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Commentary

EHR audit logs: A new goldmine for health services research?

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ABSTRACT

A byproduct of the transition to electronic health records (EHRs) is the associated observational data that capture EHR users' granular interactions with the medical record. Often referred to as *audit log data* or *event log data*, these datasets capture and timestamp user activity while they are logged in to the EHR. These data – alone and in combination with other datasets – offer a new source of insights, which cannot be gleaned from claims data or clinical data, to support health services research and those studying healthcare processes and outcomes. In this commentary, we seek to promote broader awareness of EHR audit log data and to stimulate their use in many contexts. We do so by describing EHR audit log data and offering a framework for their potential uses in quality domains (as defined by the National Academy of Medicine). The framework is illustrated with select examples in the safety and efficiency domains, along with their accompanying methodologies, which serve as a proof of concept. This article also discusses insights and challenges from working with EHR audit log data. Ensuring that researchers are aware of such data, and the new opportunities they offer, is one way to assure that our healthcare system benefits from the digital revolution.

1. Introduction

Health services research encompasses a wide range of domains and topics that seek to identify the most effective ways to organize, manage, finance, and deliver high-quality care, as well as reduce medical errors and improve patient safety [1]. Health services researchers value the ability to capture what happens on the front lines of care delivery, where clinical decisions and workflows shape the processes and outcomes experienced by patients. Historically, health services research has relied on claims data that capture care utilization trends as well as on some key health data, such as diagnoses. With the widespread adoption of electronic health records (EHR), electronic clinical data has rapidly become a new source of insights for health services researchers studying healthcare processes and outcomes. Traditionally, electronic clinical data include the core contents of the patient medical record, which reflect the patient's clinical state (e.g., vital signs, problems), as well as care decisions (e.g., medications, orders) and associated documentation (e.g., clinical notes).

A byproduct of the creation of electronic clinical data is the associated EHR observational data that capture EHR users' granular interactions with the medical record. Such interactions predominantly involve the medical professionals who document and view clinical data in the EHR, but may also include administrators, patients (via the patient portal), and others who draw on clinical data (e.g., billers, schedulers) for other purposes. The resulting data offer the opportunity to study in detail the healthcare production process [2], with a specific focus on clinical information creation and consumption. This approach enables researchers to closely observe what Kenneth Arrow notes as the activities of producing medical care that are unobservable through the lens of administrative data [3]. By focusing on clinical work, these data also support efforts seeking to study and improve the work life of those who deliver care [4], particularly by targeting EHR burden and resulting provider burnout [5,6].

The EHR audit log (or event log) refers to a particular subset of data that tracks who is logged in to the EHR, what tasks or events they perform (typically tied to specific patients and/or encounters), and when (via timestamps). EHR audit log data exist because of the need, under HIPAA, to be able to audit inappropriate access to protected health information. However, many EHRs generate logs that capture a broader range of actions than is required by HIPAA (e.g., the steps in

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the process of generating and signing a clinical note), resulting in the potential uses of EHR audit and other log data as a window into clinical care that goes far beyond HIPAA auditing and offers particularly exciting opportunities for health services research.

In the past, a study that required capturing when clinicians undertook certain tasks (e.g., placed an order or viewed a note) necessitated time- and resource-intensive primary data collection methods, such as time-motion studies, surveys, or interviews; however, even these methods did not always succeed in capturing the variability in these tasks over time. Research efforts on clinical time allocation [7] and decision making [8] have used direct observation (e.g., video and audio recordings of clinical visits), which is also labor-intensive and limited in scale. By facilitating detailed measurement of the specific clinician documentation behaviors and patient-provider interactions that are mediated by the EHR, those who seek to understand what drives the safety, quality, cost, and resulting outcomes of care have a new source of insight available. The overarching purpose of this paper is to promote broader awareness of EHR log data (including but not limited to the audit log, though we use the term audit log in the remainder of the paper) and to stimulate their use in health services research and beyond. We do so by describing EHR audit log data and offering a framework for its potential uses. The framework is illustrated with select examples and their accompanying methodologies. We also discuss the insights and challenges from working with EHR audit log data and offer concluding thoughts on the evolution of its use.

2. What are EHR audit log data?

Mandated by HIPAA and the Meaningful Use criteria, all computerized systems in healthcare must implement robust security auditing mechanisms for detecting malicious access to, or alteration of, protected health information. Specifically, audit logs capture and timestamp user activity while logged in to the EHR. However, there are only narrow standards for audit logs and no standards for other types of EHR logs, such that the level of granularity and comprehensiveness of the user behaviors that are logged, and how they relate to other measures (e.g., encounters, workstation, clinical data content, role type) may differ across EHR systems. Some log data may approximate clickstream data, capturing detailed mouse movements on varied EHR screens. More commonly, to decrease the volume of log data and associated storage requirements, the data are represented at a more aggregated level in which specific events tied to specific EHR screens or documents are logged, but the underlying clicks are not.

As compared to clinical data, which are typically patient-centric or encounter-centric, audit log data are user-centric and typically bounded by log-in and log-out events. It therefore lends itself to characterizing how much time users spend on different EHR-related tasks, as well as the order of those tasks. For example, it would be evident if a user bounced back and forth between two different tasks before moving on to a third task and whether such actions are for a single patient or across multiple patients. These patterns are often described as capturing user workflow, though they are limited to work that is observed via the EHR.

Prior audit log work typically aggregated task type and user type into commonly understood categories. In terms of task type, high-level categories included view tasks (a user viewing a type of information), update tasks (a user making a change to information that already exists in the record), and document tasks (the creation of new documentation). For example, in prior work, common task categories included Chart Review (View), Notes (Document), Orders (Document), Results (View), Clinical Summary Review (View), Medication List Review/Reconciliation (View and/or Update), and Problem List Review/Reconciliation (View and/or Update). However, many other types of important tasks – such as provider alerting and associated alert responses – may not be sufficiently captured by these categories. To illustrate the variability in the current literature, Appendix Table 1 lists a convenience sample of 16 studies using EHR audit log data and an abstraction of the associated task type categories examined. User type categories typically relate to primary role, such as attending physician, physician trainee (e.g., residents), nurse, etc. While role may seem to be more straightforward to categorize, in our complex healthcare system, users often have multiple roles or roles that change over time, which may or may not be reflected in the audit log data. As a result, the level of aggregation and specific categories of focus must be intentionally selected and measured, informed by the needs of the individual study.

3. What are potential research applications of EHR audit log data?

Fig. 1 illustrates the range of topics that can be informed by research using EHR audit log data, using the health care quality domains put forth by the Institute of Medicine (now the National Academy of Medicine) (1) to organize the topics. Notable in the topics is that some are more focused on informatics domains (e.g., assessing user interface design), while others are more focused on broader domains, such as team structure, that are simply observed via audit log data.

To more clearly illustrate the potential of EHR audit log data across a range of topics, we provide examples of prior work and associated methodologies in the domains of safety and efficiency.

3.1. Safety domain

Medical errors occur frequently in healthcare and may cause serious harm. It is estimated that there are 250,000 deaths annually as a result of medical errors in the US [9]. Until recently, quantifying the extent of medical errors relied on voluntary reporting, which is known to be vastly underestimated [10–12]. The Wrong-Patient Retract-and-Reorder (RAR) measure was developed to use EHR audit log data to quantify wrong-patient errors and to test interventions aimed at preventing them. This measure is an automated, validated, and reliable method of extracting a large volume of order data to detect one or more orders placed for a patient, retracted within 10 min, and placed by the same clinician for a different patient within the next 10 min. The need to identify the individual clinician's ordering sequence is what requires the use of audit log data.

The Wrong-Patient RAR measure uses a query programmed into the EHR or data warehouse, and is run against every order and its associated audit log data over a specified time period to provide sufficient data and outcome events for research and surveillance purposes. In the initial validation study, real-time confirmatory interviews with clinicians who placed and retracted orders demonstrated that the Wrong-Patient RAR measure correctly identified near-miss, wrong-patient orders in 170 of 223 cases (positive predictive value 76.2%; 95% CI 70.6%–81.9%). The measure identified 5246 of more than 9 million orders that were placed on the wrong-patient over a 1-year period in a large academic medical center, translating to 58 wrong-patient orders per 100,00 orders [13]. Using audit log data, the Wrong-Patient RAR measure enables health systems and researchers to systematically monitor wrong-patient orders and test interventions to prevent them. The measure has been successfully adapted and implemented in a range of EHR systems and healthcare settings.

A series of interventions focused on preventing wrong-patient orders used the Wrong-Patient RAR measure as the primary outcome [13–18]. A randomized controlled trial used the measure to evaluate

Safe	Effective	Patient-Centered	Timely	Efficient	Equitable
Order entry errors Diagnostic errors User interface design	Provider responsiveness to alerts and reminders User interface design	Patient portal usage Provider responsiveness to patient calls/ messages	Wait-times Clinical workflows Team structure and function	EHR "burden" and associated solutions, including: time spent on desktop medicine technical and clinical workflows staffing, delegation and division of labor	Clinical decision-making biases and heuristics

Fig. 1. Example Topics Supported by Audit Log Data Research, by IOM (NAM) Quality Domain.

the effect of alerts that prompted clinicians to verify patients' identity prior to placing orders. An alert that displayed the patient's identifiers and required a click to proceed significantly reduced wrong-patient orders by 16%; an alert that required typing the patient's initials, age, and gender reduced these errors by 41% [13].

The Wrong-Patient RAR measure was used as the outcome measure in a large randomized trial to assess the risk of wrong-patient orders in an EHR configuration limiting clinicians to one patient record open at a time (restricted) versus a configuration that allowed up to four records open concurrently (unrestricted) [18]. Among 3,356 randomized clinicians (1,669 to the restricted group; 1,687 to the unrestricted group), who placed more than 12 million orders during the study period, there was no significant difference in wrong-patient order errors between the two configurations overall (90.7 versus 88.0 per 100,000 order sessions; OR 1.03; 95% CI, 0.90–1.20; $P = .60$) or in the emergency department, inpatient, or outpatient settings.

The use of EHR audit log data in this study provided novel insights into previously unknown clinician ordering practice. An audit log was created for the study to track the number of records open at the time when each order was placed. Given the capability to open up to four patient records concurrently, two-thirds of all orders were placed with a single record open by clinicians in the unrestricted configuration. However, in the high-volume setting of the emergency department, where clinicians care for multiple patients simultaneously, clinicians more frequently utilized the multiple-records capability and placed one third of orders with the maximum of 4 records open. Even in this setting, there was no difference in the risk of wrong-patient order errors between configurations (OR 1.00). Although this study measured only one type of error, the results call into question national recommendations to configure EHRs to display one patient record at a time [19,20], and demonstrate the potential impact on policy of using log data in health services research.

Over the past decade, government bodies with oversight of EHR adoption, standards, and monitoring have called for development of methods to assess the safety of health IT, standardized testing procedures, and performance of ongoing surveillance [21–23]. Further, the 21st Century Cures Act [24] mandates the creation of the EHR Reporting Program, which requires testing and reporting of functionality related to security, usability, interoperability, and other priority areas including patient safety. Nationwide adoption of the Wrong-Patient RAR measure, potentially by EHR vendors as built-in functionality, would align with these goals and enable health systems to use EHR log data to test interventions to reduce error.

3.2. *Efficiency domain – Time spent*

EHR audit logs offer the opportunity to examine how physicians spend their clinical time in the EHR era and to explore the associated implications. In the ambulatory setting, the typical visit workflow consists of the physician opening the EHR soon after entering the room and accessing it while talking to the patient (e.g., entering information or looking up lab values). To protect patient privacy, physicians routinely log out of the EHR when leaving the room. This typical workflow offers a potential for the use of log data to estimate the length of office visits as well as the amount of time physicians spent in various sections of the EHR.

To examine the validity of this approach to estimating time spent face-to-face with patients, the research team first compared visit lengths calculated by log data with two other approaches: (1) in-person observation, and (2) audio-recordings of visits. On average, the log-based estimates were two minutes shorter when compared to in-person observation and three minutes shorter than estimates based on audio-recordings [25].

After completing validation work, the research team examined how

471 primary care physicians in a large healthcare system allocate their time. Administrative and log data revealed that these physicians performed clinical work in the EHR records of 765,129 patients, 637,769 of whom were seen at least once in the 2,842,109 face-to-face ambulatory care visits during the four-year study period. These physicians spent similar amounts of time in face-to-face visits (average of 3.08 h/day) as in desktop medicine (average of 3.17 h/day). More specifically, the average number of visits per physician per day was 12.3 (median: 12; SD: 5.3). The log data recorded an average of 15.0 (SD: 10.7) minutes for a face-to-face visit in the exam room. If 3 min is added to account for the underestimation of visit length by the log data, the average visit length becomes 18 min which is consistent with the literature [7].

In addition to time spent inside exam rooms during patient visits, physicians often use the EHR outside of visits, performing "desktop" medicine. The daily average of desktop medicine time included 2.82 h spent in the clinic and 13 min outside of the clinic. Log data show physicians accessing charts of patients with appointments before patients' arrival to order tests, send messages, and review test results, prescriptions, or referrals. Log data also document extensive desktop medicine work *after* patients' visits: documenting in progress notes, ordering tests, reviewing results, submitting referrals, and prescribing medications. Of the 51% of physicians' time spent on desktop medicine, 34% was spent on progress notes, 9% on documenting telephone encounters, 3% on messaging patients, 2% on prescription refills, and 3% on other tasks. Importantly, half of desktop medicine activities occurred in the charts of patients who did not have a face-to-face visit in the billing records on the day of logged desktop medicine work.

3.3. Efficiency domain – Work and workflow process

One of the unintended consequences of EHR use is its impact on clinicians' activities in terms of changing their clinical workflow in negative ways. Little is known about how clinicians' work activities are influenced (and potentially changed) as a result of the use of the EHRs in their clinical practice. Therefore, in two Emergency Departments (EDs), a research effort was undertaken to develop and implement novel methods that would leverage EHR audit logs alongside data on clinicians' movement generated from a tracking tool, Radio-Frequency Identification (RFID), which is a sensor-based technology. The data from these studies were collected in the adult ED at the Mount Sinai Hospital in New York City with Epic ASAP 2014 system [26,27], and at the Mayo Clinic in Phoenix, Arizona with Cerner Advance system [28,29]. The former used two sources of data, EHR audit logs and data from an RFID tracking system [26,27], and the latter added two additional data sources (interviews and ethnographic observations) to develop a more comprehensive picture of clinical workflow [28,29]. While the research team did not have access to the vendors' underlying logic used to capture tasks in the logs, the goal of the study was to identify attributes that stood out based on joining and correlating those multiple data sources. Each of the clinicians carried an RFID tag that recorded their locations as they performed various clinical tasks. These tags recorded the location of the clinicians at various places including their primary workstations for electronic documentation on the EHR. Data analysis involved translating the EHR audit logs into a sequential set of clinical events and coding to classify events into more aggregated categories of similar clinical activities. Next, based on the timestamp data on these clinical activities, RFID-recorded events (i.e., locations) matched to the clinical activities were collected and overlaid to provide a more comprehensive picture.

At the Mount Sinai site, across all the EHR audit log files, log events were characterized into 138 unique activities and these activities were grouped into a set of four thematic categories: documentation, chart review, orders, and on-screen navigation. Using a mapping procedure, several aspects of the clinical workflow were computed: (a) location of the clinicians (at computer/workstations or engaged in patient care-related activities); (b) time spent at each location, (c) percentage of time at each location that was spent on EHR-related activities, and (d) the EHR-related activities associated with each of the clinicians at each location [26]. Similarly, at Mayo Clinic, data from various sources were overlaid or integrated.

The authors found that physicians, at times, read several patient charts at a single session in the EHR, prior to visiting the patient rooms, a behavior that could potentially lead to increasing the cognitive burden on the physicians, as they would have to remember patient-specific details for both patients when returning to the workstation to chart the results of the patient encounters. An instance of a multi-patient visit was defined as occurring when a physician is noted to have visited more than one exam room between sessions interacting with the EHR, as tracked by the RFID system. These *multi-patient* visits were compared to every attribute in data provided by Cerner Advance system (e.g., documentation, chart review, and medication orders) to find the measures that were most highly correlated. Correlation coefficient (Pearson) and p-value for each attribute in the EHR usage data (from data logs), and the multi-patient visits per day for each physician were computed. Multiple visits were found to be positively correlated with the documentation time in the EHR, suggesting process inefficiencies.

Similarly, information transfer (interaction between physicians and nurses, as tracked by RFID) is an important element in clinical workflow, and it reflects the information needs of the physicians as well as the EHR's ability (or lack thereof) to support such information needs. Information transfer or the number of encounters between physicians and nurses, as reflected by movement of physicians to nurses and stations (as tracked by RFID), correlated positively with the ordering features of the EHR, suggesting inadequate EHR support to answer queries related to orders, leading to inefficient workflow process. Such findings provide detailed granularity about the relationship of EHRs to specific clinician activities [28,29].

4. Insights and challenges from using audit log data

The above research domains and specific studies demonstrate the breadth of potential insights from use of EHR audit log data. First, they demonstrate the ability of EHR audit logs to systematically capture medical errors. Prior to the development of the wrong-patient RAR measure, there was no automated method for quantifying order errors on the scale of a large health system. The audit log-based RAR methodology overcomes several biases of voluntary reporting and limitations of traditional methods of investigating such errors, minimizing 1) reporting bias, in that are all errors meeting specifications are captured systematically, 2) selection bias, as it does not rely on labor-intensive methods of chart review on a subset of cases, and 3) recall bias, in that errors can be identified and investigated in real-time. Although these are near-miss errors, they reveal system vulnerabilities that lead to error and provide sufficient outcome events to power intervention studies aimed at making systems more resilient to error. The RAR methodology can be extended to other error types in future research using EHR audit log data to create systems that have multiple defenses to prevent human error and patient harm. These errors may include orders involving medications, diagnostic tests, and procedures that are placed, cancelled, and reordered for the same patient with some aspect of the order changed. For example, audit log data could be used to measure provider busyness (via number of open charts, number of events, etc. during the diagnostic window) and its relationship to a misdiagnosis (measured using clinical data).

A second domain in which EHR audit logs hold the potential for valuable new insights is through the ability of EHR audit logs to inform efforts to address physician burnout and related concerns by corroborating the time physicians report spending on activities outside of direct face-to-face visits [30–33]. For example, the finding on extensive time on progress notes calls for re-examination of workflow processes that may have placed excessive demand on physicians. If scribes or automatic speech recognition technology can be deployed to assist with documentation, physicians may be able to reduce their time on documentation and reallocate their time to increase the face-to-face time with patients. Furthermore, the finding may also have implications on payment policies. While working on progress notes could be considered part of the preservice or postservice efforts [34], desktop medicine efforts that are not linked to a face-to-face visit are not reimbursable under typical contractual and regulatory arrangements in the fee-for-service paradigm. EHR audit log data can therefore help make the case that desktop medicine is valuable to the delivery system and to patients, such that scheduling and design of primary care practices should reflect this value in payment. Related to this domain, there is the potential to use EHR audit logs for trainee assessment and feedback as a unique input into clinical education.

As a third domain, the process of data-driven iterative workflow redesign using overlaid data from quantitative (log data and movement data from sensor-based technology) and qualitative sources (observations and shadowing) allow for the assessment of potential workflow inefficiencies, including interruptions that may affect efficiency, effectiveness and safety of the care-delivery process. Such analyses can inform design or redesign of technology (as well as workflow) to more precisely support the adaptation to observed perturbances in the workflow. The methods also generalize to the assessment and redesign of workflow in a variety of other settings, both in clinical medicine and beyond. For example, prior work has used audit log data to identify physician actions following non-interruptive alert opening, which offers valuable insight into the workflow implications of different approaches to alerting [35].

To increase the ability of researchers to derive such insights from EHR audit log data, there are common challenges to be addressed. In each example, there was substantial effort to validate audit log data, which in part reflects the newness of working with this type of data. Over time, the body of available validation work will likely expand (including across different settings) and as a result, there will be less need and expectation to do validation work in every study using EHR audit log data. However, the challenge of inferring "front-end" behaviors from audit log data is likely to persist. For example, in the time-spent study, if physicians did not use the EHR at all during a visit, relying on audit log data would fail to record any face-to-face visit time. Likewise, while time spent on documenting telephone encounters is captured, time spent on talking on the phone is not captured in the log data [30]. There is also a potential over-estimation of time if a physician walks away from the computer without logging out although the EHR usually times out after a pre-specified time (e.g., 5 min) of inactivity. Relatedly, because audit logs do not capture eye movement, it is not currently possible to differentiate the time spent on different viewing-based activities when a screen that includes multiple types of data is open. For example, a chart review screen may present many types of data and if the goal is to assess whether and for how long a physician reviewed lab results, it would not be possible to tell that if the chart review screen included lab results as well as other types of data. Similarly, during face-to-face encounters, it is not possible to know whether the physician was actively looking at the screen, versus talking with and/or examining the patient.

Additional challenges to working with audit log data include the organizational resources to build queries and analyze large data sets. Often audit log data are orders of magnitude larger than clinical data and require high-performance computing infrastructure for timely queries. Finally, log queries may not be easily generalizable to other EHR platforms since there are few standards for the structure or content of log files. There is only one standard included in EHR certification criteria for audit logs [36], and it specifies a very basic structure for audit logs and how they capture user interaction with protected health information (PHI). Specifically, it defines a minimum set of data elements that audit logs must contain, which includes type of action (addition, deletion, change, queries, print, copy), date and time of event, patient identification, user identification, and identification of the patient data that was accessed. It is therefore insufficient to ensure authenticity, accuracy and reliability of audit logs and their broad possible research uses. Given the nature of EHR audit log data and the types of research questions they support, development and implementation of standards that capture task types, user types, and time are particularly crucial.

5. Conclusion

While audit log data have been heavily used in other settings, in healthcare they have typically been used for targeted purposes, such as HIPAA compliance audits. With ongoing challenges related to quality, safety, and cost, health services researchers will likely find EHR audit log data to be a valuable new source of insights into how to better structure informatics tools to improve clinical decision-making, as well as broader questions about how care is and should be delivered. As researchers become aware of this new source of data and integrate it into their research, it will become more readily accepted (akin to the widespread use of claims and EHR data) and the tools for working with audit log data will improve. In parallel, there will be pressure to develop common terminologies and data models for audit log data, which will make it easier to work with these data across multiple institutions and with different EHRs at scale. While the transition to EHRs has brought many frustrations, it has also opened up new opportunities for researchers. Ensuring that researchers are aware of such data, and the new insights they offer, is one way to assure that our healthcare system benefits from the digital revolution.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Table 1

Table 1
EHR Task Categories Reported in EHR Audit Log Studies (Convenience Sample of 16 Studies).

	Agniel (2018)	Chen (2018)	Ouyang (2016)	Ouyang (2016)	Chen (2018)	Tai-Seale (2017)	Arndt (2017)
Chart Review		Medical hx and condition, medication management, information exchanges between between healthcare professionals, clinical communication	Medical chart review, patient list review			Chart reviews	Imaging, laboratories, medications, notes
Notes			Notes	Generating notes	Nursing, procedure, progress, clinic, operative, admission, emergency, discharge	Progress notes	
Results			Results review	View lab results	Lab result		Results
Orders	When lab test ordered		Order entry	Place Orders	Orders	Orders for services	Order Entry
Medications				Performing medication reconciliation	Medication administration	Prescription refills	Refills
Problem List					Problem list		Point of Care Problem List
Summaries					Discharge summary		
Other					History & Physical, respiratory care, misc report, vital signs, clinical communication, rehab, discharge letter, discharge instructions, admin, consult request, anesthesiology, operative report, immunizations, ECHO	Logging telephone encounters, letters for external use, scanned documents, secure messages	EBM, Letter generation, MyChart Portal, Telephone call, Administrative, Billing and Coding, Documentation, System Security

(continued on next page)

Table 1 (*continued*)

	Johnson (2011)	Hirsch (2017)	Everson (2017)	Koopman (2011)	Fabbri (2013)	Hripcsak (2011)	Vawdrey (2011)	Chen (2012)	Bowes (2010)
Chart Review			Clinician View of outside info: Appointments and allergies						
Notes						Authoring and viewing notes	Reading and authoring clinical notes		Notes, Coded Notes
Results	Test Reports, aggregated lab results, site-specific lab results		Clinician view of outside info: lab and radiology results				Review lab test results		Results
Orders		Number of lab & medication orders as predictors of encounter times			Radiology orders, services/orders, labs		Reviewing and entering electronic orders		
Medications	Aggregated medication lists		Clinician View of outside info: Medications		Inpatient/outpatient medications		Medications administered		Medications
Problem List									Problems
Summaries	Discharge summaries		Clinician View of outside info: Visit Summaries						
Other	Demographic data	Number of procedures as predictors of encounter times		10 specific diabetes elements	Appointment, diagnosis, documents, inpatient visit		Documenting vital signs, fluid intakes/outputs	Accessing patient records and assigning diagnosis	ED System, Messages, Notifications, Encounters, Allergies, Ht&Wt, Vitals, Demographics, Prenatal Web Form, Web Forms

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