Background/Aims: We assessed the effectiveness of eCare for Moods™ (patent pending), a patient-centered, highly interactive, web-delivered patient self-management and care management program on patients treated for recurrent or chronic depression in specialty psychiatry through a randomized clinical trial with two-year follow-up. **Methods:** Patients with recurrent or chronic depression were randomly assigned to eCare (N = 51) or usual specialty mental health care (N = 52). The 12-month eCare program provided patients with individualized self-monitoring, tailored patient education and training in depression self-management including relapse prevention. eCare was integrated with participants' ongoing depression care, linked to their electronic medical records. It provided clinicians with panel management and clinical decision support. Participants were interviewed at baseline and 6, 12, 18, and 24 months after enrollment. Telephone interviewers blind to treatment assignment used a timeline follow-back method to estimate depression severity on a 6-point scale for each of the 105 study weeks (including the baseline). Differences between groups in weekly severity over two years were examined by generalized estimating equations. **Results:** Participants in eCare experienced more reduction in depressive symptoms (estimate=–.74 on the 6-point scale over two years; 95% confidence interval [CI]=–1.38 to –.09, P = .025) and were less often depressed (–.24 over two years; CI=–.46 to –.03, P = .026). At 24 months, 43% of eCare and 30% of usual-care participants were depression free; the number needed to treat to attain one additional depression-free participant was 8. eCare participants had other favorable outcomes: improved general mental health (P = .002), greater satisfaction with specialty care (P = .003) and with learning new coping skills (P <.001), and more confidence in managing depression (P = .006). **Conclusions:** Patient-centered, web-delivered care management improves outcomes in patients treated for recurrent and chronic depression.
Keywords: Internet-delivered care; Depression
doi:10.3121/cmr.2014.1250.b1-4

C3-1:
Footprints in the Sand: Tracking Physician Work Efforts in Primary Care Using Access Logs in an Electronic Health Record

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Background/Aims: Using EpicCare Electronic Health Record (EHR) data in a large multispecialty ambulatory delivery system, we explore a unique opportunity in which existing EHR data may offer clues on how clinicians use time, a scarce yet critical resource in health services delivery. Traditional means of studying physician time use during clinical encounters (e.g., direct observation) are costly and ignore pre-service and post-service work of physicians' services. The EpicCare EHR offers an alternative, unobtrusive portal to study time use through analysis of access logs. **Methods:** We used EHR access log data for one month in 2013 from 49 physicians in two primary care departments who cared for 22,174 patients in a large multispecialty ambulatory delivery system. Over 3 million EHR transactions are examined to explore individual physicians' style of time use on different tasks, as reflected by the access log. In-depth key informant interviews are used to complement the access log data on how physicians use the EHR and the activities that are more or less likely to be captured by the access log. **Results:** About 43.7% of physicians' total time for the month involved in-person face-to-face visits, 33.8% involved pre and post visit time, 11.4% telephone calls, 5.6% secure messaging to patients, 2.6% prescription refills, and 1.6% on orders for labs, medications or referrals. The earliest EHR access in the office occurred at 12:00 am and the latest logging out time in the office was at 11:59 am the following day. For each patient visit, an average of 16.7 minutes was logged in the exam room and 7.9 minutes logged outside of the exam room. **Conclusions:** The access log is a valuable tool for studying physician work efforts. Our findings highlight the significant amount of time clinicians spend outside of office visits. Unless there is a fixed ratio of in-office to total time, visit-centric FFS payment may undercompensate the significant efforts outside of visits. As "desktop medicine" (e.g., via phone, messaging) increases in the age of the Internet, smart phones, and EHRs, reforming provider payment mechanisms to account for work outside of office visits is warranted.
Keywords: Physician work efforts; EHR access log
doi:10.3121/cmr.2014.1250.c3-1

C3-2:
All-In-One: How Group Health Organizes Clinical Text from Clarity for Research

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Background/Aims: Group Health Cooperative runs Epic as its Electronic Medical Record. The clinical text stored in Clarity, Epic's relational reporting database, is valuable to research at Group Health Research Institute (GHRI). However, due to a number of factors, GHRI's access to this data was limited. These factors included: 1) a limited window during the day allotted to GHRI due to higher priority reports on Group Health's care delivery side, 2) Clarity splitting text notes into lines of about 5,000 characters, and 3) restrictions on managing the database itself, like adding a full-text index. We sought to make the clinical text more valuable for research by making it available at all times, combining all the content of a note into one record, and allowing for more database management options. **Methods:** We have developed a nightly Python process that moves clinical text from four Clarity tables into one full-text-indexed table on our own server. In addition, we store metadata about each note--including note type, encounter date, department, and provider--in a parallel table. **Results:** This conversion process, begun in 2010, converts about 60,000 notes per night and has converted every extant note in Group Health's Clarity database for a total of 123 million notes as of October 2013. The notes' availability has sped development of sophisticated NLP algorithms in the years since its inception. Another benefit is nightly automated status e-mails sent to the developers. When there was a recent import of several years of historical notes from legacy systems into Epic, GHRI knew immediately that a greater history of notes was available for research. **Conclusions:** The text store at GHRI has strengthened research and grant submissions. Due to Clarity's consistent data model and large footprint throughout the nation's medical community, the solution should be easily transferable to other sites wishing to realize the same advantages. The solution is amenable to enhancement as needs arise for more metadata or for clinical text from other parts of Clarity. Remaining challenges are tracking changes to notes in Clarity and improving performance.
Keywords: Natural language processing; Clarity
doi:10.3121/cmr.2014.1250.c3-2

C3-4:
An Algorithm to Combine Machine Learning and Structured Data to Automate De-identification of Clinical Text

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Background/Aims: Clinical text is an important resource for research. To maintain patient privacy when researching this text, we use de-identification. The hiding in plain sight (HIPS) method is promising; it replaces personally identifiable information (PII) with realistic surrogates so any remaining real PII would be hard to distinguish from the fake information. However, there remain some challenges with HIPS, such as overlooked PII. We explored these challenges and hypothesized that we could find more PII by combining structured data with a machine learning algorithm. **Methods:** The machine learning de-identification software we used, developed by MITRE, is the MITRE Identification Scrubber Toolkit (MIST). Trained chart abstractors annotated Family Practice notes with the following PII types: address, age, date, provider name, email, IP address, consumer number, organization name, other id, phone, patient name, room id, social security number, and URL address. Structured data included in this experiment are patient's address, age, date of birth, email, phone, consumer number, social security number, the visit provider name, visit date, and visit location. We queried this data from Clarity, a relational reporting database for Group Health's electronic health record (EHR) system. Our first test experiment used MIST to train a model on 100 documents then tested on 10 notes. We reviewed the remaining PII and determined if they are available in the structured data.