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Research and Applications

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Does autotext usage decrease documentation time among resident physicians? A retrospective analysis of electronic health record usage data

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Abstract

Objective: Usage of autotext or "dotphrases" is ubiquitous among provider workflows in electronic health records (EHRs). Yet, little is known about the impact of these tools in inpatient settings and among resident physicians. We aimed to evaluate the association between autotext usage and documentation time among resident physicians in an academic medical center using the Cerner EHR.

Materials and Methods: The association between autotext executions and documentation time per patient seen for 705 resident physicians rotating at a large academic medical center from July 2021 to June 2023 was analyzed via linear regression after controlling for specialty, post-graduate year (PGY), provider gender and patient volume.

Results: There was no significant overall association between autotext executions per patient seen and documentation time per patient seen in specialties using Dynamic Documentation as their primary workflow ($\beta = -0.1$ min per autotext execution per patient seen, 95% CI −0.6 to 0.5 min, $P = .79$). However, there was increased documentation time among residents with no autotext usage compared to residents who used autotext, and this effect was mediated by use of personalized autotexts. Specialty, PGY, gender and patient volume were significant determinants of documentation time.

Discussion: Efforts to decrease documentation time among resident physicians should encourage autotext adoption but should not be focused on promotion of autotext usage alone. Further research should address the questions of identifying other determinants of documentation time, autotext design standards, and how autotext usage affects measures of note quality.

Conclusion: Autotext adoption decreases documentation time among resident physicians, but among those who adopt autotext, higher levels of usage show no benefit.

Lay Summary

Physicians and other health care providers spend a significant portion of their working day entering documentation into the electronic health record, and the burden of completing documentation is a major cause of burnout. Providers often make use of tools known as "autotexts" to insert blocks of prepared text into their documentation; autotexts may be either pre-made as part of the system or personalized and customizable. While the intent of autotexts is to allow for faster documentation, there is minimal research available on whether they actually do improve the speed at which documentation is completed, especially in the specific case of resident physicians (physicians who have not yet completed their training). This article studied resident physicians at a single health system. The results showed that while residents who did not use any autotexts at all took longer to document than those who used customizable, personal autotexts, among residents who did use autotexts higher levels of use did not result in statistically meaningful improvements in time spent documenting. These findings suggest that, while customizable, personal autotexts in particular are helpful at low levels of usage, autotexts have rapidly diminishing returns with higher levels of usage and other strategies should also be pursued to reduce documentation burden for resident physicians.

Key words: clinical informatics; medical residency; electronic health record; documentation; occupational burnout.

Background and significance

Electronic health record (EHR) use is a major component of the workload for physicians and other healthcare providers, with one study finding family physicians spending 5.9 h during clinic hours and 1.4 h of after-hours time per day on EHR tasks[1] and a systematic review showing that EHR

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implementation increased overall burden of documentation time for attending physicians, nurses, and interns.[2] A large body of evidence links the burden of EHR workload to rising rates of physician burnout, decreased performance metrics, and decreased communication with patients.[3–5]

Many commercially available EHRs incorporate a tool variously referred to as "AutoText" (in the Cerner EHR), "SmartPhrases" (in the Epic EHR) or "dotphrases" in which standard blocks of text can be selected, entered into documentation, and edited to expedite workflow. This functionality will henceforth be referred to as "autotext." Past studies have implemented autotexts for a myriad of research and quality improvement applications.[6–20] A normalized metric of documentation time has been proposed as one of seven core measures of EHR use to assess practice efficiency.[21] Cerner specifically describes the goal of autotext as faster, more efficient documentation,[22] but EHR tools may fail to accomplish the purposes for which they were designed.[23] Research in the ambulatory setting focused on attending physicians has addressed the impact of autotext usage on documentation time as compared to other note composition modalities[24] and found that the relationship follows a nonlinear and relatively flat curve.[25] Resident physicians in inpatient settings, given differences in workflow and level of experience, may show a distinct relationship between autotext usage and documentation time that deserves further exploration in light of their importance to the clinical workforce and risk of burnout.[26,27]

Beyond these studies, there is a dearth of research examining whether and how autotext usage impacts documentation time in real-world settings. A PubMed search for the terms "autotext," "dotphrase," or "smartphrase" reveals only a single study related to autotext usage that specifically addresses impact on documentation efficiency.[28] Although it includes residents, this study is limited to an emergency room setting using the Epic EHR, and uses time to final signature of documentation rather than time in documentation workflows as an endpoint, finding no correlation with autotext usage. Further research is needed covering a wider range of settings and EHRs, and with special attention to resident physicians.

Objectives

The purpose of our study was to determine if increased autotext usage leads to progressively decreasing documentation time among resident physicians working primarily in inpatient settings, a question that appears to have gone unaddressed in prior research. As secondary goals we sought to evaluate the impact of system vs personal autotext adoption as well as patient volume, PGY, medical specialty and gender as determinants of documentation time and total EHR time.

Materials and methods

Setting

All data were collected from Cerner Millennium (Cerner Corporation, Kansas City, MO) workflows at a large academic medical center located in a midsize metropolitan area. Sites include an urban hospital offering full range cardiovascular services, a freestanding urban children's hospital, a suburban center with surgical and obstetrical services, and a small primary care footprint. Cerner is the major EHR. Depending on training program, residents also rotate at other health systems throughout the region utilizing non-Cerner EHRs for which data was not included. Residents do not have access to scribes. The study protocol was approved by the University at Buffalo IRB (protocol #STUDY00007121).

Data sources

The primary sources of the data used in the study were the Cerner Lights On Network and Cerner Advance, integrated EHR efficiency toolkits used in previous studies to evaluate documentation time and other EHR measures.[29–32] Gender, specialty, and PGY were determined from a separate list compiled through a provider credentialing system.

Participants/inclusion criteria

Monthly data regarding total autotext executions, patients seen, note count by type, documentation time, and total EHR time from the two academic years July 2021-June 2022 and July 2022-June 2023 were downloaded. It was not possible to assess time outside of scheduled hours or "after hours" work from the available data given the inconsistency of inpatient schedules. Residents in combined medicine-pediatrics were excluded due to ambiguous specialty classification. All other resident physicians with at least one patient seen during the study period were included. The data was examined for outliers, upon which a single data point with one patient seen and 14 autotext executions was identified, felt to be clearly attributable to experimentation with the utility, and excluded from all figures and analyses. For radiation oncology residents, while data was included in all analyses, specialty-specific results (coefficients, summary statistics) are not reported in order to preserve confidentiality given low sample size ($N=2$).

Metrics

Autotexts may be pre-built by the vendor or institution and available to all users ("system" autotexts) or created and maintained by users for personal use ("personal" autotexts). One "patient seen" is defined per Cerner convention as a calendar day for a given patient with at least one note signed by the provider under consideration. Thus, two notes on the same patient on the same day count as one patient seen; two notes on the same patient on consecutive days count as two patients seen.

Residents were defined as autotext non-adopters if they had no autotext usage, whether system or personal, over the course of the academic year being studied. Data on total number of system vs personal autotext executions by provider were not available. However, the variety of system vs personal autotexts in use were reported on a monthly basis, allowing residents to be classified as adopters or nonadopters of system and personal autotext.

Patient volume (defined as total patients seen over the course of the academic year), autotext executions per patient seen, total EHR time per patient seen, and documentation time per patient seen over the course of each academic year were calculated. Data was aggregated by academic year to control for variability due to rotation on different services by month; the unit of analysis is a single "resident-year," with some individual residents thus contributing two resident-years to the data due to their presence in both academic years.

Analysis

Unadjusted variation in variables of interest by specialty and PGY and for autotext adopters vs nonadopters was assessed for statistical significance by chi squared test, Kruskal-Wallis or Wilcoxon rank sum test, including all residents. For these tests, residents with data in both academic years were given a random, fixed assignment to drop data from one academic year in order to account for non-independent observations. Predictors of documentation time per patient seen and total EHR time per patient seen were studied by linear regression with robust errors clustered at the resident level. Comparisons were two-sided with α set to 0.05. All analyses were conducted using STATA 17.0 (College Station, Texas, United States).[33]

During the study period, anesthesiology and emergency medicine encounters were documented using a Cerner functionality called Powernote, whereas residents in other specialties primarily utilized Dynamic Documentation except when rotating in an emergency medicine setting. While autotext is supported in Powernote, it is not well-suited to Powernote's highly templated format, and users frequently make use of an alternative tool with similar function ("macros") for which data was not available. We include anesthesiology and emergency medicine in summary statistics and figures to support general insights into documentation burden and autotext use; however, to focus our analysis on users with primary workflows appropriate to our research question, we present all regressions and results of statistical tests after excluding these specialties.

Cerner Advance reports a monthly total time in EHR metric that takes the total time in all EHR workflows for all patients, regardless of whether a note is authored on that patient, and divides it by the number of patients seen, which is calculated solely on the basis of note authorship as described above. This procedure may significantly decrease the validity of calculated total EHR time per patient seen when applied to senior residents in a supervisory role, as these residents may spend considerable EHR time on chart review, order entry, etc for their patients while delegating most documentation tasks to junior residents. Consistent with this phenomenon, review of the data for outliers showed that the 37 residents with the highest total EHR time per patient seen (>120 min) were all internal medicine residents in their PGY-2 or PGY-3 year. Given the sensitivity of linear regression to outliers, considerable bias would be introduced by including these residents in regressions studying total EHR time per patient seen. To mitigate this concern, for regressions including total EHR time, resident-years with greater than 120 min of total EHR time per patient seen were assumed to represent data primarily from residents in supervisory roles and excluded. As a sensitivity analysis these regressions were repeated with the cutoff adjusted to 60 min.

Results

Data were available for 705 residents (42% female) across 18 specialties over the two years, with 327 residents present across both academic years, for a total of 1032 "resident-years" of data. This was decreased to 578 residents with 842 resident-years of data after excluding anesthesiology and emergency medicine residents. Summary statistics by specialty and PGY are presented in Table 1. Figure 1 presents distribution of residents by specialty graphically, while Figure 2 depicts the variation in autotext usage and documentation time among different specialties. There were 681 308 patients seen. Mean documentation time across the entire sample was 13.2 min (standard deviation 8.2 min) and mean autotext usage was 0.86 executions per patient seen (standard deviation 0.79).

The remainder of this results section excludes specialties that primarily use Powernote, namely anesthesiology and emergency medicine. With these residents removed, 17% of encounters were in ambulatory settings, and 5% of notes were Powernotes. In unadjusted comparisons, autotext executions per patient seen, documentation time per patient seen, and percentage autotext nonadopters varied significantly by specialty ($P < .001$) (Table 1); documentation time per patient seen varied significantly by PGY year ($P < .001$), whereas percentage nonadopters and autotext executions per patient seen did not ($P = .61$ and $P = .19$, respectively). By linear regression, autotext executions per patient seen was not significantly associated with patient volume, PGY, or gender after controlling for specialty. Autotext nonadopters comprised a group of 164 resident-years. In unadjusted comparisons, autotext nonadopters did not differ significantly from adopters with respect to documentation time per patient seen (median 12.3 vs 13.4 min, respectively, $P = .16$) but did differ with respect to patient volume (median 22 vs 528 patients, respectively, $P < .001$). For residents with data present in both academic years, both autotext executions per patient seen and documentation time per patient seen were highly correlated across the 2 years (R^2 0.80 and 0.73, respectively, $P < .001$).

After controlling for specialty, higher PGY and larger patient volume were strongly associated with a decrease in documentation time per patient seen while female gender was associated with an increase ($\beta = 1.7$ min, 95% CI 0.8 to 2.7 min, $P < .001$), however the effect of autotext executions per patient seen was not significant ($\beta = -0.1$ min per autotext execution per patient seen, 95% CI −0.6 to 0.5 min, $P = .79$) (Table 2, panel A). Results of the overall regression were similar when the sample was restricted to autotext adopters (Table 2, panel B) or to residents with PGY = 1 and PGY >1 (not shown) or expanded to include residents in anesthesia and emergency medicine (not shown). Specialty was a significant predictor (Table 2, panel A). Regressions stratified by specialty showed similar results.

There was significantly decreased documentation time per patient seen for autotext adopters vs nonadopters in the adjusted analysis ($\beta = -2.3$ min, 95 CI −4.2 min to −0.4 min, $P = .02$) (Table 3, panel A). When simultaneously controlling for system and personal autotext adoption, personal autotext adoption significantly reduced documentation time per patient seen ($\beta = -2.2$ min, 95% CI −3.7 min to −0.8 min, $P = .002$) while system autotext adoption had no significant association (Table 3, panel B).

Sensitivity analyses were performed for the results in Tables 2 and 3 and showed similar results as reported in Appendix Tables S1-S3.

Similar regressions to those in Tables 2 and 3 were performed to evaluate the effect of autotext executions per patient seen as well as autotext adoption status on total EHR time measured in minutes per patient seen (Appendix Tables S4 and S5). The results demonstrate no association with autotext executions per patient seen or PGY, while patient volume, gender, and specialty demonstrated similar relationships to total EHR time per patient seen as to documentation time per patient seen.

Table 1. Summary statistics by specialty and PGY.[a]

Department	N	Documentation time per patient seen (min): mean (standard deviation)	Total EHR time per patient seen (min): mean (standard deviation)	Autotext executions per patient seen: mean (standard deviation)	Autotext nonadopters (percent)
Anesthesiology	94	6.5 (7.2)	15 (14.1)	0.14 (0.29)	51 (54)
Dental	18	6.2 (6.1)	11.1 (7.6)	0 (0)	18 (100)
Emergency Medicine	96	11.1 (4.0)	26.9 (6.1)	0.13 (0.20)	33 (34)
Family Medicine	100	16.7 (5.4)	39.0 (14.0)	0.69 (0.59)	13 (13)
Gynecology/Obstetrics	67	11.1 (2.8)	26.3 (8.3)	1.85 (0.86)	0 (0)
Internal Medicine	217	20.1 (7.1)	76.2 (45.0)	1.05 (0.63)	9 (4)
Neurology	40	22.3 (5.2)	42.3 (8.8)	1.69 (0.68)	0 (0)
Neurosurgery	37	5.6 (2.2)	17.5 (5.7)	1.44 (1.11)	0 (0)
Ophthalmology	17	9.3 (4.1)	16.1 (8.0)	0.62 (0.64)	4 (24)
Oral Maxillofacial Surgery	16	11.8 (3.4)	20.3 (4.9)	0.34 (0.45)	5 (31)
Orthopedics	50	4.1 (1.8)	12.7 (6.3)	0.55 (0.71)	11 (22)
Otolaryngology	18	4.7 (2.6)	13.2 (12.0)	1.01 (1.02)	1 (6)
Pediatrics	94	17.1 (4.5)	47.7 (14.3)	1.51 (0.55)	0 (0)
Psychiatry	27	22.8 (12.3)	40 (16.6)	0.26 (0.35)	12 (44)
Radiation Oncology	2	(omitted)	(omitted)	(omitted)	(omitted)
Radiology	9	11.7 (5.4)	22.3 (9.9)	0.39 (0.41)	3 (33)
Surgery	101	8.2 (2.2)	21.1 (6.4)	0.89 (0.41)	1 (1)
Urology	29	5.2 (1.3)	13.3 (3.5)	0.62 (0.47)	1 (3)
PGY					
PGY-1	315	16.0 (7.5)	34.3 (15.0)	0.88 (0.67)	23 (7)
PGY-2	282	14.0 (8.2)	44.1 (36.6)	0.95 (1.09)	41 (15)
PGY-3	265	12.3 (7.0)	44.7 (43.2)	0.81 (0.84)	67 (25)
PGY-4	116	9.3 (8.6)	22.9 (18.2)	0.79 (0.89)	28 (24)
PGY-5	43	5.4 (3.2)	16.0 (11.4)	0.88 (0.90)	4 (9)
PGY-6	5	5.8 (2.5)	20.5 (4.6)	1.51 (1.96)	1 (20)
PGY-7	7	6.5 (3.3)	20.2 (5.0)	0.71 (1.17)	0 (0)

[a] As noted, data for residents in radiation oncology are omitted to preserve confidentiality due to low sample size ($N = 2$).

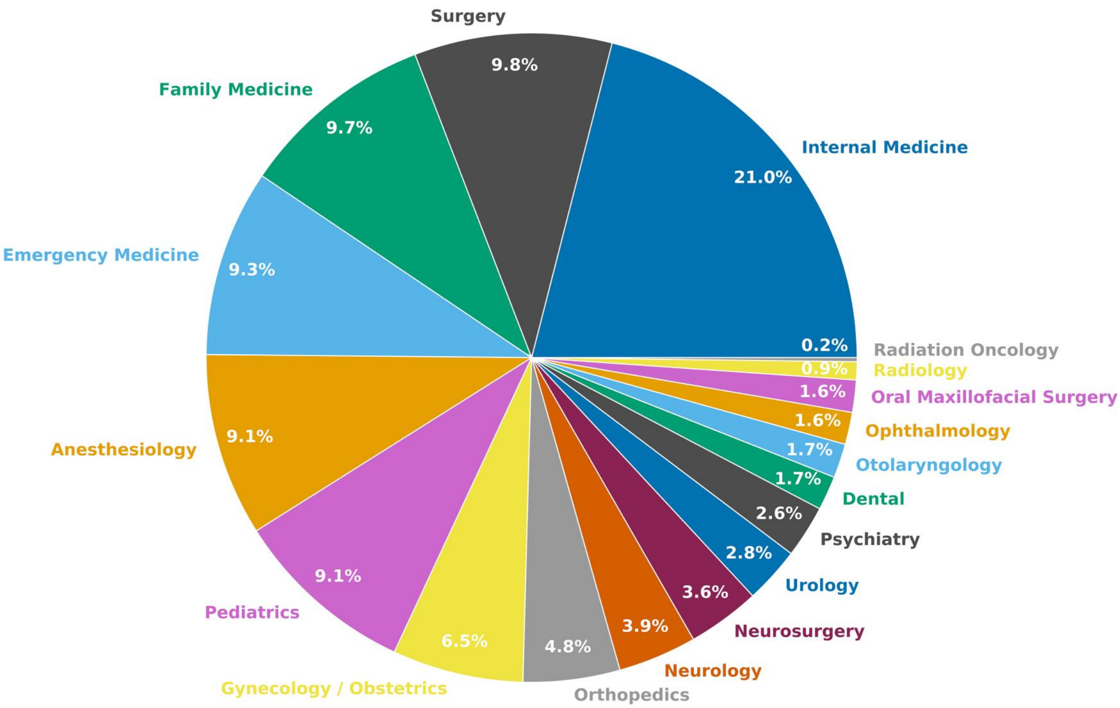

Figure 1. Distribution of resident-years by specialty.

To further explore the effect of autotext adoption and check for evidence of a nonlinear relationship between autotext usage and documentation time, we conducted another regression in which residents were stratified into five groups representing autotext nonadopters and adopters by quartile. The results are presented in Figure 3, showing similar

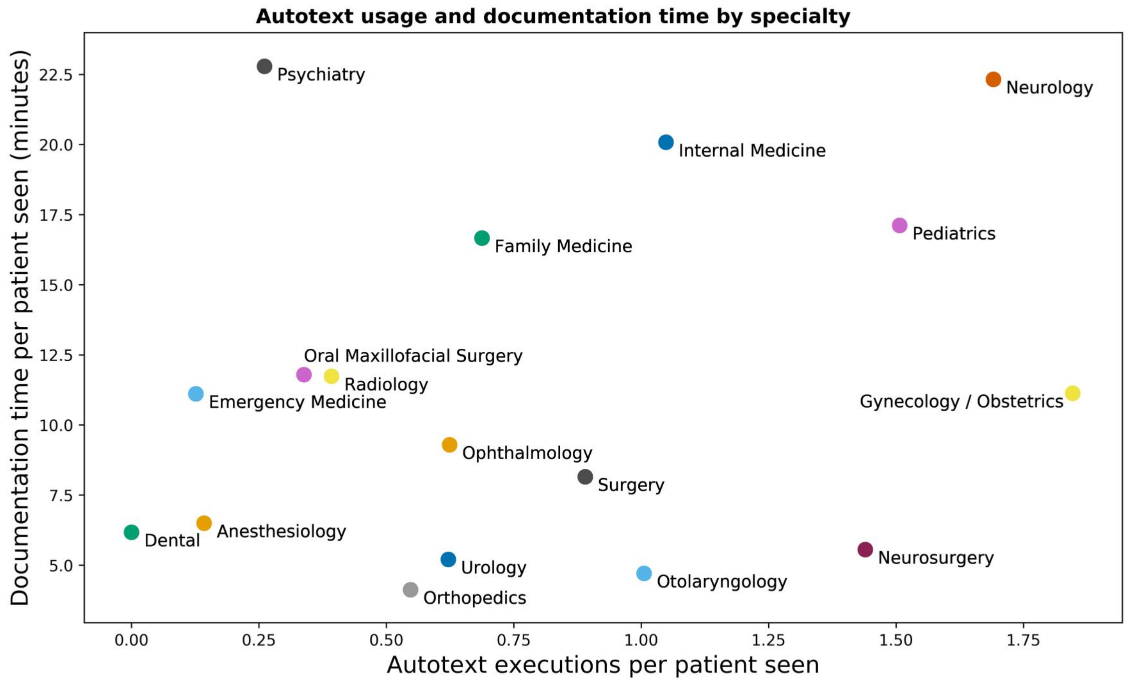

Figure 2. Scatterplot of autotext executions per patient seen and documentation time per patient seen. Data for residents in radiation oncology are omitted to preserve confidentiality due to low sample size ($N = 2$).

coefficients across the four quartiles, all with a significant decrease compared to nonadopters.

Discussion

Key results

We found that adopters of autotext have significantly decreased documentation time compared to nonadopters after controlling for other important variables, a relationship that holds across all four quartiles of autotext usage by adopters, and is mediated by adoption of personal autotext specifically. However, higher levels of autotext usage among adopters are not associated with any change in documentation time.

Autotext nonadopters appear to be a distinct population, and the significant difference in documentation time between adopters and nonadopters seems to be mediated by the adoption of personal (and not system) autotext in analyses adjusted for both specialty and the relatively low patient volume among nonadopters. That is, while higher levels of autotext usage do not appear to decrease documentation time, having at least a minimal usage of personal autotexts is related to consistent benefit. The apparently paradoxical result is mathematically possible because the relationship between autotext usage and documentation time is flat for autotext usage greater than zero (Figure 3). Our analysis cannot elucidate any particular mechanism, but we speculate that, instead of autotext, nonadopters may utilize strategies such as copy-paste and manual entry that have been shown to be relatively disadvantageous.[24,25] Customizable personal autotexts may be better suited for expediting each user's most burdensome stereotyped tasks.

The prior study most closely related to this one utilized a large national dataset of ambulatory encounters in the Epic EHR.[25] It found a relatively flat, nonlinear relationship between autotext usage and documentation time with a statistically significant but small (0.53 min) decrease in documentation time per patient seen associated with the top decile of autotext usage, as well as a similar decrease in the bottom decile compared to median, in contrast to our finding on increased documentation time for autotext nonadopters. We speculate that differing results at the lowest end of autotext usage may be related to the way alternative documentation strategies (eg, dictation, Epic's NoteWriter) integrate into the respective EHRs in lieu of autotext. Otherwise, the overall relationship appears consistent with the results of our study, which extends the result by showing strikingly similar findings in a very different population (limited to resident physicians), EHR (Cerner) and practice setting (predominantly inpatient as opposed to exclusively outpatient encounters).

The failure to find an association between higher levels of auto text usage and decreased documentation time, while consistent with past work,[24,25] is unexpected given the intended purpose of autotext in reducing time spent documenting. It is possible that by introducing a large body of text that requires extensive editing, autotext tends to negate the effect of fewer keystrokes to summon necessary text. This may involve introduction of extraneous text ("note bloat"). Documentation time per patient is not synonymous with efficiency—autotext users may appreciate efficiency gains unrelated to time burden, such as fewer keystrokes or the ability to create a longer, more "complete" note or one more closely matching their own preferences (especially with personal autotext use). Autotext content may act as a form of clinical decision support, prompting clinicians to consider new diagnostic or therapeutic avenues that require further elaboration in the final note. There was no relationship between level of autotext use or adoption and total EHR time, suggesting that the documentation time savings for autotext adopters are offset by more time in other workflows important for patient care, such as chart review.

Table 2. Predictors of documentation time per patient seen (min) among various subsamples.[a]

Panel A: Main sample (N = 842)[b]

Predictor	Coefficient (95% CI)	*P* value
Autotext executions per patient seen	−0.1 (−0.6, 0.5)	.79
PGY	−1.3 (−1.7, −0.9)	<.001
Patient volume	−0.0027 (−0.0036, −0.0018)	<.001
Gender, male as reference		
Female	1.7 (0.8, 2.7)	<.001
Department, Internal Medicine as reference		
Dental	−16.2 (−19.1, −13.3)	<.001
Family Medicine	−3.2 (−4.7, −1.6)	<.001
Gynecology/Obstetrics	−6.1 (−8.0, −4.1)	<.001
Neurology	3.2 (1.0, 5.4)	.004
Neurosurgery	−8.7 (−10.8, −6.6)	<.001
Ophthalmology	−9.8 (−11.9, −7.6)	<.001
Oral Maxillofacial Surgery	−8.3 (−10.3, −6.2)	<.001
Orthopedics	−13.9 (−15.2, −12.6)	<.001
Otolaryngology	−13.8 (−15.9, −11.8)	<.001
Pediatrics	−2.1 (−3.8, −0.5)	.013
Psychiatry	2.3 (−2.0, 6.7)	.319
Radiation Oncology	omitted	omitted
Radiology	−7.6 (−11.4, −3.8)	<.001
Surgery	−9.6 (−11.0, −8.3)	<.001
Urology	−10.8 (−12.5, −9.2)	<.001

Panel B: Excluding autotext nonadopters (N = 762)[c]

Predictor	Coefficient (95% CI)	*P* value
Autotext executions per patient seen	0.2 (−0.3, 0.7)	.31
PGY	−1.4 (−1.8, −1.1)	<.001
Patient volume	−0.0028 (−0.0038, −0.0019)	<.001
Gender, male as reference		
Female	1.7 (0.7, 2.6)	<.001
Controlling for specialty	Yes	

[a] As noted, coefficient for residents in radiation oncology is omitted to preserve confidentiality due to low sample size ($N = 2$). Panel A includes the main sample, with 578 residents and $N = 842$ resident-years encompassing the indicated specialties. Panel B additionally excludes all resident years with no autotext executions (autotext nonadopters.) Specialty coefficients omitted in Panel B for brevity.
[b] Adjusted $R^2 = 0.59$, $F(19, 577) = 108.4$, $P < .001$.
[c] Adjusted $R^2 = 0.63$, $F(17, 523) = 99.9$, $P < .001$.

Our study was powered to exclude a clinically significant improvement in documentation time with higher levels of autotext usage. The 95% confidence interval for the change in documentation time with execution of one additional autotext per patient seen for autotext adopters had a lower bound of −0.3 min, 2% of the mean documentation time per patient seen across the sample. Thus, even under the most optimistic scenario, there are likely to be more fruitful strategies for decreasing documentation time among users who have already adopted autotext.

There does appear to be a modest benefit from adoption of personal autotexts not seen with adoption of system autotexts; perhaps the greater customizability of personal autotexts makes them optimal for use in elements of documentation that are both highly repetitive and unique to each provider (physical exams, common counseling points) and for which autotext is most able to produce time savings. While training in autotext, including the creation of personal

Table 3. Regression results showing effect of autotext adoption on documentation time per patient seen (min) controlling for PGY, patient volume, gender and specialty.[a]

Panel A: Adoption vs nonadoption (N = 842)[b]

Predictor	Coefficient (95% CI)	*P* value
Autotext adoption	−2.3 (−4.2, −0.4)	.02
PGY	−1.4 (−1.7, −1.0)	<0.001
Patient volume	−0.0027 (−0.0036, −0.0018)	<0.001
Gender, male as reference		
Female gender	1.7 (0.8, 2.7)	<0.001
Controlling for specialty	Yes	

Panel B: Personal vs system adoption (N = 842)[c]

Predictor	Coefficient (95% CI)	*P* value
Personal autotext adoption	−2.2 (−3.7, −0.8)	.002
System autotext adoption	−0.9 (−2.1, 0.3)	.14
PGY	−1.3 (−1.8, −0.9)	<0.001
Patient volume	−0.0024 (−0.0033, −0.0015)	<0.001
Gender, male as reference		
Female gender	1.7 (0.8, 2.6)	<0.001
Controlling for specialty	Yes	

[a] The sample with represented specialties is the same as in Table 2, panel A; coefficients by specialty are again omitted for brevity. For panel A, adoption status of any autotext is represented by a dummy variable, with autotext nonadoption as reference compared to autotext adoption. Panel B shows a similar regression with separate dummy variables for personal and system autotext adoption. Personal autotext nonadoption is the reference compared to personal autotext adoption; system autotext nonadoption is the reference compared to system autotext adoption.
[b] Adjusted $R^2 = 0.60$, $F(19, 577) = 100.6$, $P < .001$.
[c] Adjusted $R^2 = 0.60$, $F(20, 577) = 97.9$, $P < .001$.

autotext, should be a basic component of EHR education so that users realize time savings from adoption, career-long coaching on other aspects of efficient EHR usage may have a greater impact.

Our study suggests that volume of autotext usage is not an important determinant of documentation time for most resident physicians, and that identifying other contributing factors will be crucial to decreasing documentation burden. We did show that, similar to findings in prior studies,[29,30,32,34–37] specialty and level of experience (measured by both PGY and patient volume) were major determinants of documentation time.

This study adds to the literature showing an increase in documentation time per patient seen and other measures of EHR burden associated with female gender.[32,38–40] This literature has tended to focus on ambulatory settings and at times specifically excluded resident physicians.[32] Further work is needed to understand the causes of this inequality at all levels of training, especially with female physicians at increased risk of burnout.[41]

Given the standardized educational curricula followed by residency programs, the mix of acuity, pathology, and encounter type across patients seen by two residents in the same specialty and PGY is expected to be broadly similar. Our study thus implicitly controls for these important but difficult-to-measure potential confounders. We chose to focus on resident physicians as a distinct population that forms the backbone of the inpatient provider workforce at many academic medical centers. In view of their typical workflow of writing complete notes as compared to cosigning previously opened notes, we believe this study does suggest the true

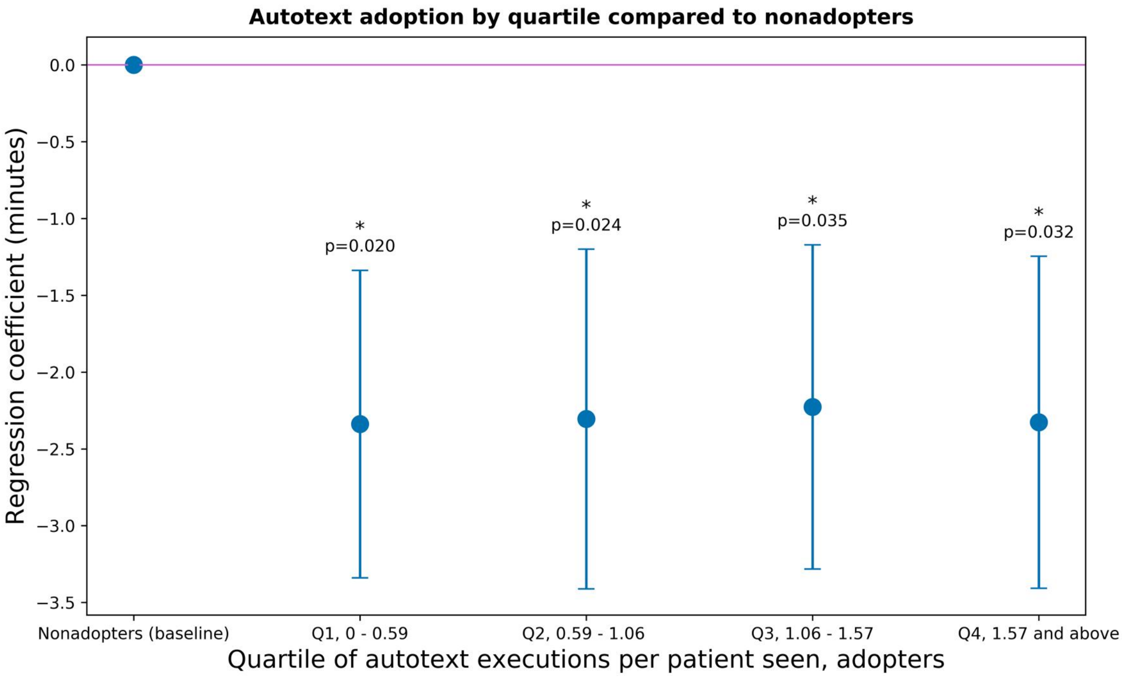

Figure 3. Effect on documentation time of autotext adoption by quartile among autotext adopters compared to autotext nonadopters, measured by regression coefficient in an OLS regression controlling for PGY, patient volume, gender, and specialty. The first group are autotext nonadopters (designated as baseline). The remaining four groups Q1-Q4 were created by calculating the 25th, 50th, and 75th percentiles of autotext usage among autotext adopters and dividing into quartiles accordingly (0.59, 1.06, and 1.57 autotext executions per patient seen, respectively). Dots mark coefficients of dummy variables representing membership in each group that were included in the regression. Bars represent standard errors. Excludes residents from anesthesiology and emergency medicine. * represents $P < .05$ compared to baseline (autotext nonadopters). Adjusted $R^2 = 0.59$, $F(22, 577) = 87.38$, $P < .001$.

impact of autotext usage on the construction of a complete summary of a clinical encounter, and thus may be generalized with caution to providers in non-academic settings.

Limitations

This was an observational study and cannot strictly be interpreted to imply causality, although we feel that appropriate variables that could lead to a confounding impact on documentation time were controlled for, allowing us to cautiously interpret the study as evidence for a lack of causal connection between high levels of autotext usage and reduced documentation time. Generalizability may be limited by this study's single-center design, despite the inclusion of multiple sites within the same health system. We do not address the impact of autotext usage on note length, accuracy, or level of billing, and we could not control for use of alternate composition strategies such as dictation. No reliable scheduling data were available to normalize times to 8 h of scheduled work as suggested in prior studies,[21,32] although documentation time per patient seen was also used in the closest antecedent to this study.[25]

Future research

Use of vendor-provided EHR audit logs[32,42–46] for studies such as this one is increasingly widespread in the informatics literature[47] and key to increasing the field's understanding of EHR usage and efficiency, thereby opening avenues to reduce burnout. Vendors should continue to develop more granular, standardized toolkits with a greater variety of measures.

As the examples cited before demonstrate,[6–20] decreasing documentation time is not the only possible goal of autotext. It remains a powerful tool to accomplish QI goals related to documentation improvement, data collection, and clinical decision support—the "what" rather than the "when" of documentation. These considerations must be balanced against the risk of autotext usage introducing "note bloat" or erroneous documentation. Recent work in the area of note templates has introduced modifications to increase the signal-to-noise ratio and address note bloat.[48–50] A similar philosophy should be applied to the implementation of autotext in the future.

We emphasize that our result regarding autotext impact on documentation time applies specifically to autotext as it is currently implemented at our institution. Improved implementation of autotext could involve coaching users on extensive customization of autotexts to fit their specific needs, or more thoughtful design and dissemination of system autotexts to allow for efficient use by clinical scenario. As this tool will likely continue to be used widely in the era of EHRs, future efforts should focus on developing standards of autotext design that will facilitate efficient composition of accurate, complete, and readable notes. To further this goal, studies of autotext-related interventions should include, where possible, balancing measures evaluating for impact on documentation time and/or note quality.

Conclusions

Documentation time was higher among autotext nonadopters as opposed to adopters, suggesting that a minimal level of autotext usage may be of benefit in facilitating efficient documentation in a relationship that appears to be mediated by the adoption of personal as opposed to system autotext. However, there is no association between higher levels of autotext usage and documentation time. PGY, patient volume, provider gender and specialty are significant influences on documentation time. Further research into autotext should focus on the development of design standards for autotext to increase efficiency as well as the impact of autotext on other measures of note quality.

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Author contributions

Noah Stanco (Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing—original draft, Writing—review & editing), Shmuel Tiosano (Formal analysis, Investigation, Methodology, Writing—review & editing), Randeep Badwal (Data curation, Formal analysis, Investigation, Methodology), William Kelly (Data curation, Formal analysis, Investigation, Methodology), and Michele R. Lauria (Conceptualization, Formal analysis, Investigation, Supervision, Writing—review & editing)

Supplementary material

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Conflicts of interest

The authors have no competing interests to disclose.

Data availability

The data in this study cannot be shared publicly due to risk of identifying subjects who constitute a vulnerable population and may be known personally to members of the research community (physicians in training). Analysis code and a short synthetic dataset illustrating the structure of the data used in this study are available from the Dryad Digital Repository at http://dx.doi.org/10.5061/dryad.xksn02vt5.

References

1. Arndt BG, Beasley JW, Watkinson MD, et al. Tethered to the EHR: primary care physician workload assessment using EHR event log data and time-motion observations. *Ann Fam Med*. 2017;15:419-426. https://doi.org/10.1370/afm.2121
2. Baumann LA, Baker J, Elshaug AG. The impact of electronic health record systems on clinical documentation times: a systematic review. *Health Policy*. 2018;122:827-836. https://doi.org/10.1016/j.healthpol.2018.05.014
3. Tran B, Lenhart A, Ross R, et al. Burnout and EHR use among academic primary care physicians with varied clinical workloads. *AMIA Jt Summits Transl Sci Proc*. 2019;2019:136-144.
4. Sinsky C, Colligan L, Li L, et al. Allocation of physician time in ambulatory practice: a time and motion study in 4 specialties. *Ann Intern Med*. 2016;165:753-760.
5. Muhiyaddin R, Elfadl A, Mohamed E, et al. Electronic health records and physician burnout: a scoping review. *Stud Health Technol Inform*. 2022;289:481-484. https://doi.org/10.3233/shti210962
6. Joseph A, Delicce M, Niu J, et al. S1330 reduce the risk of gastrointestinal bleeding by increasing the appropriate use of aspirin for primary prophylaxis—a primary care quality improvement project. *Am J Gastroenterol*. 2021;116:S613.https://doi.org/10.14309/01.ajg.0000778852.97568.95
7. Deeds S, Carr S, Garrison M, et al. Delivery of standardized patient instructions in the after-visit summary reduces telephone calls between clinic visits. *Am J Med Qual*. 2018;33:642-648. https://doi.org/10.1177/1062860618770043
8. Alencar MC, Thomassen A, Shah S, et al. Implementation of a flowsheet in an electronic medical record (EMR) to standardize chimeric antigen receptor T-cell (CAR T-cell) toxicity reporting. *Biol Blood Marrow Transplant*. 2019;25:S98-S99.
9. Farley T, Hickson R. 808: implementing a checklist to improve transition to end-of-life care. *Crit Care Med*. 2020;48:384. https://doi.org/10.1097/01.ccm.0000631372.67935.32
10. Perez A. Using smart phrases in an electronic medical record to document the plan of care and decision making process during time sensitive acute ischemic stroke patient interventions. *Stroke* 2014;45:AWP293.
11. Kaushal T, Lord K, Olsen R, et al. Improving disposition decision-making for pediatric diabetic ketoacidosis: a quality improvement study. *Pediatr Qual Saf*. 2020;5:e260. https://doi.org/10.1097/pq9.0000000000000260
12. Villacis-Nunez DS, Orenstein E, Selvaggio P, et al. Improving hepatitis B screening prior to rituximab: a quality improvement project. *Children (Basel)*. 2023;10:1142-1251. https://doi.org/10.3390/children10071142
13. Cabo J, Graham K, Chen H, et al. Increasing utilization of the TWIST score in workup of patients with acute scrotal pain: role in diagnosis and risk stratification. *J Pediatr Urol*. 2022;18:845.e1-845.e8. https://doi.org/10.1016/j.jpurol.2022.09.018
14. Garg T, Lee JY, Evans KH, et al. Development and evaluation of an electronic health record-based best-practice discharge checklist for hospital patients. *Jt Comm J Qual Patient Saf*. 2015;41:126-131. https://doi.org/10.1016/s1553-7250(15)41017-7
15. Lamsal R, Johnson JK, Mulla M, et al. Improving communication by standardizing pediatric rapid response team documentation. *J Healthc Qual*. 2022;44:e1-e6. https://doi.org/10.1097/jhq.0000000000000334
16. Kieffer H, Carlton K, Adams S, et al. Quality improvement sustainability to decrease utilization drift for therapeutic hypothermia in the NICU. *J Perinat Med*. 2023;51:956-961. https://doi.org/10.1515/jpm-2022-0421
17. Jones FJS, Smith JR, Ayub N, et al. Implementing standardized provider documentation in a tertiary epilepsy clinic. *Neurology*. 2020;95:e213-e223. https://doi.org/10.1212/wnl.0000000000009778
18. Claudel SE, Valente C, Serafin H, et al. Structured handoff to improve communication from inpatient to outpatient dialysis units: a quality improvement project. *Hemodial Int*. 2023;27:146-154. https://doi.org/10.1111/hdi.13060
19. Lamba S, Berlin A, Goett R, AAHPM Research Committee Writing Group, et al. Assessing emotional suffering in palliative care: use of a structured note template to improve documentation. *J Pain Symptom Manage*. 2016;52:1-7.
20. Offerman SR, Rauchwerger AS, Nishijima DK, et al. Use of an electronic medical record "dotphrase" data template for a prospective head injury study. *West J Emerg Med*. 2013;14:109-113. https://doi.org/10.5811/westjem.2012.11.13400
21. Sinsky CA, Rule A, Cohen G, et al. Metrics for assessing physician activity using electronic health record log data. *J Am Med Inform Assoc*. 2020;27:639-643. https://doi.org/10.1093/jamia/ocz223
22. Understand Auto Text Usage. Secondary Understand Auto Text Usage. https://wiki.cerner.com/display/public/reference/Understand+Auto+Text+Usage. Accessed January 10, 2023.

23. Feblowitz J, Takhar SS, Ward MJ, et al. A custom-developed emergency department provider electronic documentation system reduces operational efficiency. *Ann Emerg Med*. 2017;70:674-682.e1. https://doi.org/10.1016/j.annemergmed.2017.05.032
24. Rotenstein LS, Apathy N, Holmgren AJ, et al. Physician note composition patterns and time on the EHR across specialty types: a national, cross-sectional study. *J Gen Intern Med*. 2023;38:1119-1126. https://doi.org/10.1007/s11606-022-07834-5
25. Apathy NC, Rotenstein L, Bates DW, et al. Documentation dynamics: note composition, burden, and physician efficiency. *Health Serv Res*. 2023;58:674-685. https://doi.org/10.1111/1475-6773.14097
26. Rodrigues H, Cobucci R, Oliveira A, et al. Burnout syndrome among medical residents: a systematic review and meta-analysis. *PLoS One*. 2018;13:e0206840. https://doi.org/10.1371/journal.pone.0206840
27. Shalaby R, Oluwasina F, Eboreime E, et al. Burnout among residents: prevalence and predictors of depersonalization, emotional exhaustion and professional unfulfillment among resident doctors in Canada. *Int J Environ Res Public Health*. 2023;20:3667-3694. https://doi.org/10.3390/ijerph20043677
28. Perotte R, Hajicharalambous C, Sugalski G, et al. Characterization of electronic health record documentation shortcuts: does the use of dotphrases increase efficiency in the emergency department? *AMIA Annu Symp Proc*. 2021;2021:969-978.
29. Overhage JM, Johnson KB. Pediatrician electronic health record time use for outpatient encounters. *Pediatrics*. 2020;146:e20194017. https://doi.org/10.1542/peds.2019-4017
30. Overhage JM, McCallie D. Jr., Physician time spent using the electronic health record during outpatient encounters: a descriptive study. *Ann Intern Med*. 2020;172:169-174. https://doi.org/10.7326/m18-3684
31. Molloy-Paolillo B, Mohr D, Levy DR, et al. Assessing electronic health record (EHR) use during a major EHR transition: an innovative mixed methods approach. *J Gen Intern Med*. 2023;38:999-1006. https://doi.org/10.1007/s11606-023-08318-w
32. Melnick ER, Ong SY, Fong A, et al. Characterizing physician EHR use with vendor derived data: a feasibility study and cross-sectional analysis. *J Am Med Inform Assoc*. 2021;28:1383-1392. https://doi.org/10.1093/jamia/ocab011
33. StataCorp. *Stata Statistical Software: Release 17*. StataCorp LLC; 2021.
34. Holmgren AJ, Lindeman B, Ford EW. Resident physician experience and duration of electronic health record use. *Appl Clin Inform*. 2021;12:721-728. https://doi.org/10.1055/s-0041-1732403
35. Chen L, Guo U, Illipparambil LC, et al. Racing against the clock: internal medicine residents' time spent on electronic health records. *J Grad Med Educ*. 2016;8:39-44. https://doi.org/10.4300/jgme-d-15-00240.1
36. Maloney SR, Peterson S, Kao AM, et al. Surgery resident time consumed by the electronic health record. *J Surg Educ*. 2020;77:1056-1062. https://doi.org/10.1016/j.jsurg.2020.03.008
37. Watson MD, Elhage SA, Green JM, et al. Surgery residents spend nearly 8 months of their 5-year training on the electronic health record (EHR). *J Surg Educ*. 2020;77:e237-e244. https://doi.org/10.1016/j.jsurg.2020.06.017
38. Rittenberg E, Liebman JB, Rexrode KM. Primary care physician gender and electronic health record workload. *J Gen Intern Med*. 2022;37:3295-3301. https://doi.org/10.1007/s11606-021-07298-z
39. Tait SD, Oshima SM, Ren Y, et al. Electronic health record use by sex among physicians in an academic health care system. *JAMA Intern Med*. 2021;181:288-290. https://doi.org/10.1001/jamainternmed.2020.5036
40. Rotenstein LS, Fong AS, Jeffery MM, et al. Gender differences in time spent on documentation and the electronic health record in a large ambulatory network. *JAMA Netw Open*. 2022;5:e223935. https://doi.org/10.1001/jamanetworkopen.2022.3935
41. Dyrbye LN, Shanafelt TD, Sinsky CA, et al. Burnout among health care professionals: a call to explore and address this underrecognized threat to safe, high-quality care. *NAM Perspect*. 2017. https://doi.org/10.31478/201707b
42. Baxter SL, Apathy NC, Cross DA, et al. Measures of electronic health record use in outpatient settings across vendors. *J Am Med Inform Assoc*. 2021;28:955-959. https://doi.org/10.1093/jamia/ocaa266
43. Adler-Milstein J, Adelman JS, Tai-Seale M, et al. EHR audit logs: a new goldmine for health services research? *J Biomed Inform*. 2020;101:103343. https://doi.org/10.1016/j.jbi.2019.103343
44. Huilgol YS, Adler-Milstein J, Ivey SL, et al. Opportunities to use electronic health record audit logs to improve cancer care. *Cancer Med*. 2022;11:3296-3303. https://doi.org/10.1002/cam4.4690
45. Kannampallil T, Adler-Milstein J. Using electronic health record audit log data for research: insights from early efforts. *J Am Med Inform Assoc*. 2022;30:167-171. https://doi.org/10.1093/jamia/ocac173
46. Sinha A, Stevens LA, Su F, et al. Measuring electronic health record use in the pediatric ICU using audit-logs and screen recordings. *Appl Clin Inform*. 2021;12:737-744. https://doi.org/10.1055/s-0041-1733851
47. Rule A, Melnick ER, Apathy NC. Using event logs to observe interactions with electronic health records: an updated scoping review shows increasing use of vendor-derived measures. *J Am Med Inform Assoc*. 2022;30:144-154. https://doi.org/10.1093/jamia/ocac177
48. Chong AZ, Lee B, Hollenbach KA, et al. Disappearing help text: implementing a note-based tool for in-line clinical decision support and note bloat reduction. *Appl Clin Inform*. 2022;13:1033-1039.
49. Feldman J, Goodman A, Hochman K, et al. Novel note templates to enhance signal and reduce noise in medical documentation: prospective improvement study. *JMIR Form Res*. 2023;7:e41223. https://doi.org/10.2196/41223
50. Kahn D, Stewart E, Duncan M, et al. A prescription for note bloat: an effective progress note template. *J Hosp Med*. 2018;13:378-382. https://doi.org/10.12788/jhm.2898

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