Chasm Between Cancer Quality Measures and Electronic Health Record Data Quality

Anna E. Schorer, MD[1]; Richard Moldwin, MD, PhD[2]; Jacob Koskimaki, PhD[3]; Elmer V. Bernstam, MD[4]; Neeta K. Venepalli, MD[5]; Robert S. Miller, MD[3]; and James L. Chen, MD[6]

original reports abstract

PURPOSE The Medicare Access and CHIP Reauthorization Act of 2015 (MACRA) requires eligible clinicians to report clinical quality measures (CQMs) in the Merit-Based Incentive Payment System (MIPS) to maximize reimbursement. To determine whether structured data in electronic health records (EHRs) were adequate to report MIPS CQMs, EHR data aggregated by ASCO's CancerLinQ platform were analyzed.

MATERIALS AND METHODS Using the CancerLinQ health technology platform, 19 Oncology MIPS (oMIPS) CQMs were evaluated to determine the presence of data elements (DEs) necessary to satisfy each CQM and the DE percent population with patient data (fill rates). At the time of this analysis, the CancerLinQ network comprised 63 active practices, representing eight different EHR vendors and containing records for more than 1.63 million unique patients with one or more malignant neoplasms (1.73 million cancer cases).

RESULTS Fill rates for the 63 oMIPS-associated DEs varied widely among the practices. The average site had at least one filled DE for 52% of the DEs. Only 35% of the DEs were populated for at least one patient record in 95% of the practices. However, the average DE fill rate of all practices was 23%. No data were found at any practice for 22% of the DEs. Since any oMIPS CQM with an unpopulated DE component resulted in an inability to compute the measure, only two (10.5%) of the 19 oMIPS CQMs were computable for more than 1% of the patients.

CONCLUSION Although EHR systems had relatively high DE fill rates for some DEs, underfilling and inconsistency of DEs in EHRs render automated oncology MIPS CQM calculations impractical.

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BACKGROUND

Reimbursement for quality of care in medicine has been key to Medicare since its inception. Recently, Congress enacted the Medicare Access and CHIP Reauthorization Act (MACRA)[1,2] as a revision to the sustainable growth rate formula that determined the Centers for Medicare and Medicaid Services (CMS) reimbursement rates. Taking effect in 2017, MACRA set up several models for adjusting quality-based physician reimbursement, including the Merit-based Incentive Payment System (MIPS).[3] CMS provides specialty-specific clinical quality measures (CQMs). The 19 cancer-related oncology MIPS (oMIPS) CQMs for 2018 are the focus of this analysis.[4]

Although MIPS provides monetary incentives or penalties for reporting measures, clinicians or their designees often must sift through multiple charts to extract the required data elements (DEs) and, in many cases, manually enter the measure statistics into a separate quality reporting system. Owing to the effort, time, and cost of reporting, the MIPS reporting requirement can discourage participation in voluntary quality reporting programs, thereby diluting the effectiveness of the quality initiatives.[5,6] MIPS reporting, and its associated data validation and auditing, would be more efficient if these MIPS measures could be derived directly from the electronic health record (EHR) without manual abstraction.[7,8] EHR data have been investigated as the input to payment-associated quality metrics.[9,10] Although the EHR has been proposed as a possible aid to data for MIPS reporting,[11] it is not clear if current EHR implementations can support MIPS submissions through standardized and structured data fields (DFs).

To determine whether EHR DEs can be leveraged for oMIPS reporting, we analyzed patient records in the CancerLinQ health technology platform developed by ASCO. CancerLinQ extracts data from the EHRs implemented at multiple practices by importing data in structured DFs and by manual abstraction facilitated by text mining.[12] For this study, we limited the use of unstructured text data to those values that could be readily matched to standard terminologies. At the time of this analysis, 63 health care institutions, representing

ASSOCIATED CONTENT

Data Supplement

Author affiliations and support information (if applicable) appear at the end of this article.

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CONTEXT

Key Objective

To determine if federal clinical quality measures for oncology can be automatically calculated from data elements (DEs) held in electronic health record (EHR) systems.

Knowledge Generated

The vast majority of oncology clinical quality measures could not be directly calculated from EHR DEs. None of the studied vendors adequately implemented the necessary clinical quality-related DEs across the full set; even when the DEs were available in an EHR, they were poorly filled.

Relevance

Federal quality initiatives for oncology have recently centered around the automated extraction of high-quality DEs from EHRs. Here, we demonstrate that automated clinical quality calculations are not feasible at present, with negative implications for public health reporting, research, and other secondary uses of EHR data. Solving this problem will require widespread creation and adoption of common DEs along with improvements in the routine capture and exchange of structured data.

eight different EHR vendors and containing records for more than 1.63 million unique patients with one or more malignant neoplasms (total of 1.73 million cancer cases), were actively contributing data as part of the CancerLinQ network. This study investigates the feasibility of deriving oMIPS CQMs directly from a variety of EHR systems through the CancerLinQ data set.

MATERIALS AND METHODS

Study Team

The data analysts comprised six oncology domain experts, including oncology informaticians from the CancerLinQ Oncology Informatics Taskforce (ASCO volunteer body under the CancerLinQ Physician Advisory Committee) and CancerLinQ staff from the medical and informatics teams. Regular meetings were held to jointly review data sets and analyses. All analyses are consistent with ASCO/CancerLinQ data privacy standards.

EHR Systems

CancerLinQ practices implemented general EHR and oncology-specific EHR products from commercial vendors with significant market share, including Allscripts (Chicago, IL), ARIA (Varian Medical Systems, Palo Alto, CA), Centricity (GE Healthcare, Chicago, IL), CureMD (New York, NY), Epic (Verona, WI), MOSAIQ (Elekta, Stockholm, Sweden), NextGen (Irvine, CA), and OncoEMR (Flatiron Health, New York, NY). EHR systems and oncology-specific modules were included in these analyses, but other specialty modules such as radiation oncology, pathology, and surgical systems were not examined. To maintain confidentiality, vendor names in all analyses and practice data have been aggregated and/or anonymized.

Oncology Practices

The CancerLinQ practices used for this analysis had completed a series of activation steps, including quality assessments and data completeness reviews. Data quality was confirmed by multiple methods including a review of the active cancer population count, quality measure scores, patient longitudinal record validation, and manual review.

Data Preparation

Structured data were extracted from predefined DFs in EHR databases and imported into the CancerLinQ database. Text strings were also converted into structured data in the canonical CancerLinQ data model as standard clinical terminologies representing diagnoses (ICD-9 or ICD-10),[13] staging terms (SNOMED CT),[14] medications (RxNorm),[15] and laboratory tests (LOINC).[16]

Development of oMIPS-Associated DEs

Nineteen oMIPS CQMs from 2018 were studied.[17] For each measure, the study team identified discrete DEs required to score patient records as meeting or not meeting the measure definition. Each DE represents a data definition for which data must be located to enable measure calculation. For example, the concept of whether a patient smokes may have an associated DE, smoking status. Review of the oMIPS measure components and the data found in each EHR system resulted in a consolidated list of DEs created in the CancerLinQ database, covering the structured data components required to calculate all 19 CQMs. DE definitions are provided in the Data Supplement.

Data Analysis

When a DE was present as a structured field in an EHR database, it was designated as a DF. A DF is a standard location or technical approach to store DE data in an EHR's database in a structured manner. For example, a DE may exist as a prespecified column in a database table or as a defined entry in a data dictionary that is available for storage of a patient's DE data in a more generic yet still-structured manner (eg, using an entity-attribute-value approach[18]). A given DF is capable of storing a patient's data for a DE. A DF may exist in multiple copies for a given patient, eg, to represent multiple successive values of a laboratory test.

Thus, a DF may be filled with DE data one or more times, or it may remain empty (unfilled) for a given eligible patient in a time frame suitable for MIPS measure calculation. Within the measure-applicable time frame, the percentage of patients that had at least one filled DF for a given DE was calculated and is called the DE fill rate. If a DF for a given DE was not present in an EHR, then the DE fill rate for that DE is zero. DE fill rates were calculated separately for each vendor and for each practice.

To highlight differences among EHR systems, data were analyzed on a per-EHR basis such that data from each EHR system had equal weight for all calculations. In particular, no weighting on the basis of practice size or total patients per vendor was performed for the analyses of DE fill rate percentages or for the calculation of any other statistic. This ensures a balanced comparison among the vendors studied and avoids skewing the results toward the vendors representing the most patients. Descriptive statistics were used to summarize our findings.

RESULTS

EHR Data set Derivations and Definitions

Data from 2010 to 2020 were extracted from the 63 CancerLinQ practices in this analysis. Data were analyzed for oMIPS CQMs pertaining to all cancers and for subsets limited to breast, prostate, and colorectal cancers. The Data Supplement presents the 19 oMIPS measures and the measure text that was used to search DFs from the eight EHR system databases. Mapping oMIPS measures to component DFs was often complex. As an example of this complexity, the Data Supplement shows the breakdown of the electronic CQM (eCQM) definition for oMIPS measure 16 (bone scans in low- or very low-risk prostate cancer), followed by a discussion of the analysis process.

Table 1 presents the breakdown of cancer patient records among the eight EHR vendors. The top four vendors comprised over 90% of the total cases analyzed.

oMIPS-Associated DEs Were Poorly Populated

For oMIPS-associated DEs, the mean fill rate across all evaluated practices was 23%. Seventy-eight percent of the DEs (49 of 63) were populated with data. Only 23 DEs were filled in consistently (ie, for ≥ 90% of the practices). No data were found in any practice for 14 DEs. Figure 1 summarizes these fill rates. For figure clarity purposes, note that Figure 1 averages the DE fill rates over the 63 practices, whereas all other figure and tables average data for each equally weighted EHR vendor.

DE Analysis Case Study: Stage Groups

Recording the stage group in EHRs for all cancers is widely considered a best practice,[19-22] and accordingly, these data are populated in almost 87% of the patients for cancer registry data imported into the CancerLinQ data set (data not shown). One hundred percent of the practices in the data set implemented the stage_group DE (Fig 1) as a DF (Fig 1, column 2), and all practices had at least one value (for at least one patient) in this DF. However, across all practices, only 38% of the stage group DFs were filled (Fig 1, column 3). The minimum fill rate for this DE was 0.1% at a single practice, and the maximum fill rate was 60.6% at a single practice, with a standard deviation over the 63 practices of 22%. Standard deviations between the 63 practices and between the eight EHRs were often large and are omitted from the figures for clarity. The complete EHR comparison data set, including a heat map demonstrating the range of DE fill rates, is found in the Data Supplement.

TABLE 1. Demographics: The Cancer Case Composition of the Eight EHR Vendor Systems

Vendor	Total Oncology Cases	Breast	Prostate	Colorectal
1	706,510	106,585	60,142	46,122
2	372,228	91,099	22,347	35,896
3	255,817	61,460	23,767	22,482
4	242,163	40,149	18,212	20,909
5	66,500	3,272	1,028	1,395
6	47,735	9,155	8,451	3,360
7	45,830	13,035	3,269	3,795
8	2,930	585	128	351
Total	1,739,713	325,340	137,344	134,310

NOTE. The three rightmost columns represent one of the tumor sites studied in this report. A row is provided for each of the eight vendor systems. Rows are sorted according to the Total Oncology Cases column, which indicates the total cancer case records covered by each EHR vendor. The total row sums case counts for each column. Note that the vendor numbers (1-8, first column) in this figure do not match the vendor numbers (1-8) in the subsequent figures to ensure anonymization.

Abbreviation: EHR, electronic health record.

DE Fill Rates Varied Substantially Among EHR Vendors

Fill rates for the individual DFs varied widely among the sites and EHR systems. Figure 2 shows the 63 oMIPS-associated DEs and their respective fill rates filtered by the EHR system. The average fill rate for all DEs across all vendors was approximately 22%.

Three registration and reimbursement-related DFs (diagnosis_code, age_dob, and gender) were available in structured fields for all sites and all EHR vendors surveyed. Similarly, other heavily referenced fields (encounter_type, diagnosisdate, and tobacco) were filled most of the time (> 78%). Conversely, over half of the DEs (32 of 63) had a fill rate of < 10% and only 21 of the 63 DEs (33%) exceeded a 25% fill rate. The average fill rate for the top 50% of the DEs was 42%. The average fill rate for the bottom 50% of the DEs was only 0.7%. Figure 2 also presents a breakout of the above-mentioned results grouped by the eight EHR vendors. To preserve vendor

DE	% of Sites With DE Fill Rate > 0	Avg Fill Rate (%)
diagnosiscode	100.0	100.0
age_dob	100.0	100.0
gender	100.0	100.0
diagnosisdate	100.0	84.7
tobacco	100.0	83.5
stage_group	100.0	38.3
date_of_death	100.0	22.9
med_admin	98.4	63.2
stage_date	98.4	36.7
chemotherapy	98.4	35.1
m_stage	98.4	33.2
t_stage	98.4	32.3
n_stage	98.4	30.9
psa	98.4	10.3
her2_neu	98.4	9.4
trastuzumab	98.4	1.9
pain_score	96.8	76.0
med_dose	96.8	62.0
med_route	96.8	56.7
anti_hypertensive_therapy	96.8	15.4
tumor_grade	96.8	14.0
cetuximab	96.8	1.0
stage_type	90.5	35.2
advance_care_plan	85.7	24.8
tobacco_cessation	85.7	24.8
systolic_bp	81.0	75.4
gleason	81.0	1.9
diastolic_bp	79.4	74.6
med_frequency	66.7	32.7
bone_scan	55.6	2.0
systolic_over_diastolic_bp	49.2	39.3
kras	49.2	0.5

DE (cont.)	% of Sites With DE Fill Rate > 0 (cont.)	Avg Fill Rate (%) (cont.)
bone_scan_value	44.4	0.4
advance_directive	38.1	38.1
surrogate_decision_maker	36.5	11.0
med_reconciliation	34.9	22.9
bone_scan_date	34.9	0.8
alcohol_use	27.0	22.0
ekg	22.2	1.3
radiation_encounter	20.6	1.5
radiation_date	15.9	0.7
radiation_procedure	15.9	0.7
radiation_dose	15.9	0.6
alcohol_counseling	15.9	0.0
three_d_conformal_xrt	14.3	0.5
margin_status	14.3	0.3
hospice_date	11.1	0.4
brachytherapy	9.5	0.1
cancer_status	1.6	1.4
alcohol_reduction	0.0	0.0
cause_of_death	0.0	0.0
consult_report	0.0	0.0
consulted_md	0.0	0.0
consulting_provider	0.0	0.0
cryotherapy	0.0	0.0
dietary_changes	0.0	0.0
er_visit	0.0	0.0
icu	0.0	0.0
lifestyle_recommend	0.0	0.0
pain_plan	0.0	0.0
physical_activity	0.0	0.0
primary_care_referral	0.0	0.0
surgical_procedure	0.0	0.0
Average	51.8	22.6

FIG 1. Fill rates for oMIPS-associated DEs, averaged over all practices. Column 1 shows a list of the 63 DEs analyzed in this study. The percentage of practices (among 63 practices) that had at least one filled DF for at least one patient is shown for each DE in column 2. The average fill rate for each DE across all practices is shown in column 3. Columns 1-3 are split into left and right panels to conserve space. The last row of the right panel computes the average values for columns 2 and 3. The rows are sorted first by column 2, then column 3, and then by DE alphabetical order. To enhance readability, all percentages are rounded to the closest integer value (0-100). The definition for each DE can be found in the Data Supplement. DEs, data elements; DF, data field; oMIPS, Oncology Merit-Based Incentive Payment System.

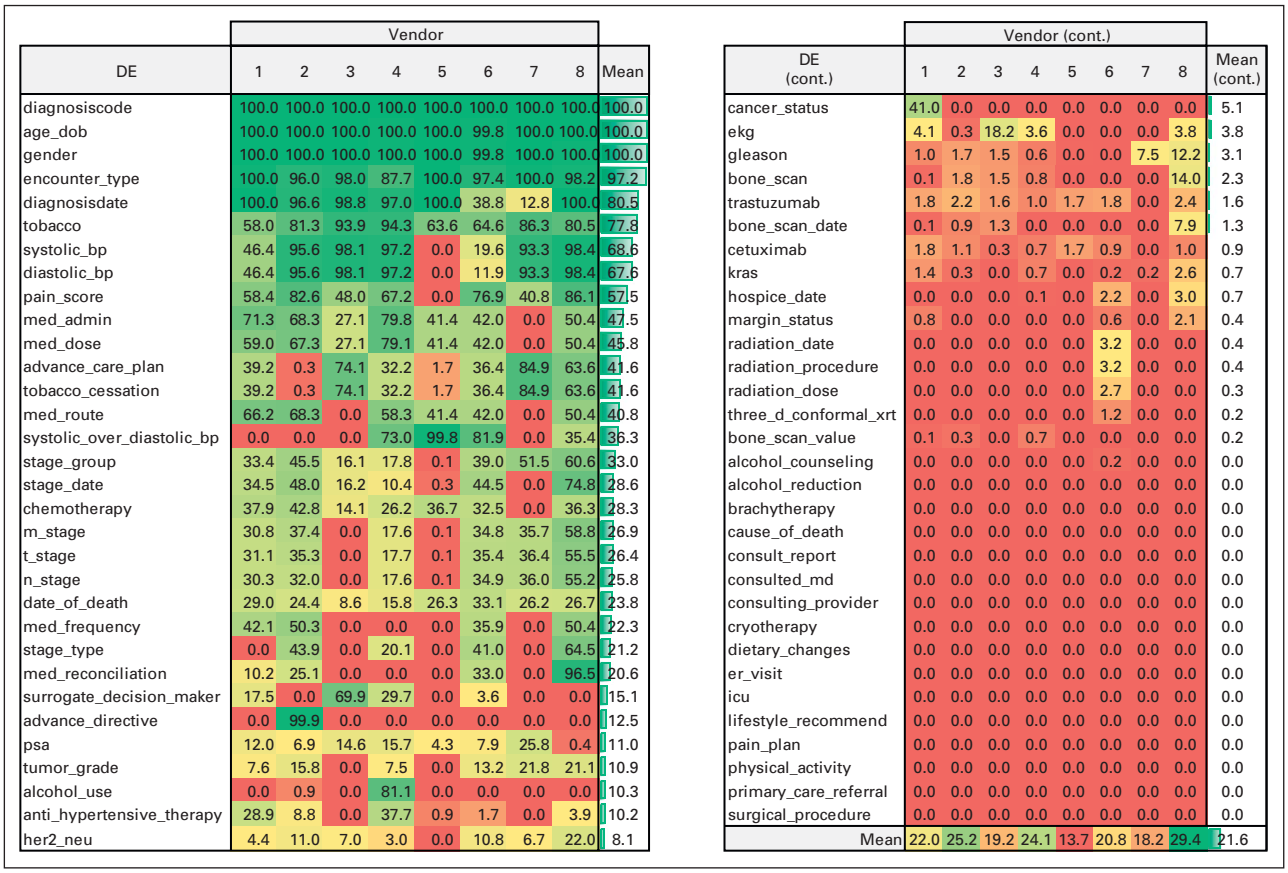
anonymity, EHR vendors are not listed in alphabetical order nor the order they appear in Table 1. Figure 2 shows that, below the top six DEs listed above, some vendors began to show DE fill rates of zero, beginning with blood pressure measurements. A DE fill rate of zero indicates that no data were received from practices using that the EHR vendor because of either lack of captured data or lack of the DF in any of the implementations. With only a single exception (date_of_death), every subsequent DE had at least one vendor with a fill rate of zero for one or more DEs. At the bottom of the DE list, 15 DEs had fill rates of zero for all vendors. These include alcohol_counseling, alcohol_reduction, brachytherapy, cause_of_death, consult_report, consulted_md, consulting_provider, cryotherapy, dietary_changes, er_visit, icu, lifestyle_recommend, pain_plan, physical_activity, primary_care_referral, and surgical_procedure.

No additional consistent patterns of DE fill rate failures among vendors were noted. However, a few fill rate outliers were detected. For example, vendors 6 and 7 had very low fill rates for diagnosisdate; vendor 8 had a 97% fill rate for med_reconciliation; vendor 2 had a 100% fill rate for advance_directive; and vendor 5 had an 81% fill rate (relatively very high) for alcohol_use. Across source systems, we do see variability across individual DEs; however, this does not correlate with score calculability for any single vendor.

oMIPS Measure Calculability Was Uniformly Poor

The probability of finding data in a given DF is equal to the DE fill rate. Therefore, the calculability for an oMIPS CQM may be approximated for most CQMs by calculating the product of the fill rates for its component DEs. Since any oMIPS CQM with a component DE fill rate of 0% results (in a DE essential for the measure calculation) in 0% calculability, 11 of the 19 oMIPS CQM had a calculability of 0%, as presented in Table 2. Only two oMIPS CQMs (M9 and M18, as defined in the Data Supplement, related to tobacco use) had calculability $>$ 1%. These two measures were likely more successful because these they had only three-four component DEs (three component DEs were shared between them), and also because tobacco cessation is a very common component of many quality initiatives.

The fraction of component DEs with a $>$ 50% fill rate, presented in Table 2 (column 4), is only loosely correlated with calculability. Higher fill rates (and no zero fill rates) would be required to usefully automate the calculation of MIPS measures from EHR data. The concept of useful fill rates is explored in more detail in the Data Supplement.



DE	Vendor 1	2	3	4	5	6	7	8	Mean
diagnosiscode	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
age_dob	100.0	100.0	100.0	100.0	100.0	99.8	100.0	100.0	100.0
gender	100.0	100.0	100.0	100.0	100.0	99.8	100.0	100.0	100.0
encounter_type	100.0	96.0	98.0	87.7	100.0	97.4	100.0	98.2	97.2
diagnosisdate	100.0	96.6	98.8	97.0	100.0	38.8	12.8	100.0	80.5
tobacco	58.0	81.3	93.9	94.3	63.6	64.6	86.3	80.5	77.8
systolic_bp	46.4	95.6	98.1	97.2	0.0	19.6	93.3	98.4	68.6
diastolic_bp	46.4	95.6	98.1	97.2	0.0	11.9	93.3	98.4	67.6
pain_score	58.4	82.6	48.0	67.2	0.0	76.9	40.8	86.1	57.5
med_admin	71.3	68.3	27.1	79.8	41.4	42.0	0.0	50.4	47.5
med_dose	59.0	67.3	27.1	79.1	41.4	42.0	0.0	50.4	45.8
advance_care_plan	39.2	0.3	74.1	32.2	1.7	36.4	84.9	63.6	41.6
tobacco_cessation	39.2	0.3	74.1	32.2	1.7	36.4	84.9	63.6	41.6
med_route	66.2	68.3	0.0	58.3	41.4	42.0	0.0	50.4	40.8
systolic_over_diastolic_bp	0.0	0.0	0.0	73.0	99.8	81.9	0.0	35.4	36.3
stage_group	33.4	45.5	16.1	17.8	0.1	39.0	51.5	60.6	33.0
stage_date	34.5	48.0	16.2	10.4	0.3	44.5	0.0	74.8	28.6
chemotherapy	37.9	42.8	14.1	26.2	36.7	32.5	0.0	36.3	28.3
m_stage	30.8	37.4	0.0	17.6	0.1	34.8	35.7	58.8	26.9
t_stage	31.1	35.3	0.0	17.7	0.1	35.4	36.4	55.5	26.4
n_stage	30.3	32.0	0.0	17.6	0.1	34.9	36.0	55.2	25.8
date_of_death	29.0	24.4	8.6	15.8	26.3	33.1	26.2	26.7	23.8
med_frequency	42.1	50.3	0.0	0.0	0.0	35.9	0.0	50.4	22.3
stage_type	0.0	43.9	0.0	20.1	0.0	41.0	0.0	64.5	21.2
med_reconciliation	10.2	25.1	0.0	0.0	0.0	33.0	0.0	96.5	20.6
surrogate_decision_maker	17.5	0.0	69.9	29.7	0.0	3.6	0.0	0.0	15.1
advance_directive	0.0	99.9	0.0	0.0	0.0	0.0	0.0	0.0	12.5
psa	12.0	6.9	14.6	15.7	4.3	7.9	25.8	0.4	11.0
tumor_grade	7.6	15.8	0.0	7.5	0.0	13.2	21.8	21.1	10.9
alcohol_use	0.0	0.9	0.0	81.1	0.0	0.0	0.0	0.0	10.3
anti_hypertensive_therapy	28.9	8.8	0.0	37.7	0.9	1.7	0.0	3.9	10.2
her2_neu	4.4	11.0	7.0	3.0	0.0	10.8	6.7	22.0	8.1

DE (cont.)	Vendor (cont.) 1	2	3	4	5	6	7	8	Mean (cont.)
cancer_status	41.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.1
ekg	4.1	0.3	18.2	3.6	0.0	0.0	0.0	3.8	3.8
gleason	1.0	1.7	1.5	0.6	0.0	0.0	7.5	12.2	3.1
bone_scan	0.1	1.8	1.5	0.8	0.0	0.0	0.0	14.0	2.3
trastuzumab	1.8	2.2	1.6	1.0	1.7	1.8	0.0	2.4	1.6
bone_scan_date	0.1	0.9	1.3	0.0	0.0	0.0	0.0	7.9	1.3
cetuximab	1.8	1.1	0.3	0.7	1.7	0.9	0.0	1.0	0.9
kras	1.4	0.3	0.0	0.7	0.0	0.2	0.2	2.6	0.7
hospice_date	0.0	0.0	0.0	0.1	0.0	2.2	0.0	3.0	0.7
margin_status	0.8	0.0	0.0	0.0	0.0	0.6	0.0	2.1	0.4
radiation_date	0.0	0.0	0.0	0.0	0.0	3.2	0.0	0.0	0.4
radiation_procedure	0.0	0.0	0.0	0.0	0.0	3.2	0.0	0.0	0.4
radiation_dose	0.0	0.0	0.0	0.0	0.0	2.7	0.0	0.0	0.3
three_d_conformal_xrt	0.0	0.0	0.0	0.0	0.0	1.2	0.0	0.0	0.2
bone_scan_value	0.1	0.3	0.0	0.7	0.0	0.0	0.0	0.0	0.2
alcohol_counseling	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0
alcohol_reduction	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
brachytherapy	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
cause_of_death	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
consult_report	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
consulted_md	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
consulting_provider	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
cryotherapy	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
dietary_changes	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
er_visit	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
icu	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
lifestyle_recommend	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
pain_plan	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
physical_activity	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
primary_care_referral	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
surgical_procedure	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mean	22.0	25.2	19.2	24.1	13.7	20.8	18.2	29.4	21.6

FIG 2. Heat map of fill rates for each DE, grouped by the vendor. The fill rate was calculated for each DE, for patient data in each of the eight EHR systems. Each column in the heat map displays DE fill rates from one of the eight vendors. Columns are split into a left and right panel to conserve space. The rightmost columns of both panels show the mean fill rate for each DE, and the last row of the right panel shows the mean fill rate for each vendor. The rows are sorted by the mean DE fill rate (right column). A heat map is applied for the 63 DEs, with green indicating higher fill rates, red indicating lower fill rates, and yellow indicating fill rates of intermediate values. A separate recalibrated heat map is applied to the last row in the second panel (mean fill rate per vendor) to better highlight the small differences in overall fill rates between vendors. The definition for each DE can be found in the Data Supplement. DE, data element; EHR, electronic health record.

Table 2 also includes the results covering measures specific for colorectal, breast, and prostate cancer.

DISCUSSION

This study exposes significant and pervasive limitations for automated EHR data extraction for oMIPS CQMs because of sparse DF availability and low fill rates. Even for the instances where DFs were available, there was little standardization across EHR vendors and practices, as well as poor fill rates for most DFs. Our results highlight the challenges preventing meaningful exchange of oncology data, despite recent enactment of the information blocking 21st Century Cures Act legislation.[23] One challenge is the complexity and frequent changes of oncology DEs, which do not lend themselves easily to standardization and maintenance of interoperable, computer-readable, and up-to-date data dictionaries. Another challenge is the lack of a mandate to implement data capture standards within EHRs. Data in structured EHR fields vary widely among implementations because data capture standards have not been widely adopted by EHR systems, and also because practices do not routinely share data capture templates.

Even when structured DFs do exist, in practice, most of the fields are sparsely populated, and many clinical concepts are captured only in unstructured text notes, commonly generated by dictation as many clinicians still prefer. Existing natural language processing (NLP) systems require significant implementation and tuning effort at each site to achieve acceptable performance.[24] Additionally, narrative text entered by clinicians and processed by NLP has no standardized lists of answer choices or predetermined value sets to guide a user when entering data into an EHR user interface. This can lead to NLP-generated data set skewing when compared with structured data capture.

Similar challenges have plagued other medical specialties. Our results are consistent with previous studies which have assessed the impact of EHR limitations and data gaps for reporting CQMs across multiple practice settings, including primary care, emergency care, postdischarge settings, and

TABLE 2. Oncology MIPS Measure Calculability

Measure	Cancer	Calculability (%)	No. of DEs Above 50% Fill Rate/No. of DEs
M9	All	32.3	2/3
M18	All	31.4	3/4
M1	All	< 1	1/4
M3	All	< 1	1/6
M4	Breast	< 1	3/7
M5	CRC	< 1	2/6
M19	Breast	< 1	4/13
M7	CRC	< 1	2/10
M2	All	0	0/4
M16	Prostate	0	3/20
M8	All	0	3/10
M15	All	0	3/6
M6	All	0	2/10
M14	All	0	2/4
M17	Prostate	0	1/10
M10	All	0	1/4
M11	All	0	1/4
M12	All	0	1/4
M13	All	0	1/4

NOTE. The ability to calculate each MIPS measure (calculability) from CancerLinQ data was assessed and presented alongside the fraction of component DEs that were more than 50% filled. MIPS measures in column 1 (see measure definitions in the Data Supplement) are sorted by column 3 and then by column 4. Column 2 shows the cancers for which each measure is intended. Calculability (column 3) is the percentage of patients for whom a measure can be calculated from its component DEs. The calculability of a MIPS measure for eligible patients was determined as the product of each measure's individual DE fill rates. Column 4 shows the number of each measure's component DEs that are more than 50% filled (numerator) over the number of component DEs for each measure (denominator). Eleven of the measures (M15 through M2) had at least one DE with a zero fill rate and thus had 0% calculability. The calculability of a MIPS measure for eligible patients was usually determined as the product of each measure's individual DE fill rates. In a few cases (eg, M6 and M16), not all DEs for a MIPS measure are essential to calculate a fill rate for each individual patient. However, the presence of a 0% fill rate in any essential DF yielded a calculability of 0% for that measure. For example, in M11-M15, the 0% fill rate for the cause_of_death DE prevented the calculation of the measure denominator (patients dying from their cancer) for even a single patient.

Abbreviations: CRC, colorectal cancer; DE, data element; DF, data field; MIPS, Merit-Based Incentive Payment System.

cardiology.[9,10,25,26] In a 2016 study,[25] the EHR extraction of nine cardiovascular CQMs took an average of almost 460 days of effort, with an average of 8.4 separate processing tasks required per measure. A 2014 study[10] evaluated DE fill rates required for evaluating five National Quality Forum CQMs and found that most measures required DEs with very low fill rates. They concluded, in part, that none of the five measures could be readily computed and that manually intensive steps including data mapping and text mining would be required to extract the measure data. A 2020 study of eCQMs[27] found inconsistencies in the definitions of measure concepts (eg, in Clinical Quality Language expressions[27-29]), logical phrases, value sets, terminologies, and the DEs required to satisfy the various measures. Our study of 19 oMIPS CQMs identified numerous examples of these problems, as exemplified by the case study described in the Data Supplement.

There are several ways to improve automated reporting from the EHR. Using a policy-based approach, CMS could retract measures that cannot be automatically extracted. CMS could also incentivize the community-based development of national standards for structured data capture of DEs. In addition, CMS could incentivize the routine automated exchange of standardized DEs between separate EHR systems and EHR modules. Data capture and transmission standards will also be required to automate the reporting of quality measures. One example of this approach is the Minimal Common Oncology Data Elements (mCODE) project, which produces oncology-specific data specifications under the auspices of ASCO and Health Level Seven International (HL7).[30]

Another example of data capture and transmission standards is the College of American Pathologists (CAP) Cancer Protocols (CCPs).[31] The CCP documents contain cancer case summaries (checklists) that guide pathologists to create reports containing standard data structures, which are essentially DEs. Beginning in 2009, CAP began releasing the CCP's checklists in a computer-readable XML format so that pathology software vendors could make the standardized data-entry forms and storage mechanisms available inside the existing pathology systems and EHRs. These widely used pathology templates are known as electronic Cancer Checklists (eCCs).[31-35]

Although we completed a comprehensive search for required data to support the measure set calculations described in this analysis, we did not have access to EHR data dictionaries for each vendor and practice. Therefore, we cannot exclude the possibility that despite considerable manual effort, desired DE data values were present in EHRs but not found. EHR implementation also frequently involves significant customization to accommodate local clinical workflows and data capture preferences. Such customization accommodates clinical workflows, but it decreases standardization and interoperability and increases the difficulty of data extraction.

Additionally, poor DE fill rates can result from multiple causes, eg, lack of standard DEs, lack of EHR DFs for DEs, lack of DE usage in EHR data-entry forms, lack of structured data entry by clinicians and other health care providers, inadequate vendor approaches to exchange of data between EHR modules and other EHRs, sites or practices, vendor systems that do not permit incorporating externally sourced structured data, and vendor systems that

exchange data in non–interoperable formats, such as narrative text, PDF, or fax. Each of these DE-related issues decreases the ability to enter, locate, and exchange standardized and structured data.

These results demonstrate that, in the oncology use case, the EHRs and oncology practices studied are incapable of satisfying oncology MIPS reporting requirements through retrieval of clinically recorded structured DEs. Crossing the chasm between quality measures and high-quality data will require widespread creation and adoption of common DEs along with improvements in the routine capture and exchange of structured data.

AFFILIATIONS

[1]Oncology Analytics, Atlanta, GA
[2]College of American Pathologists, Northfield, IL
[3]CancerLinQ, American Society of Clinical Oncology, Alexandria, VA
[4]The University of Texas School of Biomedical Informatics at Houston and Division of General Internal Medicine, McGovern Medical School, The University of Texas Health Science Center at Houston, TX
[5]Department of Medicine, The University of Illinois, Chicago, IL
[6]Departments of Internal Medicine and Biomedical Informatics, The Ohio State University, Columbus, OH

CORRESPONDING AUTHOR

James L. Chen, MD, Ohio State University, James Cancer Hospital Medical Oncology, 320 W 10th Ave, Columbus, OH 43210-1280; e-mail: james.chen@osumc.edu.

EQUAL CONTRIBUTION

A.E.S., R.M., and J.K. contributed equally to this work.

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AUTHOR CONTRIBUTIONS

Conception and design: Anna E. Schorer, Richard Moldwin, Jacob Koskimaki, Elmer V. Bernstam, Neeta K. Venepalli, Robert S. Miller, James L. Chen
Collection and assembly of data: Anna E. Schorer, Richard Moldwin, Jacob Koskimaki, Neeta K. Venepalli, Robert S. Miller, James L. Chen
Data analysis and interpretation: Anna E. Schorer, Richard Moldwin, Jacob Koskimaki, Elmer V. Bernstam, Neeta K. Venepalli, Robert S. Miller, James L. Chen
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Final approval of manuscript: All authors
Accountable for all aspects of the work: All authors

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Anna E. Schorer
Employment: Oncology Analytics

Richard Moldwin
Other Relationship: College of American Pathologists

Jacob Koskimaki
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Elmer V. Bernstam
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Honoraria: Lilly

James L. Chen
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