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Changes in Clinician Time Expenditure and Visit Quantity With Adoption of Artificial Intelligence–Powered Scribes
A Multisite Study

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Editorial

Supplemental content

IMPORTANCE Artificial intelligence (AI)–enabled scribes have been proposed to reduce electronic health record (EHR) burden and improve clinician satisfaction. There is limited evidence about their associated results across multiple sites and relative benefits for different clinician groups.

OBJECTIVE To assess the association of AI scribe adoption with changes in EHR time expenditure and visit volume and how associations vary by clinician characteristics.

DESIGN, SETTING, AND PARTICIPANTS Multisite, longitudinal cohort study of AI scribe adoption conducted at 5 US academic health care institutions that introduced AI scribes to their clinicians between June 2023 and August 2025. Participants were ambulatory clinicians.

EXPOSURES AI scribe adoption, defined as receiving access to an AI scribe. This was determined by opt-in decisions by eligible physicians at 4 of the 5 sites.

MAIN OUTCOME AND MEASURES Total time spent on the EHR, time spent on documentation, and time spent on the EHR outside scheduled hours or on unscheduled days, all normalized to 8 scheduled patient hours; weekly visit volume.

RESULTS The sample comprised 8581 clinicians, including 1809 AI scribe adopters. Participants were 57.1% female and were split between primary care (24.4%), medical (62.4%), and surgical (13.2%) specialties. Most (74.1%) were attending physicians, with 18.1% advanced practice clinicians and 7.8% resident physicians. In a difference-in-differences analysis, AI scribe adoption was associated with 13.4 (95% CI, 9.1-17.7) fewer minutes of EHR time, 16.0 (95% CI, 13.7-18.3) fewer minutes of documentation time, and 0.49 (95% CI, 0.17-0.81) additional weekly visits delivered. Electronic health record time outside work hours did not change significantly. Changes associated with AI scribe adoption were greatest for primary care specialists, advanced practice clinicians, female clinicians, and clinicians who used AI scribes in 50% or more of visits.

CONCLUSIONS AND RELEVANCE AI scribe adoption was associated with modest decreases in total EHR time and documentation time and with a modest increase in weekly visit volume.

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Documentation in the electronic health record (EHR) requires substantial physician time,[1] averaging 2.3 hours per 8 hours of patient care.[2] EHR time, particularly when occurring outside work hours, is associated with burnout among physicians.[3-5] Further, EHR burden may limit clinical capacity, patient access, and quality of care.[3,4]

Human scribes can reduce EHR time, but their scalability is constrained by cost and workforce availability.[6-10] Artificial intelligence (AI)–enabled ambient documentation tools, or AI scribes, have been introduced as a more scalable alternative. Early studies suggest these tools may reduce EHR burden[11-14] and improve clinician satisfaction.[15-18] However, findings have varied across sites, practice settings, clinician types, and specialties, and the specific details of a single site's implementation approach or vendor may limit generalizability. Further, many studies use different constructions of EHR use measures, limiting comparability and making meta-analysis challenging. There is limited literature regarding which clinicians benefit most from AI scribes. Similarly, there is limited evidence on the association of AI scribes with changes in productivity.[16-18] Both of these factors are critical to informing health system decision-making on where to invest in and deploy finite resources.

To address these gaps, this study evaluated the association of AI scribe adoption in the context of real-world introductions of these technologies with changes in total EHR time, documentation time, work outside of work, and weekly visit volume across 5 health systems. Analyses also examined whether associations varied by specialty, clinician type, sex, and intensity of AI scribe use.

Key Points

Question How is adoption of artificial intelligence (AI) scribes associated with changes in electronic health record (EHR) time expenditure and weekly visit volume?

Findings In 5 academic medical centers, AI scribe adoption was associated with decreases in total EHR and documentation time of 13.4 and 16.0 minutes, respectively, and an increase of 0.49 visits per week. Changes associated with AI scribe adoption were greatest for primary care specialists, advanced practice clinicians, female clinicians, and clinicians who used AI scribes in 50% or more of visits.

Meaning These findings indicate initial, moderately beneficial associations of AI scribes with changes in key EHR activity measures and visit volume.

Methods

Study Setting and Population

The study sample included 5 academic health care institutions (Mass General Brigham; Emory Healthcare; University of California, San Francisco; Yale New Haven Health; and the University of California, Davis) in multiple regions of the United States that introduced AI scribes to their clinicians starting in June 2023. Institutions were selected for the study based on their having made AI scribes available to their ambulatory clinicians, and their willingness and capability to pool data for the study. Sites were asked to provide data for both AI scribe adopters, as well as any clinician who did not adopt AI scribes but practiced in a specialty in which at least 1 clinician adopted the tool. eTable 1 in Supplement 1 displays characteristics of the institutions and their AI scribe rollouts, including how clinicians at individual sites were selected for AI scribe adoption. In general, sites defined the clinicians who were eligible for gaining access to the tool (eg, ranging from no restrictions on eligibility to restrictions based on clinical volume or eligibility based on leadership nomination), and clinicians subsequently opted-in to adoption. All sites used Ambience, Nuance DAX Copilot, or Abridge (individually or in combination) and Epic as their EHR vendor. This study was approved by the University of California, San Francisco institutional review board.

The study population consisted of ambulatory clinicians—attending physicians (including clinical fellows), advanced practice clinicians (nurse practitioners and physician assistants), and resident physicians—who had the option to use an AI scribe during the study period. Each institution provided information on clinicians who received access to AI scribes, regardless of whether they used the tool, as well as the clinicians in the same division or department who did not receive access. Clinicians given access to AI scribes were considered AI scribe adopters, beginning on the date each institution reported that clinician received access.[1] Nonadopters were those who did not receive access to AI scribes at that time. The primary analysis included all adopters and nonadopters, while sensitivity analyses explored the association of AI scribe use with the outcomes among clinicians with measured intensity of AI scribe use. Each institution provided data for a minimum of 12 weeks, including 6 preadoption and 6 postadoption weeks for adopters.

Variables

Institutions provided demographic information including clinicians' role (attending, advanced practice clinician, or resident), sex, specialty (categorized into primary care, medical specialties, or surgical specialty, as specified in eTable 2 in Supplement 1), and the proportion of encounters for which clinicians used an AI scribe (when available; some AI scribe vendors could not provide usage-level data, and it could not be inferred from Epic Signal metadata described below).

These data were linked with month-level EHR metadata derived via Epic's Signal database, with 3 time-based outcomes normalized to 8 scheduled patient hours[19]: total time spent on the EHR (EHR-8), time spent on the EHR outside of scheduled hours or on unscheduled days (work outside of work [WOW-8]), and time spent on documentation (DocTime-8). Consistent with variables available in the Epic Signal database, data also included the number of weekly ambulatory visits delivered, the proportion of new vs established patient evaluation and management (E/M) encounters, and the proportion of encounters at each E/M level. Clinicians with fewer than 5 ambulatory visits per month in any study month were excluded because Signal does not calculate complete measures for those clinicians.

Main Analytic Approach

The primary analytic approach was a difference-in-differences framework using multivariable ordinary least-squares models. Assumptions underlying these models are described in the eMethods in Supplement 1. All models controlled for number of weekly visits (except for when visit volume was the model outcome), clinician fixed effects, and month fixed effects. Standard errors were clustered at the clinician level. To evaluate the effect of AI scribes over time and to assess the parallel pretrends assumption, we specified an event study that estimated the dynamic effect in each period before and after adoption, using a Callaway and Sant'Anna estimator.[20]

Subgroup Analyses

To assess how the association of AI scribes with our main outcomes varied by clinician characteristics, we used the same difference-in-differences regression framework with an interaction term for the clinician characteristic such as specialty, role, sex, and AI scribe use intensity, with 1 model for each characteristic-outcome pairing. See the eMethods in Supplement 1 for additional details.

Numeric Comparison of Preadoption and Postadoption Trends

While our consideration of both never-adopters and those who may later become adopters substantially increases the size of our control group, it does not facilitate simple descriptive comparisons of preadoption and postadoption trends for adopters compared with control clinicians. As described in the eMethods in Supplement 1, we defined a descriptive post period to facilitate numeric comparison of preadoption and postadoption trends.

Sensitivity Analyses

To ensure results were not driven by a single site, we repeated our difference-in-differences models excluding each site sequentially. Second, we ran our models again specifying our treatment variable to exclude clinicians with unknown use intensity. Third, we repeated our models excluding resident physicians. Fourth, we excluded clinicians who never adopted AI scribes, using only preadoption months of eventual AI scribe adopters as control observations. Fifth, we ran our models with time-based outcomes without controlling for weekly visits. Sixth, we used the Callaway and Sant'Anna[20] estimator in aggregate in addition to the event study described above to facilitate comparisons with our 2-way fixed-effect results. Last, we assessed heterogenous treatment effects across 5 categories of AI scribe use.

Revenue Analysis

In an exploratory analysis, we estimated marginal E/M revenue associated with AI scribe adoption. We first generated a monthly E/M revenue estimate for each clinician by multiplying the number of billed visits at each E/M service level by the corresponding 2025 Medicare Physician Fee Schedule national payment rate. See the eMethods in Supplement 1 for the relevant equation. We used the difference-in-differences framework described above to estimate the monthly marginal E/M visit revenue associated with general AI scribe adoption and conducted an analysis of heterogeneity of treatment effects as for other outcomes.

Table. Characteristics of Clinicians Who Did and Did Not Adopt AI Scribes Across 5 Institutions, 2023-2025

Characteristic	No. (%) AI scribe adopters (n = 1809)	No. (%) AI scribe nonadopters (n = 6772)
Institution		
Yale New Haven Health System	77 (63.6)	44 (36.4)
Emory Healthcare	453 (53.7)	390 (46.3)
University of California, Davis Health	342 (43.3)	447 (56.7)
University of California, San Francisco Health	552 (38.4)	884 (61.6)
Mass General Brigham	385 (7.1)	5007 (92.9)
Clinician role		
Attending (including fellows)	1574 (24.7)	4787 (75.3)
Advanced practice clinician	198 (12.8)	1352 (87.2)
Resident	37 (5.5)	633 (94.5)
Clinician sex		
Female	1047 (21.4)	3853 (78.6)
Male	762 (20.7)	2919 (79.3)
Specialty		
Primary care[a]	509 (24.3)	1583 (75.7)
Medical specialties[a]	1080 (20.2)	4277 (79.8)
Surgical specialties[a]	220 (19.4)	912 (80.6)
Mean intensity of clinician AI scribe use		
<50% of notes	780	NA
≥50% of notes	577	NA
Unknown	452	NA

Abbreviations: AI, artificial intelligence; NA, not applicable.

[a] Please refer to eTable 2 in Supplement 1 for delineation of specialties in each of these categories.

Results

Sample Characteristics

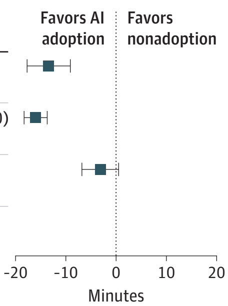
The sample included 8581 clinicians, including 1809 clinicians who adopted AI scribes and 6772 clinicians who did not adopt AI scribes over 181 273 clinician-month observations (**Table**). The majority (74.1%) of the sample consisted of attending physicians, more than one-half (57.1%) were female, and clinicians were split between primary care (24.4%), medical specialties (62.4%), and surgical specialties (13.2%). The distribution of clinicians into individual specialties is shown in eTable 2 in Supplement 1.

Unadjusted EHR Time Expenditure and Visit Volume

Baseline values for EHR time and weekly ambulatory visit volume are shown in **Figure 1**. Descriptive preadoption and postadoption trends for each outcome using the descriptive postadoption period for each clinician are shown in eFigure 1 in Supplement 1.

Figure 1. Electronic Health Record Time Expenditure and Weekly Ambulatory Visit Volume Among AI Scribe Adopters and Nonadopters, for the Overall Sample

Outcome	AI scribe adopters, mean (SD) (n = 1809)			AI scribe nonadopters, mean (SD) (n = 6772)			Adjusted difference in differences (95% CI)
	Preadoption[a]	Postadoption[a]	Difference	Preadoption[a]	Postadoption[a]	Difference	
Total EHR time (h/8 PSH)	7.36 (3.90)	6.77 (3.61)	-0.59	7.03 (4.28)	6.87 (4.31)	-0.16	-13.40 min (-17.70 to -9.10)
Documentation time (h/8 PSH)	2.68 (1.76)	2.57 (1.73)	-0.11	2.55 (1.88)	2.66 (1.97)	0.11	−16.00 min (-18.30 to -13.70)
Work outside work (h/8 PSH)	3.53 (3.08)	3.28 (2.83)	-0.24	3.53 (3.50)	3.50 (3.52)	-0.03	-3.10 min (-6.80 to 0.50)
Weekly ambulatory encounters[a]	28.20 (18.70)	26.80 (18.70)	-1.47	26.30 (19.60)	24.50 (18.70)	-1.83	0.49 visits (0.17 to 0.81)



Unadjusted preadoption and postadoption outcome measures for each group are derived via designation of a descriptive post period for all clinicians in an organization beginning in the month when the first clinician in that organization adopted the artificial intelligence (AI) scribe. Difference-in-difference estimates are derived from a multivariable ordinary least-square regression model that adjusts for clinician fixed effects, time fixed effects, and weekly ambulatory visit volume to estimate the relative impact of AI scribe adoption vs no AI scribe adoption (reference) on each outcome. EHR indicates electronic health record; PSH, patient scheduled hours.

[a]Not plotted because unit is not compatible with scale.

Difference-in-Differences Estimates of Changes in EHR Time Expenditure and Visit Volume

AI scribe adoption was associated with 13.4 (95% CI, 9.1-17.7) fewer minutes of total EHR-8 time and 16.0 (95% CI, 13.7-18.3) fewer minutes of DocTime-8 (Figure 1). WOW-8 changes (−3.1 [95% CI, - 6.8 to 0.5] minutes) with AI scribe adoption were not statistically significant. AI scribe adoption was associated with delivery of 0.5 (95% CI, 0.2-0.8) additional weekly visits (Figure 1). Temporal trends in each of the outcomes are shown in **Figure 2**, and the numbers of AI scribe adopter and nonadopter observations available at each time point are reported in eTable 3 in Supplement 1. The majority of preadoption estimates had a 95% CI overlapping 0, providing support that the parallel pretrends assumptions were met.

Similar results were seen in sensitivity analyses that sequentially excluded each study site (eTable 4 in Supplement 1), although significant decreases in WOW-8 time were seen in analyses excluding Mass General Brigham and University of California, Davis. Consistent results were additionally seen in a sensitivity analysis excluding adopters whose utilization intensity was unknown (eTable 5 in Supplement 1) and excluding residents (eTable 6 in Supplement 1). Excluding those who never adopted AI scribes from contributing control data to the difference-in-differences analysis (eTable 7 in Supplement 1) also revealed similar findings, as did models without controls for visit volume (eTable 8 in Supplement 1) and models using the Callaway and Sant'Anna estimator (eTable 9 in Supplement 1). AI scribe adoption was also associated with a decrease in WOW-8 time in the latter analysis.

Difference-in-Differences Estimates by Clinician Group

As shown in **Figure 3**, **Figure 4**, and eTable 10 in Supplement 1, the association of AI scribe adoption varied by clinician characteristics and AI scribe use intensity. For example, compared with primary care clinicians who did not adopt AI scribes, those who did spent 25.0 (95% CI, 16.9-33.1) fewer minutes of EHR-8 time (Figure 3A) and 26.9 (95% CI, 22.1-31.7) fewer minutes of DocTime-8 (Figure 3B). Female clinician adopters spent 19.0 (95% CI, 13.3-24.6) minutes fewer in EHR-8 (Figure 3A), 19.9 (95% CI, 16.7-23.0) minutes fewer in DocTime-8 (Figure 3B), and 6.2 (95% CI, 1.3-11.1) minutes fewer in WOW-8 (Figure 4A) compared with nonadopters. Advanced practice clinicians and residents who adopted AI scribes had significantly lower EHR-8, WOW-8, and DocTime-8 and had more weekly visits (Figure 4B).

Last, clinicians who used an AI scribe for 50% or more of their visits spent 21.3 (95% CI, 13.9-28.7) minutes less of EHR-8 (Figure 3A), 27.3 (95% CI, 23.1-31.6) minutes less of DocTime-8 (Figure 3B), and 5.5 (95% CI, −0.9 to 12.0) minutes less of WOW-8 (Figure 4A) compared with nonadopters. They delivered 1.0 (95% CI, 0.5-1.6) more visit per week (Figure 4B). The association of AI scribe adoption and changes in EHR time measures and visit volume by more granular utilization groups is shown in eTable 11 in Supplement 1 and revealed incremental reductions in DocTime-8 with increasing levels of AI scribe utilization.

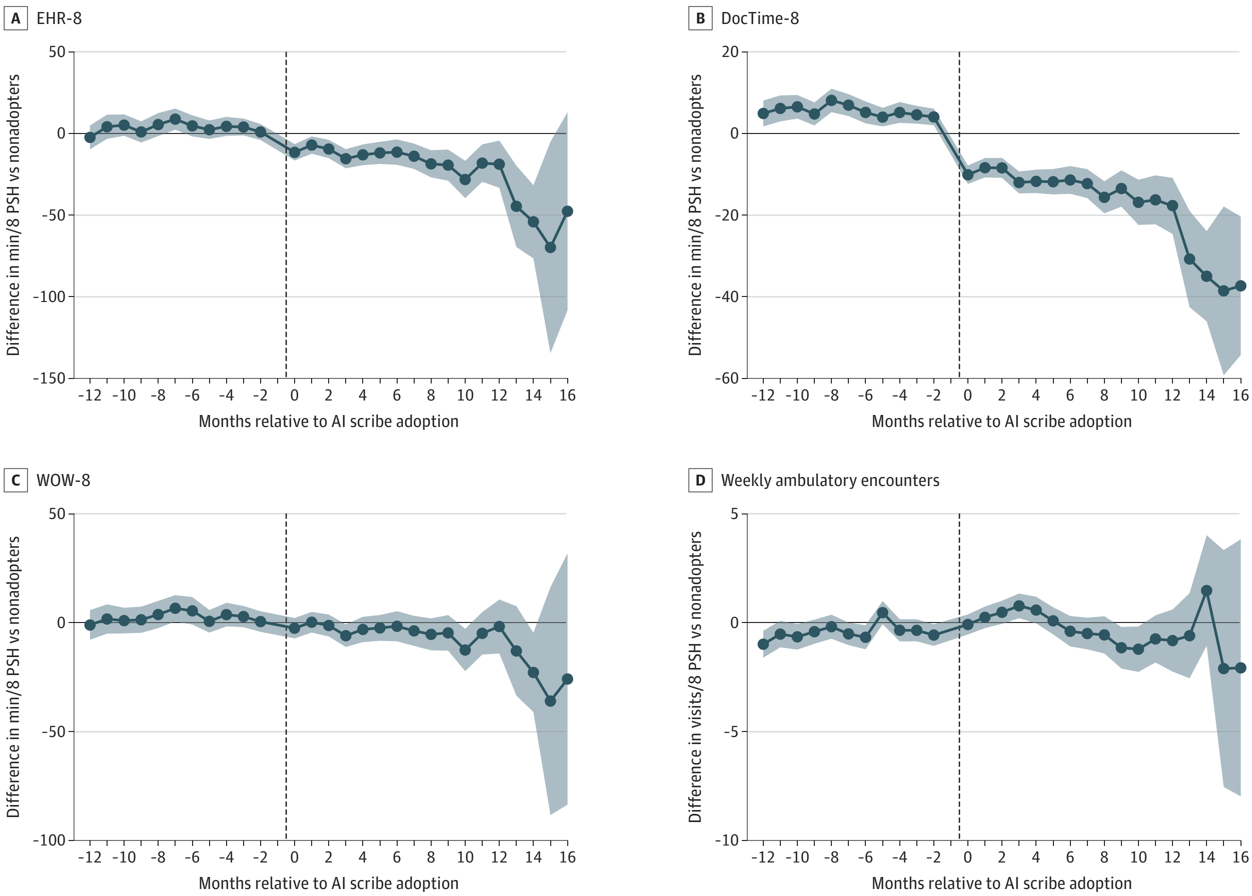
Estimated E/M Revenue Increases With AI Scribe Adoption

AI scribe adoption was associated with an additional $167.37 (95% CI, $86.52-$248.21) per clinician who adopted an AI scribe per month (eFigure 2 and eTable 12 in Supplement 1). Marginal E/M revenue estimates by clinician type and utilization intensity are shown in eTable 12 in Supplement 1.

Discussion

This study in 5 academic medical centers found that adoption of AI scribes was associated with modest reductions in total EHR time and documentation time. AI scribe adopters spent 13 minutes fewer using the EHR in total and 16 minutes fewer on documentation per 8 hours of scheduled patient care, representing 3.0% and 10.0% relative decreases in time spent, respectively. Specific groups—including female clinicians, ad-

Figure 2. Difference-in-Differences Models as Event Studies, for EHR-8, DocTime-8, WOW-8, and Weekly Ambulatory Encounters



Each panel shows the Callaway and Sant'Anna event study estimate of the association between artificial intelligence (AI) scribe adoption and the outcome, relative to the month of adoption (vertical dashed line). Shaded areas indicate 95% CIs. Solid horizontal line at y = 0 indicates no effect. Larger confidence intervals in later postadoption periods reflect lower numbers of observations. The full observation count by AI scribe adoption status for each relative month is available in eTable 3 in Supplement 1. DocTime-8 indicates time spent on documentation; EHR-8, total time spent on the electronic health record; PSH, patient scheduled hours; and WOW-8, time spent on the electronic health record outside of scheduled hours or on unscheduled days.

vanced practice clinicians, resident physicians, and primary care and medical specialists—experienced greater desirable changes associated with AI scribe adoption. Clinicians who used the AI scribe 50% or more of the time experienced twice the reduction in total EHR time and 3 times the reduction in documentation time. Last, AI scribe adoption was associated with a 1.7% increase in weekly visit volume, translating to a conservatively estimated additional $167 in monthly E/M visit revenue per clinician.

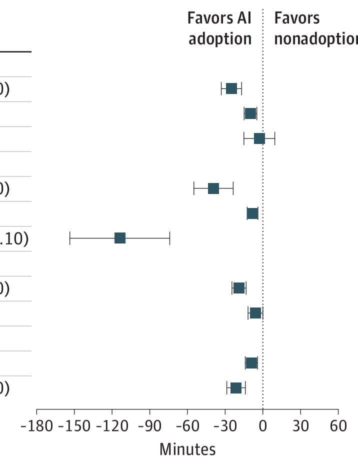
These multisite findings extend evidence from a growing body of single-site studies regarding the EHR time benefits of AI scribes that overall suggest varying levels of efficacy of the tools. In a single-site randomized clinical trial comparing 2 AI scribe products with a control group, one vendor's product was associated with a 9.5% reduction in time spent on documentation, while the other's was not.[21] In a separate single-site randomized clinical trial, AI scribe use was associated with significant reductions in total EHR time but not in work outside work after excluding outliers.[22] Two other studies in single academic health systems have reported 8.5% lower EHR time per appointment and 15.9% lower time in notes per appointment,[12] and 20.4% less time in notes per appointment and 30.0% less after-hours work time per workday,[15] respectively, with AI scribe use. In contrast, the present analysis demonstrates that overall EHR time decreased by 3.3% and documentation time decreased by 11.7%, without significant reductions in work outside work. Given their derivation from pooled data from 5 health systems, these estimates are less likely to be biased by site-specific implementation details and represent generalizable results regarding the relative time savings associated with clinicians adopting AI scribes in real-world settings.

It is notable that estimates for documentation time reductions exceeded reductions in total EHR time expenditure and that AI scribe adoption was not ultimately associated with significant changes in work outside of working hours. This is consistent with previous studies[12,13] and suggests that while clinicians may save time on documentation with AI scribe use, some of those time savings may be reallocated to other patient care activities, such as reviewing current or prior documentation for accuracy, answering electronic inbox mes-

Figure 3. Total Electronic Health Record Time and Documentation Time Among AI Scribe Adopters and Nonadopters, by Clinician Subgroup

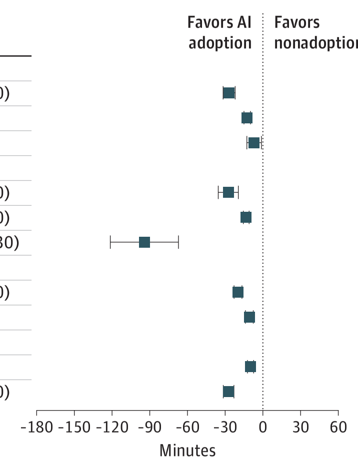
A EHR-8

	AI scribe adopters, mean (SD) hours per 8 PSH (n = 1809)			AI scribe nonadopters, mean (SD) hours per 8 PSH (n = 6772)			
	Preadoption	Postadoption	Difference	Preadoption	Postadoption	Difference	Adjusted difference in differences (95% CI), min
Specialty							
Primary care (n = 509 adopters; 1583 nonadopters)	8.74 (3.72)	8.01 (3.44)	-0.73	8.44 (3.94)	7.98 (4.06)	-0.46	-25.00 (-33.10 to -16.90)
Medical specialties (n = 1080 adopters; 4277 nonadopters)	6.92 (3.69)	6.48 (3.49)	-0.44	6.80 (4.18)	6.77 (4.24)	-0.03	-9.90 (-14.90 to -4.80)
Surgical specialties (n = 220 adopters; 912 nonadopters)	5.93 (4.38)	5.37 (3.70)	-0.56	5.66 (4.65)	5.68 (4.57)	0.02	-2.80 (-15.10 to 9.50)
Clinician type							
Advanced practice clinician (n = 198 adopters; 1352 nonadopters)	8.58 (4.03)	8.24 (4.06)	-0.34	8.41 (4.73)	8.22 (4.77)	-0.19	-39.30 (-54.90 to -23.60)
Attending (n = 1574 adopters; 4787 nonadopters)	7.02 (3.75)	6.56 (3.46)	-0.46	6.57 (3.94)	6.30 (3.85)	-0.27	-8.20 (-12.50 to -3.90)
Resident (n = 37 adopters; 633 nonadopters)	14.02 (4.31)	12.31 (5.20)	-1.71	14.45 (6.12)	12.53 (5.96)	-1.92	-113.90 (-153.60 to -74.10)
Clinician sex							
Female (n = 1047 adopters; 3853 nonadopters)	8.24 (3.98)	7.47 (3.66)	-0.76	7.90 (4.44)	7.68 (4.47)	-0.22	-19.00 (-24.60 to -13.30)
Male (n = 762 adopters; 2919 nonadopters)	6.13 (3.44)	5.81 (3.30)	-0.32	6.01 (3.83)	5.86 (3.86)	-0.15	-5.90 (-11.80 to 0)
AI scribe use intensity							
Low or medium use (n = 1232 adopters; 6772 nonadopters)	7.12 (3.94)	6.56 (3.63)	-0.56	7.03 (4.28)	6.87 (4.31)	-0.16	-9.10 (-14.00 to -4.20)
High use (n = 577 adopters; 6772 nonadopters)	7.94 (3.74)	7.21 (3.52)	-0.73	7.03 (4.28)	6.87 (4.31)	-0.16	-21.30 (-28.70 to -13.90)



B DocTime-8

	AI scribe adopters, mean (SD) hours per 8 PSH (n = 1809)			AI scribe nonadopters, mean (SD) hours per 8 PSH (n = 6772)			
	Preadoption	Postadoption	Difference	Preadoption	Postadoption	Difference	Adjusted difference in differences (95% CI), min
Specialty							
Primary care (n = 509 adopters; 1583 nonadopters)	3.02 (1.69)	2.79 (1.64)	-0.23	2.79 (1.73)	2.98 (1.88)	0.19	-26.90 (-31.70 to -22.10)
Medical specialties (n = 1080 adopters; 4277 nonadopters)	2.62 (1.70)	2.60 (1.73)	-0.02	2.58 (1.90)	2.70 (1.96)	0.12	-12.50 (-15.10 to -9.90)
Surgical specialties (n = 220 adopters; 912 nonadopters)	2.08 (2.04)	1.91 (1.75)	-0.17	1.98 (1.90)	2.00 (1.95)	0.02	-7.00 (-12.80 to -1.20)
Clinician type							
Advanced practice clinician (n = 198 adopters; 1352 nonadopters)	3.25 (1.88)	3.10 (1.87)	-0.15	3.18 (2.15)	3.22 (2.14)	0.04	-27.60 (-35.60 to -19.60)
Attending (n = 1574 adopters; 4787 nonadopters)	2.52 (1.66)	2.49 (1.68)	-0.03	2.36 (1.74)	2.43 (1.81)	0.07	-13.30 (-15.60 to -11.00)
Resident (n = 37 adopters; 633 nonadopters)	6.19 (2.15)	4.94 (2.49)	-1.25	4.96 (2.20)	4.90 (2.47)	-0.06	-94.40 (-121.60 to -67.30)
Clinician sex							
Female (n = 1047 adopters; 3853 nonadopters)	3.09 (1.78)	2.91 (1.75)	-0.17	2.95 (1.98)	3.06 (2.03)	0.11	-19.90 (-23.00 to -16.70)
Male (n = 762 adopters; 2919 nonadopters)	2.11 (1.57)	2.10 (1.58)	-0.01	2.09 (1.64)	2.17 (1.77)	0.08	-10.80 (-13.90 to -7.70)
AI scribe use intensity							
Low or medium use (n = 1232 adopters; 6772 nonadopters)	2.61 (1.74)	2.55 (1.75)	-0.06	2.55 (1.88)	2.66 (1.97)	0.11	-9.80 (-12.30 to -7.40)
High use (n = 577 adopters; 6772 nonadopters)	2.85 (1.79)	2.60 (1.68)	-0.25	2.55 (1.88)	2.66 (1.97)	0.11	-27.30 (-31.60 to -23.10)

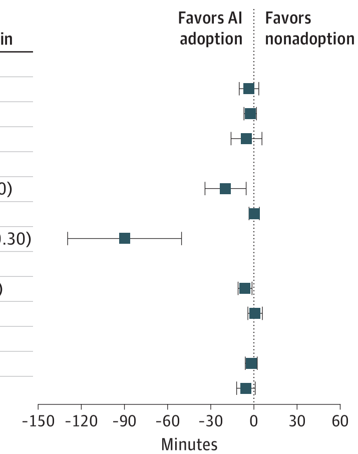


Times reported in hours per 8 patient scheduled hours (PSH). Reference group in each row is artificial intelligence (AI) scribe nonadopters. Unadjusted preadoption and postadoption outcome measures for each group are derived via designation of a descriptive post period for all clinicians in an organization beginning in the month when the first clinician in that organization adopted the AI scribe. Difference-in-difference estimates are derived from a multivariable ordinary least-square regression model that adjusts for clinician fixed effects, time fixed effects, and weekly ambulatory visit volume, and additionally includes an interaction term between each characteristic (eg, specialty, clinician type, clinician sex, intensity of AI scribe use) and AI scribe adoption to estimate the relative impact of AI scribe adoption vs no AI scribe adoption on each outcome for each specialty, clinician type, clinician sex, and intensity of AI scribe use profile. DocTime-8 indicates time spent on documentation; EHR-8, total time spent on the electronic health record.

Figure 4. Electronic Health Record Work Outside of Working Hours and Weekly Ambulatory Visit Volume Among AI Scribe Adopters and Nonadopters, by Clinician Subgroup

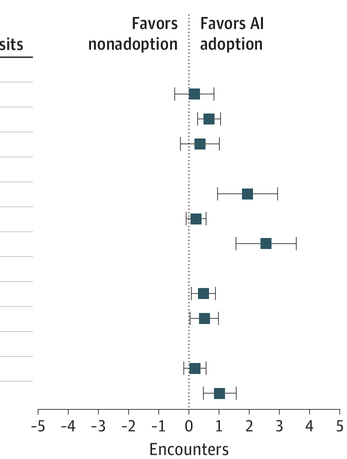
A WOW-8

	AI scribe adopters, mean (SD) hours per 8 PSH (n = 1809)			AI scribe nonadopters, mean (SD) hours per 8 PSH (n = 6772)			Adjusted difference in differences (95% CI), min
	Preadoption	Postadoption	Difference	Preadoption	Postadoption	Difference	
Specialty							
Primary care (n = 509 adopters; 1583 nonadopters)	3.69 (3.27)	3.45 (2.96)	-0.24	3.89 (3.57)	3.82 (3.66)	-0.07	-3.40 (-10.20 to 3.40)
Medical specialties (n = 1080 adopters; 4277 nonadopters)	3.49 (2.92)	3.28 (2.79)	-0.21	3.48 (3.40)	3.47 (3.45)	-0.01	-2.60 (-6.90 to 1.80)
Surgical specialties (n = 220 adopters; 912 nonadopters)	3.30 (3.38)	2.93 (2.77)	-0.37	3.16 (3.73)	3.21 (3.62)	0.05	-5.10 (-15.90 to 5.60)
Clinician type							
Advanced practice clinician (n = 198 adopters; 1352 nonadopters)	3.82 (3.55)	3.78 (3.49)	-0.04	4.15 (4.17)	4.11 (4.18)	-0.04	-19.70 (-34.00 to -5.40)
Attending (n = 1574 adopters; 4787 nonadopters)	3.42 (2.92)	3.20 (2.70)	-0.22	3.30 (3.17)	3.17 (3.07)	-0.13	0.20 (-3.40 to 3.80)
Resident (n = 37 adopters; 633 nonadopters)	7.68 (4.09)	7.11 (4.92)	-0.57	9.21 (6.01)	8.54 (5.41)	-0.67	-89.90 (-129.50 to -50.30)
Clinician sex							
Female (n = 1047 adopters; 3853 nonadopters)	3.96 (3.32)	3.62 (3.03)	-0.34	4.04 (3.81)	3.97 (3.80)	-0.08	-6.20 (-11.00 to -1.30)
Male (n = 762 adopters; 2919 nonadopters)	2.94 (2.60)	2.84 (2.48)	-0.10	2.95 (3.00)	2.94 (3.06)	-0.01	0.80 (-4.20 to 5.90)
AI scribe use intensity							
Low or medium use (n = 1232 adopters; 6772 nonadopters)	3.40 (3.05)	3.20 (2.78)	-0.20	3.53 (3.50)	3.50 (3.52)	-0.03	-1.90 (-6.00 to 2.30)
High use (n = 577 adopters; 6772 nonadopters)	3.83 (3.13)	3.47 (2.93)	-0.36	3.53 (3.50)	3.50 (3.52)	-0.03	-5.50 (-12.00 to 0.90)



B Weekly encounters

	AI scribe adopters, mean (SD) encounters per wk (n = 1809)			AI scribe nonadopters, mean (SD) encounters per wk (n = 6772)			Adjusted difference in differences (95% CI), visits
	Preadoption	Postadoption	Difference	Preadoption	Postadoption	Difference	
Specialty							
Primary care (n = 509 adopters; 1583 nonadopters)	36.30 (19.60)	35.60 (20.80)	-0.70	30.70 (20.40)	27.60 (18.50)	-3.10	0.18 (-0.47 to 0.83)
Medical specialties (n = 1080 adopters; 4277 nonadopters)	24.80 (17.20)	23.10 (16.50)	-1.70	25.30 (19.80)	23.80 (19.40)	-1.50	0.67 (0.29 to 1.05)
Surgical specialties (n = 220 adopters; 912 nonadopters)	24.60 (17.10)	24.60 (16.80)	0	23.30 (15.60)	22.80 (15.40)	-0.50	0.37 (-0.28 to 1.01)
Clinician type							
Advanced practice clinician (n = 198 adopters; 1352 nonadopters)	30.70 (16.90)	30.50 (16.50)	-0.20	26.30 (17.70)	24.90 (16.20)	-1.40	1.94 (0.95 to 2.94)
Attending (n = 1574 adopters; 4787 nonadopters)	27.90 (19.00)	26.50 (18.90)	-1.40	26.60 (20.10)	25.00 (19.40)	-1.60	0.24 (-0.09 to 0.57)
Resident (n = 37 adopters; 633 nonadopters)	9.00 (3.60)	10.40 (5.10)	1.40	8.30 (4.30)	8.30 (5.30)	0	2.56 (1.56 to 3.56)
Clinician sex							
Female (n = 1047 adopters; 3853 nonadopters)	28.10 (17.90)	26.40 (17.90)	-1.62	25.00 (17.90)	23.40 (17.20)	-1.59	0.48 (0.08 to 0.88)
Male (n = 762 adopters; 2919 nonadopters)	28.40 (19.70)	27.20 (19.70)	-1.28	27.90 (21.30)	25.80 (20.40)	-2.02	0.51 (0.04 to 0.98)
AI scribe use intensity							
Low or medium use (n = 1232 adopters; 6772 nonadopters)	27.40 (17.80)	25.30 (17.70)	-2.10	26.30 (19.60)	24.50 (18.70)	-1.80	0.20 (-0.17 to 0.57)
High use (n = 577 adopters; 6772 nonadopters)	30.20 (20.50)	29.80 (20.30)	-0.40	26.30 (19.60)	24.50 (18.70)	-1.80	1.02 (0.48 to 1.57)



Encounters indicates encounters per week. Reference group in each row is artificial intelligence (AI) scribe nonadopters. Unadjusted preadoption and postadoption outcomes are derived via designation of a descriptive post period for all clinicians in an organization beginning in the month when the first clinician in that organization adopted the AI scribe. Difference-in-difference estimates are derived from a multivariable ordinary least-square regression model that adjusts for clinician fixed effects, time fixed effects, and weekly ambulatory visit volume, and additionally includes an interaction term between each characteristic (eg, specialty, clinician type, clinician sex, intensity of AI scribe use) and AI scribe adoption to estimate the relative impact of AI scribe adoption vs no AI scribe adoption on each outcome for each specialty, clinician type, clinician sex, and intensity of AI scribe use profile. PSH indicates patient scheduled hours; WOW-8, time spent on the electronic health record outside of scheduled hours or on unscheduled days.

sages from patients, addressing test results, or conducting medical record review. While AI scribes may not greatly reduce EHR time, given evidence regarding the burnout benefits of these technologies,[16,17] it is possible that clinicians view reallocation of time from documentation as valuable, thus influencing improvements in clinician satisfaction.

The multisite nature of this study allowed for a larger sample size, which enabled well-powered exploratory analyses regarding which groups using AI scribes may see the greatest benefits associated with AI scribe use. Compared with individuals in these groups who did not adopt AI scribes, time savings and in some cases productivity improvements were significantly greater for female clinicians, primary care and medical specialty clinicians, and advanced practice clinicians and residents who adopted AI scribes. Additionally, clinicians who used an AI scribe 50% or more of the time derived greater time and productivity benefits than those who used the AI scribes less. These findings regarding greater relative benefit for female and primary care and medical specialty clinicians are consistent with those seen in prior single-site studies.[12,23] Use of AI scribes among residents is an area of ongoing discussion and study,[24,25] given the critical nature of documentation for learning and unknown implications for resident learning. Notably, the population of residents who used AI scribes was limited at the institutions in this study; thus, further dedicated investigation is needed, related to both the impact of AI scribes on resident time expenditure and their influence on resident learning. Last, despite disproportionate benefits for those who used AI scribes more than one-half of the time, only about 32% of adopters used their AI scribe that frequently, emphasizing the need for robust training and support for adopters.

Last, assuming baseline 2025 Medicare Physician Fee Schedule conversion rates, AI scribe adoption was associated with statistically significant yet numerically minimal marginal E/M visit revenue generation of $167 per month. Given that none of the organizations in the study required that clinicians book additional patients to qualify for AI scribe use, this marginal revenue may have derived from increased visits booked in available or nontemplated time or changes in the composition of level-4 and level-5 E/M visits coded facilitated by better documentation, as suggested by prior single-site evidence.[26] These estimates could be interpreted as a conservative lower bound of the financial benefits of AI scribes and could be compared with site-specific implementation costs.

This study has both strengths and limitations. Strengths include the large sample size across multiple institutions, clinician types, and specialties. The quasiexperimental difference-in-differences study design with robust controls helps mitigate some concerns of potential bias, strengthening the validity of the estimates. Assessment of AI scribe adoption (rather than a specific level of AI scribe use) and use of an intention-to-treat analysis approach helps identify a floor of benefit associated with AI scribe use, with greater benefits seen in specific groups.

Limitations

These strengths are balanced by limitations. First, this was an observational study rather than a randomized clinical trial; thus, characteristics of control clinicians do not perfectly reflect those of AI scribe adopters. Second, while clinician and time fixed effects were used in all models, it cannot be ruled out that the observed associations may be driven by unobserved confounders. Third, implementation details varied across the study sites; thus, estimates reflect averages and assessments of real-world implementation experiences rather than measurements of maximal efficacy of AI scribes. Fourth, the study's focus on academic institutions, where the average weekly visit volume was about 20 encounters per week, may not reflect the experiences of clinicians in nonacademic settings who have higher visit volumes. Fifth, while marginal revenue analyses generated conservative estimates of E/M revenue gains associated with AI scribe use, costs of AI scribe purchase and implementation vary; thus, the analyses cannot generalize to cost-benefit considerations. Sixth, the present study did not measure physician burnout or assess reallocation of time across activities associated with AI scribe use. Seventh, while many of the control observations derived from 1 institution (Mass General Brigham) given data collection specifications, the sensitivity analysis excluding data from Mass General Brigham suggested that inclusion of data from this site only makes the presented estimates more conservative. Eighth, due to limitations from a subset of the AI scribe vendors in this study, detailed data on intensity of AI scribe use were missing for some clinicians. Ninth, the influence of AI scribe adoption was estimated for a limited period after adoption (with the most robust estimates available for up to 5 months after adoption), and the influence of adoption on EHR metrics, productivity, and revenue may differ over time as clinicians become more comfortable with AI scribe use.

Conclusions

This multisite, multivendor, controlled study at 5 academic medical centers found that AI scribe adoption was associated with modest but significant 3.0% relative decreases in total EHR time and 10.0% relative decreases in documentation time, as well as 1.7% relative increases in visit volume. Greater benefits were observed in specific clinician groups. Given the nonrandomized nature of the study, the observed associations could be due to AI scribe implementation but may also be due in part to unmeasured differences between the adopters and nonadopters studied. Future studies should assess the longevity and reproducibility of these observations, as well as specific workflows and supports that can enhance the benefits of this technology.

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