promise for use in quality reporting. Strategies to maximize data capture in EHRs are needed to optimize the use of EHR data for service documentation.

BACKGROUND AND SIGNIFICANCE

Healthcare organizations are increasingly required to measure and report the quality of care they deliver, for regulatory and reimbursement purposes.[1–5] Such quality evaluations are often based on insurance claims data,[6–8] which have been shown to accurately identify patients with certain diagnoses,[9–12] but to be less accurate in identifying services provided, compared to other data sources.[6–8 13 14]

Electronic health records (EHRs) are an emergent source of data for quality reporting.[15 16] Unlike claims, EHR data include unbilled services, and services provided to uninsured persons, or those with varied payers. Yet the use and accuracy of EHRs for service documentation and reporting may vary significantly.[16–28] While EHR-based reports have been validated against Medicaid claims for provision of certain diabetes services,[6 13] little is known about how EHR and claims data compare in documenting the delivery of a broad range of recommended preventive services.[6 13 14 16 24]

We used EHR data and Medicaid claims data to assess documentation rates of 11 preventive care services in a population of continuously insured adult Medicaid recipients served by a network of Oregon community health centers (CHCs). Our intent was not to evaluate the quality of service provision among patients due for a service, but to measure patient-level agreement for documentation of each service across the two data sources.

MATERIALS AND METHODS

Data sources

OCHIN EHR dataset

We obtained EHR data from OCHIN, a non-profit community health information network providing a linked, hosted EHR to >300 CHCs in 13 states.[29] The OCHIN EHR data contains information from Epic practice management (eg, billing and appointments) as well as demographic, utilization, and clinical data from the full electronic medical record. Using automated queries of structured data, we extracted information for the measurement year (2011) from OCHIN's EHR data repository for the 43 Oregon CHCs that implemented OCHIN's practice management and full electronic medical record before January 1, 2010.

Medicaid insurance dataset

We obtained enrollment and claims data for all patients insured by Oregon's Medicaid program for 2011. This dataset was obtained 18 months after December 31, 2011 to account for lag time in claims processing. This study was approved by the Institutional Review Board of Oregon Health and Science University.

Study population

We used Oregon Medicaid enrollment data to identify adult patients aged 19–64 years throughout 2011, who were fully covered by Medicaid in that time and had ≥1 billing claim. We used Medicaid identification numbers to match patients in the Medicaid and EHR datasets; we then identified cohort members who had ≥1 primary care encounter in ≥1 of the study clinics in 2011 (n=18 471).[30] We excluded patients who had insurance coverage in addition to Medicaid (n=3870), were pregnant (n=1494), or died (n=6) in the study period. The resulting dataset included 13 101 patients who were continuously, solely covered by Medicaid throughout 2011, and appeared in both the OCHIN EHR and Medicaid claims datasets.

Preventive service measures

The intent of this analysis was to compare the datasets in their documentation of whether a service was done/ordered for a given patient, *not* to identify who should have received that service. In other words, we did not examine whether the service was due in 2011 (eg, whether a 52-year-old woman had a normal mammogram in 2010 and was, therefore, not likely due for another until 2012).

To that end, we assessed documentation of 11 adult preventive care services during 2011: screening for cervical, breast, and colorectal cancer (including individual screening tests—colonoscopy, fecal occult blood test (FOBT), flexible sigmoidoscopy—and an overall colon cancer screening measure); assessment of body mass index (BMI) and smoking status; chlamydia screening; cholesterol screening; and influenza vaccination.[31 32] Each service was measured in the eligible age/gender subpopulation for whom it is recommended in national guidelines (table 2 footnotes).

To identify services in each dataset, we used code sets commonly used for reporting from each respective data source. In the EHR, we used codes based on Meaningful Use Stage 1 measures.[4] These included ICD-9-CM diagnosis and procedure codes, CPT and HCPCS codes, LOINC codes, and medication codes. We also used relevant code groupings and codes specific to the OCHIN EHR, used for internal reporting and quality improvement. These codes could identify ordered and/or completed services; some codes may capture ordered services that were never completed. The codes used to capture service provision in the Medicaid claims data were based on the Healthcare Effectiveness Data and Information Set (HEDIS) specifications as they are tailored to claims-based reporting.[3] These included standard diagnosis, procedure, and revenue codes. The 2013 HEDIS Physician measures did not include specifications for influenza vaccine or cholesterol screening, so the code sets used for assessing these measures in claims were the same as those used for the EHR data. A given service was considered ‘provided’ if it was documented as ordered, referred, or completed at least once during the measurement year. Online supplementary appendix A details the codes and data fields used to tabulate the numerator and denominator in each dataset for each measure.

Analysis

We described the study sample demographics using EHR data. We then assessed documentation of each preventive service in three ways. First, we tabulated the percentage of eligible patients with documented services in the EHR, and in Medicaid claims. Next, we calculated κ statistics to measure *level of agreement* between EHR and Medicaid claims at the patient level. The κ statistic captures how well the datasets agree in their ‘observation’ of whether a given individual received a service, compared to agreement expected by chance alone. We considered κ statistic scores >0.60 to represent substantial agreement, 0.41–0.60 moderate agreement, and 0.21–0.40 fair agreement.[33] Last, we tabulated the total percentage of services captured in the combined EHR–claims dataset (ie, the percentage obtained when combining the EHR and claims data).

RESULTS

Patient demographics

The 13 101 patients in the study population were predominantly female (65.6%), white (74.2%), English speaking (82.7%), and from households earning ≤138% of the federal poverty level (91.6%). The study population was evenly distributed by age (table 1).

Receipt of screening services

Medicaid claims documented a greater number of the following services than did EHR: cervical and breast cancer screening, colonoscopy, chlamydia screening, and cholesterol screening. Absolute differences ranged from 2.6% to 8.4% (table 2). The EHR data identified more patients with documented services than did claims data for total colorectal cancer screening, FOBT, influenza vaccine, BMI, and smoking assessment. The absolute differences in these services ranged from 6.7% to 91.8%, with two services (BMI and smoking screening) ranking highest among all services documented in the EHR, but minimally present in Medicaid claims. Flexible sigmoidoscopy was rarely documented in both datasets. Combining the EHR and Medicaid claims data yielded the highest documentation rates.

Agreement between EHR and Medicaid claims

We observed similar levels of documentation and high levels of agreement (κ>0.60) between the two datasets for cervical cancer screening (κ=0.71, 95% CI 0.70 to 0.73), influenza vaccine (κ=0.77, 95% CI 0.75 to 0.79), and cholesterol screening (κ=0.80, 95% CI 0.79 to 0.81) (table 2). EHR and Medicaid claims data captured similar rates of services but lower levels of agreement for breast cancer screening (κ=0.34, 95% CI 0.31 to 0.37), colorectal cancer screening-combined

Table 1 Demographic characteristics of study sample

	Patients appearing in both EHR and claims (N=13 101)	
	No.	%
Gender		
Female	8600	65.6
Male	4501	34.4
Race		
Asian/Pacific Islander	772	5.9
American Indian/Alaskan native	180	1.4
Black	1409	10.8
White	9720	74.2
Multiple races	143	1.1
Unknown	877	6.7
Race, ethnicity		
Hispanic	1186	9.1
Non-Hispanic, white	8943	68.3
Non-Hispanic, other	2441	18.6
Unknown	531	4.1
Primary language		
English	10 836	82.7
Spanish	618	4.7
Other	1647	12.6
Federal poverty level*		
≤138% FPL	11 996	91.6
>138% FPL	838	6.4
Missing/unknown	267	2.0
Age in years†		
19–34	4632	35.4
35–50	4681	35.7
51–64	3788	28.9
Mean (SD)	40.6 (12.3)	

*Average of all 2011 encounters, excluding null values and values ≥1000% (which were considered erroneous).
†As of January 1, 2011.
EHR, electronic health record; FPL, federal poverty level.

Table 2 Receipt of screening services and agreement by data source, 2011

Measure	Total eligible* patients	OCHIN EHR No. (%)	Claims No. (%)	Combined EHR and claims No. (%)	κ statistic (95% CI)
Cervical cancer screening†	7509	2100 (28.0)	2533 (33.7)	2777 (37.0)	0.71 (0.70 to 0.73)
Breast cancer screening‡	4173	1435 (34.4)	1627 (39.0)	2174 (52.1)	0.34 (0.31 to 0.37)
Colon cancer screening, any§	3761	1199 (31.9)	870 (23.1)	1425 (37.9)	0.48 (0.45 to 0.51)
Colonoscopy§	3761	270 (7.2)	433 (11.5)	590 (15.7)	0.26 (0.21 to 0.30)
Flexible sigmoidoscopy§	3761	0 (0.0)	7 (0.2)	7 (0.2)	–
FOBT‡	3761	1106 (29.4)	500 (13.3)	1130 (30.0)	0.50 (0.47 to 0.53)
Chlamydia screening¶	523	224 (42.8)	268 (51.2)	309 (59.1)	0.52 (0.45 to 0.59)
Cholesterol screening**	12 817	5060 (39.5)	5400 (42.1)	5836 (45.5)	0.80 (0.79 to 0.81)
Influenza vaccine††	3788	1573 (41.5)	1318 (34.8)	1653 (43.6)	0.77 (0.75 to 0.79)
BMI assessed	13 101	11 392 (87.0)	141 (1.1)	11 409 (87.1)	0.0002 (−0.001 to 0.002)
Smoking status assessed	13 101	12 021 (91.8)	0 (0.0)	12 021 (91.8)	–

Denominator: patients appearing in both OCHIN EHR and claims datasets (N=13 101).
*Age/gender categories in which screening is appropriate.
†Women aged 19–64 with no history of hysterectomy.
‡Women aged ≥40 with no history of bilateral mastectomy.
§Men and women aged ≥50 with no history of colorectal cancer or total colectomy.
¶Sexually active women aged 19–24.
**Men and women aged ≥20; cholesterol screening includes low density lipoprotein, high density lipoprotein, total cholesterol, and triglycerides.
††Men and women aged ≥50.
BMI, body mass index; EHR, electronic health record; FOBT, fecal occult blood test.

(κ=0.48, 95% CI 0.45 to 0.51), colonoscopy (κ=0.26, 95% CI 0.21 to 0.30), and chlamydia screening (κ=0.52, 95% CI 0.44 to 0.59), indicating that the data sources were identifying services received by varying patients in our datasets. FOBT (κ=0.50, 95% CI 0.47 to 0.53) had differing documentation rates but also had lower agreement. κ statistics could not be computed for two measures, as no documented screenings for smoking assessment were present in Medicaid claims, and the EHR had no flexible sigmoidoscopies. The poor agreement between data sources for BMI was likely due to the low number of patients with recorded BMI assessments in Medicaid claims compared to the EHR (1.1% vs 87.0%, respectively).

DISCUSSION

For most of the preventive services we examined, EHR data compared favorably to Medicaid claims in documenting the percentage of patients with service receipt. Not surprisingly, services usually performed in the primary care setting (eg, cervical cancer screening, FOBT, cholesterol screening) were more frequently observed in the EHR compared to claims; services that are often referred out (eg, mammography, colonoscopy) were less frequently observed in the EHR.

For some measures, each dataset alone captured a similar percentage of patients receiving screening, but had low individual-level agreement, and much higher documentation of rates when using a combined EHR–claims dataset (table 2), suggesting that each dataset captured some service provision in varying patients, depending on the service. We hypothesized that the location of service delivery might also explain these differences. Services with high agreement between the EHR and claims datasets (eg, cervical cancer screening, cholesterol screening, influenza vaccination) are often performed within the primary care setting, and generate a billable charge that appears in claims data. Services that are usually referred out to other providers, such as breast and colorectal cancer screening, demonstrated lower agreement. Patients may have had a service ordered by a primary care provider but did not receive the service or did not have it billed to Medicaid, resulting in documentation in the EHR but not claims. Conversely, patients may have received a billable service but never had an associated order or communication back to the primary care clinic, resulting in documentation in claims data but not the EHR.

We examined whether location of service delivery could help to explain agreement between the two data sources for billable services using κ statistics. As in figure 1, higher κ values were associated with services more likely to be received in the primary care setting, and lower κ values with services more likely to be referred out. To our knowledge, this observation has not previously been demonstrated in a dataset of this size; thus, these results imply that health systems should emphasize strategies for incorporating outside records into their EHR. Smoking and BMI assessment likely had poor agreement between data sources because these screenings are rarely billed, and therefore are not present in claims. This asymmetry is important because reporting on these measures will be

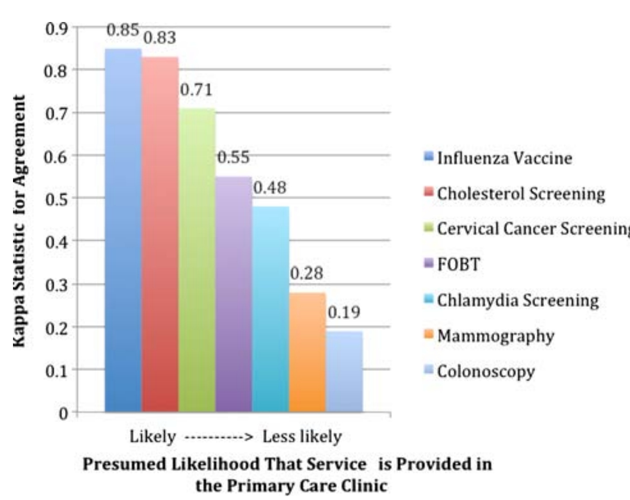

Figure 1 Decreasing κ statistic for agreement between electronic health record and Medicaid claims potentially related to location of service provision. Flexible sigmoidoscopy, body mass index, and tobacco assessment were not included because of low overall numbers.

mandated by Meaningful Use, and these results show that claims-based reporting is likely insufficient to adequately capture these types of services.

Our results suggest that a combination of EHR and claims data could provide a reporting foundation for the most complete current assessment of healthcare quality. However, use of such a 'hybrid' method is not an efficient long-term solution, as it restricts quality assessments to patients with a single payer source. Restricting performance measurement solely to claims data often ignores health behavior assessments and counseling activities (eg, smoking assessment and BMI calculation) performed at the point of care. Our findings suggest that EHRs are a promising data source for assessing care quality. To maximize the use of EHRs for reporting and quality purposes, strategies to improve clinical processes that expand data capture of referrals and completed services within the EHR are needed. This will also help clinicians to ensure patients receive needed prevention. Improved clinic workflows, user-friendly provider interfaces, and systems to improve rapid cycle or point of care feedback to providers could all improve the capture of reportable data.

Another method for augmenting EHR data for reporting purposes is natural language processing (NLP), which may be used to mine non-structured clinical data. NLP has been used in controlled research settings to detect falls in inpatient EHRs, to conduct surveillance on adverse drug reactions and diseases of public health concern in outpatient EHRs, and to examine some preventive service use/counseling in narrow settings.[34–43] However to our knowledge, NLP has not been used to detect broad preventive service provision in a large dataset with heterogeneous data. NLP holds great promise for improved reporting accuracy, but it is not currently being routinely used by community practices for quality reporting, is not routinely available at the point of care, and does not have the ability to efficiently respond to federal reporting mandates (eg, Meaningful Use) that require structured data formats, which is why it was not a part of our analysis.[4 44] However, should NLP technologies continue to progress in their accessibility to clinical staff working in heterogeneous, broad, datasets, they will be invaluable in complementing structured data queries. Future research should focus on how NLP can optimize the use of EHR data for supporting these functions.

Limitations

First, we only included patients who were continuously insured by Medicaid and received services at Oregon CHCs, which may limit generalizability of our findings. Second, although the selection of this continuously insured population allowed us to have the same population denominator in both datasets, these analyses do not fully represent the extent to which EHR data capture a larger and more representative patient population than claims data (eg, EHRs include services delivered when patients are uninsured). Third, for some services, especially those commonly referred out, EHR data might only capture whether the service was ordered but not whether it was completed; however, for some care quality measures, the ordering of a given service is the metric of interest. In contrast, Medicaid claims generally reflect only completed services but not services recommended or ordered by providers but never completed by patients; this again varies by service. Fourth, the intent of our analysis was to conduct a patient-level comparison of services documented in 1 year in each dataset; we did not assess whether the patient was due for the services. Therefore, the rates reported should not be compared to national care quality rates. Future studies should use longitudinal, multi-year EHR data sources to assess services among those who are due for them, in order to expand these methods to a direct study of quality measures. Such efforts would benefit from capture/recapture methodology to estimate population-level screening prevalence. Finally, we may have missed services that were not coded in the automated extraction of EHR data. However, other analyses have revealed insignificant differences between the results of automated queries of structured data versus reviews that include unstructured data.[45] Further examination is needed to determine where certain data 'live' in the EHR and how these data might be missed in automated queries.

CONCLUSION

Primary care organizations need reliable methods for evaluating and reporting the quality of the care they provide. EHRs are a promising source of data to improve quality reporting. Suggestions for how EHR data can better reflect the quality of preventive services delivered include further investigation into data location in EHRs, the development of standardized workflows and improvement processes for preventive service documentation, and electronic information exchanges to facilitate information about outside services getting back into the primary care EHR. Approaches like these may enable a more complete evaluation of the robustness and optimal use of emerging EHR data sources.

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Contributors All authors approved the final version of the manuscript and drafted/revised the manuscript for important intellectual content. JH, SRB, and JED made substantial contributions to study design, analysis, and interpretation of data. MJH and TL executed the acquisition and analysis of data. MM assisted with data analysis, and he and RG contributed to data interpretation and study design. JPO'M assisted with study design, data analysis, and interpretation. SC assisted with study design and data interpretation. AK contributed to data interpretation.

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