Using Electronic Health Record Audit Logs to Study Clinical Activity: A Systematic Review of Aims, Measures, and Methods

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ABSTRACT

Objective: To systematically review published literature and identify consistency and variation in the aims, measures, and methods of studies using electronic health record (EHR) audit logs to observe clinical activities.

Materials and Methods: In July 2019, we searched PubMed for articles using EHR audit logs to study clinical activities. We coded and clustered the aims, measures, and methods of each article into recurring categories. We likewise extracted and summarized the methods used to validate measures derived from audit logs and limitations discussed of using audit logs for research.

Results: Eighty-six articles met inclusion criteria. Study aims included examining EHR use, care team dynamics, and clinical workflows. Studies employed six key audit log measures: counts of actions captured by audit logs (e.g., problem list viewed), counts of higher-level activities imputed by researchers (e.g., chart review), activity durations, activity sequences, activity clusters, and EHR user networks. Methods used to preprocess audit logs varied, including how authors filtered extraneous actions, mapped actions to higher-level activities, and interpreted repeated actions or gaps in activity. Twenty studies validated results (23%), but only nine (10%) through direct observation, demonstrating varying levels of measure accuracy.

Discussion: While originally designed to aid access control, EHR audit logs have been used to observe diverse clinical activities. However, most studies lack sufficient discussion of measure definition, calculation, and validation to support replication, comparison, and cross-study synthesis.

Conclusion: EHR audit logs have potential to scale observational research but the complexity of audit log measures necessitates greater methodological transparency and validated standards.

BACKGROUND AND SIGNIFICANCE

Recently mandated logging of electronic health record (EHR) access in audit logs provides a promising resource for researchers to observe clinical activities at scale. Informaticians currently use diverse methods to study both clinical activities and use of health information technology (HIT) including surveys, interviews, and time-motion studies.[1–5] Time-motion studies in particular have seen wide adoption as they avoid many of the biases and inconsistencies of self-report through surveys and interviews. However, the most common form of time-motion study – continuous observation by an external observer – is time-consuming, expensive, and difficult to scale in terms of the diversity, duration, and detail of activity that can be recorded.[1–3] Researchers can scale certain aspects of observational studies with sensors such as Bluetooth beacons and video recorders, but this equipment can be difficult to set up and may provide, depending on the sensor, either a limited stream of data or multi-faceted recordings that require extensive ethnographic analysis.[6,7] Despite the many methods at their disposal, informaticians struggle to observe clinical activity and HIT use accurately, efficiently, and at scale.

Starting in 2005, the Security Rule of the Health Insurance Portability and Accountability Act (HIPAA) required all healthcare organizations to "*implement hardware, software, and/or procedural mechanisms that record and examine activity in information systems that contain or use electronic protected health information.*"[8] As part of the second stage of the Meaningful Use regulations in 2014,[9] the ONC further clarified that certified EHRs would need to maintain audit logs adhering to the ASTM E2147 standard for tracking HIT use.[10] Due to these regulations, virtually all EHRs in the United States now track at least four pieces of information about every episode of patient record access including *who* accessed *which* patient record at *what* time and the *action* they performed in that record such as adding, deleting, or copying information (**Table 1**). Depending on the vendor, EHR audit logs may track additional information about the computer, user, or record involved in each action, track those actions at different levels of granularity, and give them different names.

Table 1: Example EHR audit log

TIME	USER	RECORD	ACTION	COMPUTER
05/12/2019 13:04:35	SMITHJANE	104738297	Edit Note Section	MED2938
05/12/2019 13:04:37	SMITHJANE	104738297	Pend Note	MED2938
05/12/2019 13:04:42	SMITHJANE	104738297	Sign Note	MED2938
05/12/2019 13:04:52	DOEJOHN	105837489	View Problem List	MED1238
05/12/2019 13:05:02	DOEJOHN	105837489	View Note	MED1238
05/12/2019 13:05:04	DOEJOHN	105837489	View Note	MED1238
05/12/2019 13:05:32	SMITHJANE	107483726	View Patient Summary	MED2938
05/12/2019 13:13:32	SMITHJANE	107483726	View Patient Summary	MED2938
…	…	…	…	…

While originally designed to monitor record access, due to widespread use of EHRs in healthcare EHR audit logs present a unique opportunity to study clinical activities at a scale unachievable with direct observation and with less setup than external sensors. However, like other forms of time-motion study, audit log research is subject to challenges and limitations. Since audit logs are not purpose-built to track workflows they may lack vital contextual information and logged actions may be difficult to map to clinical activities such as chart review or patient exams. Nor do all clinical activities involve EHR use. While EHR audit logs have been used to study diverse clinical activities, there has been little synthesis of the aims of this research, or examination of the variation and validity of measures and methods employed. This lack of synthesis hampers efforts to replicate, generalize, and compare research in areas that may benefit from audit log analysis such as EHR usability and provider burnout.[11–17]

Objective

With this systematic review we identify consistency and variation in the aims, measures, and methods of audit log research. Moreover, we consolidate evidence for the validity of measures derived from audit logs and limitations of using audit logs to observe clinical activities. With this review we aim to improve the quality and generalizability of audit log research and provide literature-driven recommendations for the design of future studies to ultimately foster knowledge discovery in areas of critical informatics research.

MATERIALS AND METHODS

We identified articles for review by searching PubMed. Since the terms used to describe audit logs vary, we first hand-selected twenty-one audit log articles familiar to us and identified the terms each used to describe audit logs (e.g., access log, usage log, EHR timestamps). Using these synonyms for "audit log" and descriptors of EHRs used in prior systematic reviews,[18,19] we searched PubMed in July 2019 for all literature referencing EHR audit logs (see Appendix for full query). The PubMed query and hand-selection together returned 1775 unique articles, with only one of the hand-selected articles not included in the PubMed results. Through manual title, abstract, and text review, one author (AR) identified 74 of these articles which the met inclusion criteria summarized in **Figure 1**. Scanning the references of included articles, we identified 12 additional articles which met inclusion criteria, yielding a total of 86 articles for review (**Figure 2**).

One author (AR) iteratively reviewed and extracted features of each article. These included *study features:* the terms used to describe audit logs, EHR vendor, users studied (e.g., physicians, nurses), duration of study, and reported sample sizes (e.g., number of users, patient records, or encounters studied). This author also extracted each article's research questions, measures, and data preprocessing methods and together with a second author (MRH) iteratively coded these into a concise set of *aims*, *measures*, and preprocessing *methods* used in audit log research. Lastly, one author (AR) extracted and summarized the methods and results of *validation studies and sensitivity analyses* reported in reviewed articles as well as *limitations* discussed of using audit logs for research.

RESULTS

Features of Audit Log Research

The 86 articles included in this review used a variety of terms to describe audit logs in their titles and abstracts (**Table 2**). Only 31 used terms including the words "audit" or "access" while the remainder referenced more ambiguous EHR data, metadata, timestamps, and logs. Articles also varied in the EHRs, features, and users studied (**Table 2**). Just over half analyzed audit-logs from commercial EHRs (28 from one vendor, Epic (Verona, WI)). Most articles (66) examined all EHR activity while a minority (20) measured interactions with specific features or data-types such as info buttons, handoff reports, or CT scans. Just over half (47 articles) examined EHR activity in individual departments such as internal medicine, outpatient primary-care, and ophthalmology, while the remainder spanned departments. Only six articles examined EHR use across multiple institutions: four of which were conducted outside the United States and two of which examined interactions with a web-based EHR. Most articles (52) studied all EHR users while the remainder largely studied physician and resident use (31) with only a small number focused on nurses and medical students (3). Most articles (74) reported the length of time studied with the median duration being one year. Articles were less consistent in reporting the number of users, actions, patient records, and encounters studied (**Table 3**). Just over half of articles were published in 2016 or later (44 articles). See **Table 4** for features by article.

Table 2: Features of studies using EHR audit logs to study clinical activity

Study Attribute		#	%
Audit Log Term	Audit (e.g., audit log, access log)	31	36
	Generic (e.g., log file, EHR log)	18	21

	Usage (e.g., usage log, usage patterns)	10	12
	Time (e.g., timestamp, time data)	7	8
	Data (e.g., EHR data, EHR metadata)	8	9
	Event (e.g., event file, event sequence)	6	7
	Other (e.g., system log, user log)	6	7
EHR Type	Vendor	45	52
	Homegrown	25	29
	Unstated	16	19
Scope	Whole EHR	66	77
	Specific Feature	20	23
Department	Multiple	39	45
	Ophthalmology	10	12
	Primary Care	9	10
	General Internal Medicine	7	8
	Emergency	6	7
	Other	15	17
Institution	Single	80	93
	Multi	6	7
Users	All	52	60
	Physicians	20	23
	Residents/Fellows	11	13
	Nurses	2	2
	Medical Students	1	1

Table 3: Amount of time, actions, users, patients, and encounters studied varied across articles

	Time (Months)	*Users*	*Actions*	*Encounters*	*Patients*
Studies Reporting	74	50	24	18	19
Minimum	0.25	15	20,249	249	100
Median	12	155	1,930,620	38,628	3,450
Maximum	120	10,659	118,000,000	3,219,910	815,114

Table 4: Select features of the 86 articles included in this systematic review

Article				Terms	Who			What			Aims					Measures						Methods			Validation		
Ref.	PMID	First Author	Year	Audit Log Term	Users Studied	Department	Multi-Institute	EHR Type	Scope	Months Logged	EHR Use	Workflow	Care Team	Model EHR Use	Model Outcome	Action	Activity	Duration	Sequence	Cluster	Network	Filter Activity	Map Activity	Gaps / Repeat	Validate Mapping Method	Validate Time Method	Sensitivity
20	8130443	Michael PA	1993	audit trail	All	All		Homegrown	Feature	9	X					X											
21	14728157	Cimino JJ	2003	log file	All	All		Homegrown	Feature	6	X					X										Survey	
22	17102263	Chen ES	2006	log file	All	All		Homegrown	Feature	18	X					X											
23	17238321	Cimino JJ	2006	log file	All	All		Homegrown	Feature	24	X					X											
24	18693813	Cimino JJ	2007	log file	All	All		Homegrown	Feature	14	X					X		X									
25	18308208	McLean TR	2008	metadata	Trainee	Surgery		Homegrown	Feature	5	X					X											
26	20180439	Bernstein JA	2010	log data	All	All		Vendor	Feature	40	X					X											
27	22874273	Ries M	2012	system log	All	All		Vendor	Feature	8	X					X											
28	25024755	Hum RS	2014	user log	All	NICU		Vendor	Feature	22	X					X											
29	25954381	Jiang SY	2014	usage log	All	All		Vendor	Feature	1	X					X				X							
30	26958202	Jiang SY	2015	audit log	All	All		Vendor	Feature	1	X					X				X		X					
31	28808942	Cutrona SL	2017	access/audit log	MD	Primary		Vendor	Feature	12	X			X		X		X									
32	29696473	Mongan J	2018	audit log	MD	Rad		Vendor	Feature	14	X					X						X					
33	30879188	Epstein RH	2019	access log	MD	Anes		Vendor	Feature	19	X					X							X				
34	-	Asaro P	2001	access log	All	All		Homegrown	EHR	12	X					X				X							
35	14728151	Chen ES	2003	log file	All	All		Homegrown	EHR	12	X					X			X	X		X	X				
36	15360766	Chen ES	2004	log file	All	All		Homegrown	EHR	12	X					X			X	X			X				
37	16779018	Clayton PD	2005	audit trail	All	All		Homegrown	EHR	60	X					X											
38	17213496	Hripcsak G	2007	audit log	All	ED		Homegrown	EHR	7	X					X											
39	18999307	Wilcox A	2008	usage statistics	MD	All		Homegrown	EHR	1	X					X											
40	20442152	Zheng K	2010	audit log	MD	Primary		Homegrown	EHR	14	X			X		X						X					
41	20841655	Bowes WA III	2010	audit log	All	All		Homegrown	EHR		X					X										Interview	
42	21292704	Sykes TA	2011	system log	All	All			EHR		X			X	X	X											
43	23909863	Park JY	2014	log data	All	All		Homegrown	EHR	24	X					X											
44	24914013	Ancker JS	2014	EHR data	All	Primary		Vendor	EHR	42	X					X											
45	26618036	Choi W	2015	log file	All	All		Homegrown	EHR	12	X					X											
46	26831123	Kim S	2016	log file	All	All		Homegrown	EHR	24	X			X		X											
47	27332378	Kajimura A	2016	access log	Nurses	IM			EHR	<1	X					X											
48	29046269	Kim J	2017	usage log	MD	All		Homegrown	EHR	10	X			X		X				X		X					
49	29237579	Lee Y	2017	usage log	All	All		Homegrown	EHR	54	X					X											
50	29295318	Kim J	2017	usage patterns	MD	All			EHR	10	X					X											
51	30240357	Shenvi EC	2018	access log	Trainee	IM		Vendor	EHR	6	X			X		X											
52	30274967	Graham TA	2018	audit log	MD	ED	X	Homegrown	EHR	18	X					X							X				
53	31183688	Cohen GR	2019	log	All	Primary	X		EHR	1	X			X		X							X		Vendor		
54	24907594	Chi J	2014	audit data	MD Stu	All		Vendor	EHR	7	X				X		X	X				X				Survey	
55	26642261	Ouyang D	2016	electronic audit	Trainee	IM		Vendor	EHR	12	X					X	X	X						X			
56	26913101	Chen L	2016	audit log	Trainee	IM		Vendor	EHR	4	X						X	X				X		X	Vendor		
57	30522828	Cox ML	2018	time data	Trainee	Surgery		Vendor	EHR	11	X			X			X	X				X					X
58	30815089	Goldstein IH	2018	audit log	MD	Ophth		Vendor	EHR	12	X						X	X						X		Survey	
59	30726208	Wang JK	2019	event log	Trainee	IM		Vendor	EHR	41	X						X	X				X		X			X

60	30664893	Goldstein IH	2019	audit log	MD	Ophth		Vendor	EHR	120	X						X	X						X			
61	27195306	Senathirajah Y	2016	log file	All	All		Homegrown	EHR	36	X					X								X			
62	30137348	Orenstein EW	2018	audit log	Trainee	Peds		Vendor	EHR	24	X			X		X											X
63	22195144	Zhang W	2011	audit log	All	All		Vendor	EHR	3	X		X		X	X											
64	29481625	Chen Y	2018	interaction patt	All	Trauma			EHR	24	X		X		X	X				X	X		X				
65	21277996	Malin B	2011	access log	All	All		Homegrown	EHR	5	X		X			X					X						
66	22195103	Gray JE	2011	data	All	All			EHR	12	X		X			X					X						
67	24511889	Adler-Milstein J	2013	task log	All	Primary	X	Vendor	EHR		X		X		X	X											
68	21292706	Hripcsak G	2011	audit log	All	All		Vendor	EHR		X		X				X	X			X						
69	29854145	Grando A	2017	event logs	All	Surgery		Vendor	Feature	<1	X	X	X	X			X	X			X					Experience	
70	29049512	Read-Brown S	2017	timestamp	MD	Ophth		Vendor	EHR	4	X	X		X			X	X						X		Observe	
71	28373331	Tai-Seale M	2017	log	MD	Primary		Vendor	EHR	48	X	X		X			X	X						X		Observe	
72	28893811	Arndt BG	2017	event log	MD	Primary		Vendor	EHR	36	X	X					X	X					X		Consensus	Observe	
73	30184241	Kannampallil T	2018	log file	MD	ED		Vendor	EHR	1.5	X	X			X		X	X					X		Observe		
74	22527782	Ben-Assuli O	2012	log file	All	ED	X		EHR	48	X	X			X	X											
75	23594488	Ben-Assuli O	2013	log file	All	ED	X		EHR	36	X	X			X	X						X					
76	24692078	Ben-Assuli O	2015	log file	All	ED	X		EHR	48	X	X			X	X											
77	26767060	Wanderer JP	2015	audit log	All	All			Feature	5	X	X	X			X		X									
78	30664473	Soh JY	2019	log	MD	All		Homegrown	EHR	12	X	X				X			X	X							
79	24701327	Gilleland M	2014	usage data	MD	IM		Vendor	EHR	3	X	X			X		X	X									
80	23942926	Hanauer DA	2013	computer log	MD	Heme		Vendor	Feature		X	X				X	X										
81	25074989	Coleman JJ	2015	audit database	Trainee	All			Feature	12	X	X		X			X	X				X		X			
82	30730293	Amroze A	2019	access/audit log	MD	Primary		Vendor	Feature		X	X		X		X							X		Observe		
83	26958173	Chen Y	2015	event log	All	All			EHR	4		X				X		X	X	X							
84	28269922	Yan C	2016	event sequence	All	Card			EHR	4		X				X			X	X			X				
85	20193841	Shine D	2010	data	Trainee	IM		Vendor	EHR	4		X					X	X						X		Survey	
86	27103047	Ouyang D	2016	audit	Trainee	IM		Vendor	EHR	12		X			X	X	X	X				X					X
87	30625502	Dziorny AC	2019	timestamp	Trainee	Peds		Vendor	EHR			X					X	X								Survey	
88	29854253	Wu DTY	2017	audit trail log	All	Primary			EHR	5		X				X	X						X		Consensus	Experience	
89	29174994	Chen Y	2018	utilization	All	All			EHR	4		X				X			X	X							
90	30807297	Karp EL	2019	event file	Nurses	IM			Feature	2		X					X	X								Observe	
91	26958290	Hribar M	2015	timestamp	All	Ophth		Vendor	EHR			X					X	X								Observe	
92	28269861	Hribar MR	2016	timestamp	All	Ophth		Vendor	EHR	24		X					X	X									
93	29854159	Hribar M	2017	EHR data	All	Ophth		Vendor	EHR	15		X					X	X									
94	29036581	Hribar MR	2018	timestamp	All	Ophth		Vendor	EHR	12		X					X	X						X		Observe	
95	30312629	Hribar MR	2019	timestamp	All	Ophth		Vendor	EHR	24		X					X	X								Observe	
96	27375293	Hirsch AG	2017	audit file	All	Primary		Vendor	EHR			X		X			X	X	X					X			
97	29854142	Goldstein IH	2017	EHR data	MD	Ophth		Vendor	EHR	12		X	X			X											
98	29121175	Goldstein IH	2018	timestamp	MD	Ophth		Vendor	EHR	12		X	X			X											
99	22574103	Vawdrey DK	2011	audit log	All	Card		Vendor	EHR	1			X			X											
100	24845147	Chen Y	2014	EHR utilization	All	Multi		Homegrown	EHR				X			X					X						
101	25710558	Soulakis ND	2015	record usage	All	All		Vendor	EHR	12			X			X					X						
102	27570217	Chen Y	2017	utilization record	All	All		Homegrown	EHR	4			X			X					X					Survey	
103	30015537	Yao N	2018	access data	All	All		Vendor	EHR	24			X			X					X						
104	30889243	Durojaiye AB	2019	metadata	All	Peds		Vendor	EHR	15			X		X	X			X	X	X			X			
105	31160011	Zhu X	2019	access-log	All	All		Vendor	EHR				X	X		X		X			X						

Ref = Reference; PMID = PubMed ID; MD = Physicians; Med Stu = Medical Students
Anes = Anesthesiology; Card = Cardiology; ED = Emergency Department; Heme = Hematology; IM = Internal Medicine; NICU = Neonatal Intensive Care Unit; Ophth = Ophthalmology; Peds = Pediatrics; Rad = Radiology

Aims of Audit Log Research

Most articles used audit logs to study *EHR use* directly (63 articles, see **Table 4** for details by article).[20–82] This included how often providers accessed individual pieces of information,[20–33] patterns of EHR use across features,[34–53,67,74–78], and the total time providers spent using EHRs.[54–60,68–73] More recently, studies began to use audit logs to examine *clinical workflows* that extend beyond the EHR, using audit log timestamps to mark the boundaries of clinical events (30 articles).[69–98] For example, a few articles calculated resident duty hours using EHR login and logout timestamps, assuming residents log into and out of the EHR near shift boundaries.[79,85–87] Other studies used timestamps to identify the start and end of clinical exams and calculate exam length or patient wait time.[91–98]. Still other workflow studies focused instead on sequences of actions providers took after specific events occurred (e.g. receiving an alert) or their typical workflow when caring for certain patient groups, such as those with complex cardiac conditions.[80–84] A third common use of audit logs was to study *care team structure and dynamics* (17 articles).[63–69,77,97–105] While a few studies used EHR access to identify care teams for individual patients,[66,99] more used co-access of the same records to identify which providers or departments consistently worked together across patients.[65,100–105]

In addition to these three core aims, many studies collected additional demographic, contextual, or outcome data to model the effect of EHR use on clinical outcomes (12 articles),[42,54,63,64,67,73–76,79,86,104] or the effect of patient, provider, and context on EHR use (15 articles).[31,40,42,46,48,53,57,62,69–71,81,82,96,105] For example, two studies modeled EHR adoption as a function of providers' demographics and professional networks.[40,46] Several other studies assessed whether accessing a patient's historical record decreased their length of stay or chances of being admitted to the hospital.[64,73–76]

Measures of Audit Log Research

Reviewed articles derived a variety of measures derived from audit logs to study these topics including 1) counts of actions captured by audit logs, 2) counts of higher-level activities imputed by researchers, 3) activity durations, 4) activity sequences, 5) activity clusters, and 6) networks of EHR users (summarized in **Figure 3,** see **Table 4** for details by article).

Counts of actions captured directly by audit logs (63 articles) [20–53,55,61–67,74–78,80,82–84,86,88,89,97–105] such as "problem list viewed" were often used to quantify use of specific features such as info buttons and radiology reports. Alternatively, these actions were sometimes aggregated to identify peak periods of EHR use throughout the day or week. *Counts of higher-level activities* (27 articles) [54–60,68–73,79–81,85–88,90–96] typically involved first mapping low-level actions to higher-level activities such as chart review and documentation. Alternatively, it might involve looking for significant gaps between actions to identify entire sessions of EHR use or work shifts. These activity boundaries could then be used to compute counts or rates, such as the number of unique EHR sessions across all users in the past month or the percent of encounters where providers reviewed the patient's historical record. Other studies grouped actions into higher-level activities not to report counts but to compute the *duration of those activities* including total time devoted to EHR use (30 articles). [24,31,54–60,68–73,77,79,81,83,85–87,90–96,105]

These first three measures were used to create more complex measures and models of activity, three of which were employed in multiple studies. Eight studies constructed *event sequences* to identify routine patterns of care and deviations from them.[35,36,78,83,84,89,96,104] Twelve studies clustered *patterns of activity* to identify recurring patterns of EHR use, such as which sections of the record providers routinely accessed.[29,30,34–36,48,64,78,83,84,89,104] Finally, eleven articles studying care teams used co-access of a patient's record to develop *networks of users or departments* that typically work together.[64–66,68,69,100–105] Across all six measures, there was one significant change in use over time: 47% of articles published since 2016 reported a time duration, whereas only 21% of the articles published before 2016 did so ($\chi^2 = 6.54$, $p = 0.01$) (**Figure 4**).

Preprocessing Methods of Audit Log Research

Computing even seemingly simple measures from audit logs such as duration of EHR use is not necessarily straightforward. Yet, less than half of articles (32) discussed how raw audit logs were preprocessed before analysis (see **Table 4** for details by article). Fewer still discussed this data wrangling in enough detail to support replication. When reported, common practices included 1) filtering actions, 2) mapping actions to higher-level clinical activities, and 3) selecting criteria to define time-periods. *Filtering actions* included removing actions that were considered incidental or irrelevant to the study.[30,32,35,40,48,54,56,57,59,75,81,86] For example, one study of medical student EHR use removed short bursts of activity on off-service days, labeling this incidental use.[54] Other studies considered all activity within 24 hours of a patient's visit as relevant,[40] or only activity in periods with "more than 3 mouse clicks (or 15 keystrokes) or 1700 mouse miles (pixels) per minute".[56] Another common preprocessing practice was *mapping individual actions to higher-level activities* such as chart review or documentation.[33,35,36,52,53,64,72,73,82,84,88] While no study reported the actual action-activity mappings, some reported the process used to develop these mappings, which varied as discussed in the next section. A final recurring practice was *selecting actions and criteria to* *define time-periods*.[55,56,58–61,70,71,81,85,94,96,104] This involved defining which actions constituted the start and end of clinical events (such as the first non-login action) and how gaps in activity would be handled. Depending on the research question, meaningful gaps ranged from 5 minutes, which could indicate the user was no longer actively using the EHR,[59] to six hours, which could indicate the end of a shift.[85] Another study identified shifts using a three-step process of 1) identifying distinct shifts based on 4-hour gaps, 2) merging shifts that were less than 7 hours apart which would result in a combined shift length of less than 30 hours, and 3) merging shifts that were less than 2 hours long and would result in a combined shift of less than 20 hours.[87]

Validating Audit Log Measures

Using EHR audit logs to study clinical activity assumes audit logs consistently and accurately track clinical activities and that the methods used to process them into more complex measures are sound. However, a minority of studies reported checking these assumptions through validation or sensitivity analyses. Validation studies, which compared measures derived from audit logs with those obtained through other methods, checked both the mapping of audit log actions to higher-level activities as well as the accuracy of activity patterns or durations derived from audit logs. Of the twenty studies that reported validation analyses, six validated activity mappings and sixteen validated patterns or durations (see **Table 4** for details by article).

The six studies that reported validating action-activity mappings used a variety of methods including consensus among two or more researchers,[88] consulting the EHR vendor,[53,56] and direct observation of clinical activities.[72,73,82] Only one of these studies reported the accuracy of mappings, noting that 6.9% of the audit log actions were originally misclassified as representing the wrong activity when compared to direct observation.[72] Of the sixteen studies that reported validating activity patterns or durations, nine compared them to data self-reported by EHR users, administrators, or the authors themselves.[21,33,41,54,69,85,87,88,102] Only seven compared timing data to values obtained through direct observation.[70–72,90,91,94,95] Of these, only five reported measure accuracy. Accuracy for EHR time per encounter ranged from overestimating by 43% (4.3 vs 3.0 minutes)[70] to underestimating by 33% (2.4 ± 1.7 vs. 1.6 ± 1.2 min).[91] Measures of appointment lengths which tend to be longer were more accurate, overestimated by just 4% in one study (13.8 ± 8.2 vs.13.3 ± 7.3 min),[95] underestimated by 14% in another (19.4 vs 22.5 min),[71] and overestimated by 29% in a third (24.4 ± 13.0 vs. 18.9 ± 11.0 min).[91]

Computing duration data in particular requires making a number of assumptions about what constitutes the start and end of certain activities and how to handle gaps in activity. Four studies reported sensitivity analyses in this vein,[57,59,62,86] such as varying the gap in actions considered idle activity from 5-10 minutes[59] or seeing what impact discarding the first and last 5% of actions in a given work shift had on calculated shift length.[86] None reported a significant change in results due to changing these parameters.

Challenges and Limitations of Audit Log Research

Finally, reviewed articles mentioned a few limitations of using audit logs to study clinical activity. First, 20 articles mentioned that audit logs do not provide a full picture of clinical activity as they only capture interactions with the EHR.[20,30,38,51,52,57,64,68,69,72,77,78,85,87,91,92,96,100,104,105] Audit logs do not track phone, pager, or face-to-face interactions nor do they track interaction with paper records and printouts. This may lead to systematic underestimation of interaction or workload. Second, 15 articles noted that gaps between timestamps and multiple concurrent timestamps can be difficult to interpret.[41,54,58,59,68,70,72,81,82,86,88,90,93–95] For example, does a long gap mean the provider was meaningfully engaged with the EHR that entire time, or had they turned their attention away? Do sequential identical audit log entries (except for the timestamp) represent a repeated or continued activity? Third, seven articles mentioned audit log data were often either too coarse or too detailed for clear interpretation.[20,49,54,69,70,100,103] Logs might capture who accessed a patient record, but not which exact note or result they were viewing. Alternatively, more detailed logs might use different names to track accessing the same piece of information through different screens. It can take researchers substantial time to map these isometric actions to higher-level activities. Lastly, 6 articles noted that audit logs may capture what a user did in the EHR, but data from more qualitative methods such as interviews or observations are needed to understand why.[21,32,38,61,68,81]

DISCUSSION

With this systematic review, we surveyed articles using EHR audit logs to study clinical activities. We found a diverse body of literature employing a range of measures to study EHR use directly, clinical workflows extending beyond the EHR, and care team dynamics. This body of research is growing with over half of reviewed articles published in the last three-and-a-half years. Moreover the increased measurement of duration of EHR use may reflect growing concern over the association between EHR use and provider burnout.[14–17]

Whereas some measures employed in this literature were relatively simple counts of actions tracked explicitly by audit logs, others required researchers to manipulate audit logs in sophisticated ways, generating durations, sequences, clusters, and networks. Many studies glossed over the details of how raw audit logs were preprocessed to compute these measures and even when methods were reported there was significant variation. This variation reflects the difficulty of interpreting audit logs which requires professional judgement and domain knowledge, such as understanding resident duty hour restrictions.

Recommendations

The variability of measures and methods in reviewed articles echoes the variability observed in prior systematic reviews of the time-motion studies in healthcare.[2] It also highlights areas where research using EHR audit logs might improve. We focus our recommendations on four areas: sample size reporting, reporting of methods used to pre-process audit logs, validation and sensitivity analyses, and methodological transparency leading to validated standards.

First, we recommend standard reporting of the time period, number of users, and patient records studied. While most studies report the duration of time studied, not all did. Just over half reported the number of users studied, and far fewer reported the number of patients or encounters analyzed. This use of time to report sample sizes likely reflects the fact that audit log data are routinely queried by time period rather than number of patient records or users desired for analysis. We suggest other reported sample size measures be clinically relevant, such as the number of patient encounters, rather than dataset measures such as number audit log rows, as these are harder to compare across vendors and institutions with different logging practices.

Second, we recommend detailed reporting of steps used to wrangle raw audit log data into measures. Given the variable accuracy of time durations reported in studies that validated them (e.g., from 33% underestimation to 43% overestimation of provider EHR time per appointment), there is still a need to develop more accurate and consistent methods of tracking activities with audit logs. Methods reporting should include any criteria used to filter logs and at least the *process* used to map granular actions into higher-level activities such as documentation or chart review. Ideally researchers would also report the exact mapping of actions to activities; however, this may not be feasible given the large number of actions that may map to a single activity or the potential for EHR vendors to consider audit log action names proprietary information. For time durations, we recommend authors report how they handle repeated actions and gaps in activity, as well as how they identify the boundaries of activities, especially if data are missing (e.g., “if a log-out action was missing, we considered the last action before a gap of 2 or more hours the end of the provider’s shift”). We recommend the audit log research community develop standards for reporting more complex measures such as activity sequences, activity clusters, and user networks.

Third, we recommend researchers take more steps to validate and test the sensitivity of their results. Ultimately, the validity of audit log research rests on assumptions that audit logs consistently and accurately track EHR use and clinical activities more broadly. While some methods seem to be approaching parity with direct observation for measuring the duration of longer activities such as patient exams, measures of shorter events such as EHR time per encounter are more varied. Validation may occur in a number of ways including surveys and member-checks, but the gold-standard should remain comparing measures derived from audit logs with those obtained through direct observation. More sensitivity analyses are also warranted as the parameters of methods used to preprocess audit logs may significantly affect results.

Finally, there is a need for greater methodological transparency and validated standards to support replication and synthesis. This includes clear documentation and sharing of data schemas, action-activity mappings, and preprocessing scripts between institutions. We recommend that vendors, institutions, and the audit-log research community work together to share methods and develop validated standards for tracking, querying, and analyzing audit logs to compute the diverse measures of clinical activity uncovered in this review. These standards could in turn support replication and comparison across departments and institutions to identify consistency and variation in EHR use and clinical workflows between them.

Limitations

This review has a few limitations. First, it does not survey use of all health-information technology logs, nor even all uses of EHR audit logs. EHR related technologies such as Personal Health Records, Health Information Exchanges, and mobile health apps often track user activity with logs similar to EHR audit logs,[106–109] and workflow researchers may use timing data directly from patient records in their studies (such as admit time or time of placing an order). EHR audit logs are also routinely used for their primary purpose of access control and several publications have explored how to use them more effectively for that purpose.[110–114] While the measures and methods used in these related domains may be similar to those reported in this review, we scoped our analysis to use of EHR audit logs to study clinical activity to provide targeting insights for this growing research community. Second, we limited our search to articles on PubMed which may exclude articles published in computer science or engineering venues not routinely indexed there. We mitigated this risk by searching the citations of included articles for relevant references, regardless of venue. Third, our coding process was largely subjective and performed by a single author. While the authors of each article may not agree with our classification, we aimed to develop a consistent coding scheme that captured the breadth of the literature by iteratively defining and applying each category label. Finally, this review likely reflects a publication bias in which some types of audit log research are more readily published than others (e.g. workflow studies vs. studies of IT infrastructure needs)

CONCLUSION

EHR audit logs have been used to study a wide range of clinical activities, extending beyond their original purpose of monitoring patient record access. The 86 articles included in this review demonstrate a diverse and growing literature, reflecting researchers' desire to gather precise data on HIT use and clinical activities at scale. However, the process of turning raw audit logs into insights is complex, requires professional judgement, and varies from study to study, when it is even reported. Moreover, there are relatively few articles in the literature that report testing the validity and sensitivity of audit log measures. This lack of rigor and reporting prevents synthesis and comparison across studies, as well as efforts to improve the accuracy of using audit logs for clinical event measurement. EHR audit logs have untapped potential to support quality improvement and research, but the continued growth of the field will require greater methodological transparency and validated standards to support replication and cross-study knowledge discovery.

COMPETING INTERESTS

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APPENDIX

PubMed Search Query

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(
  (“audit”[All Fields] AND (log[All Fields] OR file[All Fields] OR data[All Fields]))
  OR (log[All Fields] AND (file[All Fields] OR "event"[All Fields] OR "access"[All Fields] OR
"system"[All Fields]
```

```
    OR "usage"[All Fields] OR "activity"[All Fields]))
  OR "timestamp"[All Fields]
  OR "interaction patterns"[All Fields]
  OR "utilization patterns"[All Fields]
)
AND
(
  ("electronic"[All Fields] AND "health"[All Fields] AND record[All Fields])
  OR (“electronic"[All Fields] AND "medical"[All Fields] AND record[All Fields])
  OR (("computerised"[All Fields] OR "computerized"[All Fields]) AND "medical"[All Fields]
    AND record[All Fields])
  OR ("electronic health records"[MeSH Terms])
  OR (“medical records systems, computerized"[MeSH Terms])
)
AND
English[lang]
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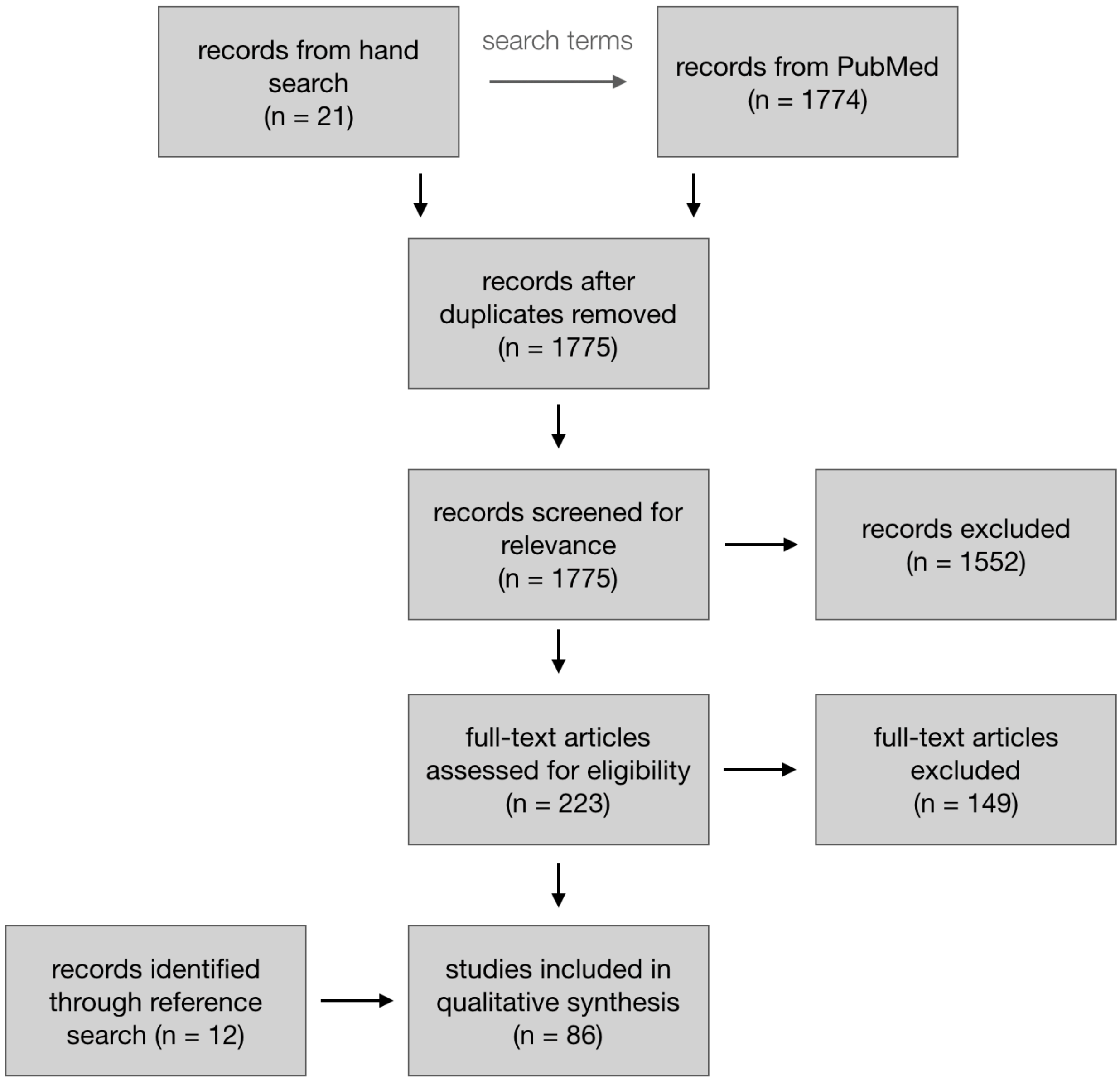
FIGURE LEGENDS

Figure 1: Article inclusion criteria

The article…

1. is **peer reviewed**
2. reports **original research**
3. is a **full paper** rather than an abstract
4. **studies use of an EHR** rather than related technologies such as Health Information Exchanges, Personal Health Records, and mobile health apps
5. **uses EHR audit log data** rather than other logs or EHR data such as admission and discharge timestamps from the patient record
6. involves **secondary use** of EHR audit logs rather than using audit logs for their original purpose of access control

Figure 2: Article review process



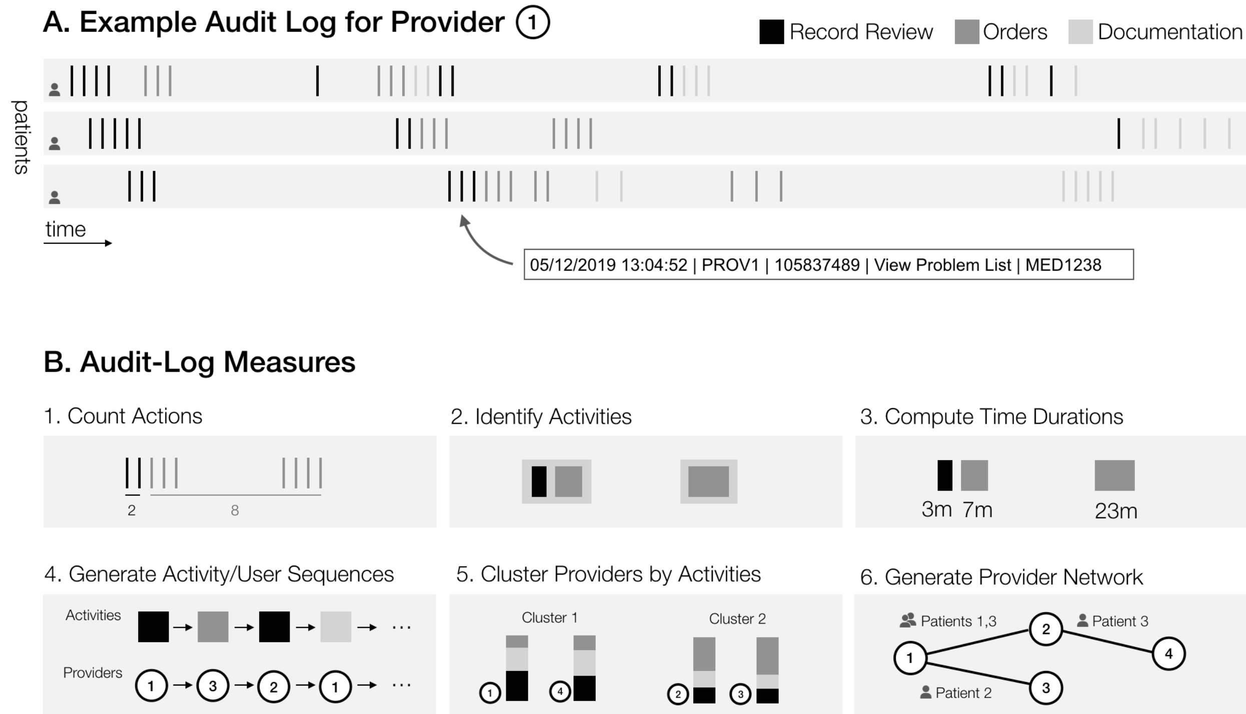


Figure 3: A) Audit logs track actions EHR users perform in patient records. Here we show a simplified example of an audit log for one provider performing actions (e.g., “View Problem List”) in three different patient records. We have already mapped these actions to three higher-level clinical activities (record review, orders, documentation). B) Audit logs can be used to compute a variety of measures including simple measures such as 1) action counts, 2) higher-level activity counts and 3) activity durations. These base measures may be used to create more complex models and measures such as 4) sequences of activities, 5) clusters of similar activity patterns, and 6) networks of providers based on their access of the same patient records.

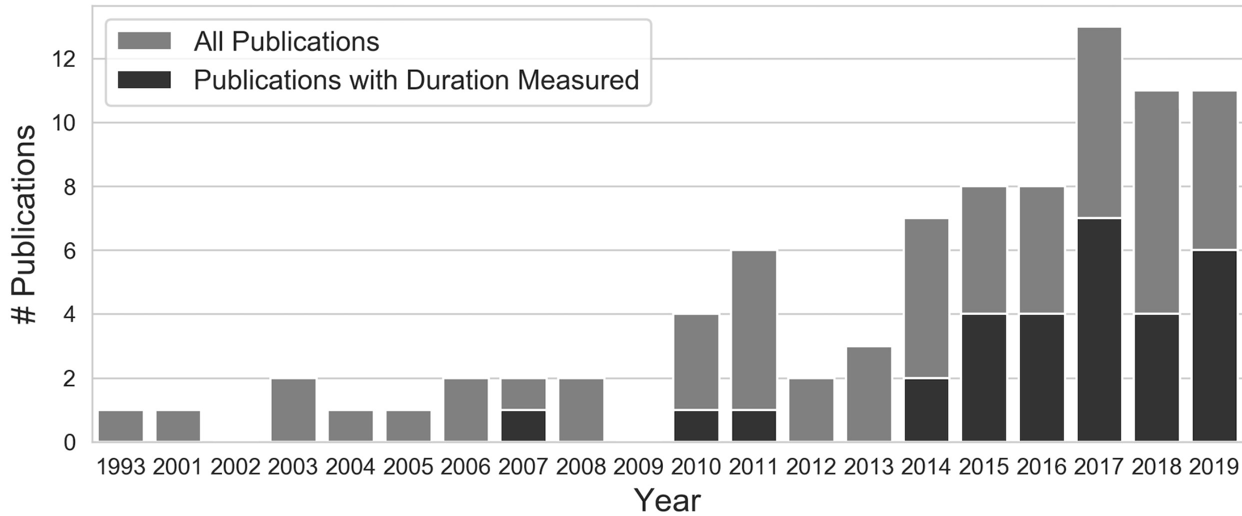


Figure 4: Audit log publications over time with publications reporting a time duration highlighted