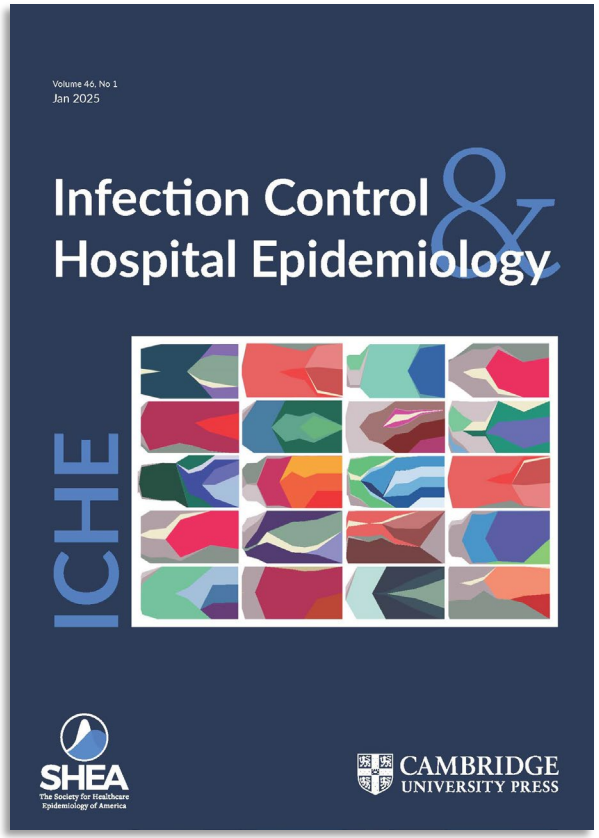
SHEA

The Society for Healthcare Epidemiology of America

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Infection Control & Hospital Epidemiology publishes scientifically authoritative, clinically applicable, peer-reviewed research on control and evaluation of the transmission of pathogens in healthcare institutions and on the use of epidemiological principles and methods to evaluate and improve the delivery of care. Major topics covered include infection control practices, surveillance, antimicrobial stewardship, cost-benefit analyses, resource use, occupational health, and regulatory issues.

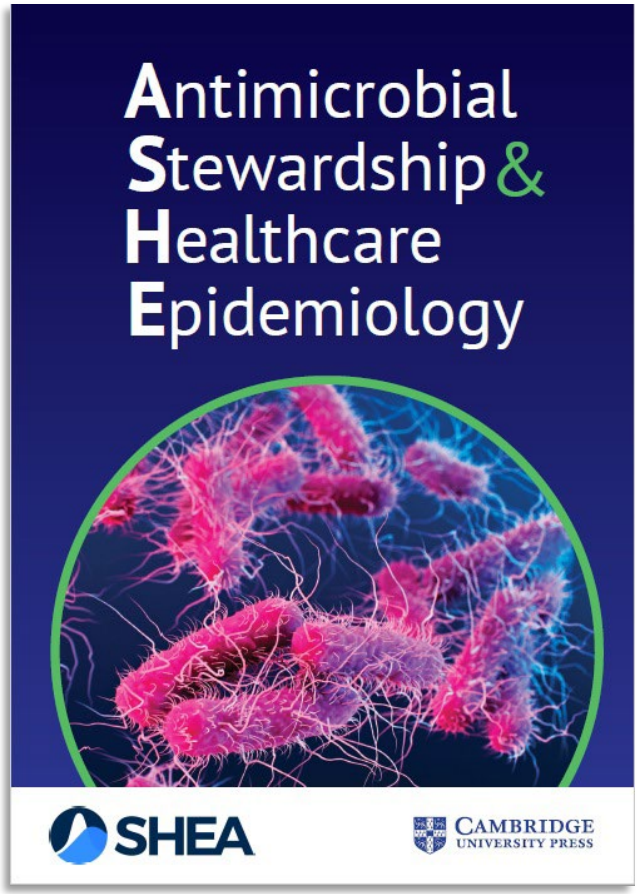
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SHEA Members Open Forum

Get ready for real discussion! This is a peer-driven, discussion-based program designed for SHEA members to connect, share experiences, and talk through real-world challenges.

October 29th at 4:00 – 5:00 pm ET

Topic: *Managing Patients with MDR-GNRs & Candida auris After Acute Care Discharge*

Moderator: Harjot K. Singh, MD, ScM

SHEA

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Improving Antibiotic Stewardship and Infection Prevention in Nursing Homes

eLearning Course



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Visit LearningCE for details!

UPCOMING LIVE PROGRAMS

Measuring the Social & Environmental Impact of Antimicrobial Stewardship & IP
November 9, 2026 | 4:00 – 5:00 pm ET

Preventing Health-Care Associated Infections in Congregate & Ambulatory Settings
November 19, 2026 | 2:30 – 3:30 pm ET
January 27, 2027 | 4:00 – 5:00 pm ET

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SHEA Webinar

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- Webinar recording, PowerPoint presentation, and references available on learningce.shea-online.org
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October Town Hall Panelists:



Dr. Bernard Camins
Mount Sinai



Dr. Katie Passaretti
Advocate Health



Dr. Chris Nyquist
Children's Hospital Colorado



Dr. Tom Talbot
Vanderbilt University

Invited Panelist:



Dr. Westyn Branch-Elliman
Greater Los Angeles VA Healthcare System and UCLA



De-Mystifying AI in Infection Prevention and Stewardship

Westyn Branch-Elliman, MD, MMSc

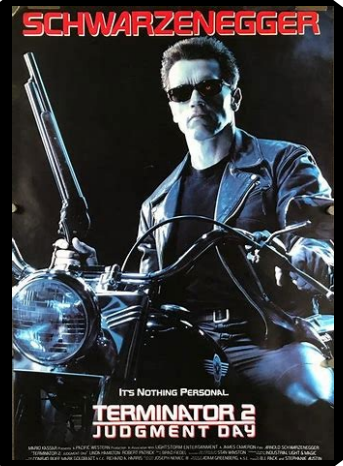
Professor of Medicine, UCLA David Geffen School of Medicine

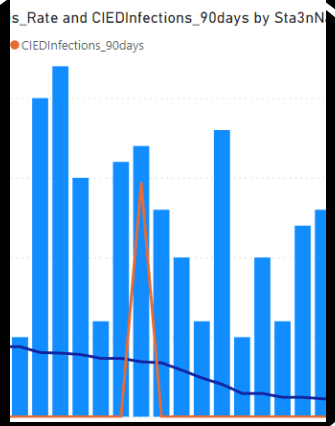
SHEA Townhall

October 28, 2026

What is “AI:”?

It Depends Upon Who You Ask!



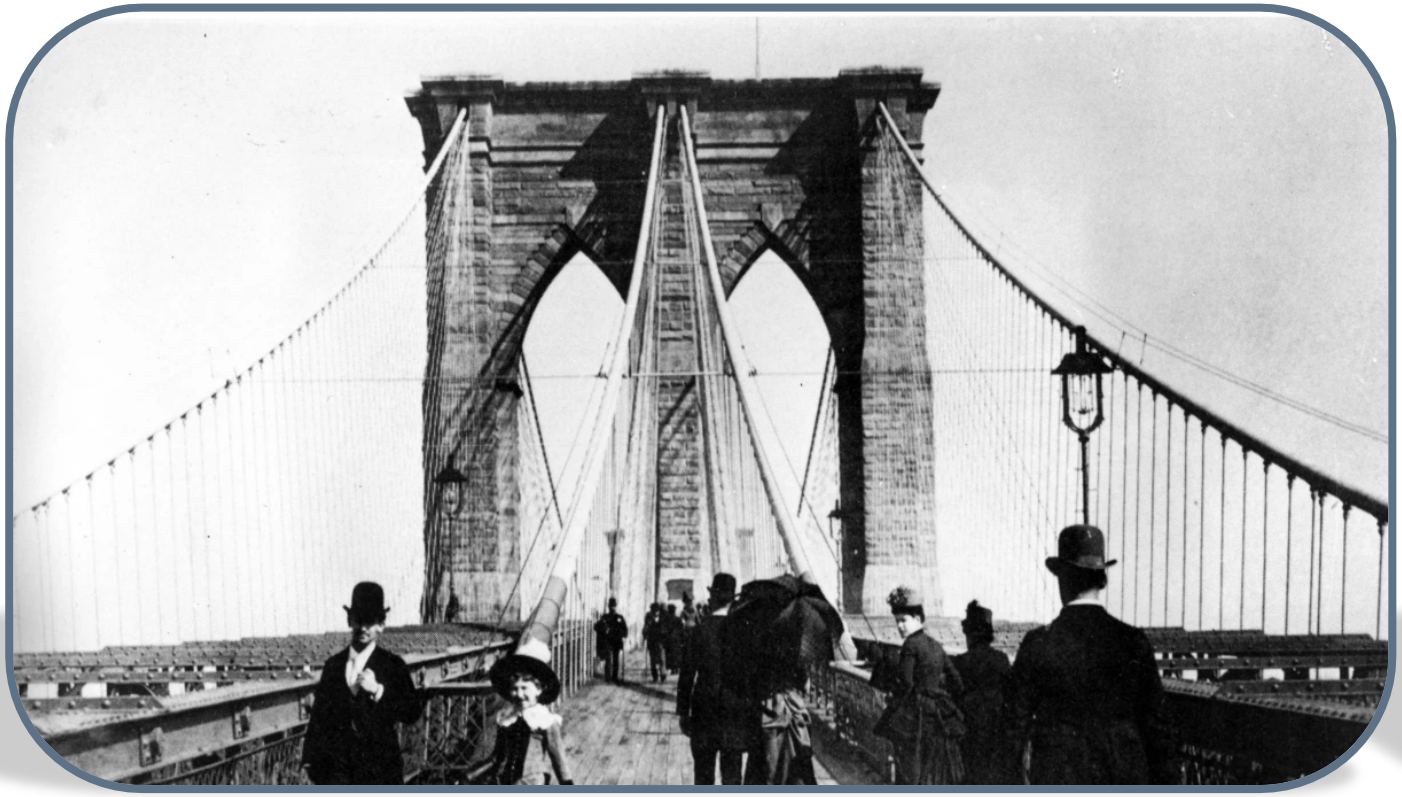






16 years…

New York, 1883



17 years…

JAMA, April 2023

News & Analysis

Medical News & Perspectives

It Takes an Average of 17 Years for Evidence to Change Practice—the Burgeoning Field of Implementation Science Seeks to Speed Things Up

Rita Rubin, MA

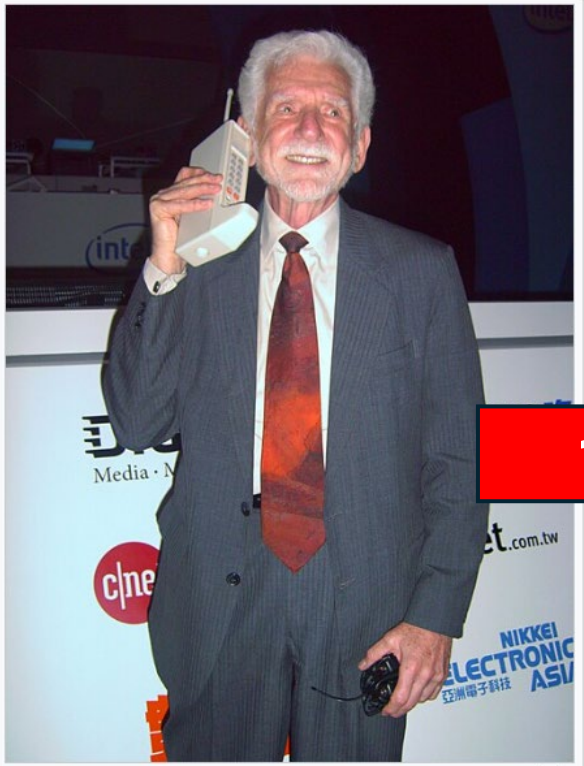


Colorectal cancer screening with an at-home stool test is more convenient than with a colonoscopy, but an ab-

Chasm might be a better word to describe the gap between research and practice. A frequently cited estimate puts that

But her "light bulb moment" came after the death of someone close to her by suicide with a firearm and the birth of her son.

The Tech Timeline Is Not all that Different!



Martin Cooper photographed in 2007 with a 1972 prototype of a Motorola handheld mobile phone

17 Years



Motorola *MicroTAC* was one of the first hinged or "clamshell" mobile phones (1989)

18 Years



First iPhone on display under glass at Macworld 2007

Photos Courtesy Wikipedia









Technically, What is AI?

- Artificial intelligence (AI) involves the development of **computer systems capable of performing tasks that typically require human intelligence**.
- AI systems may use approaches such as deep learning with neural networks, to recognize patterns and make predictions based on large amounts of data.
- Such systems **can learn abstract concepts and patterns**, making them effective for tasks like image recognition and natural language processing.

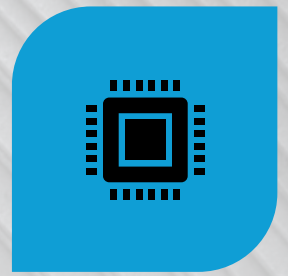
Common AI Applications In Healthcare



NATURAL LANGUAGE PROCESSING (NLP): IS A SUBFIELD OF AI THAT ENABLES COMPUTERS TO UNDERSTAND AND INTERACT WITH HUMAN LANGUAGE



LARGE LANGUAGE MODELS (LLMS): MODELS THAT PERFORM NLP TASKS AND OFTEN GENERATE OUTPUT

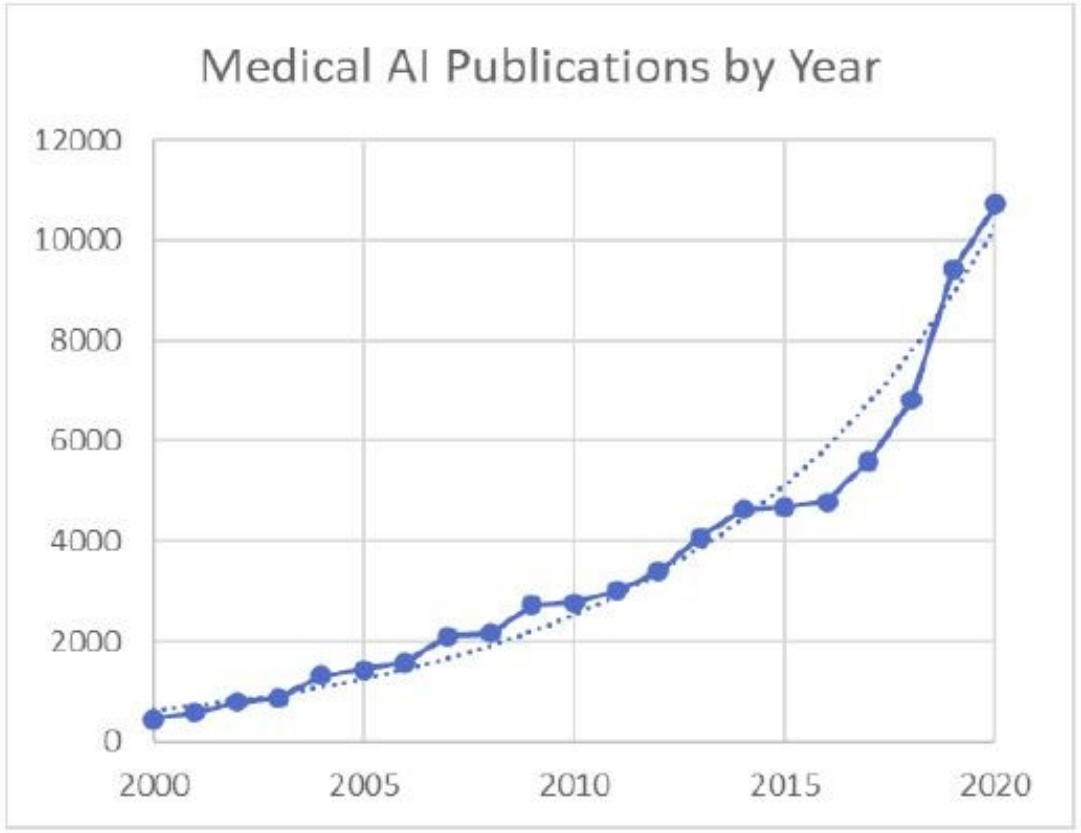


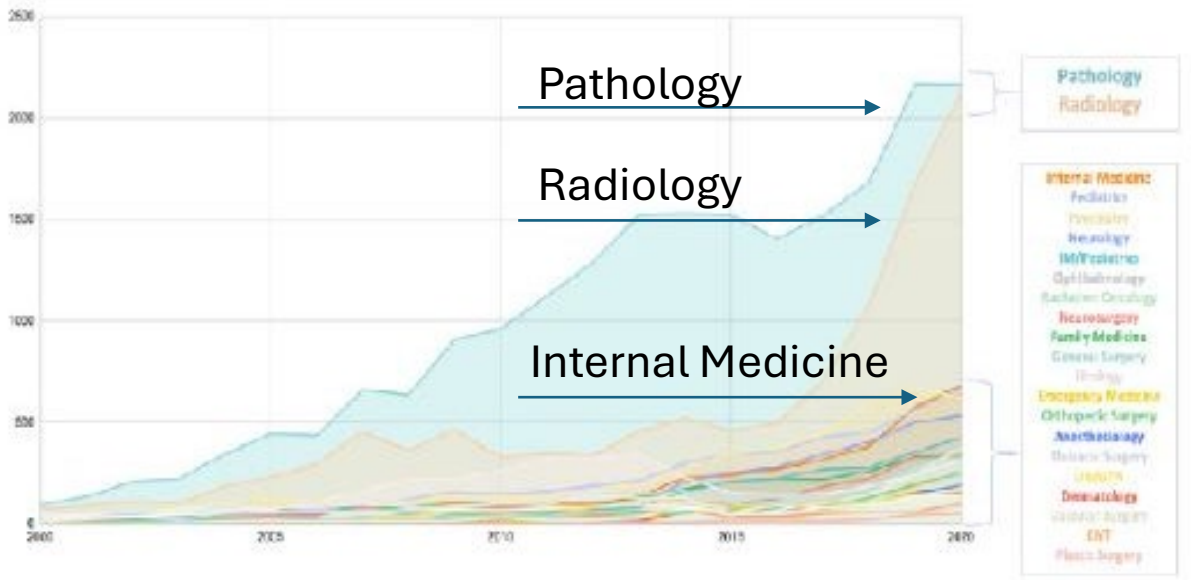
COMPUTER VISION: IMAGING ANALYSIS SUCH AS IMAGE CLASSIFICATION, OBJECT DETECTION AND SEGMENTATION



PREDICTIVE (RISK PREDICTION) MODELING: ANALYZE CLINICAL DATA AND MAKE PREDICTIONS ABOUT FUTURE EVENTS

AI In Healthcare: Diagnostic Fields Lead the Charge



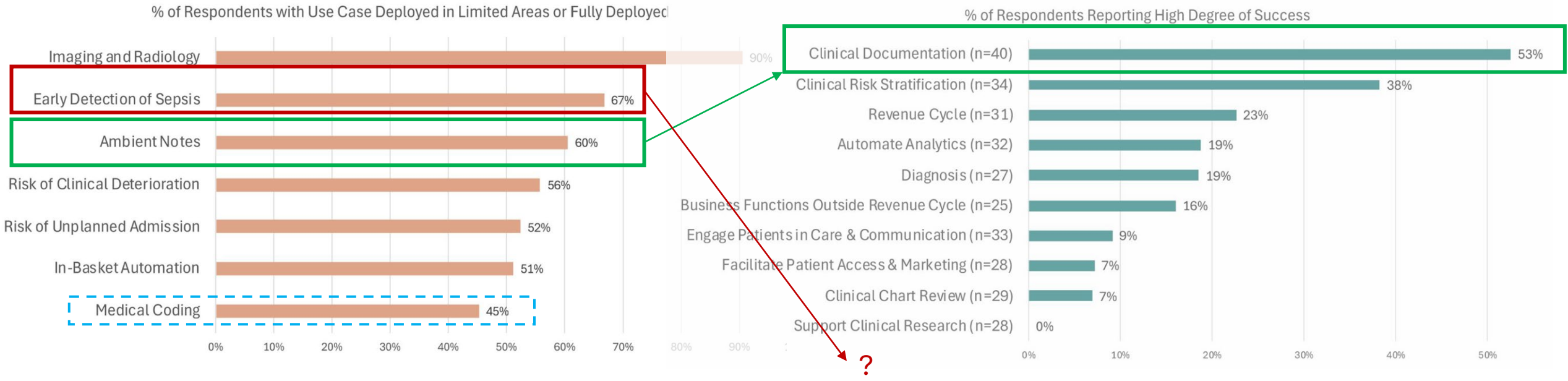


Reference: Perera N, Perchik JD, Perchik MC, Tridandapani S. Trends in medical artificial intelligence publications from 2000-2020: Where does radiology stand?. Open J Clin Med Images. 2022; 2(2): 1052.

The Other Big Bucket: Ambient Scribes and Document Summarization

National survey of 67 health systems

- 43 responses (64% response rate)
- Time period 2023-24
- Looked at indications with high levels of deployment and high degrees of success



Reference: Poon *et al*. Adoption of Artificial Intelligence In Healthcare: Survey of Health System Priorities, Successes, and Challenges. *JAMIA*. May, 2025. *In press*.

Ambient Scribes: A Quick Overview



1. Consent

The provider obtains verbal consent

2. Activate App

The provider turns on app, which listens to the conversation

3. Clinic Visit

The patient and provider have their clinic and conversation

4. Audio Processing

The digital scribe software processes the audio from a microphone

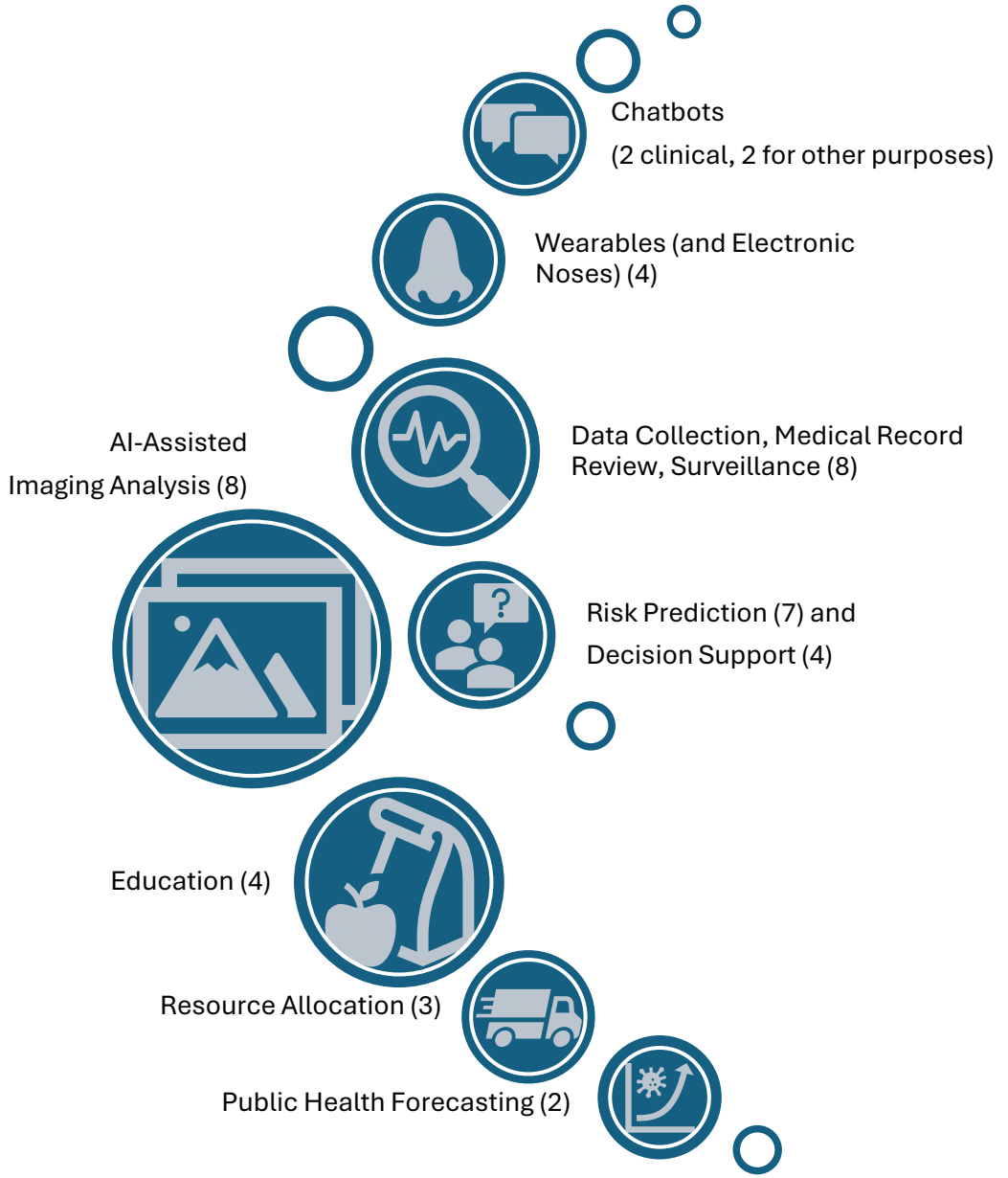
5. Clinical Notes

The software generates clinical notes

6. Review and Edit Notes

The provider confirms note accuracy

Evidence Map: Where Have We Seen Successful *Implementation* in Infection Prevention, Stewardship, and Associated Fields (not Impact…)



Scoping Review: Implementation of AI and ML into Clinical Care:

- Search terms: Artificial intelligence or machine learning or natural language processing and infection control/prevention or antimicrobial stewardship or pandemic preparation or sepsis or bacteremia during the last 7 years
- N= 9,230 Unique Studies Identified
  - 9,144 studies excluded for a variety of reasons, mostly due to lack of prospective implementation in healthcare
    - Risk prediction and AI-assisted radiology the most common topics, but limited uptake (particularly of risk prediction) into clinical practice
  - 84 studies **(0.9%)** identified that were actually implemented and used in a clinical or public health setting
    - 9 RCTs, one meta-analysis, almost all in "sepsis risk prediction"
    - Meta-analysis found benefit when observational studies were included but no impact when limited to randomized trials.

THEME	QUOTE	REFERENCE
Retrospective versus real-time data	"The applicability to clinical settings, and the **actual clinical utility is still unclear**; thus, **further prospective study is warranted** to evaluate the clinical usefulness."	Okada et al. J of Intensive care. 2021.
Minimal improvement over existing analytic options	"This study demonstrates that **classical models** built on robust, hand-chosen predictor variables **may not be inferior** to data-driven models for NCGC risk prediction." "The diagnostic accuracy of the AI algorithm in the Chinese-German test dataset was 76.5%. **Without AI assistance**, the eight radiologists' diagnostic accuracy was **79.1%** and increased **with AI assistance** to **81.5."**	Huang et al, JCO Clin Cancer Informatics. June 2022. Meng et al. Euro Radiol June 2023.
Just because you build it, does not mean they will come	"The self-made web-based risk calculator **can be** conveniently used to predict the prognosis for patients after discharge."	Tian et al. Health and Quality of Life Outcomes. 2023.
Failure to consider context of data collection – Limited retrospective dataset not representative of the "real world."	"Furthermore, it detected COVID-19 subjects successfully with a maximum sensitivity of 94.21%, specificity of 94.96%, and area under the receiver operating characteristic (AUROC) curves of 0.90." [Compared **120 COVID+** to **120 healthy** patients]	Alkhodari et al. PLoS One. 2022.

Data Considerations for Clinical Applications



Retrospective Data

- Clean
- Complete
- Curated
- Static
- Predictable
- Low-Stakes



Real-Time Data

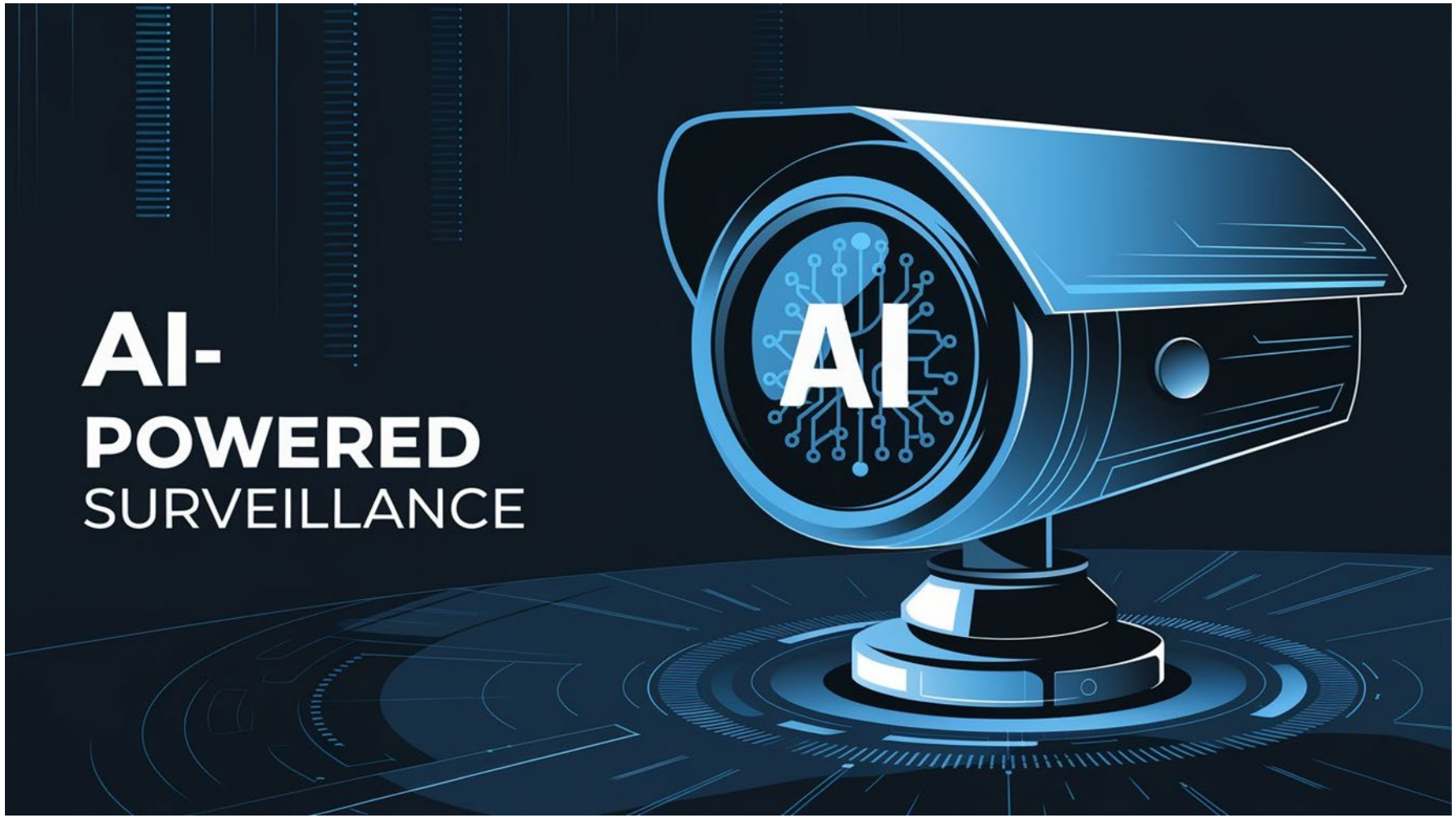
- Imperfect
- Incomplete
- Unpredictable
- Delayed
- Missing (In non-random ways)
- High-Stakes
- Occurring in a constantly changing system with different goals, guidelines, and applications



Impact

- End-User Engagement and Training
- Need Dedicated Staff and Support to Realize Potential
- Additional Workload May Contribute to Burnout
- Appropriateness of the Intervention
- Dynamic solutions to match a dynamic system

Retrospective Surveillance Activities



LLM-ASSISTED PATIENT SAFETY SURVEILLANCE (CHART REVIEW DATA EXTRACTION)

- 11 VA Site National Phase 0 pilot
- 110 CLABSI cases, 110 non-CLABSI cases
- Facility randomly assigned cases to review from another facility
- Cases reviewed in 3 ways: Expert alone, LLM-alone, LLM-Augmented/Assisted
- Accuracy compared to facility reported determination
- LLM-Augmented with highest accuracy and associated with time savings and high satisfaction
  - Reduced facility-level variation (and overcalls) may be most useful for resource-limited facilities
  - 85% still felt that additional chart review to ver output was necessary
- Not a fully automated or scalable system

Table 2. Agreement of Different Methods of Review Compared to Facility Reporting

Type of Review	Overall Agreement With Facility Reporting	Positive Percent Agreement With Facility Reporting	Negative Percent Agreement With Facility Reporting	% Cases With Disagreement Due to Errors in Facility Reporting	Accuracy (agreement With Facility Reporting or Refereeing Panel)
AI-assist	83.6% (184/220; 95% CI, 75.3–90.0)	76.4% (84/110; 95% CI, 67.3–83.9)	90.9% (100/110; 95% CI, 83.9–95.6)	58.3% (21/36; 95% CI, 40.7–74.4)	93.2% (205/220; 95% CI, 89.0–96.1)
AI-alone	83.6% (184/220; (95% CI, 75.4–90.0)	82.7% (91/110; 95% CI, 74.3–89.3)	84.5% (93/110; 95% CI, 76.4–90.7)	38.9% (14/36; 95% CI, 23.1–56.5)	90.0% (198/220; 95% CI, 85.3–93.6)
Repeat expert	78.2% (86/110; 95% CI, 69.3–85.5)	69.0% (40/58; 95% CI, 55.4–80.5)	88.5% (46/52; 95% CI, 76.6–95.6)	45.8% (11/24; 95% CI, 25.6–67.2)	88.2% (97/110; 95% CI, 80.1–93.6)

Proportion of error attributed to facility reporting determined by adjudication committee review. Exact Clopper-Pearson 95% CIs were estimated using the binomial distribution.
Abbreviations: AI, artificial intelligence; 95% CI, 95% confidence interval.

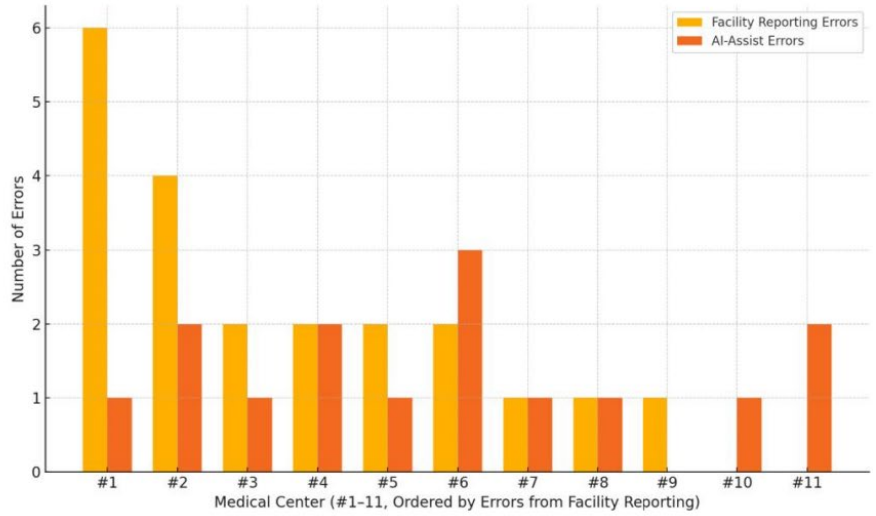
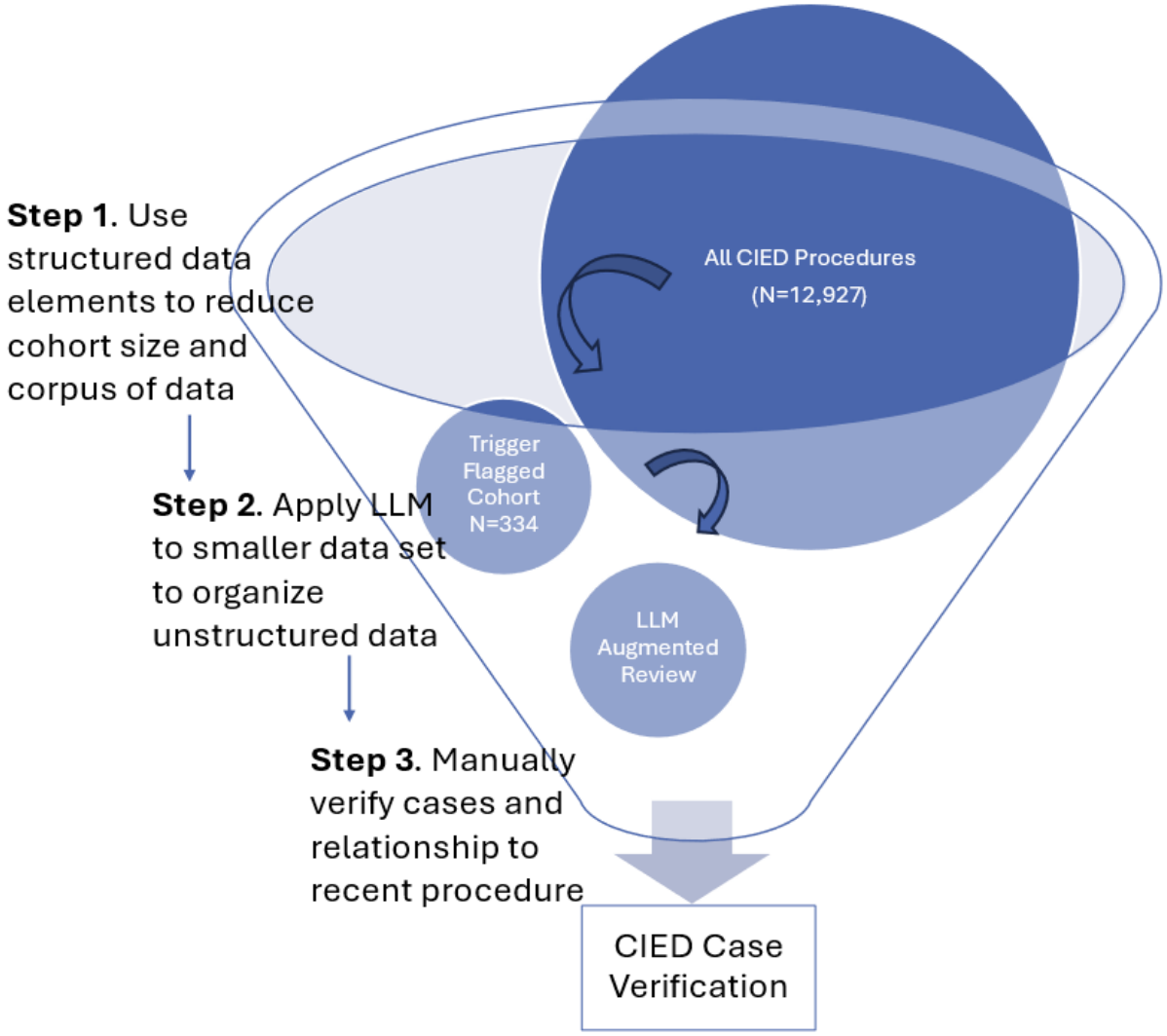


Figure 2. Variation in number of errors in central line–associated blood stream infection (CLABSI) determination by medical center, displaying number of errors at each center that occurred with facility reporting and artificial intelligence (AI)-assisted review.

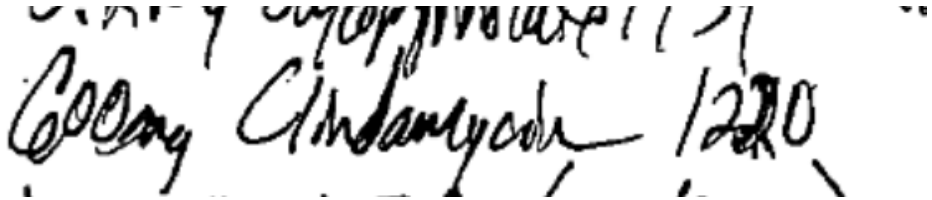
D Morgan *et al*, *Clinical Infectious Diseases*, 2025

LLMs can be used as part of a phased approach to surveillance (saves time and limits compute costs)

- Large language models have substantial IT, computer infrastructure, and computational resource needs
- Proof-of-concept studies that focus on small retrospective datasets do not address the challenges of implementation and scaling
- Other models or approaches are needed – for CIED infections, we applied a hybrid approach using structured data elements to direct the manual GPT review to the highest yield cohort
  - Directing the LLM to the highest probability cases reduced compute requirements and person time for chart review
  - Tool was not accurate enough for a stand-alone tool – human review was necessary to validate findings and reduce “overcalls”



A Tale of Two Prompts..



Prompt 1: What does this say?

Output:

The handwriting reads:

Gedung Cendanayoda 1220

(or possibly "Gedung Cendanyoda 1220")

It appears to be a building name and number, likely an address — "Gedung" means **"building"** in Indonesian/Malay.

Prompt 2: You are an infection surveillance nurse. I am going to provide you with a physician note. I want you to read all of it, including any hand-written portions, and convert the information into structured data elements for standardized reporting. Use only the information I provide you and do not make anything up or supplement it.

Output: Here is the structured data extracted from the handwritten note:

Field	Value
Medication	Clindamycin
Dose	1200
Route/Frequency	Not visible/not documented in provided image

Some Practical Tips

- Context is very important – All AI systems do is make predictions based on probability – the better the contextual window, the better the output will be.
  - Spending time updating and iterating your prompts (“prompt engineering”) generally pays dividends in the long-term.
  - You don’t need to start from scratch – papers that report on the effectiveness of LLMs for surveillance *should* include prompts. These can serve as examples or a place to start
- Keep in mind that there is a big gap between what has been done retrospectively, with limited datasets, and the medical record
  - This may be counter-intuitive, but adding more information is likely to worsen performance, as there is a lot more “noise” introduced.
- AI Tools and outputs have their own biases
- Despite the hype, errors of OMISSION are more common than errors of COMISSION (e.g., hallucinations)







Questions/Open Forum