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Research and Applications

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Secondary use of electronic health record data for clinical workflow analysis

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ABSTRACT

Objective: Outpatient clinics lack guidance for tackling modern efficiency and productivity demands. Workflow studies require large amounts of timing data that are prohibitively expensive to collect through observation or tracking devices. Electronic health records (EHRs) contain a vast amount of timing data – timestamps collected during regular use – that can be mapped to workflow steps. This study validates using EHR timestamp data to predict outpatient ophthalmology clinic workflow timings at Oregon Health and Science University and demonstrates their usefulness in 3 different studies.
Materials and Methods: Four outpatient ophthalmology clinics were observed to determine their workflows and to time each workflow step. EHR timestamps were mapped to the workflow steps and validated against the observed timings.
Results: The EHR timestamp analysis produced times that were within 3 min of the observed times for >80% of the appointments. EHR use patterns affected the accuracy of using EHR timestamps to predict workflow times.
Discussion: EHR timestamps provided a reasonable approximation of workflow and can be used for workflow studies. They can be used to create simulation models, analyze EHR use, and quantify the impact of trainees on workflow.
Conclusion: The secondary use of EHR timestamp data is a valuable resource for clinical workflow studies. Sample timestamp data files and algorithms for processing them are provided and can be used as a template for more studies in other clinical specialties and settings.

Keywords: workflow, electronic health records, computer simulation, secondary use of electronic health record data

INTRODUCTION

Providers currently face pressures to see more patients in less time, often for less reimbursement, but frequently lack guidance and information on how to meet these demands.[1,2] For busy outpatient specialties, physicians typically see 15–40 patients or more in a half-day session, utilize multiple exam rooms simultaneously, work with ancillary staff (eg, nurses, technicians), and examine patients at multiple stages (eg, before and after procedures). This creates challenges in workflow and scheduling and large variability in operational approaches. In addition, many providers feel that electronic health records (EHRs) have added more time pressure.[3–5] At Oregon Health and Science University (OHSU), we completed a successful EHR implementation in 2006. Yet published studies show that OHSU ophthalmologists saw 3–5% fewer patients after the EHR implementation and required >40% additional time for each patient appointment compared to paper-based documentation.[6]

Managing these time pressures and reducing patient wait time are essential for maintaining productivity and efficiency in outpatient clinics. Patient wait time results from pressures on provider time, and clinic inefficiencies cause excessive patient wait times, which in turn cause decreased patient satisfaction and barriers to health care.[7,8] Studying clinic workflow is a critical way to gain insight for improvements, but requires large quantities of detailed timing data because of the inherent variability of clinic activities. Time-motion methods can provide data about clinic workflows, but are resource-intensive and prohibitive for large-scale studies.[9–11] Automated tracking and data-collection methods, such as radiofrequency identification tagging, can provide large-scale data, but are costly and difficult to implement.[12–14]

One promising approach for studying workflow is to use the vast amount of timing data currently available in EHR systems, through timestamps recorded in audit logs during routine use.[15–17] A major benefit of EHR systems is that clinical data may be applied for secondary use beyond direct provision of clinical care; current efforts have focused on areas such as clinical research, public health, adverse event reporting, and quality assurance. We are studying the use of timestamps of EHR data entries to reconstruct the timing of workflow events, which has multiple applications for analysis.[15,16,18]

In this paper, we show the details of mining and validating EHR timing data for workflow events in outpatient clinics at OHSU. We use ophthalmology as a representative study domain with lessons that are broadly generalizable, because it is a high-volume specialty with both medical and surgical components and has a clinical workflow that is common to many other specialties (initial staff exam followed by provider exam). The purpose of this paper is to demonstrate how EHR timing data can be collected and analyzed. We provide sample EHR timing data files in a Supplementary Appendix, along with descriptions of the algorithms we used for processing them. We then demonstrate how secondary use of this processed timing data can be applied to clinical workflow studies: (1) workflow simulation, (2) analysis of EHR use, and (3) impact of trainees on clinic workflow. These applications show the power of using existing EHR timing data for clinical workflow studies that would not have been possible otherwise and the possibilities for applying these methods to studies in other clinical settings. Including the data, processing algorithms, and examples of their applications provides a template for others to extend this work to other domains and research questions.

METHODS

This study was approved by the Institutional Review Board at Oregon Health and Science University.

Study environment

OHSU is a large academic medical center in Portland, Oregon. The ophthalmology department includes >50 faculty physicians who perform >115 000 outpatient examinations annually. The department provides primary eye care and serves as a major referral center in the Pacific Northwest and nationally.

Over several years, an institution-wide EHR system (EpicCare; Epic Systems, Verona, WI, USA) was implemented throughout OHSU. This vendor develops software for midsize and large medical practices and is a market share leader among large hospitals. In 2006, all ophthalmologists at OHSU began using this EHR. All ambulatory practice management, clinical documentation, order entry, medication prescribing, and billing tasks are performed using components of the EHR.

Workflow observation and reference data collection

Four ophthalmology physicians from different subspecialties (comprehensive ophthalmology, cornea, glaucoma, and pediatrics) were observed using time-motion methods to measure workflow between September 1, 2013, and December 31, 2016. Initial interviews with staff and observations determined the basic clinic workflow. A patient: (1) checks in and waits to be seen; (2) has an initial exam by an ancillary staff member; (3) may have an additional workflow step (dilating drops instilled), which requires going to the waiting room to wait for dilation to occur (~25 min) before returning to an exam room; (4) is examined by the physician; and (5) checks out and leaves. Patient wait times can occur before the initial staff exam and the physician exam.

Observers used mobile devices and software (Numbers; Apple, Cupertino, CA, USA) to record time-motion timing data of workflow steps, including exam times and EHR use times, for a total of 286 appointments among the 4 physicians. Three observers performed parallel observation and compared observations to ensure that the data collected were consistent. Time-motion data were processed to determine the duration of time spent in exam rooms with patients and time spent using the EHR. This manually collected timing data served as our reference data for validation of EHR timestamp data.

Collection of EHR timestamp data

Through preliminary iterative data collection and analysis, we identified a set of EHR timestamp data that represents the workflow within OHSU's EHR clinical data warehouse (EpicCare). While these timestamps are specific to OHSU's implementation in ophthalmology, comparable timestamps are available for other vendors, installations, and specialties.

We collected the following EHR data for the 286 observed appointments: (1) Start and end of patient appointment: these were obtained using check-in and check-out timestamps. These timestamps are part of visit data available in all EHRs. (2) Start and end of staff and physician exams: These were obtained using audit log timestamped entries. All EHRs are mandated to collect audit data, including timestamps, during normal EHR use. (3) Additional workflow step (dilation status): This was obtained using a structured ophthalmology documentation form, which included eye dilation information.

Finally, we manually collected lists of staff and physician user IDs, as well as exam room workstation IDs. This allowed us to select relevant timestamps from the audit log.

Calculation of workflow timings from EHR data

We used 2 different algorithms to calculate workflow timings based on these EHR data. The first one, given in Figure 1, describes the algorithm we developed for using EHR timestamps and visit data to estimate the time spent on each step of the appointment workflow. First, the duration of the appointment was calculated from the check-in and check-out times. Next, we determined the length of the staff and physician exams with audit log timestamps; we assumed that the exam began when the first relevant timestamp was logged

Algorithm for Determining Workflow Timings from EHR Timestamps

For each appointment:

1. *Calculate the total appointment time.*
   a. Select appointment check-in and check-out times (from visit datamart).
   b. Subtract the check-in time from the check-out time.
2. *Calculate the time spent examining the patient.*
   a. *Collect all relevant timestamps that relate appointment.* Select audit log entries (timestamp, user ID, workstation ID) that:
      i. Occurred between the check in and check out times for the appointment (timestamp field)
      ii. Were generated by ancillary staff and providers (match the user ID field)
      iii. Were entered from exam room workstations (match the workstation ID field)
   b. *Determine the start and end of each exam (initial staff & provider).* Find the first and last relevant timestamp for each user ID (staff & provider).
   c. *Calculate the duration of each exam (initial staff and provider).* Compute the difference between the first and last timestamp for each user ID (staff & provider).
   d. *Identify any time that was not spent on the exam.* Order timestamped entries for each user ID. Calculate gaps between subsequent timestamped entries. Count gaps between timestamps that are greater than the average exam time as time not spent on the exam.
   e. *For each exam (staff & provider), total all time spent on the exam.* Subtract any time found in step d that was not spent on the exam from the exam durations found in step c.
3. *Calculate time for any additional workflow steps (i.e. dilation in ophthalmology).*
   a. Select timestamp for dilation (field in template form)
   b. If there is a recorded time for dilation, add 25 minutes for this step; otherwise add 0.
4. *Calculate wait time.* Sum exam times for each user ID and additional workflow steps times, then subtract from the total appointment time.

Figure 1. Algorithm for calculating workflow timings from EHR timestamps. This algorithm describes the steps for calculating the timings for workflow: initial staff and provider exams, additional workflow step (ie, dilation), wait time.

and ended with the last logged timestamp. Relevant timestamps were those generated by the physician from an exam room workstation while the patient was checked in for the appointment. There were times, however, when exams were interrupted (eg, if a patient required additional dilating drops, if an urgent phone call or emergency occurred, etc.). We assumed that if there was a gap between timestamps that was greater than the average exam time, this time was not spent on that appointment's exam. Then, we counted 25 min for dilation for those appointments where a dilation time was recorded, and 0 min otherwise. Finally, we subtracted the exam times and dilation time from the appointment duration to calculate the wait time.

The second algorithm we developed was to determine the amount of time the clinician used the EHR time during an appointment, given in Figure 2. For this analysis, we obtained all timestamps for an appointment for each staff member and physician. We counted the minutes with timestamped entries in the audit log records both during (between patient check-in and check-out) and after the appointment until it was completed. When there were timestamped entries for multiple appointments within the same minute, we assigned a fraction of that minute to each of the appointments, proportional to the number of timestamps recorded for the appointment. We used this heuristic to assign EHR use time for each timestamped entry as an initial guess because of its simplicity.

Validation of EHR timestamp data

After the workflow and EHR use timings were calculated from the EHR data, they were compared to the reference timing data from our observations. Summary statistics and visualizations were used to compare the EHR predictions to the observed times for the workflow and EHR use.

All data processing and analysis were performed in R.[19]

RESULTS

Collection of EHR timestamp data

We collected audit log entries for 1 year of encounters in ophthalmology (10 852 208 audit log entries from 54 937 appointments for 33 providers). We then gathered the relevant audit log, visit, and dilation data from the EHR for our study set of 286 appointments,

Algorithm for Calculating EHR Use Time from EHR Timestamps

For each appointment:

1. *Find relevant timestamps.* Select all audit log timestamps generated by provider and staff before the encounter is closed.
2. *Count and sum all timestamped minutes for each user (staff & provider).*
   a. Each timestamped minute gets counted as one full minute.
   b. If multiple appointments have timestamps during the same minute, count a fraction of a minute proportional to the number of time stamps for the appointment.

Figure 2. Algorithm for calculating EHR use from EHR timestamps. This algorithm describes the steps for calculating the duration of time of EHR use by staff and providers for an outpatient appointment.

which are provided in 2 data files (Supplementary Appendix). For brevity and simplicity, we present the data for only the physician exams; the data and process for staff exams are similar. The audit log file (auditLog.csv) contains 9106 relevant timestamps for the appointments – those recorded by the physicians during patient appointments from exam room workstations. The visit data file (visitData.csv) contains the EHR visit data for the 286 appointments necessary for the analysis.

Calculation of workflow timings from EHR data

Using the EHR data and the previously described algorithms, we calculated the physician exam time and EHR use time for each appointment. We provide these calculated values along with the observed values in the workflow data file (Supplementary Appendix workflowCalcAndObs.csv).

Validation of EHR timing data to estimate physician exams

We validated our EHR timestamps and calculations by comparing them to the observed reference standard data. Table 1 presents the observed and calculated physician exam times: for 3 physicians, the EHR calculated exam times were within 1 min of the observed reference exam times on average, and >80% of the EHR calculated exam times were within 3 min of the observed times. The fourth physician's EHR calculated exam times were on average almost 3 min longer than observed, and only a little over half of the calculated times were within 3 min of the observed times.

Next, we created visualizations to compare the observed and EHR timings for physician exams. Figure 3 shows that the density plots of the EHR calculated and observed exam times have similar shapes and demonstrates areas of overlap for all physicians.

Validation of EHR timing data to estimate EHR use times

To validate the use of EHR timing data to estimate EHR use times, we compared the observed and EHR calculated times for physician EHR use during patient exams (Table 2). On average, we observed physicians using the EHR for 2.4 ± 1.7 min during patient exams, while the EHR timestamp analysis predicted that the average use was 1.6 ± 1.2 min. We calculated the average difference per appointment, which was <1 min for all physicians, and 84.3% of EHR timestamp predictions for appointments were within 3 min of the observed EHR use.

Plotting histograms of these differences in Figure 4 shows that for the bulk of appointments, the EHR use time predicted from EHR timestamps was close to the observed EHR use time. In the majority of cases, the difference between the observed and predicted times was positive; the EHR timestamps underestimated the true EHR use time.

Table 1. Validation of EHR calculated physician exam times

Physician	No. of appointments	Physician exam (mean ± SD) in minutes			
		Observed	EHR calculated	Average difference	Within 3 min (%)
Physician 1	85	10.9 ± 5.3	10.9 ± 7.2	0.0 ± 5.3	80.00
Physician 2	39	11.3 ± 4.9	14.1 ± 7.7	−2.8 ± 4.9	53.85
Physician 3	60	10.3 ± 4.9	9.4 ± 3.9	0.9 ± 4.5	88.33
Physician 4	102	13.3 ± 7.3	13.8 ± 8.2	−0.5 ± 4.9	85.29
All	286	11.7 ± 6.1	12.1 ± 7.3	−0.4 ± 5.1	80.10

The average calculated exam times are compared to the observed exam times. Three out of the 4 physicians' times are within 3 min of observed reference standard data for >80% of the EHR calculated exam times.

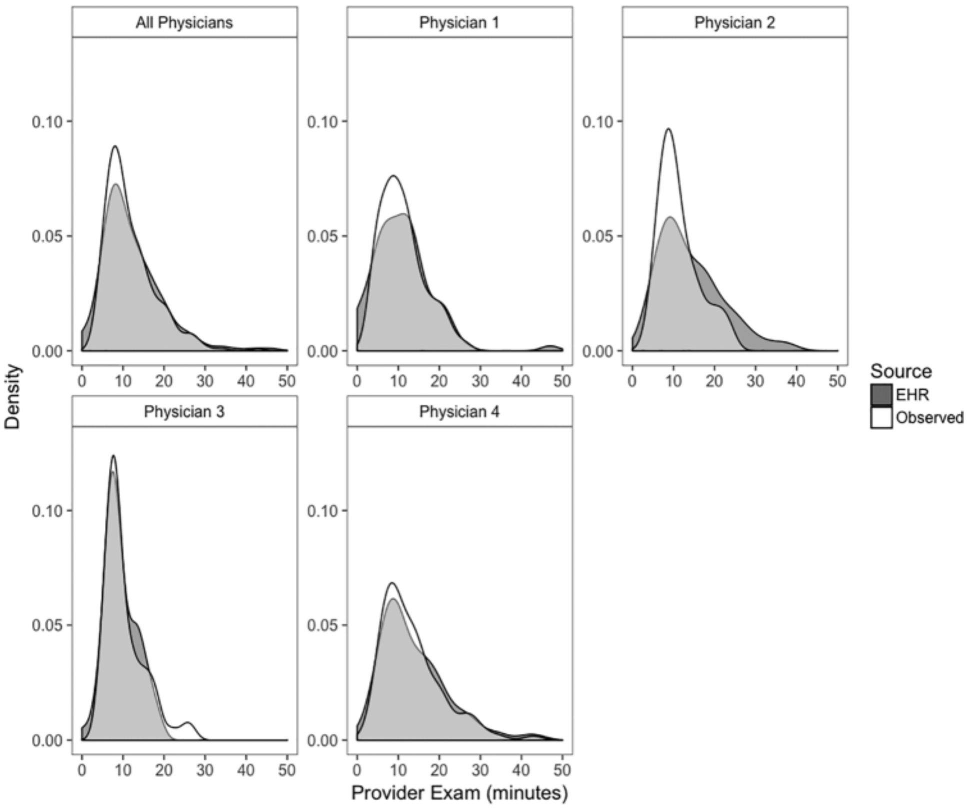

Figure 3. Density plots of EHR calculated and observed provider exam times. The shapes of the density plots for the EHR and observed exam times were similar, and there was significant overlap of the 2 density plots.

Table 2. Comparison of observed and calculated EHR use times during physician exams

Physician	No. of appointments	Physician EHR use time (mean ± SD) in minutes			
		Observed	EHR calculated	Average difference	Within 3 min (%)
Physician 1	85	2.0 ± 1.7	1.2 ± 1.0	0.8 ± 2.0	83.53
Physician 2	39	2.3 ± 1.7	2.4 ± 1.7	0.0 ± 2.1	89.74
Physician 3	60	2.6 ± 1.6	2.2 ± 1.2	0.4 ± 2.0	86.67
Physician 4	102	2.8 ± 1.6	1.3 ± 1.0	1.6 ± 1.7	81.37
All	286	2.4 ± 1.7	1.6 ± 1.2	0.9 ± 2.0	84.27

The average calculated values are less than the observed ones, but the average difference was close to zero for most physicians. The EHR calculations were within 3 min of the observed times for >80% of the appointments for all physicians.

DISCUSSION

Our analysis of using timestamps for workflow timings has 3 key findings: (1) EHR timestamps provided a reasonable approximation of exam times, (2) the accuracy of the exam time approximations was dependent on use patterns of the EHR, and (3) timestamps reasonably estimated the amount of EHR use but in many cases

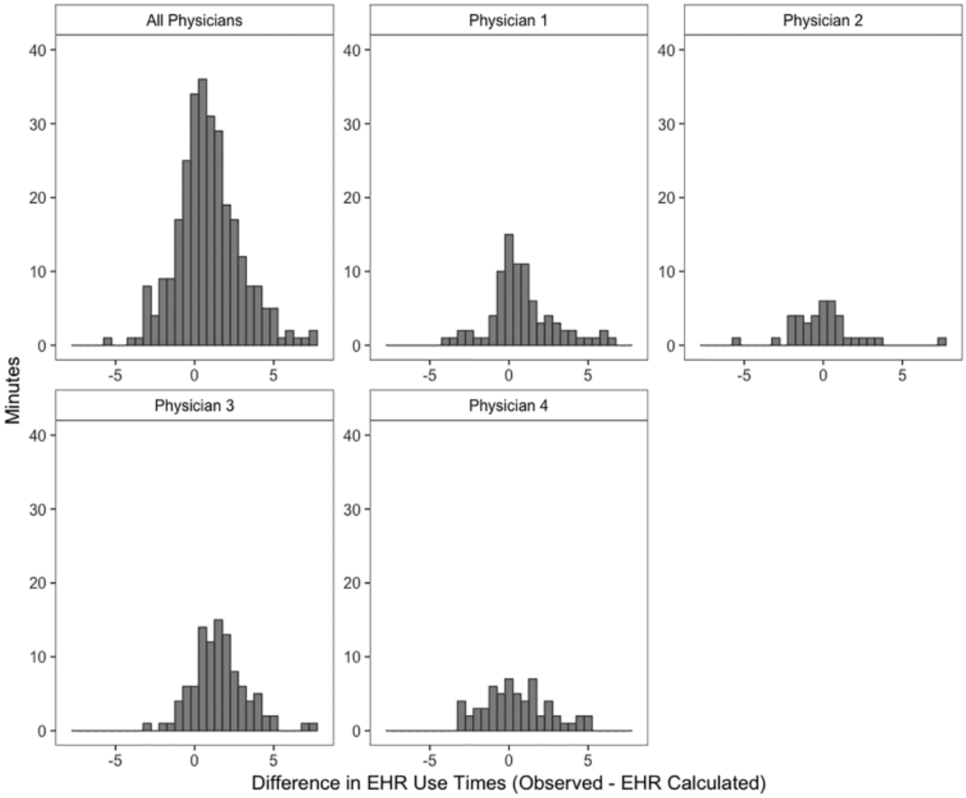

Figure 4. Histogram plots of the difference between the observed and EHR calculated provider EHR use times. For the bulk of the encounters, the difference between the observed and calculated EHR use times was close to zero. In general, the calculated EHR use times underestimated the observed use times.

underestimated it. These findings have implications for how these timestamps can be used to study clinical workflow.

Using EHR timestamps to calculate exam times overall had reasonable accuracy. The EHR timestamps predicted exam times that were within 0.4 s of the observed times on average, and just over 80% of predictions were within 3 min of the observed times. The density plots of the EHR and observed exam times were similar in shape and had a significant amount of overlap, indicating that they would be represented by similar probability density functions – an important part of simulation models.[16]

We found that there was some variation among physicians in how accurate the timestamps predicted exam times and what the source of the inaccuracy was. For 3 out of the 4 physicians, the average difference between the EHR and observed exam times was close to zero, but for the other it was almost 3 min different. To determine the source of the errors, we compared the start and end times for the EHR calculations and the observed data. The results are given in Table 3. Negative differences indicate that the EHR time overestimated the exam time; positive ones indicate that the EHR time underestimated the exam time. Most of the average differences were negative and were due to the physician working with the EHR before and/or after the exam. For example, Physician 1 often reviewed the chart for the next exam before entering the room, and both Physicians 1 and 2 often stayed in the exam room documenting after the patient left. When the difference was positive, the physician spent time examining the patient before and/or after using the EHR during the exam. For the vast majority of appointments, the start and end times from the EHR were very close to the observed times.

We looked more carefully at the start and end times for Physician 2, who had the least accurate EHR calculated exam times. The EHR start time was on average 4 min later than the observed start time, which indicates that the physician started the exam talking to the patient, not logging in to the EHR. This physician's EHR end time was 2.4 min after the observed time, which indicates that the physician continued to work in the EHR after the exam was completed. These 2 differences account for the decreased accuracy of Physician 2's estimated exam times.

The overall accuracy of using EHR timestamps and our algorithm for predicting exam times are dependent on EHR usage patterns. Using the EHR at the very beginning and end of the exam ensures that the exam time calculations will be correct. Understanding the source of inaccuracies for EHR-predicted exam times can help make adjustments; for example, a constant or varying amount of time can be added to or subtracted from the timestamps to make them more accurate. Also, if timestamps are regularly used for analysis, clinical users can be encouraged to alter their patterns of EHR use so that they regularly log in at the start of the exam and log out at the end. Nevertheless, even with errors, the predicted exam times are still useful for applications such as simulation models (discussed below).

EHR timestamps also provided a reasonable approximation of EHR use. Our method predicted that the EHR use time was 1.6 min, which was about 14% of the overall appointment time. On average, the EHR use time calculated from timestamps was about 1 min less than the observed EHR use time. This difference was due to the method we used to estimate from timestamps – we counted 1 min for each timestamped event in the audit log, but the event could have corresponded to more or less than 1 min of EHR use. From our validation, we concluded that our method mostly underestimated EHR use and can be used to establish a lower bound on EHR use.

Table 3. Analysis of differences between EHR and observed exam time start and end times

Physician	Physician exam start time		Physician exam end time	
	Average Difference (Obs-EHR)	Within 3 min (%)	Average Difference (Obs-EHR)	Within 3 min (%)
Physician 1	−1.0 ± 6.9	96.5	−4.2 ± 21.0	80.0
Physician 2	4.2 ± 12.6	64.1	−2.4 ± 19.8	84.6
Physician 3	−0.4 ± 1.7	95.0	1.0 ± 3.5	86.7
Physician 4	−0.6 ± 8.9	92.2	0.2 ± 3.1	89.2
All	0.0 ± 8.2	88.1	−1.3 ± 13.9	77.6

Most of the EHR times were close to the observed times.

Table 4. Dataset size and validation results for simulation model validation

Provider	Number of encounters			Mean wait time		
	Simulation	EHR tests	Observed	Simulation	EHR tests	Observed
Provider 1	2239	550	17	42.6	44.3	41.9
Provider 2	2161	591	21	42.5	41.7	49.3
Provider 3	1839	449	27	33.5	31.9	31.8
Provider 4	2486	644	120	30.7	34.7	32.6
All	8725	2234	185	37.3	38.1	38.9

The simulation models were built with timing data from >8000 appointments. The wait times from the simulation models were compared to the wait times calculated from the EHR tests dataset, with >2000 appointments. The wait times from the simulation model, the EHR tests, and the observed appointments were within a few minutes of each other.

There are many possible uses of this large set of timing data available from all EHRs. We have performed 3 studies based on this dataset, and we present summaries of these studies to demonstrate the potential applications of large-scale timing data.

Workflow analysis using simulation

Discrete event simulation is a method for analyzing processes with high variability; it uses probability distributions to represent times for process steps.[16] The accuracy and effectiveness of the simulation models are dependent on the accuracy of the probability distributions, so large amounts of timing data are needed. While simulation models cannot be used to solve for absolute optimality, they can be used to evaluate different scenarios to determine relative behavior.

We used Arena simulation software[20] to build a discrete event simulation model of each of the 4 study clinic's workflows. The initial staff and physician exam times are represented by probability distributions based on EHR timestamps for 2 years of patient appointments. As shown in Figure 3, the distributions of EHR timestamp predicted exam times were close in shape to the observed exam times, which suggests that they would be useful in simulation models. Probability density functions were generated from the dataset of EHR predicted exam times; during each iteration of the simulation, an exam time value was sampled from the distribution. We validated the 4 clinics' simulation models by comparing the total average wait time to the EHR test dataset and observed times; overall, the models were within 6% of the observed wait times.[16] Table 4 presents the sizes of the datasets and the validation results. This demonstrates that despite the inaccuracies in some of the EHR predicted exam times, they are still useful in simulation models.

The validated models were used to test staff and exam room allocations and scheduling strategies to prevent long wait times.[16] The models showed that adding staff and exam rooms would not help patient wait times, since the physician is the bottleneck. The models also showed that scheduling patients who need more time near the end of the clinic day reduced patient wait times. Since most clinics schedule those patients at the start of the day to avoid overtime, this represented a big shift for schedulers. We have since implemented this strategy in clinic and confirmed that it does reduce patient wait times when followed.[21]

EHR use time

For this study, we used EHR timestamps to calculate the amount of time physicians use the EHR for outpatient appointments (Read-Brown S, et al. IOVS 2017;58: ARVO E-Abstract 5087).[22] We collected appointment timestamp data for 27 ophthalmology physicians and their 46 516 appointments during 2014. We found that the average EHR use time during an exam was 5.9 ± 2.3 min, and after the exam was 4.8 ± 4.7 min, for a total of 10.8 ± 5.0 min per appointment. This translates to a total of about 3.7 h EHR use time for a full-day clinic. Having a large dataset of EHR use times allowed us to analyze different factors that affect EHR use; we found that clinic volume and appointment complexity were 2 significant ones.[22] In general, as volume increases, the amount of EHR use per appointment decreases, while the overall time for all appointments in a clinic increases. The amount of this decrease is mitigated by the complexity of the appointment, however. As appointment complexity increases, so do EHR use time requirements. Not surprisingly, the physicians with the highest clinic volumes see less-complex patients, and vice versa. This suggests that clinic volume is limited by the work required during exams, of which EHR use is a significant part.[22]

Impact of trainees on workflow

Education of residents and fellows in an academic clinical setting affects clinic workflows, but to our knowledge there has not been a thorough analysis of this impact. We analyzed 49 448 outpatient appointments during 2014 for 33 ophthalmology physicians at OHSU for the impact of trainees (29 residents and 23 fellows) on the attending's appointment times (Goldstein I, et al. IOVS 2017;58: ARVO E-Abstract 5060).[18] Since there is no standard method for recording trainee involvement in appointments in the EHR, the EHR timestamps provided an easy way to determine involvement. A trainee was considered present for an appointment if he or she used the EHR for >2 min during the appointment. This cutoff was chosen to account for appointments where trainees briefly used the EHR but were not truly involved in the appointment. To validate this cutoff method, we examined 50 appointments and found that this method had 97% specificity and 100% sensitivity for identifying appointments where trainees were truly involved, compared to manual chart review. Sessions were divided into those with vs without trainees, with the appointment times for appointments in sessions without trainees serving as the control.

The results show that trainees are associated with significantly longer appointment times for both fellows and residents. Trainees even lengthened appointments in the same sessions that had no trainee involvement: up to 2.6 min longer for some appointments. This large-scale study shows the significant impact of trainees on clinic workflow, affecting the efficiency, productivity, and financial viability of academic medical centers.[18]

LIMITATIONS

Several study limitations should be noted: (1) This study was limited to 4 subspecialists within a single field (ophthalmology). For that reason, it is not clear whether findings will generalize to other physicians in other fields. However, we feel that the workflow we observed in ophthalmology (ie, initial ancillary staff exam followed by physician exam) is very common and applies to many other medical fields. Future validation studies will be important to examine the generalizability of this approach. (2) The accuracy of the EHR timestamps for representing exam times depends on the EHR being used at the very beginning and end of the patient exam. EHR use patterns that do not match this may require exam times to be adjusted or providers to change usage patterns. (3) EHR use time was calculated using the assumption that EHR timestamped entries represent at most 1 min of EHR activity, which may not be accurate for all EHR activity. Methods for estimating the time based on the type of EHR activity may improve accuracy.

CONCLUSIONS

EHRs collect timestamps in audit logs that can be used to study workflow. We have shown that these timestamps can be used to predict exam times and EHR use times for ophthalmology providers, and that inaccuracies of timestamps relate to patterns of EHR use. In particular, using the EHR at the start and end of an exam results in timestamps that accurately represent the start and end of that exam. These EHR timing data are available for large-scale studies where it is too resource-intensive to collect observational data, such as those demonstrated in this paper. Now this "Big Data" (10 852 208 audit log entries from 54 937 appointments for 33 providers) can be analyzed, which up until now would not have been possible. These studies can lead to improvements in scheduling, justification for EHR improvements, and better planning and reimbursement models for clinics' training activities. By providing sample timestamp data files (Supplementary Appendix) and algorithms for processing them (Figures 1 and 2), we hope to stimulate future workflow studies in more medical specialties and clinic settings.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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REFERENCES

1. Blumenthal D, Collins S. Health care coverage under the Affordable Care Act: a progress report. *N Engl J Med*. 2014;371:275–81.
2. Hu P, Reuben DB. Effects of managed care on the length of time that elderly patients spend with physicians during ambulatory visits: National Ambulatory Medical Care Survey. *Med Care*. 2002;40:606–13.
3. Shea S, Hripcsak G. Accelerating the use of electronic health records in physician practices. *N Engl J Med*. 2010;362:192–95.
4. Chiang MF, Boland MV, Margolis JW, *et al*. Adoption and perceptions of electronic health record systems by ophthalmologists: an American Academy of Ophthalmology survey. *Ophthalmology*. 2008;115:1591–97.
5. Boland MV, Chiang MF, Lim MC, *et al*. Adoption of electronic health records and preparations for demonstrating meaningful use: an American Academy of Ophthalmology survey. *Ophthalmology*. 2013;120:1702–10.
6. Chiang MF, Read-Brown S, Tu DC, *et al*. Evaluation of electronic health record implementation in ophthalmology at an academic medical center (an American Ophthalmology Society thesis). *Trans Am Ophthalmol Soc*. 2013;111:34–56.
7. McMullen M, Netland PA. Wait time as a driver of overall patient satisfaction in an ophthalmology clinic. *Clin Ophthalmol* 2013;7:1655–60.
8. Lee BW, Murakami Y, Duncan MT, *et al*. Patient-related and system-related barriers to glaucoma follow-up in a county hospital population. *Invest Ophthalmol Vis Sci*. 2013;6542–48.
9. Almeida R, Paterson WG, Craig N, *et al*. A patient flow analysis: identification of process inefficiencies and workflow metrics at an ambulatory endoscopy unit. *Can J Gastroenterol Hepatol*. 2016;2016:2574076.
10. Victores AJ, Coggins K, Takashima M. Electronic health records and resident workflow: a time-motion study of otolaryngology residents. *The Laryngoscope*. 2015;125:594–98.
11. Lopetegui M, Yen P-Y, Lai A, *et al*. Time motion studies in healthcare: what are we talking about? *J Biomed Inform*. 2014;49:292–99.
12. Lin Y-C, Padman R. Process visibility analysis in ambulatory care: a simulation study with RFID data. *Stud Health Technol Inform*. 2013;192:768–72.
13. Yao W, Chu C-H, Li Z. The adoption and implementation of RFID technologies in healthcare: a literature review. *J Med Syst*. 2012;36:3507–25.
14. Vakili S, Pandit R, Singman EL, *et al*. A comparison of commercial and custom-made electronic tracking systems to measure patient flow through an ambulatory clinic. *Int J Health Geogr*. 2015;14:32.
15. Hribar MR, Read-Brown S, Reznick LG, *et al*. Secondary use of EHR timestamp data: validation and application for workflow optimization. In: AMIA Annual Symposium Proceedings. 2015;2015:1909–17.
16. Hribar MR, Biermann D, Read-Brown S, *et al*. Clinic workflow simulations using secondary EHR data. In: AMIA Annual Symposium Proceedings. 2016;2016:647–56.
17. Hirsch AG, Jones JB, Lerch VR, *et al*. The electronic health record audit file: the patient is waiting. *J Am Med Inform Assoc*. 2017;24:e28–34.
18. Goldstein I, Hribar MR, Read-Brown S, *et al*. Quantifying the Impact of Trainee Providers on Outpatient Clinic Workflow Using Secondary EHR Data. In: AMIA Annual Symposium Proceedings (In Press).
19. R Core Team. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing 2016. www.R-project.org. Accessed August 31, 2017.
20. Arena Simulation Software. 2017. www.arenasimulation.com/. Accessed August 31, 2017.
21. Hribar MR, Read-Brown S, Reznick LG, *et al*. Evaluating and improving an outpatient clinic scheduling template using secondary electronic health record data. In: AMIA Annual Symposium Proceedings (In Press).
23. Read-Brown S, Hribar MR, Reznick LG, *et al*. Time requirements for electronic health record use in an academic medical center. *JAMA Ophthalmol* (In Press).