Delivering on-demand evidence via an informatics consultation service

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Abstract

Clinicians are often faced with situations where published treatment guidelines do not provide a clear recommendation. In these challenging scenarios, on-demand evidence generated from data captured in electronic health records (EHRs) can aid in decision making. We operate a specialty consultation service staffed by a team of medical and informatics experts to summarize 'what happened to patients like mine' using data from EHRs and other health utilization data sources. Our service translates physician inquiries about situations with evidence gaps into actionable reports by keeping experts in the loop and enabling rapid iteration for electronic phenotyping, cohort definition and result interpretation. We describe our experience offering this service as a year-long pilot study. Our goal is to summarize our learning to enable others to implement such a service in their own health systems using their existing OMOP CDM formatted data.

Motivation

Randomized controlled trials (RCTs) are widely considered the best source for evidence to support clinical decisions. The cost of conducting RCTs and the narrow band of the patient population they are applicable to, however, limits their use for decisions that clinicians must make on a daily basis[1]. The increasing volume and availability of EHR data as well as the development of standards to harmonize their representation and analysis by the OHDSI community, are making it possible to offer clinical decision support powered by observational health data. We have begun offering an informatics consult service[2,3] at our academic medical center, staffed by a team of medical and informatics experts, with the goal of providing on-demand evidence with the turnaround time of a send out laboratory test.

Service workflow and learning from the first 150 consults

Given a clinical question, our service provides a summary of similar patients, the treatments and exposures those patients had, and the outcomes that occurred. A clinician requests a consultation by email, which is followed up with a brief discussion with our team to clarify the underlying clinical situation motivating their request, and formalize it into a question that specifies the relevant population, intervention, comparator, outcome and timeframe (PICOT). We support two variants of causal inference – treatment effect estimation and survival analysis, as well as exploratory analyses. Exploratory analyses vary in design from simply compiling patient counts, to statistical tests such as the chi-squared test or calculating sensitivity/specificity, to complex bespoke summaries of data such as quantifying the rate of specific clinical event sequences, or patterns in events' duration, as requested by a clinician.

We use three sources of data in the service: (1) EHRs from 3 million patients seen at Stanford Health Care (SHC), consisting of diagnosis and procedure codes, medications prescribed, laboratory tests conducted and their results, and clinical note content; health insurance claims records from (2) Truven MarketScan and (3) Optum Clinformatics, which capture employer and Medicare claims records for roughly 150 million lives and 50 million lives, respectively.

To allow iterative, rapid phenotyping and cohort construction, we developed novel A Cohort Engine (ACE), that uses a temporal query language to search a persistent in-memory database of patient objects populated by reading data stored in the OMOP Common Data Model (CDM). We are in the process of adapting the OHDSI analysis packages for use in our service, to streamline statistical analyses, to provide data and analysis diagnostics in our consult reports, and to enable the adoption of our consult service at other academic medical centers in the OHDSI network.

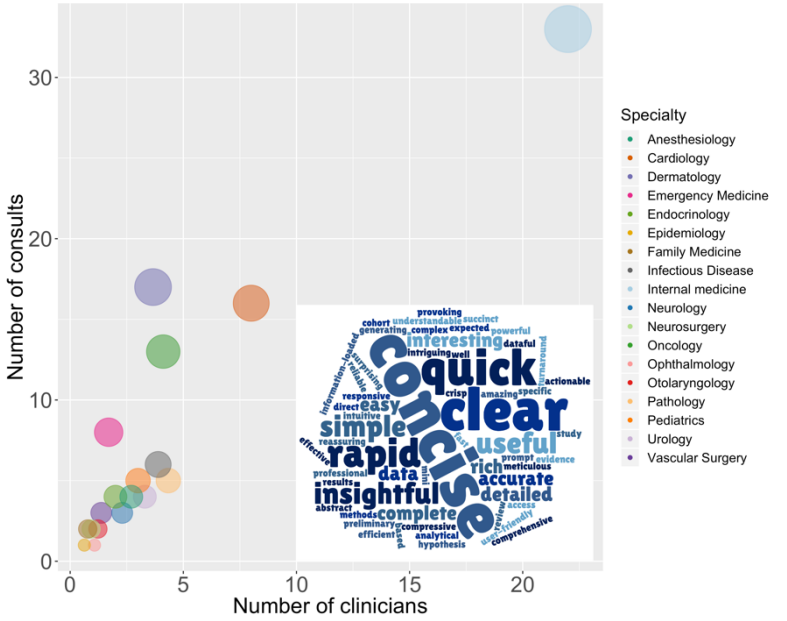

Figure 1: *Summarizes the first 150 consults including the breakdown by the clinical specialties that have requested the service. The inset tag cloud is created from the top three words used by the clinicians to describe the report they receive.*

Because the consult service relies on observational data, there is always a chance that treatment effects derived from these data via our analyses are spurious. We carry out quality control processes and auxiliary analyses to minimize the chance of providing a wrong answer, convey the uncertainty of the results to the requesting clinician, and aid interpretation. In a given consult request, we examine outcomes not expected associated with the intervention in question to estimate false positive rate. At the entire service level, we analyze community compiled[4,5] known associated and non-associated exposure-outcome pairs to quantify false positive and false negative rates. We also generate synthetic positive associations with and without confounding and analyze these as a positive control. We include e-values[6] in the causal inference consult reports, which help convey the degree of uncontrolled confounding that would have to be present to produce the observed effect. The in-person debrief for every consult request, in combination with the above analyses, allow us to summarize and convey our impression of how reliable a given result is. During our debrief with the requesting clinician, we also conduct a survey to get feedback on the report and overall service.

Conclusion

Response to our service has been positive, with more than 60 clinicians using the service over 150 times, and all expressing that they would use the service again. As we design the next iteration of our service, we plan to investigate the degree of automation to pursue at question intake, the appropriate level of self-service to create tooling for, and whether to optimize for bed-side use or as a rapid medical hypothesis-generation/research service.

Advances in data harmonization and analysis enabled by efforts such as OHDSI give us the unique opportunity to reuse patient data captured via EHR systems for closing the evidence gap between evidence available in clinical guidelines and what is needed to provide personalized treatment. Ideas of learning from similar patients have been proposed in the medical community as far back as 1972, where Feinstein et al[7] created a command line, conversational mode computer program for proposing and iteratively refining a cohort of patients for estimating treatment prognosis. Only by launching efforts such as our consult service, to bring evidence distilled from similar patients to bear on decision making at the bedside, can we study the *value and impact* of learning from the record of routine clinical practice for patient care and health system processes.

References

1. Stewart, WF, Shah, NR, Selna, MJ, Paulus, RA, Walker, J. M. Bridging the inferential gap: the electronic health record and clinical evidence. Health Aff. 2007; 26:w181–91.
2. Schuler, A, Callahan, A, Jung, K, Shah, NH. Performing an Informatics Consult: Methods and Challenges. J Am Coll Radiol. 2018; 15:563–568.
3. Gombar, S, Callahan, A, Califf, R, Harrington, R, & Shah, NH. It is time to learn from patients like mine. npj Digit Med. 2019; 2:16.
4. Ryan PB, Schuemie MJ, Welebob E, Duke J, Valentine S, Hartzema AG. Defining a reference set to support methodological research in drug safety. Drug Saf. 2013; 36 Suppl 1:S33-47.
5. Schuemie, MJ, Ryan, PB, DuMouchel, W, Suchard, MA, Madigan, D. Interpreting observational studies: why empirical calibration is needed to correct p-values. Stat Med. 2014; 33:209-218.
6. VanderWeele, TJ, Ding, P. Sensitivity Analyses in Observational Research: Introducing the E-Value. Ann Int Med. 2017; 167:268-274.
7. Feinstein, AR, Rubenstein, JF, & Ramshaw, WA. Estimating prognosis with the aid of a conversational-mode computer program. Ann Int Med. 1972;76, 911-921.