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Research and Applications

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Primary care physicians' electronic health record proficiency and efficiency behaviors and time interacting with electronic health records: a quantile regression analysis

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ABSTRACT

Objective: This study aimed to understand the association between primary care physician (PCP) proficiency with the electronic health record (EHR) system and time spent interacting with the EHR.

Materials and Methods: We examined the use of EHR proficiency tools among PCPs at one large academic health system using EHR-derived measures of clinician EHR proficiency and efficiency. Our main predictors were the use of EHR proficiency tools and our outcomes focused on 4 measures assessing time spent in the EHR: (1) total time spent interacting with the EHR, (2) time spent outside scheduled clinical hours, (3) time spent documenting, and (4) time spent on inbox management. We conducted multivariable quantile regression models with fixed effects for physician-level factors and time in order to identify factors that were independently associated with time spent in the EHR.

Results: Across 441 primary care physicians, we found mixed associations between certain EHR proficiency behaviors and time spent in the EHR. Across EHR activities studied, QuickActions, SmartPhrases, and documentation length were positively associated with increased time spent in the EHR. Models also showed a greater amount of help from team members in note writing was associated with less time spent in the EHR and documenting.

Discussion: Examining the prevalence of EHR proficiency behaviors may suggest targeted areas for initial and ongoing EHR training. Although documentation behaviors are key areas for training, team-based models for documentation and inbox management require further study.

Conclusions: A nuanced association exists between physician EHR proficiency and time spent in the EHR.

Key words: EHR use, EHR optimization, primary care physicians, documentation burden

INTRODUCTION

Researchers have increasingly reported on the association between the burden imposed by the use of electronic health record (EHR) systems and physician burnout.[1–5] EHR-related burden stems from many factors, such as usability issues, systems implementation issues (eg, lack of sufficient EHR support, training), and documentation burden from the payer and quality reporting requirements.[1,6] Consequently, EHR vendors, federal agencies, and healthcare organizations are exploring solutions to reduce clinicians' EHR-related burden.[3,7–11]

Physicians spend an estimated 50% of their time on EHR tasks,[12–15] which include documentation, inbox management, and chart review.[15–21] However, physician-level factors, such as specialty, may influence differences in EHR-related burden.[17,21–24] For instance, primary care physicians (PCPs) spent more time in the EHR when compared with specialists.[17,25,26] This EHR burden is likely to grow over time, as patient complexity (eg, comorbidities, aging of the population) increases and new payment models are developed.[27–31] Thus, additional information will be needed to identify how PCPs' EHR use patterns may be adapted to increase efficiency.

Improving EHR proficiency skills, through optimal use of EHR proficiency and efficiency tools to facilitate workflow, has been suggested as a path to reducing time spent in the EHR.[32–36] A 2020 single-center study found that self-reported after-hours time spent in the EHR was positively associated with EHR-derived measures of after-hours use.[37] However, self-reported EHR proficiency showed mixed associations with after-hours EHR use.[37] EHR proficiency scores, as calculated by the EHR vendor, were negatively correlated with EHR-derived measures of time spent in the EHR after-hours.[37] These EHR proficiency scores are challenging to interpret, in part, due to the scores' proprietary calculations.[37,38] To improve our understanding of what drives clinicians' time spent in the EHR, there is a need to parse out which specific EHR proficiency tools and EHR efficiency behaviors affect time spent in the EHR.

To address this gap, our study utilizes EHR-derived measures to assess whether the use of EHR proficiency tools and EHR efficiency behaviors were associated with reduced time interacting with the EHR. Findings may guide healthcare organization leaders in identifying key training areas to emphasize during onboarding of new physicians, post-onboarding support, refresher training, and EHR optimization efforts.

MATERIALS AND METHODS

Setting and sample

Study data focused on one academic health system in North Central Florida that offers multiple services, such as primary care, to patients throughout the state. This health system spans 2 metropolitan areas and utilizes Epic as its EHR provider (Epic Systems, Verona, WI).

The sample included all physicians (ie, attending physicians, residents/fellows), who practiced in ambulatory primary care during the study period, November 2019 to October 2020 inclusive. We defined primary care to include those in general internal medicine, general pediatrics, and family medicine. We focused on primary care due to the known substantial documentation burden,[14,17] an established driver of time spent in the EHR.[16,18,19,21,39–42] We excluded all physicians practicing in other settings and other clinician types (eg, nurse practitioners).

Data

Our data source was Epic Signal, an analytical platform developed by Epic that computes and stores EHR use measures for ambulatory clinicians.[8,43] Health system clients can use these measures to assess the impact of interventions (eg, training) on the use of proficiency tools and time spent in the EHR. Since healthcare organizations have access to these measures and resulting dashboards for their internal use, we restricted all measures for this study to only those that healthcare organizations could access. The Institutional Review Boards at the University of Florida and the University of Alabama at Birmingham approved the study protocol.

Measures

The EHR automatically collected multiple data points for each clinician that uses the EHR system. These variables include the amount of time spent interacting with the EHR, amount of time on specific EHR activities, use of EHR tools (eg, macros), and patient workload (eg, average number of appointments per day). Most measures were non-negative continuous variables and a few were reported as dichotomous variables (eg, any use of chart search features). All EHR use measures were reported on a clinician-week level.

Outcome measures

We used 4 variables to measure time spent in the EHR. First, we assessed the overall time spent in the EHR, which is defined as the mean number of minutes spent per day. Second, we examined time spent outside scheduled hours, which is defined as the mean number of minutes spent in the EHR outside of scheduled appointments per day. This definition considers any EHR activity recorded more than 30 minutes before the first scheduled appointment or more than 30 minutes after the final appointment ended to be "outside of scheduled hours." Although alternate options were considered to assess after-hours EHR use (eg, time outside of 7:00 AM to 7:00 PM), studies have raised questions about the heterogeneity and validity of time intervals used.[43,44] Other measures (eg, time outside scheduled days) were not feasible given the academic setting (ie, many physicians in the study spent half of the day in clinic and the other half on educational, research, or administrative duties). Third, we reviewed time spent in the EHR writing notes per day, which is defined as the mean number of minutes spent writing notes. Lastly, we studied time spent on inbox management per day, which is defined as the mean number of minutes spent on the In Basket interface. These 4 outcome variables were selected due to their documented association with physician burnout.[1]

Independent variables

Our main independent variables were the use of EHR proficiency tools and EHR efficiency behaviors provided by the data source. We considered EHR proficiency tools to be any EHR tool implemented to improve a clinician's productivity. These included the Chart Search feature, QuickActions (ie, macroed workflows), NoteSpeed buttons (ie, shortcuts to pulling in SmartPhrases), NoteWriter macros, QuickFilters (ie, applies pre-specified search criteria when reviewing information), SmartPhrases (ie, personal documentation templates), and bookmarked orders. We considered EHR efficiency behaviors to be measures describing how fast a clinician completed tasks. These included documentation length, signing visits on the same day, writing notes manually, volume of completed messages, time spent per message, and turnaround times for messages. We selected these variables as we hypothesized they may be associated with time spent in the EHR. Other proficiency-related variables, such as creating diagnosis and level of service speed buttons, were not analyzed because it was unclear how they might affect time spent in the EHR, had significant missing data, or were not calculated at the clinician-level.

Additional covariates

We included other variables known to influence EHR use patterns, such as patient load (number of appointments each day, proportion of the 7-day week with appointments, proportion of new patient visits),[18,39,45,46] patient complexity (proxied by average patient age and average problem list length),[47,48] having assistance on EHR tasks from support staff,[49–51] and use of the EHR on mobile devices.[52,53] New patient visits were defined as those with Current Procedural Terminology codes 99201 through 99205. At the study site, these billing codes are used for both patients who are new to the organization and those who have not been seen in over 3 years.

Analytic approach

We summarized the sample's characteristics using median, interquartile range (IQR), and range for continuous variables and percentages for categorical variables. Since all outcomes of interest had a skewed distribution, rather than using traditional methods (eg, linear regression), we chose a multivariable quantile regression approach, allowing us to estimate the differential effect of model covariates across the various quantiles of the outcome distribution.[54,55] For the analyses, we used the 10th, 25th, 50th, 75th, and 90th quantiles. We controlled for physician-level factors (in light of the limited demographic variables offered by the data source) and weekly variations in EHR use by including physician-level and time fixed effects. Since our study period overlapped with the coronavirus pandemic, we controlled for pandemic-related effects on EHR use (eg, switching to telemedicine) by including a dichotomous variable that represents whether a given week occurred during or after the state's governor issued the executive order to cease elective services.[56] We used complete case analysis to address missing data for variables of interest. Multicollinearity analysis was conducted to test for high correlations between predictors. A *P*-value of $<.05$ was interpreted as significant. All analyses were calculated using Stata SE 16.0 (Stata-Corp, LP, College Station, TX, USA), using the "xtqreg" commands.[57]

RESULTS

Sample characteristics

Our sample consisted of 441 primary care physicians. Over half of the physicians were female (54.2%), and the plurality of physicians practiced general internal medicine (38.8%). The median total time spent on various EHR activities is listed in Table 1 and the usage level of each of the proficiency tools studied is listed in Supplementary Table S1.

Table 1. Sample characteristics ($n = 441$)

Variables EHR use measures (in minutes/day)	Median (IQR)	Range
Total time in EHR	70.5 (106.5)	0.6–417.2
Total time in EHR outside scheduled hours	40.9 (43.8)	0.0–278.7
Time spent in EHR documenting	22.8 (46.2)	0.2–143.5
Time spent in In Basket	5.9 (13.5)	0.1–70.7
Physician demographics, *n* (%)		
Sex		
Male	196 (44.4%)	—
Female	239 (54.2%)	—
Unknown	6 (1.4%)	—
Primary care specialty		
Family medicine	139 (31.5%)	—
General internal medicine	171 (38.8%)	—
General pediatrics	131 (29.7%)	—
Patient load		
Proportion of new patient visits	0.0 (0.0)	0–1
Number of appointments in a day	5.0 (7.5)	1–30
Number of problems in problem lists	10.1 (8.7)	0.9–34.9
Patient age (in years)	48.6 (47.9)	2–76
Proportion of week with appointments	0.3 (0.4)	0.1–1

EHR, electronic health records; IQR, interquartile range.

Total time interacting with the EHR

After controlling for other factors, increased availability of NoteSpeed buttons was associated with less time spent in the EHR per day at the 50th (β: −2.00, $P < .01$), 75th (β: −2.54, $P < .01$), and 90th quantiles (β: −3.02, $P < .05$). Conversely, as the number of QuickActions available increased, greater time was spent in the EHR per day at the 10th (β: 1.01, $P < .01$), 25th (β: .97, $P < .001$), 50th (β: .93, $P < .001$), 75th (β: .88, $P < .001$), and 90th quantiles (β: .84, $P < .05$). As the number of SmartPhrases created by the physician increased, greater time was spent in the EHR per day at the 10th (β: .15, $P < .05$), 25th (β: .15, $P < .01$), 50th (β: .16, $P < .001$), 75th (β: .16, $P < .001$), and 90th quantiles (β: .17, $P < .01$). Use of NoteWriter macros, QuickFilters, proportion of notes written manually, and In Basket turnaround time had no association with time spent interacting with the EHR. Further details are reported in Table 2.

As the proportion of notes written by other team members increased, less time was spent in the EHR per day at the 10th (β: −16.10, $P < .05$), 25th (β: −19.36, $P < .001$), 50th (β: −23.78, $P < .001$), 75th (β: −28.34, $P < .001$), and 90th quantiles (β: −32.50, $P < .001$). As the proportion of non-medication orders (eg, referrals) prepared by team members for the physician to sign increased, less time was spent in the EHR per day at the 75th (β: −2.81, $P < .05$) and 90th quantiles (β: −4.20, $P < .01$) (Table 2).

Time in EHR outside scheduled appointment hours

After controlling for other factors, none of the studied proficiency behaviors were associated with less time spent in the EHR outside scheduled hours per day. However, as the number of QuickActions available increased, greater time was spent in the EHR outside scheduled hours per day at the 25th (β: .48, $P < .01$), 50th (β: .54, $P < .001$), 75th (β: .60, $P < .01$), and 90th quantiles (β: .66, $P < .05$). As the number of SmartPhrases created by the physician increased, greater time was spent in the EHR outside scheduled hours per day at the 25th (β: .08, $P < .05$) and 50th quantiles (β: .08,

Table 2. Adjusted beta coefficient estimates of factors associated with total EHR use (in minutes/day) ($n = 431$)[a,b]

Variables	10th quantile	25th quantile	50th quantile	75th quantile	90th quantile
Patient load					
Proportion of new patient visits	−0.06	0.64	1.46	2.36	3.19
Number of appointments in a day	0.30	0.49**	0.71***	0.95***	1.17***
Proportion of week with scheduled appointments	141.12	133.14***	123.79***	113.51***	104.12***
Patient complexity					
Patient age	0.11	0.13	0.15*	0.16	0.18
Number of problems on problem list	−0.11	−0.08	−0.05	−0.02	0.01
EHR proficiency and efficiency behaviors					
Chart search feature used					
No	Ref	Ref	Ref	Ref	Ref
Yes	3.86	3.55*	3.19**	2.79*	2.42
Number of QuickActions	1.01**	0.97***	0.93***	0.88***	0.84*
Number of NoteSpeed buttons	−1.11	−1.52	−2.00**	−2.54**	−3.02*
Number of NoteWriter macros	0.24	0.19	0.14	0.07	0.02
Number of QuickFilters	0.48	0.36	0.22	0.06	−0.08
Number of SmartPhrases created	0.15*	0.15**	0.16***	0.16***	0.17**
Number of order bookmarks created	0.01	0.04	0.07**	0.11**	0.14**
Proportion of orders used from bookmarks without additional changes	11.70**	10.58***	9.27***	7.82**	6.50
Documentation length per appointment	0.002***	0.002***	0.002***	0.002***	0.002***
Proportion of visits closed same day	0.08	2.99	6.40***	10.14***	13.56***
Proportion of note written manually	6.04	7.22	8.60	10.12	11.51
Number of completed In Basket messages	0.76	0.86**	0.98***	1.11***	1.23**
Seconds spent per message	0.01	0.05	0.09***	0.13***	0.17***
In Basket turnaround	−0.002	0.01	0.03	0.05	0.07
Team-based care behaviors					
Proportion of note written by team members	−16.10*	−19.36***	−23.78***	−28.34***	−32.50***
Proportion of medications orders prepared by team members	−0.93	−0.95	−0.96	−0.98	−1.00
Proportion of non-medications orders prepared by team members	1.26	0.08	−1.29	−2.81*	−4.20**
Mobile device EHR behaviors					
Placed orders					
No	Ref	Ref	Ref	Ref	Ref
Yes	−3.83	−3.95	−4.10	−4.26	−4.41
Wrote notes					
No	Ref	Ref	Ref	Ref	Ref
Yes	0.89	0.87	0.84	0.81	0.78
In Basket management					
No	Ref	Ref	Ref	Ref	Ref
Yes	0.57	0.49	0.40	0.29	0.20
COVID-related effects					
Onset of COVID					
Pre	Ref	Ref	Ref	Ref	Ref
Post	−6.32***	−6.85***	−7.48***	−8.17***	−8.80***

EHR, electronic health records.

[a]Fixed effects on time and physician-level factors.

[b]Multicollinearity analysis revealed high correlations between some predictors. Consequently, percent of orders placed from bookmarks and level of service entered using speed buttons were removed from the model.

*$P < .05$, **$P < .01$, ***$P < .001$.

$P < .01$). Use of the Chart Search function, NoteSpeed buttons, NoteWriter macros, QuickFilters, order bookmarks, proportion of notes written manually, completed message volume, and In Basket turnaround had no association with time spent in the EHR outside scheduled clinic hours. Further details are reported in Table 3.

Time spent writing notes

After controlling for other factors, none of the studied proficiency behaviors were associated with less time spent writing notes per day. As the number of QuickActions available increased, greater time was spent writing notes per day (β: .40, $P < .05$). As the number of SmartPhrases created by the physician increased, greater time was spent writing notes per day at the 50th (β: .12, $P < .05$) and 75th quantiles (β: .14, $P < .05$). As the proportion of the note written manually increased, greater time was spent writing notes per day at the 25th (β: 13.98, $P < .05$), 50th (β: 16.91, $P < .01$), 75th (β: 2.31, $P < .01$), and 90th quantiles (β: 23.52, $P < .05$). Chart Search, NoteSpeed buttons, NoteWriter macros, QuickFilters, and order bookmarks had no association with time spent writing notes. Further details are reported in Table 4.

As the proportion of the note written by other team members increased, less time was spent writing notes per day at the 10th (β: -19.10, $P < .01$), 25th (β: -21.90, $P < .001$), 50th (β: -25.40, $P < .001$), 75th (β: -29.46, $P < .001$), and 90th quantiles (β: -33.30, $P < .001$) (Table 4).

Time spent in In Basket

After controlling for other factors, no proficiency behavior was associated with time spent in the In Basket per day (Supplementary Table S2).

DISCUSSION

This cross-sectional study assessed the association between EHR proficiency tools and efficiency behaviors and time spent in the EHR among PCPs at one academic health system. To our knowledge, this is the first study to report on individual EHR proficiency behaviors, as opposed to vendor-derived EHR proficiency composite scores. Overall, we found a nuanced association between EHR proficiency measures and time spent in the EHR. Certain individual EHR proficiency behaviors were associated with time spent in the EHR (Figure 1).

Our study builds on a 2020 study that found EHR vendor-derived proficiency composite scores were not associated with time spent interacting with the EHR during after-hours.[37] Although we found many EHR proficiency behaviors were not associated with time spent in the EHR outside scheduled hours, we found several that showed a surprising positive association (eg, QuickActions, SmartPhrases). Across 14 EHR proficiency and efficiency behaviors that we studied, only one (NoteSpeed buttons) was associated with reduced time spent interacting with the EHR. These findings may, in part, suggest issues in feature design or use. Furthermore, the findings could indicate that PCPs who spent more time in the EHR may be more likely to use these EHR features as well as create longer notes. Indeed, prior studies found the use of documentation tools (eg, structured templates) were associated with longer notes.[58–61] Alternatively, the findings may suggest that such features may only be truly useful for limited types of clinical encounters. The present results also highlight the need for future qualitative research on the reasons for use or non-use of documentation support tools, as different interventions may be required based on the predominant reasons discovered (eg, lack of awareness vs. lack of utility). These studies could also identify types of clinical encounters when certain tools may be more useful. Examining between-physician and within-physician variability in use of the tools may also elucidate their association with other EHR-related behaviors.

We found that PCPs who had greater support from their care team in writing notes (eg, scribes) spent less total time interacting with the EHR per day and less time in documentation-specific activities per day. These findings suggest that PCPs may experience reductions in EHR-related burden and documentation burden by decentralizing documentation responsibilities. These findings were consistent with other studies' findings.[49–51] Healthcare organizations could implement various team-based documentation models by utilizing nursing staff,[62,63] medical assistants,[58,63,64] medical students,[65–67] third-party scribing companies,[64,66] or internally developed scribing programs to assist with this role.[63,68] However, it is unclear which group will yield the most benefit. For instance, scribes have high turnover (1–2 years) but require at least 6 months of training to maximize productivity.[64] Meanwhile, there are mixed perceptions regarding the delegation of clerical tasks to nursing staff.[62,69] With the federal 2019 Patients Over Paperwork elimination of requirements to re-document trainees' notes,[70] researchers have found promising results from incorporating clinical documentation training and responsibilities into medical students' clerkships.[65,67] Although the care team can offload some documentation burden from physicians, healthcare organizations could amplify these benefits by enabling patients to assist in documentation tasks. For instance, offering patients structured pre-visit questionnaires through the patient portal may allow for the PCP to obtain history information that may integrate with the EHR's existing tools to auto-populate in the note. In general pediatrics, the Bright Futures questionnaire is used to assess developmental milestones and to screen for at-risk behaviors, such as tobacco use.[71] Healthcare organizations that convert these paper screening tools into electronic forms in the patient portals may enable PCPs to immediately import information directly into the note using the existing integration between patient portals and EHRs. However, additional research should assess the feasibility of implementing pre-visit questionnaires and its impact on physicians' documentation burden.

Another key finding was that PCPs who manually wrote a greater proportion of their notes spent more time in the EHR writing notes per day. Consequently, interventions targeting this specific efficiency behavior may reduce documentation burden. In our sample, use of some documentation-related proficiency tools (eg, use of macros) were recorded for less than half of studied physicians. Together, these findings suggest targeted approaches for training initiatives to improve EHR proficiency. Indeed, researchers have highlighted the need for both initial and ongoing training on EHR workflows and proficiency tools, especially as EHR interfaces are continually updated.[35,72–74] Clinicians may benefit from practicing new EHR skills in a training environment as scenario-based training and simulations have been shown to improve educational outcomes with EHR use.[75–77] Furthermore, if EHR features are impacted by EHR updates, healthcare organizations could consider re-training or dissemination of impacts to features (eg, icon moved to new location) to sustain feature use. Lastly, ease of set-up and use may influence physicians' adoption of features. For instance, voice dictation may require considerable time for set-up.[78] With physicians reporting limited time for documentation,[79,80] EHR features that are perceived as cumbersome to set up may lead to lower adoption rates. Future research assessing the use of EHR features should measure perceived ease of set-up and use.

Table 3. Adjusted beta coefficient estimates of factors associated with total after-hours EHR use (in minutes/day) ($n = 390$)[a,b]

Variables	10th quantile	25th quantile	50th quantile	75th quantile	90th quantile
Patient load					
Proportion of new patient visits	−11.18	−10.81	−10.34	−9.77	−9.23
Number of appointments in a day	0.03	0.04	0.06	0.08	0.10
Proportion of week with scheduled appointments	29.64***	20.45***	8.47**	−5.73	−19.14**
Patient complexity					
Patient age	0.07	0.05	0.01	−0.03	−0.08
Number of problems on problem list	0.05	0.11	0.19	0.29	0.38
EHR proficiency and efficiency behaviors					
Chart search feature used					
No	Ref	Ref	Ref	Ref	Ref
Yes	1.89	1.85	1.79	1.72	1.65
Number of QuickActions	0.44	0.48**	0.54***	0.60**	0.66*
Number of NoteSpeed buttons	−1.20	−1.10	−0.97	−0.82	−0.68
Number of NoteWriter macros	0.11	0.09	0.05	0.02	−0.02
Number of QuickFilters	0.13	0.43	0.83	1.29	1.74
Number of SmartPhrases created	0.08	0.08*	0.08**	0.08	0.08
Number of order bookmarks created	−0.02	−0.02	−0.02	−0.02	−0.02
Proportion of orders used from bookmarks without additional changes	5.97	4.87	3.44	1.74	0.13
Documentation length per appointment	0.001***	0.001***	0.001***	0.002***	0.002***
Proportion of visits closed same day	7.03*	7.91***	9.06***	10.43***	11.72**
Proportion of note written manually	1.21	3.91	7.42	11.58	15.51
Number of completed In Basket messages	0.01	0.03	0.06	0.09	0.12
Seconds spent per message	0.01	0.02	0.04*	0.06*	0.08
In Basket turnaround	0.04	0.03	0.01	−0.003	−0.02
Team-based care behaviors					
Proportion of note written by team members	−4.35	−3.57	−2.55	−1.34	−0.21
Proportion of medications orders prepared by team members	−1.03	−0.62	−0.08	0.55	1.15
Proportion of non-medications orders prepared by team members	3.81*	3.36*	2.77**	2.07	1.41
Mobile device EHR behaviors					
Placed orders					
No	Ref	Ref	Ref	Ref	Ref
Yes	2.30	−0.02	−3.05	−6.63	−10.02
Wrote notes					
No	Ref	Ref	Ref	Ref	Ref
Yes	1.54	0.84	−0.06	−1.14	−2.16
In Basket management					
No	Ref	Ref	Ref	Ref	Ref
Yes	−2.12	−2.35*	−2.65**	−3.01*	−3.34
COVID-related effects					
Onset of COVID					
Pre	Ref	Ref	Ref	Ref	Ref
Post	−0.50	−1.35	−2.47***	−3.79***	−5.04**

EHR, electronic health record.

[a]Fixed effects on time and physician-level factors.

[b]Multicollinearity analysis revealed high correlations between some predictors. Consequently, percent of orders placed from bookmarks and level of service entered using speed buttons were removed from the model.

*$P < .05$, **$P < .01$, ***$P < 0.001$.

Table 4. Adjusted beta coefficient estimates of factors associated with time spent documenting (in minutes/day, $n = 432$)[a,b]

Variables	10th quantile	25th quantile	50th quantile	75th quantile	90th quantile
Patient load					
Proportion of new patient visits	1.40	1.49	1.60	1.73	1.85
Number of appointments in a day	0.14	0.26	0.41**	0.58**	0.75*
Proportion of week with scheduled appointments	64.78***	60.07***	54.18***	47.34***	40.88***
Patient complexity					
Patient age	0.03	0.02	0.004	−0.01	−0.03
Number of problems on problem list	−0.07	−0.06	−0.03	−0.01	0.02
EHR proficiency and efficiency behaviors					
Chart search feature used					
No	Ref	Ref	Ref	Ref	Ref
Yes	0.13	0.33	0.59	0.88	1.16
Number of QuickActions	0.28	0.33	0.40*	0.49	0.56
Number of NoteSpeed buttons	−1.02	−1.09	−1.18	−1.28	−1.38
Number of NoteWriter macros	0.18	0.16	0.15	0.13	0.12
Number of QuickFilters	0.68	0.67	0.65	0.62	0.60
Number of SmartPhrases created	0.09	0.10	0.12*	0.14*	0.16
Number of order bookmarks created	0.01	0.02	0.04	0.06	0.07
Proportion of orders used from bookmarks without additional changes	6.51	5.41	4.04	2.46	0.96
Documentation length per appointment	0.001	0.001***	0.001***	0.002***	0.002**
Proportion of visits closed same day	1.39	2.43	3.73	5.25*	6.67
Proportion of note written manually	11.64	13.98*	16.91**	20.31**	23.52*
Team-based care behaviors					
Proportion of note written by team members	−19.10**	−21.90***	−25.40***	−29.46***	−33.30***
Proportion of medications orders prepared by team members	0.23	0.10	−0.06	−0.25	−0.42
Proportion of non-medications orders prepared by team members	0.62	0.36	0.03	−0.34	−0.70
Mobile device EHR behaviors					
Placed orders					
No	Ref	Ref	Ref	Ref	Ref
Yes	−0.76	−0.98	−1.27	−1.60	−0.42
Wrote notes					
No	Ref	Ref	Ref	Ref	Ref
Yes	0.37	0.40	0.44	0.49	0.54
COVID-related effects					
Onset of COVID					
Pre	Ref	Ref	Ref	Ref	Ref
Post	−3.79*	−4.40***	−5.17***	−6.05***	−6.89***

[a]Fixed effects on time and physician-level factors.

[b]Multicollinearity analysis revealed high correlations between some predictors. Consequently, percent of orders placed from bookmarks and level of service entered using speed buttons were removed from the model.

*$P < .05$, **$P < .01$, ***$P < .001$.

Furthermore, our In Basket model revealed no association across many predictors, suggesting the proficiency tools, as designed or implemented, may not be as helpful during inbox management. This finding may also suggest that interventions outside of EHR proficiency tools may be more beneficial. Notably, the data source contained no variables to capture the use of team-based models in the In Basket (eg, shared inbox among team members, active triage by support staff). Further research should assess for other unmeasured proficiency behaviors, such as message batching,[81] and examine the impact of team-based models on time spent managing messages. Other informatics-based interventions may include the use of machine learning to flag certain messages for review based on analysis of message content.[82]

Notable limitations are as follows: first, this was a single-center study, which may limit generalizability to nonacademic organizations and those using other EHR products. Physicians in our sample had less clinical load due to concurrent teaching, research, or administrative responsibilities, which may influence their extent of interactions with the EHR. Second, we were precluded from assessing time

Activity Theme	EHR Proficiency Tools and EHR Efficiency Behaviors	Total Time	Outside Scheduled Hours	Writing Notes	In Basket
General	QuickActions	+	+	+	=
	NoteSpeed buttons	−	=	=	=
	NoteWriter macros	=	=	=	=
	SmartPhrases	+	+	+	=
	Bookmarking orders	+	=	=	=
	Using bookmarked orders without making further changes	+	=	=	=
Writing Notes	Documentation length	+	+	+	Not applicable
	Signing visits on same day	+	+	=	Not applicable
	Writing notes manually	=	=	+	Not applicable
In Basket	Volume of completed messages	+	=	Not applicable	=
	Seconds per message	+	+	Not applicable	=
	Message turnaround time	=	=	Not applicable	=
Chart Review	Chart Search	+	=	=	Not applicable
	QuickFilters	=	=	=	=

Figure 1. Summary of predictors' association with time spent throughout the electronic health records system at the 50th quantile. Plus signs represent a positive association. Minus signs represent a negative association. Equal signs represent a null association.

spent in more granular units due to how EHR measures were reported by the vendor. Third, we were unable to control for practice-level differences, as some physicians practiced in multiple clinics. Fourth, we were unable to obtain information on how many scheduled appointments were canceled or whether the problem list length is calculated before or after the appointment. Future studies should use additional datasets to explore how these nuances may affect time spent in the EHR. Other variables that may affect EHR use patterns, but were not reported by our data source, include medication list length and whether visits were for wellness checks, follow-up of chronic care, or for a sick visit. Additional research should examine EHR proficiency tool use and time spent in the EHR for specific visit types. Lastly, the use of EHR logs and derived measures may underestimate EHR and documentation burden among clinicians because the measures may not capture care activities done outside the EHR (eg, patient emails to institutional email accounts).[15]

CONCLUSION

Among PCPs, mixed associations were found between certain EHR proficiency behaviors and the relative amount of time spent interacting with the EHR, suggesting targets for future training. Additionally, support from other members of the care team was an important determinant of PCPs' time spent in the EHR. Future research is needed to elucidate reasons for non-use of specific documentation support tools and test team-based models for their impact on EHR-related burden.

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AUTHOR CONTRIBUTIONS

This work represents the original research of the authors. This work has not been previously published. OTN, KT, NCA, LJM, and SSF conceptualized the study. OTN analyzed the data. All authors interpreted the data. OTN drafted the manuscript. All authors provided critical revisions to the manuscript and approved the submission.

SUPPLEMENTARY MATERIAL

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

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CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY

The data underlying this article will be shared on reasonable request to the corresponding author.

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