Challenges impacting data extraction from Electronic Health Record (EHR) systems in Small and Medium sized practices in the Midwest.

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Background

Agency for Healthcare Research and Quality funded Healthy Hearts in the Heartland (H3)2 research study as part of EvidenceNow®: Advancing Heart Health in Primary Care settings. The goal of the H3 research study in the Midwest (Illinois, Indiana and Wisconsin), was to:

- Engage small and medium sized practices, (defined as practices with 20 or fewer primary care providers), to implement quality improvement (QI) strategies geared towards advancing cardiovascular care.
- H3 study recruited 226 small and medium sized practices across the Midwest
- QI work at participating practices/clinics focused on evaluating four clinical measures:
  - Aspirin – Prescribing Aspirin to prevent x when appropriate (NQF#0068)
  - Blood Pressure control (NQF0018)
  - Cholesterol management (PCRS 438)
  - Smoking Cessation (NQF#0028)

Objectives

One of the primary objectives of H3 study was to extract and analyze EHR data to calculate Clinical Quality Measures for the ABCS. The study also implemented popHealth tool, which provided centralized dashboards and reports for practice facilitators and providers to guide study QI intervention strategies.

Methods

We evaluated practice EHRs for its capability to output clinical-patient level data. We relied on vendor documentation to determine how patient clinical data was structured and stored in the EHR system. In some instances we were able to consult directly with vendors on how to extract clinical batch data. In the H3 study, we utilized the following three methods to extract clinical-patient data from seven EHRs.

1. Standard data extract: We evaluated EHRs capabilities to batch export clinical-patient data into:
   - CCDA – Consolidated Clinical Document Architecture
   - CCD – Continuity of Care Document

2. Direct database extract: We evaluated EHRs capability to allow direct database connection to run data queries on specific measure.

3. EHR report builder extracts:
   - Custom reports – reports that allowed us to choose customizable data elements
   - Native reports – reports that provided a prescribed set of data elements

Note: We evaluated application programming interface (API) for one EHR, but we did not utilize this method to extract data for the study.

For practices that we established a data extract method, data was extracted and uploaded to central data servers using aproprietary secure software. The data was transformed using different ETL process and formatted for popHealth.

Results

Of the 22 EHR systems represented in the study we successfully evaluated N=7 EHRs (32.8%) for capability to extract patient level data for use in popHealth. The seven EHRs represented a total of 128 out of 226 practices (56.6%) that had capability to export clinical data. Of the 128 eligible practices, a few opted out of connecting to popHealth. The total final number of practices that we successfully exported clinical data to popHealth was 118 practices which was representative of 92.2% of practices running on one of the seven evaluated EHRs.

Figure-2 below, shows a high number of connected practices for EHR-4. This particular EHR was used by 77 small practices under two separate networks. Due to the centralized setup of the networks and shared IT resources, we were able to extract clinical-patient data from multiple practices at the same time. As a result there were 95.2% practices connected to popHealth that ran EHR-4.

Figure-3 below, shows that we had the best success in extracting data from the three EHR systems that allowed direct database extract. This method of data extraction accounted for 75.4% of practices running one of the seven evaluated EHRs.

Figure 2. Number of practice connected to popHealth by EHR

Figure 3. Number of practice connected to popHealth by connection method

EHR Data extraction challenges

In the process of evaluating the seven EHRs capabilities to export patient level data for use in popHealth, we observed several challenges that are worth highlighting.

1. We found no easy way of automating the data extraction and upload process. Hence we relied on a manual process that was often impacted by practice availability.
2. Lack of vendor support and documentation made it challenging to understand how data was stored in EHR systems. This meant that in most cases we did not have a way of verifying, for example what EHR measure logic the vendor was using.
3. The differences on how data was captured and stored in EHR system, also meant that extracted data varied in quality and completeness. For example CCDA formats, yielded clinical-patient data sets that were not uniform from one vendor to another.
4. Vendors quoted prohibitive cost to upgrade practice EHR with packages that allowed batch data and customizable data extraction.
5. Lack of local practice EHRIT expertise at the practice significantly influenced our success in extracting data from a practice.

Discussion

The challenges of extracting EHR data for secondary use, for example in healthcare research, evident in the H3 study underscores the need for continued efforts towards refining EHR data “input” and “output” standards. “Good data in” would improve the quality and usability of clinical data in both patient care as well in secondary use cases.

Also evident through the study was a need for vendors to provide easier and safer access to the EHR data and provide better mechanism for batch data extract. One such promising initiative by the Office of the National Coordinator for Health Information Technology, would be require EHR vendors to enable open Application Programming Interfaces (open API)^1.

Reference

1. AHRQ https://www.ahrq.gov
3. popHealth – OSEHRA: https://www.osehra.org/popHealth

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