JAMA | Original Investigation | AI IN MEDICINE

Clinician Use of an Artificial Intelligence–Enabled Clinical Information Platform

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IMPORTANCE Despite growing interest in the use of artificial intelligence (AI) in medicine, empirical evidence on how clinicians use these tools is limited.

OBJECTIVE To characterize clinician use of an AI-enabled clinical information platform, the distribution of use across the clinical workforce, and the purpose of submitted queries.

DESIGN, SETTING, AND PARTICIPANTS This cross-sectional study analyzed clinicians with National Provider Identifier–verified accounts of a commonly used AI-enabled clinical information platform, OpenEvidence, from January 1, 2024, through June 30, 2026. A large language model was used to classify the clinical purpose and topic areas of a stratified random sample of 38.8 million queries.

MAIN OUTCOMES AND MEASURES The number of active users and clinical queries, the share of queries relative to representation in the national workforce, and the clinical purpose and topic of queries were examined.

RESULTS Overall, 952 008 clinicians (58.5% female), including 556 200 physicians, submitted 271 million queries during the 2.5-year study period. Monthly active users increased from 355 in January 2024 to 703 265 in June 2026, and average monthly queries per active user rose from 18.0 to 39.5. Nurse practitioners (44.5) and physician assistants (44.5) submitted more queries per active user-month than physicians (37.1). A higher share of queries relative to the national workforce was submitted by physicians within a decade of graduation (use ratio, 2.54) and residents and fellows (1.84). Use was also higher than average among physicians specializing in oncology and hematology (use ratio, 2.00), internal medicine (1.88), and family medicine (1.80), but lower in procedural and diagnostic specialties (ophthalmology, 0.23; radiology, 0.24; orthopedics, 0.24). Most queries addressed clinical decision-making (51.9%), particularly treatment and management (33.1%), whereas diagnosis accounted for 13.9% of queries. Queries addressing topics outside physicians' own specialties ranged from 35% among oncologists and hematologists to 88% among emergency department physicians.

CONCLUSIONS AND RELEVANCE Over 2.5 years, more than 950 000 US clinicians submitted greater than 270 million queries to an AI-enabled clinical information platform. Use varied across clinician types, specialties, and career stages and was frequently for treatment decisions rather than diagnostic tasks.

Editor's Note

Supplemental content

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JAMA. doi:10.1001/jama.2026.21868
Published online October 15, 2026.

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Interest in the use of artificial intelligence (AI) for clinical care is growing rapidly,[1-4] yet empirical evidence on who uses these tools, how often, and for what clinical purposes remains limited. In a national survey, 39% of physicians reported using AI to summarize medical research and standards of care, the most commonly cited use of clinical AI.[5] Studies of internet traffic data have also shown increased visits to AI-enabled clinical decision support platforms and a corresponding decline in visits to traditional platforms in recent years.[6] However, these estimates rely on self-report or indirect measures, cannot distinguish experimentation from routine use, and do not characterize the purpose of clinician-AI interactions.

Unlike traditional clinical resources, AI-enabled tools synthesize available evidence in response to a clinician's specific question, changing how clinicians access a body of medical knowledge that has long exceeded what any individual can retain.[7-9] Policymakers, professional societies, and health systems are developing guidelines around the use of AI in clinical practice, yet these efforts have proceeded without empirical data on how these tools are used.[10-12] The same is true of efforts to evaluate how well these tools perform, which have focused primarily on diagnostic accuracy and medical knowledge recall, without evidence on the tasks clinicians actually bring to them.[13-15]

To address these gaps, this study analyzed approximately 271 million clinician queries submitted to the most commonly used AI-enabled clinical information platform in the US, OpenEvidence,[16] to characterize the volume and patterns of use, characteristics of users relative to the national workforce, and the clinical purpose of their queries.

Key Points

Question How do US clinicians use an artificial intelligence (AI)–enabled clinical information platform?

Findings In this cross-sectional study, 952 008 US clinician users submitted 271 million AI-enabled clinical queries over the 2.5-year study period. Physicians comprised 556 200 users and submitted an average of 37.1 queries per active user-month. Early-career physicians (use ratio, 2.54) and those in oncology and hematology (2.00), internal medicine (1.88), and family medicine (1.80) submitted a higher-than-average share of queries; treatment and management accounted for 33.1% of physician queries and diagnosis for 13.9%.

Meaning Clinician use of an AI-enabled clinical information platform is increasing, with use primarily for treatment and management decisions rather than diagnosis.

Methods

OpenEvidence is an AI-enabled clinical information platform that uses large language models (LLMs) to synthesize responses to free-text clinical queries, with in-line citations to peer-reviewed journals and professional society guidelines.[17] Access is free and restricted to health care professionals with a valid National Provider Identifier (NPI). The platform is compliant with the Health Insurance Portability and Accountability Act (HIPAA).

The study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines and was approved by the Harvard Medical School Institutional Review Board with a waiver of informed consent because it was a secondary analysis of existing data.

Data Sources

We analyzed user query logs from January 1, 2024, through June 30, 2026, for all OpenEvidence accounts with a verified NPI. We excluded clinicians whose NPI did not match a record in the National Plan and Provider Enumeration System (NPPES) and those who submitted no queries during the study period. Clinicians were categorized as physicians, nurse practitioners, physician assistants, pharmacists, or other licensed clinicians (eFigure 1 in Supplement 1).

Query logs contained the date and time of each submission and user metadata, including specialty self-reported at registration. A query was defined as a single free-text question entered by a user generating a synthesized response, with follow-up questions counted as separate queries. Logs captured only queries entered in the platform's main question interface, excluding other product features and institution-specific deployments (eMethods in Supplement 1). We linked NPIs to the NPPES to obtain sex, years in practice (from the NPI enumeration date), and practice region information for all clinicians and, for physicians, career stage (attending vs resident or fellow).[18] Missing data were infrequent for all characteristics (eTable 1 in Supplement 1); clinicians with missing data were retained in the analysis, and comparisons with the national workforce were restricted to clinicians without missing data. For physicians, the comparator was the national active physician workforce from the American Medical Association's Physician Professional Data (April 2026).[19] For other clinician types, we used records of all currently registered clinicians in NPPES. For query content classification, we drew a stratified random sample of 14.4% of study period queries, sampled at a fixed rate within strata defined by calendar month, clinician type, and self-reported specialty (eMethods in Supplement 1).

Classification of Query Content

We classified each query along 2 dimensions: clinical purpose and medical topic. Clinical purpose refers to the type of information sought (eg, treatment and management, diagnosis, medication information) and medical topic refers to the clinical subspecialty domain addressed (eg, cardiology, oncology).

Each query was independently classified by an LLM (OpenAI's GPT-5.6 Terra) prompted with standardized category definitions, examples, and labeling rules (eMethods and eTables 2 and 3 in Supplement 1). For each dimension, the model returned a primary label reflecting what the query was mainly about, which was used in all analyses. Clinical purpose was assigned to 1 of 17 subcategories nested within 5 higher-order categories—clinical decision-making, clinical

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Table. Categorization of Query Purposes[a]

Subcategory	Definition	Synthetic example
Clinical decision-making: queries seeking actionable guidance to inform a specific patient care decision		
Treatment and management	Selecting or managing therapy for a clinical condition, including treatment strategies, medication dosing and adjustment for a specific patient, drug safety, and management of complications	"What is the recommended treatment for acute herpes zoster?"
Diagnosis	Identifying or differentiating a medical condition, including differential diagnoses and diagnostic criteria, determining the appropriate diagnostic workup, and interpreting a specific patient's test or imaging results	"What is the differential diagnosis for a 30-year-old male who experienced syncope after exercise?"
Risk and prognosis	Assessing risk stratification, prognostic scoring, or predicted outcomes for clinical decision-making	"What is the CHA_2DS_2-VASc score for a patient with atrial fibrillation and hypertension?"
Screening and prevention	Seeking recommendations for screening asymptomatic populations or for preventive interventions, including appropriate tests, timing, and eligibility criteria	"Should my patient with a 30 pack-year smoking history undergo low-dose CT lung cancer screening?"
Clinical knowledge: queries seeking factual medical knowledge not tied to an immediate patient care decision		
Medication information	Retrieving pharmacologic properties of drugs, including pharmacokinetics, adverse effects, and mechanisms of action, without reference to a specific patient	"What is the half-life of temozolomide and its clinical implications?"
Disease information	Understanding pathophysiology, etiology, mechanisms, or characteristics of diseases and syndromes	"How does portal hypertension lead to hepatorenal syndrome?"
Tests and imaging information	Understanding what tests and imaging studies measure, how they are performed, reference ranges, or the general significance of abnormal results	"What are common causes of a falsely elevated troponin?"
Procedures	Understanding procedural techniques, preparation requirements, or step-by-step protocols	"What are the correct steps for measuring orthostatic blood pressure?"
Anatomy and physiology	Recalling normal anatomic structures, physiologic processes, or normal growth and development	"What is the normal diameter of the common bile duct in adults?"
Evidence: queries seeking published evidence, clinical practice guidelines, or specific literature		
Literature search	Searching or synthesizing the research literature, including locating publications, reviewing the evidence on a clinical question, and asking what published data show about a treatment or outcome	"What is the evidence for SGLT2 inhibitors in heart failure with preserved ejection fraction?"
Guidelines	Retrieving recommendations from clinical practice guidelines issued by professional societies or consensus bodies	"What are the current guideline-directed medical therapies for heart failure with reduced ejection fraction?"
Specific studies and trials	Seeking the design, findings, or interpretation of a particular named clinical trial or research study	"What were the outcomes of the ATLANTIS trial?"
Administrative tasks: queries related to nonclinical operational tasks in medical practice		
Other administrative	Billing and coding inquiries, operational logistics, legal and regulatory questions, or insurance-related matters	"What are the work relative value units for *CPT* code 99214?"
Documentation	Drafting or structuring clinical notes, discharge summaries, letters of medical necessity, or appeal letters	"Write a discharge summary for a patient admitted with heart failure and hypertension."
Patient education	Creating or finding patient-facing educational materials or communication strategies for health literacy	"How should I explain elevated cholesterol levels to a patient?"
Medical education: queries primarily oriented toward teaching, learning, or professional development		
Educational content	Generating or obtaining instructional materials, such as presentations, lecture outlines, or teaching cases	"Can you create a presentation outline for a grand rounds on heart failure management?"
Examination preparation	Preparing for board certification, licensure, or in-training examinations, including study strategies and practice questions	"What are the most important topics to study for USMLE Step 3?"

Abbreviations: CHA_2DS_2-VASc, congestive heart failure, hypertension, age ≥75 years (doubled), diabetes, stroke/transient ischemic attack/thromboembolism (doubled), vascular disease (prior myocardial infarction, peripheral artery disease, or aortic plaque), age 65-75 years, sex category (female); *CPT*, *Current Procedural Terminology*; CT, computed tomography; SGLT2, sodium-glucose cotransporter-2; USMLE, US Medical Licensing Examination.

[a] Definitions summarize those in the classification prompt, and synthetic examples are illustrative of clinician queries within each subcategory; the examples shown are not those used in the prompt, and actual queries were not reproduced to protect user privacy. The full prompts, including the precise definitions and examples provided to both the large language model and the clinician annotators, are shown in the eMethods and eTables 2 and 3 in Supplement 1.

knowledge, evidence, administrative tasks, and medical education (**Table**)—and medical topic was assigned to a primary clinical subspecialty. Queries whose purpose could not be determined or that fell outside clinical use (0.5%) were excluded from the content analysis (eFigure 1 in Supplement 1). To protect confidentiality, classification was performed in bulk within a HIPAA-compliant compute environment and only categorical labels, not query text, were extracted.

To assess classification accuracy, 6 clinicians blinded to the model's output independently labeled 200 queries containing no protected health information, sampled so that every purpose and topic label was represented; 100 queries were labeled by 2 clinicians, allowing model-clinician and clinician-clinician agreement to be compared on the same queries (eMethods in Supplement 1). The model agreed with clinicians at least as often as clinicians agreed with one another (primary

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purpose, 73.6% vs 66.3%; difference, 7.3 percentage points [95% CI, −0.6 to 14.6]; topic, 54.5% vs 52.8%; difference, 1.7 percentage points [95% CI, −9.0 to 11.8]). Across all model-clinician judgments on all 200 queries, agreement on purpose rose from 74.5% at the subcategory level to 82.3% at the 5 higher-order categories, indicating that much of the remaining disagreement fell between neighboring subcategories. Additional details on classification and validation appear in the eMethods in Supplement 1, and synthetic examples of queries within and outside physicians' specialties appear in eTables 4 and 5 in Supplement 1.

Statistical Analysis

Data were analyzed from July to September 2026. We defined an active user in each calendar month as a clinician who submitted at least 1 query that month and query intensity as the number of queries submitted per active user per month. We described monthly active users and query volume, overall and by clinician type, and characterized the distribution of use across users, including new vs returning active users, continued use after adoption, and queries per active user.

We compared the distribution of use across the US workforce by calculating use ratios: the percentage of all queries submitted by each group of clinicians divided by the percentage of the national workforce belonging to that group. A use ratio of 1 indicates query volume proportionate to a group's share of the workforce. Because the numerator is a group's share of queries rather than its share of users, the ratio captures both clinician volume and intensity of use. Nonparametric bootstrapping was used to estimate 95% CIs, resampling clinicians with replacement. We also compared query intensity across clinician types and physician characteristics.

Among queries sampled for content classification, we examined the distribution of query purposes and topics across all clinician types and by years in practice. We then restricted the sample to physicians and examined these distributions by specialty, as well as the proportion of queries directed outside a physician's own specialty and the purpose of those queries, restricted to physicians with a reported specialty and queries assigned to a clinical specialty topic. All proportions were estimated using logistic regression with marginal standardization over sex, specialty, and years in practice; from each model we excluded any characteristic that defined the comparison of interest or did not apply across clinician types (eg, specialty for nonphysician clinicians). Analyses were performed using Python version 3.9.6 (Python Software Foundation).

Results

Between January 1, 2024, and June 30, 2026, a total of 952 008 US clinicians submitted 271 million clinical queries. Physicians accounted for 556 200 users (58.4%) and 172.1 million queries (63.5%), while the remainder of users included nurse practitioners (171 034), physician assistants (93 241), pharmacists (35 819), and other licensed clinicians (95 714) (eTable 1 in Supplement 1). Monthly active users—clinicians submitting at least 1 query in a given month—rose from 355 in January 2024 to 703 265 in June 2026. Monthly queries rose from approximately 6000 to 27.8 million over the same period (**Figure 1**).

Queries per active user rose from 18.0 per month in January 2024 to 38.3 in July 2024 and remained between 32.1 and 40.4 per month thereafter, reaching 39.5 in June 2026 (Figure 1, C). Month-over-month retention—the share of clinicians active in one month who queried again the next—rose from approximately 70% in early 2024 to 90% in 2026, and by June 2026, 92.5% of active users were returning users rather than brief adopters. In every month after the month of first use, at least 68% of clinicians observable at that point remained active. Only 9.6% of clinicians queried on a single day and never returned (eFigure 2 in Supplement 1).

Query Intensity Across Clinician Types

Query intensity was highest among nurse practitioners (44.5 queries per active user-month) and physician assistants (44.5), followed by physicians (37.1), pharmacists (29.3), and other clinicians (19.9) (eTable 1 in Supplement 1). Clinicians with fewer than 10 years in practice submitted 43.4 queries per user-month compared with 29.9 among those with 20 or more years in practice. Among physicians, residents and fellows submitted 43.2 queries per user-month vs 35.3 among attending physicians, and intensity varied across specialties, from 51.7 in family medicine and 49.7 in oncology and hematology to 19.9 in ophthalmology and 18.5 in orthopedics.

Distribution of Use Across the Physician Workforce

Physician users spanned every career stage, specialty, and region, but use was distributed unevenly relative to the US physician workforce (**Figure 2**). The sharpest contrasts were by career stage. Physicians within a decade of medical school graduation made up 24.3% of the workforce but 45.2% of users and 61.8% of queries (use ratio, 2.54); residents and fellows, 14.8% of the workforce, submitted 27.2% of queries (use ratio, 1.84); and physicians 20 or more years from graduation, 53.0% of the workforce, submitted 16.5% of queries (use ratio, 0.31). Across specialties, use was highest in oncology and hematology (1.9% of the workforce, 3.8% of queries; use ratio, 2.00), internal medicine (14.5% and 27.3%; 1.88), and family medicine (12.5% and 22.5%; 1.80), and was lowest in procedural and diagnostic specialties, including ophthalmology (1.9% and 0.4%; 0.23), radiology (4.3% and 1.1%; 0.24), orthopedics (3.0% and 0.7%; 0.24), and anesthesiology (5.0% and 1.8%; 0.37). Use among female individuals (use ratio, 1.13) and among those practicing in the West Census Region (1.10) slightly exceeded their workforce share. Corresponding comparisons for other clinician types are shown in eFigure 3 in Supplement 1.

Query Purpose

Among the 38.8 million classified queries, clinical decision-making was the most common purpose across every clinician type except pharmacists. Among physicians, it accounted for 51.9% of queries, followed by clinical knowledge (37.2%), evidence (7.0%), administrative tasks (3.0%), and medical education (0.9%). The most frequent query purposes were treatment and management (33.1%) and medication information

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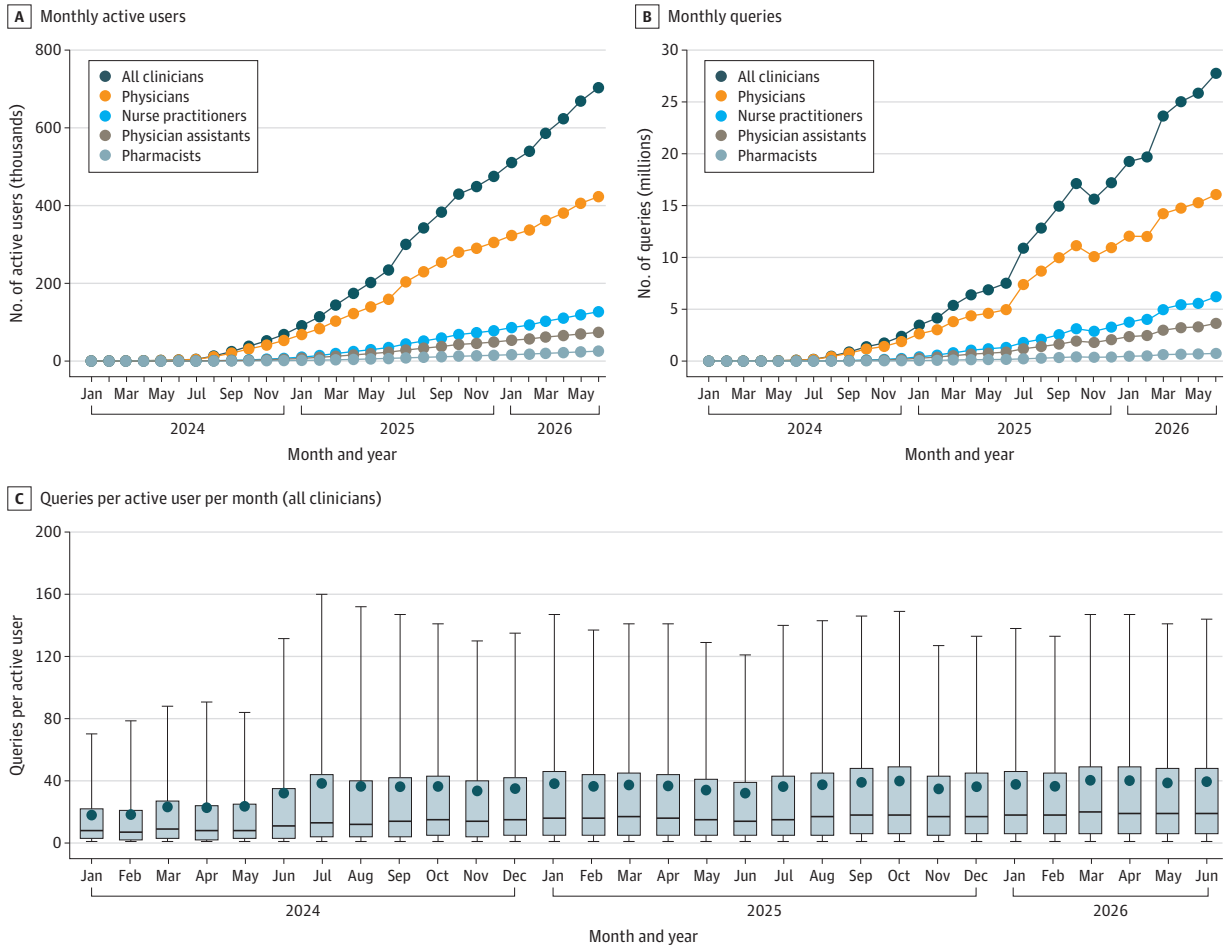
Figure 1. Line Graphs and Box Plot of Trends in Use of an Artificial Intelligence–Enabled Clinical Information Platform Among US Clinicians



A user is counted as active in a month if they submitted at least 1 query that month; a query is defined as a single free-text question generating a synthesized response, with follow-up questions counted as separate queries. Other licensed clinicians (eg, dentists, registered nurses, physical therapists, and psychologists) are included in the all clinicians series and are not plotted separately. C, Boxes indicate the interquartile range, horizontal lines the median, whiskers the 5th to 95th percentiles, and dots the mean. The platform became available for public use on August 1, 2023; the study period began on January 1, 2024.

(14.1%); diagnosis accounted for 13.9%. Purposes among nurse practitioners and physician assistants closely resembled those of physicians, whereas queries among pharmacists concentrated in medication information (32.8%) and treatment and management (32.0%) (**Figure 3**).

Across physician specialties, query purposes reflected domain-specific clinical priorities. For example, medication information queries were most common in psychiatry (29.1% vs 14.1% among physicians overall), queries about specific studies and trials were most common in oncology and hematology (3.5% vs 0.7%), and practice guideline queries were most frequent in gastroenterology and cardiology (4.2% and 3.6%, respectively, vs 2.1%).

Purposes differed modestly by years in practice: treatment and management queries were less common among clinicians with 20 or more years in practice than among those with fewer than 10 years (29.7% vs 34.7%), whereas literature searches (5.1% vs 2.9%), risk and prognosis (3.9% vs 2.4%), and medication information (15.5% vs 14.8%) were more common (eFigure 4 in Supplement 1).

Query Topic

Among physicians, the most common query topics were cardiology (8.6%), infectious disease (7.5%), and oncology and hematology (7.4%), while the least common were anesthesiology (1.1%), ophthalmology (1.2%), and radiology (1.3%) (eFigure 5 in Supplement 1). Queries from nurse practitioners, physician assistants, and other clinicians spanned generalist topics, whereas pharmacists' queries concentrated in pharmacotherapy-intensive domains, such as cardiology (11.3%), infectious disease (10.4%), and endocrinology (10.0%).

Topic selection also varied with years in practice. Clinicians earlier in practice more often queried pediatrics (5.9% among those with fewer than 10 years in practice vs 3.3% among those with 20 or more years), emergency medicine (2.7% vs 1.6%), and internal medicine (2.0% vs 1.2%) topics,

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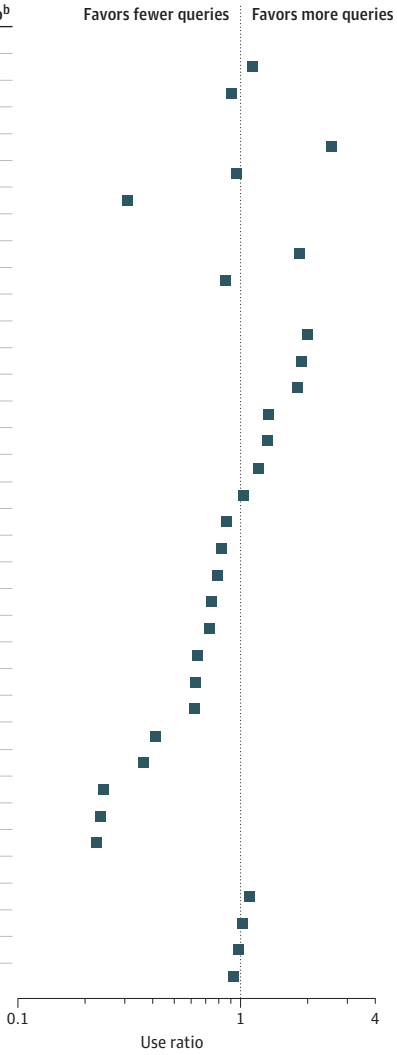
Figure 2. Dot Plot of Subgroup Analysis of Use of an Artificial Intelligence–Enabled Clinical Information Platform Relative to the US Physician Workforce by Physician Characteristics

Characteristic	Physician users, No. (%)	Physician queries, No. in millions (%)	US physician workforce,[a] No. (%)	Use ratio[b]
Sex				
Female	254 473 (45.9)	79.5 (46.4)	499 091 (41.0)	1.13
Male	300 178 (54.1)	91.9 (53.6)	717 847 (59.0)	0.91
Years in practice				
<10	251 405 (45.2)	106.4 (61.8)	291 912 (24.3)	2.54
10-19	168 786 (30.4)	37.3 (21.7)	271 754 (22.6)	0.96
≥20	136 009 (24.4)	28.4 (16.5)	636 017 (53.0)	0.31
Career stage				
Resident/fellow	110 135 (19.8)	46.8 (27.2)	181 129 (14.8)	1.84
Attending	446 065 (80.2)	125.2 (72.8)	1 041 052 (85.2)	0.85
Specialty				
Oncology/hematology	15 323 (2.8)	6.5 (3.8)	22 175 (1.9)	2.00
Internal medicine	105 353 (19.2)	46.5 (27.3)	169 854 (14.5)	1.88
Family medicine	79 525 (14.5)	38.3 (22.5)	146 537 (12.5)	1.80
Infectious disease	6382 (1.2)	2.5 (1.5)	12 888 (1.1)	1.33
Gastroenterology	12 598 (2.3)	3.9 (2.3)	20 399 (1.7)	1.32
Neurology	15 252 (2.8)	5.2 (3.0)	29 362 (2.5)	1.21
Emergency medicine	42 748 (7.8)	10.4 (6.1)	69 321 (5.9)	1.03
Critical care	8227 (1.5)	2.1 (1.2)	16 766 (1.4)	0.86
Dermatology	8944 (1.6)	2.2 (1.3)	18 247 (1.6)	0.83
Nephrology	6809 (1.2)	1.7 (1.0)	14 767 (1.3)	0.79
Cardiology	19 349 (3.5)	4.2 (2.5)	38 847 (3.3)	0.74
Pediatrics	45 381 (8.3)	10.4 (6.1)	98 333 (8.4)	0.72
Pulmonology	7671 (1.4)	2.0 (1.2)	21 862 (1.9)	0.64
Psychiatry	24 339 (4.4)	6.0 (3.5)	65 730 (5.6)	0.63
Obstetrics and gynecology	25 228 (4.6)	5.0 (2.9)	55 410 (4.7)	0.62
Surgery	26 838 (4.9)	4.4 (2.6)	72 832 (6.2)	0.42
Anesthesiology	21 026 (3.8)	3.1 (1.8)	57 976 (5.0)	0.37
Radiology	11 881 (2.2)	1.8 (1.1)	50 381 (4.3)	0.24
Orthopedics	10 836 (2.0)	1.2 (0.7)	34 883 (3.0)	0.24
Ophthalmology	6534 (1.2)	0.7 (0.4)	22 487 (1.9)	0.23
Census region				
West	128 829 (23.4)	41.5 (24.4)	264 184 (22.2)	1.10
Midwest	112 950 (20.5)	35.9 (21.0)	245 948 (20.6)	1.02
Northeast	128 735 (23.4)	37.6 (22.1)	266 125 (22.3)	0.99
South	179 838 (32.7)	55.4 (32.5)	414 952 (34.8)	0.93



[a]The US physician workforce comparator reflects a single year, whereas platform users and queries spanned the full study period.

[b]Defined as the percentage of all physician queries submitted by a subgroup divided by the percentage of the US physician workforce belonging to that subgroup (ie, the ratio determines whether a group's use is proportionate to its size in the workforce). Ratios above 1 (more queries) indicate that a subgroup submitted a larger share of queries than its share of the workforce and ratios below 1 (fewer queries), a smaller share.

For each subgroup, the number and percentage of physician users and physician queries and the corresponding number and percentage of the US physician workforce from the American Medical Association's Physician Professional Data (April 2026) are shown. This is restricted to physicians; comparisons for nonphysician clinicians are shown in eFigure 3 in Supplement 1. All 95% CIs fall within the plotted markers.

whereas those later in practice more often queried oncology and hematology (9.1% vs 5.9%), endocrinology (8.0% vs 6.3%), and neurology topics (6.0% vs 5.3%) (eFigure 6 in Supplement 1). The distribution of purposes across topics is shown in eFigure 7 in Supplement 1.

Queries Outside a Physician's Specialty

Physicians frequently queried beyond their own specialty, including subspecialists (eFigure 5 in Supplement 1). For example, surgeons directed 70% of queries to nonsurgical topics and anesthesiologists 73% to nonanesthesiology topics. Even in oncology and hematology, where within-specialty querying was highest, 35% of queries addressed other specialties. Representative topics within and outside each specialty, with synthetic example queries, are shown in eTables 4 and 5 in Supplement 1.

Within- and outside-of-specialty queries differed in purpose. Within-specialty queries were more often directed at evidence (9.1% vs 6.4% outside specialty), particularly literature searches (5.0% vs 3.8%) and guidelines (3.0% vs 2.0%).

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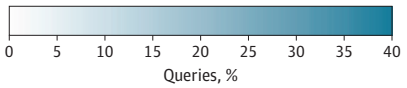
Figure 3. Heat Map of the Purpose of Clinical Queries to an Artificial Intelligence–Enabled Clinical Information Platform by Clinician Type and Physician Specialty



		Clinical decision-making				Clinical knowledge					Evidence			Administrative tasks			Medical education	
		Treatment and management	Diagnosis	Risk and prognosis	Screening and prevention	Medication information	Disease information	Tests and imaging information	Procedures	Anatomy and physiology	Literature search	Guidelines	Specific studies and trials	Other administrative	Documentation	Patient education	Educational content	Examination preparation
Clinician type	Nurse practitioners	34.3	17.3	1.9	1.5	16.0	11.7	6.4	1.0	1.1	1.8	1.2	0.1	1.4	2.0	1.9	0.2	0.1
	Other clinicians	26.6	10.7	3.9	1.6	13.9	14.3	5.6	2.9	3.2	7.9	1.6	0.8	2.0	2.0	1.4	1.0	0.6
	Pharmacists	32.0	3.3	2.0	1.0	32.8	6.6	3.7	1.3	1.0	6.1	3.0	1.8	1.6	1.0	0.9	1.0	0.8
	Physician assistants	35.5	17.4	2.2	1.7	14.8	11.5	6.3	1.5	1.2	1.7	1.2	0.1	0.9	1.6	1.7	0.2	0.3
	Physicians	33.1	13.9	3.1	1.8	14.1	12.6	6.9	1.9	1.7	4.2	2.1	0.7	1.1	1.0	0.9	0.5	0.4
Physician specialty	Anesthesiology	31.1	7.5	4.3	0.8	17.7	10.3	6.0	6.3	4.1	5.7	2.3	0.6	1.2	0.6	0.3	0.7	0.5
	Cardiology	28.1	9.6	5.1	1.4	13.6	11.6	10.7	2.4	2.5	6.2	3.6	1.8	1.0	0.8	0.4	0.6	0.5
	Critical care	32.2	10.9	3.6	0.8	12.4	13.9	8.4	2.8	2.4	5.7	2.4	1.3	1.1	0.6	0.2	0.7	0.6
	Dermatology	29.3	11.1	3.2	1.3	17.5	15.0	4.4	2.3	1.4	7.7	1.1	0.7	1.3	1.4	1.1	0.7	0.3
	Emergency medicine	40.0	13.3	2.7	0.8	12.9	11.2	5.5	2.4	1.5	3.2	1.3	0.4	1.0	1.5	1.3	0.4	0.5
	Endocrinology	25.5	13.6	3.4	1.5	16.9	13.3	9.8	0.7	2.4	5.2	2.6	1.1	1.0	1.1	1.1	0.6	0.4
	Family medicine	35.0	16.9	2.4	2.9	14.3	10.5	6.6	1.1	1.2	2.5	2.1	0.2	1.3	1.1	1.4	0.3	0.2
	Gastroenterology	31.2	13.0	3.5	2.3	12.0	14.1	6.9	2.5	1.3	4.8	4.2	0.6	0.8	0.9	0.8	0.5	0.5
	Infectious disease	34.1	12.4	2.7	2.1	13.0	16.1	7.0	0.7	0.7	5.4	2.5	0.7	1.0	0.5	0.3	0.5	0.3
	Internal medicine	35.6	14.8	2.4	1.6	14.1	12.8	7.4	1.4	1.4	2.7	2.0	0.5	0.9	0.8	0.6	0.4	0.3
	Nephrology	29.4	11.4	3.4	1.2	17.5	14.5	7.8	1.3	2.4	5.0	1.8	1.1	1.0	0.6	0.3	0.6	0.6
	Neurology	24.7	15.8	3.5	0.6	14.1	18.2	8.0	1.2	2.6	5.3	1.3	1.3	0.9	1.1	0.6	0.6	0.3
	Obstetrics and gynecology	33.0	8.9	5.9	2.5	13.4	10.8	6.7	3.1	2.3	5.0	3.3	0.9	1.1	1.0	1.2	0.5	0.4
	Oncology/hematology	35.9	10.5	5.3	1.1	12.1	11.6	5.6	0.8	1.0	7.5	2.4	3.5	0.7	0.9	0.5	0.5	0.4
	Ophthalmology	26.3	14.3	4.7	1.2	11.9	15.1	5.6	3.3	2.5	8.4	1.2	1.5	1.3	1.1	0.6	0.8	0.4
	Orthopedics	30.4	7.0	6.8	0.8	6.5	9.7	4.5	8.4	3.3	13.8	1.2	1.7	2.2	1.4	0.5	1.3	0.5
	Pediatrics	28.2	17.5	3.2	2.9	10.3	15.6	7.0	1.3	2.7	4.3	2.1	0.5	1.1	1.1	1.2	0.7	0.4
	Psychiatry	28.5	7.7	2.8	0.8	29.1	11.0	4.0	0.7	1.5	7.5	0.9	0.7	1.8	1.4	0.8	0.7	0.3
	Pulmonology	28.9	12.1	3.9	1.2	11.9	15.1	9.2	2.2	2.0	6.2	2.4	1.3	1.2	0.8	0.3	0.6	0.6
	Radiology	23.5	16.0	4.1	0.9	7.8	12.2	13.6	3.8	3.4	6.2	2.1	1.4	1.2	2.2	0.4	0.9	0.4
	Rheumatology	25.6	15.5	3.0	1.1	14.3	18.7	8.1	0.7	1.1	5.8	1.4	1.0	0.9	1.3	0.7	0.5	0.4
	Surgery	33.7	7.9	5.0	0.9	8.8	11.9	5.4	8.0	2.9	7.1	2.4	1.5	1.7	1.0	0.4	0.9	0.6
	Other	27.9	12.0	3.6	1.3	13.4	14.8	6.9	2.9	2.6	6.1	2.0	1.1	1.6	1.5	0.7	0.9	0.7

Query purpose

Cells show the adjusted percentage of artificial intelligence–enabled clinical queries within a given query purpose for each clinician type and physician specialty. Percentages were adjusted for sex and years in practice, using logistic regression with marginal standardization, and reflect a stratified random sample of 38.8 million queries (eMethods in Supplement 1). Each query is analyzed according to its primary purpose; purposes are defined in the Table. Clinician type rows are shaded by rank order; physician specialty rows are shaded according to the color bar. Percentages within each row sum to 100%, allowing for rounding. Physician specialties include the 20 with the most physician users (Figure 2), plus endocrinology and rheumatology, which were among the 20 specialties with the most classified queries; the remaining specialties are grouped as "Other."

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Outside-of-specialty queries were more often directed at clinical knowledge (36.8% vs 28.0%), particularly disease information (14.2% vs 9.1%) and medication information (11.4% vs 9.0%) (eFigure 8 in Supplement 1).

Discussion

In this national study of an AI-enabled clinical information platform, 952 008 US clinicians—of whom 556 200 were physicians—collectively submitted more than 270 million clinical queries over 2.5 years, over which time the number of monthly active users grew from the hundreds to the hundreds of thousands while the number of queries per active user more than doubled. Use relative to workforce share was highest among trainees and early-career physicians and those specializing in oncology and hematology, internal medicine, and family medicine. In a content analysis of 38.8 million clinical queries, the clinical questions submitted were most often about treatment and management, not the diagnostic reasoning and medical knowledge queries emphasized in prior evaluations of clinical AI.[13-15] Among subspecialists, a substantial proportion of queries addressed topics outside the physician's own specialty, indicating that these tools are frequently used for questions beyond a physician's primary practice area.

Professional societies, educators, policymakers, and health systems are developing frameworks to guide AI use in clinical practice, largely without empirical data on how clinicians use these tools.[10,12] The study findings provide a foundation for such efforts by characterizing the scale, distribution, and clinical content of clinician-AI interactions across a large platform's user base.

The higher use among trainees and early-career physicians may reflect differences in training environments and familiarity with digital information tools across career stages[20-22] or substitution of AI for the references and search tools clinicians have traditionally used. The content of queries also differed by career stage: early-career physicians more often sought guidance for clinical decision-making and more experienced physicians more frequently queried the underlying evidence, consistent with a transition from building clinical decision-making frameworks to maintaining established ones.[23] This echoes what has been described as an "inversion of expertise," in which learners may be more adept with emerging technologies than their supervisors.[24,25]

Prior evaluations of clinical AI have focused predominantly on diagnostic reasoning and medical knowledge recall, using benchmarks such as the US Medical Licensing Examination and clinical vignette-based diagnostic tasks.[15,26-28] These efforts have demonstrated that LLMs now perform at or above the level of physicians on these benchmarks.[29,30] Yet physicians most often sought assistance with treatment and medication information, suggesting that many of the tasks used to evaluate clinical AI may not match the tasks for which physicians actually use it. The performance of these tools on treatment selection, medication guidance, and evidence synthesis—tasks that dominate real-world use—remains largely unmeasured, limiting clinicians' ability to assess reliability where these tools are most often applied. Evaluation and oversight frameworks should be weighted accordingly, with a focus on evaluating these tools on the treatment and medication questions clinicians ask and linking use to subsequent clinical decisions and patient outcomes.

Sustained, widespread use suggests these tools address an unmet need in clinical practice. Nonphysician clinicians accounted for more than 40% of users, and nurse practitioners and physician assistants used the platform at least as intensively as physicians. Growth in query volume was driven predominantly by new users, with queries per active user remaining stable for most of the study period. Use was highest in oncology and hematology, internal medicine, and family medicine, and lowest in radiology and perioperative specialties—a pattern that may reflect both the clinical relevance of text-based evidence synthesis to different practice styles and the current capabilities of the platform. Cross-specialty information seeking predates these tools, but the finding that subspecialists frequently queried outside their specialty quantifies how often they are used for questions that physicians may feel less equipped to manage independently. Traditional mechanisms for assessing physician knowledge, such as board examinations and maintenance of certification assessments, are typically confined to a physician's own specialty and may not capture these cross-disciplinary information needs. Real-world patterns of AI-assisted information seeking may offer complementary insight, with implications for continuing medical education.

Taken together, these findings suggest that the relationship between clinicians and clinical knowledge is changing. For much of modern medicine, clinicians have been expected to internalize a body of knowledge through training and maintain it through continuing education. Study findings suggest a growing share of knowledge access is shifting from recall to retrieval. Whether this transition improves the quality and efficiency of care will depend on the accuracy of these tools, the training clinicians receive in using them, and the willingness of institutions to adapt how AI is taught, evaluated, and governed.[31-35]

Limitations

This study had limitations. First, data from a single AI-enabled clinical information platform were analyzed, which therefore underestimates clinician use of these tools and may limit generalizability. Because only queries entered in the main question interface were captured, user and query counts are also lower bounds on use of the platform itself. However, an independent survey of physicians found that the platform is used by more physicians than all other clinical AI tools.[16] Relatedly, reliable workforce denominators were available only for physicians, and comparisons for other clinician types relied on NPPES registration records, which include some clinicians no longer in active practice. For context, published estimates of the active US physician workforce range from approximately 870 000 to 1.4 million, depending on the source and definition of active practice.[18,19,36] Second, query classification relied on an LLM rather than human annotation, which

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may have introduced misclassification. However, in a blinded validation, the model agreed with clinician annotators at least as often as clinicians agreed with one another, and most residual disagreement fell between neighboring subcategories. In particular, topic labels are a heuristic for the subject matter of queries rather than a definitive classification, and because generalist practice spans these areas, most generalist queries necessarily fall under multiple specialties. Third, we could not determine whether queries occurred during patient encounters, clinical preparation, or nonclinical settings. The patterns may therefore reflect a mixture of point-of-care decision support and broader knowledge seeking that available data cannot distinguish. Fourth, the study design could neither distinguish substitution of AI for traditional information sources from a change in information need, nor determine whether cross-specialty querying substitutes for or precedes specialty consultation. Fifth, because OpenEvidence holds content partnerships with several major medical publishers, use patterns may not generalize to tools without comparable content access, and cross-specialty querying in particular may partly reflect the breadth of available content.

Conclusions

AI-enabled clinical information platforms have been widely used by US clinicians, particularly among trainees, early-career physicians, and nonprocedural specialists—a distribution that may reflect a generational shift in how physicians search for and access clinical knowledge. Clinicians predominantly sought information on treatment and medication decisions and physicians frequently queried outside their own specialty, patterns that diverge from the diagnostic tasks emphasized in current evaluations of clinical AI. These findings highlight the growing role of AI-enabled clinical information platforms in clinical practice and suggest that efforts to evaluate, teach, and integrate AI in clinical medicine should be informed by empirical studies of its use in actual practice.

ARTICLE INFORMATION

Accepted for Publication: September 28, 2026.

Published Online: October 15, 2026. doi:10.1001/jama.2026.21868

Author Contributions: Drs Patel and Finlayson had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Drs Patel and Finlayson contributed equally. Drs Zack and Jena contributed equally.
Concept and design: All authors.
Acquisition, analysis, or interpretation of data: All authors.
Drafting of the manuscript: Patel, Finlayson, Liu-Hass, Zack, Jena.
Critical review of the manuscript for important intellectual content: All authors.
Statistical analysis: Patel, Finlayson, Liu-Hass, Zack, Jena.
Obtained funding: Finlayson.
Administrative, technical, or material support: Patel, Finlayson, Ray.
Supervision: Finlayson, Liu-Hass, Zack, Jena.

Conflict of Interest Disclosures: Dr Patel reported receiving grant support from the National Institute of Biomedical Imaging and Bioengineering (F32EB040202) of the National Institutes of Health. Dr Finlayson reported being a salaried employee of OpenEvidence, which provided data and contributed to study analysis, during the conduct of the study. Dr Liu-Hass reported receiving personal fees from Accompany Health for consulting outside the submitted work. Dr Ray reported receiving personal fees from OpenEvidence as a full-time employee during the conduct of the study. Dr Zack reported being the chief medical officer of OpenEvidence during the conduct of the study. Dr Jena reported receiving personal fees from Analysis Group, Freakonomics, MD, Doubleday Books, *The New York Times*, *Los Angeles Times*, *The Wall Street Journal*, and Harry Walker Agency outside the submitted work and serving as an unpaid board member for the United Network for Organ Sharing. No other disclosures were reported.

Data Sharing Statement: See Supplement 2.

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