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Data Driven Scheduling for Improving Patient Efficiency in Ophthalmology Clinics

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Abstract

Objective: To improve clinic efficiency through development of an ophthalmology scheduling template developed using simulation models and electronic health record (EHR) data.

Design: We created a computer simulation model of one pediatric ophthalmologist's clinic utilizing EHR timestamp data, which was used to develop a scheduling template based on appointment length ("short", "medium", or "long"). We assessed its impact on clinic efficiency after implementation in the practices of five different pediatric ophthalmologists.

Subjects, Participants, and/or Controls: We observed and timed patient appointments in-person (n=120) and collected EHR timestamps for two years of appointments (n=650). We calculated efficiency measures for 172 clinic sessions pre-implementation vs. 119 clinic sessions post-implementation.

Methods, Intervention, or Testing: We validated clinic workflow timings calculated from EHR timestamps and the simulation models based on them with observed timings. From simulation tests, we developed a new scheduling template and evaluated it with efficiency metrics pre- vs. post-implementation.

Main Outcome Measures: Measurements of clinical efficiency (mean clinic volume, patient wait time, exam time, and clinic length).

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Results: Mean physician exam time calculated from EHR timestamps was 13.8 ± 8.2 minutes, and was not statistically different from mean physician exam time from in-person observation (13.3 ± 7.3 minutes) ($p=0.7$), suggesting that EHR timestamps are accurate. Mean patient wait time for the simulation model (31.2 ± 10.9 minutes) was not statistically different from the observed mean patient wait times (32.6 ± 25.3 minutes) ($p = 0.9$), suggesting that simulation models are accurate. After implementation of the new scheduling template, all five pediatric ophthalmologists showed statistically-significant improvements in clinic volume (mean increase of 1-3 patients/session, $p = 0.05$ for 2, $p = 0.008$ for 3), while four of five had improvements in mean patient wait time (average improvements of 3–4 minutes/patient, statistically-significant for 2 providers, $p = 0.008$). All of the ophthalmologists' exam times remained the same pre- and post-implementation.

Conclusions and Relevance: Simulation models based on “big data” from EHRs can test clinic changes before real-life implementation. A scheduling template using predicted appointment length improves clinic efficiency and may generalize to other clinics. EHRs have potential to become tools for supporting clinic operations improvement.

PRÉCIS

This study used timing data from the EHR to develop a new scheduling template based on appointment length (“short”, “medium”, “long”) that improved average patient wait time while increasing average clinic volumes.

While electronic health records (EHRs) have potential for improving the efficiency and quality of healthcare, many physicians find their use burdensome and time consuming.^{1–6} Further, federal regulations and new reimbursement models are increasing the requirements for documentation in the EHR, as well as changing clinic revenues.^{7,8} As a result, ophthalmologists often report feeling pressured to see more patients to maintain revenue, while having less available time for patient care.^{9–11} Without approaches to manage these pressures, the situation may become untenable and result in decreased quality of care and physician burnout.^{12,13}

Reducing clinic inefficiencies can help physicians manage these pressures. For example, ophthalmology clinics generally maximize efficiency by using multiple exam rooms and ancillary staff, so that patients are examined during multiple stages (e.g., before and after dilation of eyes, before and after ophthalmic imaging studies). When the flow of patients does not match availability of resources (e.g. exam rooms, ancillary staff, ophthalmologists), clinic inefficiency and longer patient wait times may result. This creates enormous challenges in workflow and scheduling, and large variability in operational approaches. Clinical practices often lack guidance on how to approach these issues; systematic data-driven methods for improving office productivity would help ophthalmologists care for more patients with greater efficiency.

Building data models of clinical workflow is an effective way of testing operational changes before implementing them in the clinic. One such type of model is discrete event simulation, which is used to represent and test highly variable processes such as outpatient clinic workflows.^{14–17} These models work best when based on large amounts of data,¹⁸ but using

traditional time-motion studies to collect large amounts of workflow data is time consuming and expensive. Instead, we have shown in a previous study that timestamp data recorded during EHR use can be used to build simulation models.¹⁹ These models showed that changes in scheduling policies can improve patient efficiency, while changes in staffing and exam rooms may have limited impact.

This paper extends our previous work by describing the development of a new clinical ophthalmology scheduling template intended to improve efficiency based on results from these computer simulation tests^{20–22}. This new template was implemented in multiple pediatric ophthalmology outpatient clinics, where the baseline templates did not schedule patients using any specific strategy beyond discussion between patients and schedulers. We evaluate the mean patient wait time, clinic volume, clinic length, and exam lengths pre- vs. post-implementation to determine the impact of the new schedule on clinic efficiency. This study demonstrates that “big data” from EHRs may be used to make better operational decisions for addressing the pressures on physicians.

METHODS

This study was approved by the Institutional Review Board at Oregon Health & Science University (OHSU).

Study environment

OHSU Casey Eye Institute is an academic ophthalmology department in Portland, Oregon, with over 50 faculty providers and over 130,000 annual outpatient examinations. The department includes all major ophthalmic subspecialties, and provides primary eye care while also serving as a tertiary referral center for the Pacific Northwest and beyond. An institution-wide EHR (EpicCare; Epic Systems, Madison, WI) has been used for all patient care, clinic management, and billing activities at OHSU since 2006. This study focused on one division (pediatric ophthalmology), which includes 6 ophthalmologists (LGR, AK, ARL, DJK, LW, MFC) and provides over 13,600 annual outpatient examinations.

Defining Ophthalmology Clinic Workflow

A combination of interviews and in-person observations were used to define the pediatric ophthalmology clinic workflow (Figure 1). Between September 2013 and November 2015, 120 patient appointments in one attending ophthalmology provider's clinic (LGR) were monitored by in-person observation using previously-published methods.^{20,21} Study personnel used mobile computing software (Numbers; Apple, Cupertino, CA) to measure time spent by the attending ophthalmologist, ancillary staff, and patients. These in-person measured times were considered reference standard data for subsequent validation.

Mapping Workflow to Electronic Health Record Data

To gather larger-scale timing data, EHR timestamp data were collected for one attending ophthalmology provider (LGR) from 1/1/2013 – 12/31/2014, using previously-published methods.^{20,21} Three different sources from the OHSU EHR data mart were used (Figure 1): (1) office visit data, which contains check-in and check-out times; (2) audit log tables, which

contain timestamped information about which part of patient records are accessed by users; and (3) ophthalmology exam template data, which contain information about whether dilation occurred during the appointment. Exam times calculated from EHR timestamp data were compared with those obtained from in-person observation.

Computer Simulation Models for Ophthalmology Clinic Workflow

Based on EHR timestamp data, discrete event simulation was used to model the clinical workflow using simulation software (Arena; Rockwell Automation, Wexford, PA). In the model, the initial staff exam and physician exam times were represented by probability distributions based on EHR timestamp data above. Patient arrival time distributions were generated from the same set of patient appointment data, and were represented as the differences between the scheduled appointment time and check-in time. We previously validated this model by comparing average simulated wait times to those obtained by in-person observation.¹⁹ Initial tests with the model varied the number of staff and exam rooms available and recorded the resulting wait time.

New Length Based Scheduling Template Development

Numerous tests using the simulation models identified the scheduling template with best balance between predicted average patient wait time and average clinic length. The resulting templates scheduled patients based on the anticipated length of their contact time with physicians and staff: “short” (fastest 25% of patient appointments), “medium”, or “long” (slowest 25% of patient appointments).

The new length-based template was implemented in April 2016 for appointments scheduled on or after September, 1 2016 in one provider’s clinic (Provider 1: LGR). In July 2017, the new scheduling template was adopted for 4 other pediatric ophthalmology providers (Providers 2-5: AK, ARL, DJK, LW) for appointments scheduled on or after January 1, 2017. Patients were scheduled into “short”, “medium”, or “long” appointment slots based on a combination of two factors as determined by providers and schedulers: (a) primary patient diagnosis (diagnoses associated with “short” and “long” appointment slots were identified by analyzing four months of retrospective appointment data), and (b) provider annotations (notes for schedulers about individual subjective patient factors associated with “short” or “long” appointment slots).

New Length Based Scheduling Template Evaluation and Data Analysis

For each provider, we compared 3 months of clinic sessions pre- (2016) vs. post- (2017) implementation, using the same months from each year to eliminate any seasonal effects: June to August 2016 vs. 2017 for Provider 1 (LGR), and October to December 2016 vs. 2017 for Providers 2–5. We defined a clinic session as a half-day session, and did not include half-days that did not use the templates, but may have had a few appointments scheduled (e.g. post-ops). To avoid potential confounding factors, we excluded appointments that did not have complete data (check-in and checkout times), entire clinic sessions with over half of appointments excluded for missing data, and clinic sessions with trainees.²³

Using EHR timestamp data, we calculated metrics to evaluate the performance of the new templates in a half-day clinic session: average patient wait time and clinic session length. Wait time was defined as beginning at the scheduled appointment time or at the beginning of the initial exam, whichever came earlier, to avoid biases from early arrivals. This wait time did not include time spent with the provider or waiting for dilation to occur. We also noted the average half-day clinic session volume and average patient exam time (face-to-face time with provider and ancillary staff), both pre- and post-implementation.

All metrics were compared pre- and post-implementation using t-tests and graphs created in R.²⁴ Statistical significance was defined as $p < .05$.

RESULTS

Clinic Workflow

Observations of 15 clinic sessions and 120 patient appointments established a standard pediatric ophthalmology clinic workflow (Figure 1). Appointments typically began with the patient check-in, and ended with check-out, and included an initial exam with ancillary staff, possible dilation, and an exam by the attending ophthalmologist.

Validation of Mapping of Electronic Health Record Timing Data

Timing data from the EHR was mapped to the clinic workflow (Figure 1). Exam times calculated from EHR timestamp data (650 appointments) were compared with those from direct in-person observation of appointments in one provider's clinic (LGR) for all appointments (LGR) with complete EHR visit data (102 [85%] of 120 total encounters). The mean physician exam time calculated using EHR timestamp estimates was 13.8 ± 8.2 minutes, and was not statistically different from the mean physician exam time from in-person observation (13.3 ± 7.3 minutes) ($p = 0.7$). Overall, 85% of patient appointments had EHR timestamp length estimates that were ± 3 minutes from the in-person observed exam times.²¹

Because the EHR timestamps were used as distributions in the simulation model, we also compared the density plots of the full EHR dataset (650 appointments) to the in-person observed dataset. Figure 2A displays similarity between plots of the total exam time (initial + physician exams) determined by the EHR timestamps vs. in-person observed timings.

Validation of Computer Simulation Models

The clinic workflow simulation model (1300 appointments) was validated against in-person observation data (120 appointments). Mean patient wait time for the simulation model was 31.2 ± 10.9 minutes, which was not statistically different from the mean patient wait time based on in-person observation (32.6 ± 25.3 minutes) ($p = 0.9$). Figure 2B shows density plots of the simulated wait time per simulation (average wait time for each of 100 simulations) and the observed wait time per appointment (120 appointments).

Simulation models were used to test the impacts of varying the number of ancillary staff and examination rooms on patient wait time (Figure 3). This showed that patient wait time

improved when using up to 2 ancillary staff (Figure 3A) and 2 exam rooms (Figure 3B), but the improvement was marginal after that point.

New Length Based Scheduling Template Development

Figure 4 displays the impact of different placements of predicted “long” patient appointments (slowest 25% of exam times) on predicted patient wait time based on computer simulation models. In general, placing the “long” patients closer to the end of the clinic reduced average patient wait time. However, this also increased predicted clinic length.

Using these simulation results and provider/staff input, a new scheduling template was created for a pediatric ophthalmology clinic (LGR, Table 1). Because of institutional EHR scheduling policies, each patient block was a standard length of 15 minutes. Predicted “short” patients were scheduled at the beginning of the clinic session, with the first slot double-booked to allow the provider to begin seeing patients as quickly as possible. Predicted “long” patients were scheduled toward the end of the clinic session. An empty slot was built-in to allow for catch-up.

“Short” and “long” appointment types were identified through discussions with providers and staff, and through review of retrospective appointment length data (Aaker, G et al. Identification of factors leading to increase pediatric ophthalmology visit times using electronic health record data. Presented at: AAO Annual Meeting, 2014; Chicago). For this particular practice, “short” appointments included retinopathy of prematurity (ROP) infant exams and post-operative exams (child and adult), “long” appointments included new patients and adult strabismus exams, and other diagnoses were considered “medium” appointments. In addition to this, providers had the opportunity to classify patients for follow-up exams in scheduling notes (as “short”, “medium”, or “long”) based on subjective patient factors.

New Length Based Scheduling Template Evaluation

Table 2 presents the results for Provider 1, which shows that the mean wait time significantly improved post-implementation (20.9 ± 15.1 minutes) vs. pre-implementation (24.7 ± 19.6 minutes) ($p = 0.008$), whereas the clinic session volume increased significantly post-implementation (15.1 ± 2.0 patients) vs. pre-implementation (13.5 ± 1.4 patients) ($p = 0.008$). Mean patient exam time and mean session length did not change significantly post-implementation vs. pre-implementation.

Because of the promising initial results with the new scheduling template for the initial provider (Provider 1 in Table 2), the same new scheduling template was implemented for the four other pediatric ophthalmologists (Providers 2-5) in July 2017. Table 2 displays results for Providers 2-5. All providers had significant increases in clinic volumes ($p = 0.05$ for 2 providers, $p = 0.008$ for 2 providers), while 3 of 4 providers had improvements in average wait times (only 1 provider statistically-significant, $p = 0.008$). Average exam times were unchanged post-implementation, but the average clinic length increased post-implementation for all four providers by approximately 15–20 minutes (only 1 provider statistically-significant, $p=0.05$).

DISCUSSION

In a complex and variable environment, it is not always apparent which operational changes will improve wait time and patient volume. Simulation modeling using EHR timestamp data is a promising method for developing and testing interventions to improve operational efficiency. Key findings from this study include: 1) simulation models based on “big data” from EHRs can test clinic changes before real-life implementation, 2) a new scheduling template based on predicted appointment length improved mean patient wait time and improved clinic volume in this study, and 3) these results have potential to generalize to other clinics with similar workflows.

The first key finding is that simulation models based on big data from the EHR can test different clinic changes before real-life implementation (Figure 2 and Figure 3). Changing operational systems in outpatient medical clinics is potentially risky and unpredictable without advanced planning and testing. Industries such as manufacturing, the military, transportation, and banking regularly use simulation models for testing changes in their operational systems before implementation.^{25,26} In the past, some health care simulation studies have struggled with collecting data using observation alone since it is time consuming, expensive, and must be repeated each time a new clinic or workflow is modeled.^{18,27} In this study, we show that the EHR is a good source of data for building such models, including data about patient arrivals, lengths of exam times, and the frequency and timing of dilation. EHR timestamp data can also evaluate metrics such as patient wait time after changes are implemented.^{21,22} While EHRs have been criticized at times for adding time and inefficiency to clinical operations^{3–6,9,28}, this study shows that EHRs can be mined for data that can actually improve clinical efficiency.

The second key finding is that an appointment length based scheduling template appears to improve average patient wait time and increase clinic volume. In all of the attending ophthalmology providers' clinics, the patient volume increased significantly. Four out of the five providers' clinics improved average patient wait time, but only two showed significant improvements ($p = 0.008$) (Table 2). These four providers' median wait times also decreased or stayed the same, indicating that wait times were uniformly decreased. Meanwhile, exam times remained the same pre- and post-implementation, suggesting that improvements in efficiency were not due to clinicians speeding up their exams. In four of five providers, mean clinic volume increased by at least one patient/clinic. Mean clinic lengths did increase for four out of the five providers (only one with statistical significance), but this appeared to be related to increased patient volume. since all five provider clinics reduced their average unit clinic length per patient.

Overall, scheduling predicted “short” patients first and predicted “long” patients toward the end of the clinic appears to improve clinic efficiency. Of note, this result was counter to what this particular clinic had done in the past: patients with complex and time-consuming problems had sometimes been scheduled first to get them “out of the way” so they did not extend the clinic length. According to simulation models in this study, this practice would result in delays from the start of the clinic that worsen as the clinic progresses (Figure 4). In fact, the average wait time of the short blocks in the new 2017 schedule for all providers was

the shortest (24.4 minutes) compared to medium blocks (28.4 minutes) and long blocks (31.3 minutes). However, when we compared the wait time of the same blocks in 2016, we found that it was longer for all the 2016 blocks that corresponded to short, medium, and long blocks in 2017 (27.8, 33.3, and 34.7 minutes in 2016, respectively). This suggests that rearranging the schedule according to patient length improved the relative average wait time for all the appointment blocks from 2016 to 2017, even though the short blocks still had shorter wait times than medium or long blocks.

Findings in this study are consistent with prior research showing that scheduling long patients near the end of the clinic session reduces patient wait time.^{29,30} Our previously published analysis also found that scheduling short patients at the start of the day reduces wait time.²⁷ One limitation of new scheduling templates is that they may not be followed by patients or schedulers (e.g. scheduler misinterpreting meaning of “long” appointment slot, patient saying “I cannot come to an 8am appointment because of a work obligation”). We have previously shown that the closer this new scheduling template is followed, the more the wait time decreases, and that this is particularly true for the “short” appointment slots.²⁷ In the current study, on average 29% of appointments were scheduled into incorrect appointment slots in the new scheduling template in each clinic session, suggesting that even more improvements in patient wait time might be realized by optimal scheduling.

The final key finding is that these results have the potential to generalize to other clinics with a similar workflow. In this study, one ophthalmology provider’s clinic was modeled and evaluated for changes in scheduling. The resulting scheduling template was then implemented in four other providers’ clinics with similar workflows but which were not modeled (Table 2). While it is possible that these four providers’ EHR timings would be different from the initial provider’s timings, the providers showed efficiency improvements after implementing the new schedule based on the initial provider’s model – suggesting that the model generalizes. Other studies have used simulation models in outpatient scheduling studies, but were very specific to solving a particular workflow problem^{27,31–33} or focused on strategies for implementing new scheduling changes such as open access scheduling or urgent add-ons.^{34,35} This study focuses on general scheduling for outpatient clinics with a very common workflow using a simple technique of binning exams into three predicted lengths (“short”, “medium”, or “long”), and has potential for extension to other clinics and clinical settings.

There are a number of limitations to this study: (1) EHR timestamps were used to calculate clinic workflow event times, but may not always represent actual clinic events depending on documentation patterns. Our validations showed, however, that exam times calculated from EHR timestamps were very close to actual observed times. In the future, using automated tracking devices such as radiofrequency identification (RFID) tags might improve the accuracy of data collection. (2) At the study institution, there was a requirement for scheduling blocks to be of equal length (Table 1) which limited flexibility in developing scheduling templates. Future studies involving variable length scheduling blocks may provide additional flexibility. (3) Simulation models did not account for variations in workflow such as visual fields, imaging studies, or office-based procedures since they are not always a part of routine pediatric ophthalmology workflow. Future studies to model

more complex workflows will be informative, particularly for image-intensive ophthalmic sub-specialties. (4) Simulation models were not used to exhaustively test all potential scheduling templates, including those that alternate long appointments with medium or short appointments. Further testing is needed to determine if more improvements can be made from these schedule variations. (5) This study excluded patient appointments with residents or fellows in order to exclude potential confounding factors from the impact of trainees on clinic workflow. Future studies including trainees may be warranted.²²

In summary, EHRs have transformed the practice of medicine, but have been criticized for their impact on workflow, documentation, and physician satisfaction.^{3,4,11,13,28} This study used EHR data to improve clinic efficiency through simulation models based on the principle of scheduling patients according to their predicted appointment length. This same EHR data may be used to identify and confirm which types of appointments fit into each of those 3 categories, and may be used to analyze the impact of scheduling changes on clinic efficiency. In this way, EHRs have potential to become a tool for supporting improvement in ophthalmology clinic operations, namely in improving efficiency and reducing waste. We hope this will be regarded as an important step in the continuous evolution of this emerging information technology.

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Figure 1. Clinic workflow and electronic health record timestamp mapping.

Patients move from check-in to check-out, and distribution of associated time requirements are gathered from EHR data mart, audit logs, and exam templates.

Validation of EHR Timestamps

Validation of Simulation Model

Figure 2. Validation of technologies for (A) using electronic health record timestamps for estimating patient exam times, and (B) using computer simulation models for predicting patient wait time.

Dark shaded density plots show in-person observation reference standard times.

Figure 3: Computer simulation tests demonstrating the impact of varying the number of ancillary staff and exam rooms on predicted mean patient wait time.

Figure 4. Example of computer simulation test results to develop new scheduling templates. Graph displays impact of placement of “long” encounters (slowest 25%) on predicted mean clinic length and predicted mean patient wait time in computer simulation models.

Table 1:
New length based scheduling template for a half-day clinic session.

Block	#Slots	Length
8:00 AM	2	Short
8:15 AM	1	Short
8:30 AM	1	Short
8:45 AM	1	Medium
9:00 AM	1	Medium
9:15 AM	1	Medium
9:30 AM	1	Medium
9:45 AM	1	Medium
10:00 AM	1	Long
10:15 AM	0	No patient
10:30 AM	1	Long
10:45 AM	1	Long
11:00 AM	1	Medium
11:15 AM	1	Medium
11:30 AM	1	Medium

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Table 2:
Comparison of clinic volume, patient wait time, exam time, and clinic session length: pre- vs. post-implementation of new scheduling templates.

Scheduling templates were created using computer simulations based on data from one pediatric ophthalmologist (LGR, Provider 1) and subsequently applied to four other pediatric ophthalmologists (Providers 2-5).

	Session Volume		Wait Time		Exam Time		Session Length	
	Mean	SD	Mean	SD (min)	Mean	SD (min)	Mean	SD (min)
Provider 1								
Pre (n = 32)	13.5	± 1.4	24.7	± 19.6	21.7	± 8.9	243.8	± 23.3
Post (n = 35)	15.1	± 2.0 [†]	20.9	± 15.1 [†]	21.7	± 9.0	243.1	± 20.2
Provider 2								
Pre (n = 24)	11.7	± 1.2	43.8	± 23.6	18.1	± 9.6	218.8	± 16.4
Post (n = 14)	13.2	± 1.5 [*]	40.3	± 26.3	18.4	± 9.6	239.0	± 35.6
Provider 3								
Pre (n = 36)	10.9	± 1.5	35.0	± 22.8	23.5	± 10.1	230.3	± 26.6
Post (n = 29)	11.7	± 1.4 [*]	30.5	± 20.8 [†]	24.1	± 9.1	244.0	± 27.5 [*]
Provider 4								
Pre (n = 45)	9.4	± 2.0	27.6	± 19.3	20.5	± 10.5	212.0	± 33.3
Post (n = 25)	12.3	± 1.4 [†]	27.8	± 19.7	21.5	± 9.4	225.2	± 30.9
Provider 5								
Pre (n = 35)	11.3	± 2.0	35.4	± 22.0	19.2	± 8.7	226.1	± 60.7
Post (n = 16)	13.1	± 1.7 [†]	31.6	± 24.0	19.3	± 9.1	246.6	± 39.3

* p 0.05

[†] p 0.008.