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Is All that Glitters Gold?

The case for artificial intelligence for infection prevention and control

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Disclosures

- I'm not a computer scientist
- Funding
 - Centers for Disease Control and Prevention (Strengthening Healthcare Infection Prevention and Control (IPC) and Improving Patient Safety in the United States; CDC-RFA-CK22-2203)
 - Assistant Secretary for Preparedness and Response (ASPR)
- Other
 - Author, Up to Date
 - Consultant, Combating Antibiotic-Resistant Bacteria Biopharmaceutical Accelerator (CARB-X)
 - Former Member, CDC Healthcare Infection Control Practices Advisory Committee (HICPAC)
 - Member, Board of Trustees, Society for Healthcare Epidemiology of America (SHEA)



Objectives

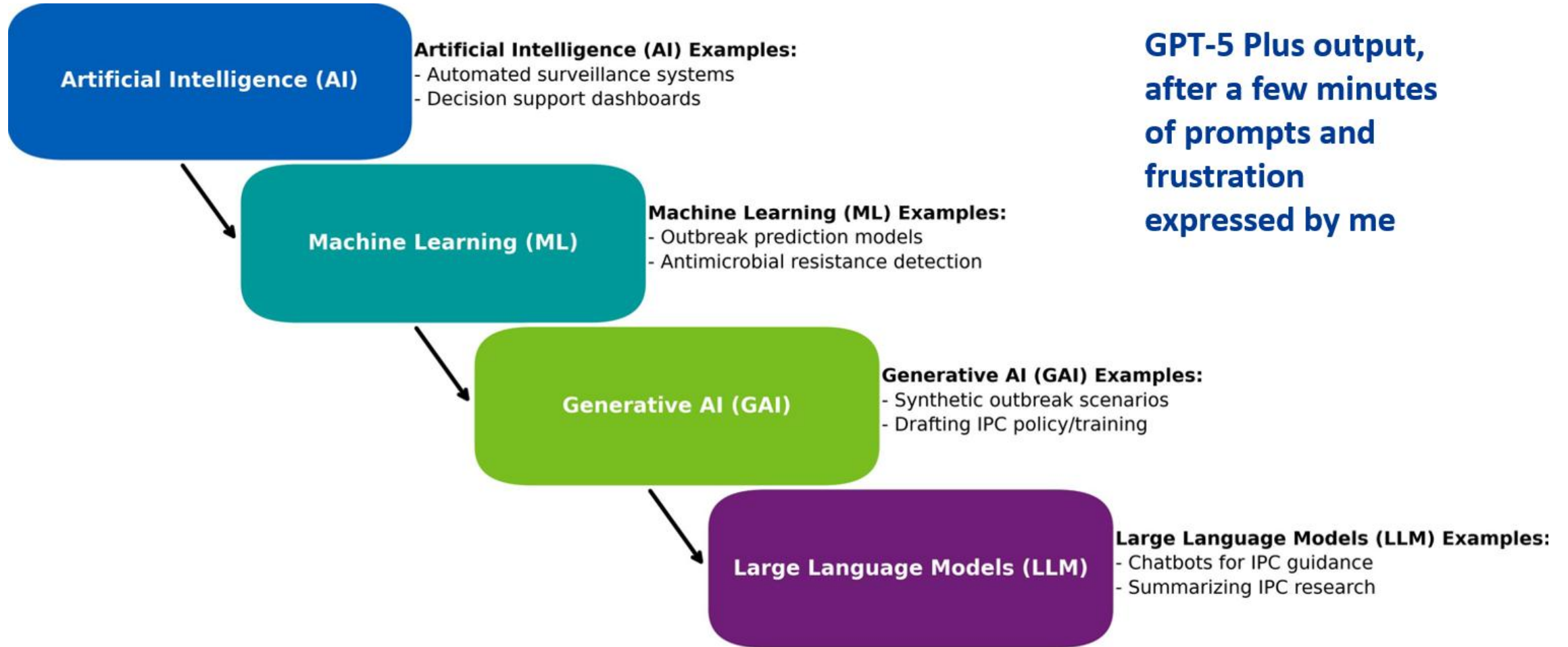
- What and Why
- Some use cases
- Are we there yet?



What and Why



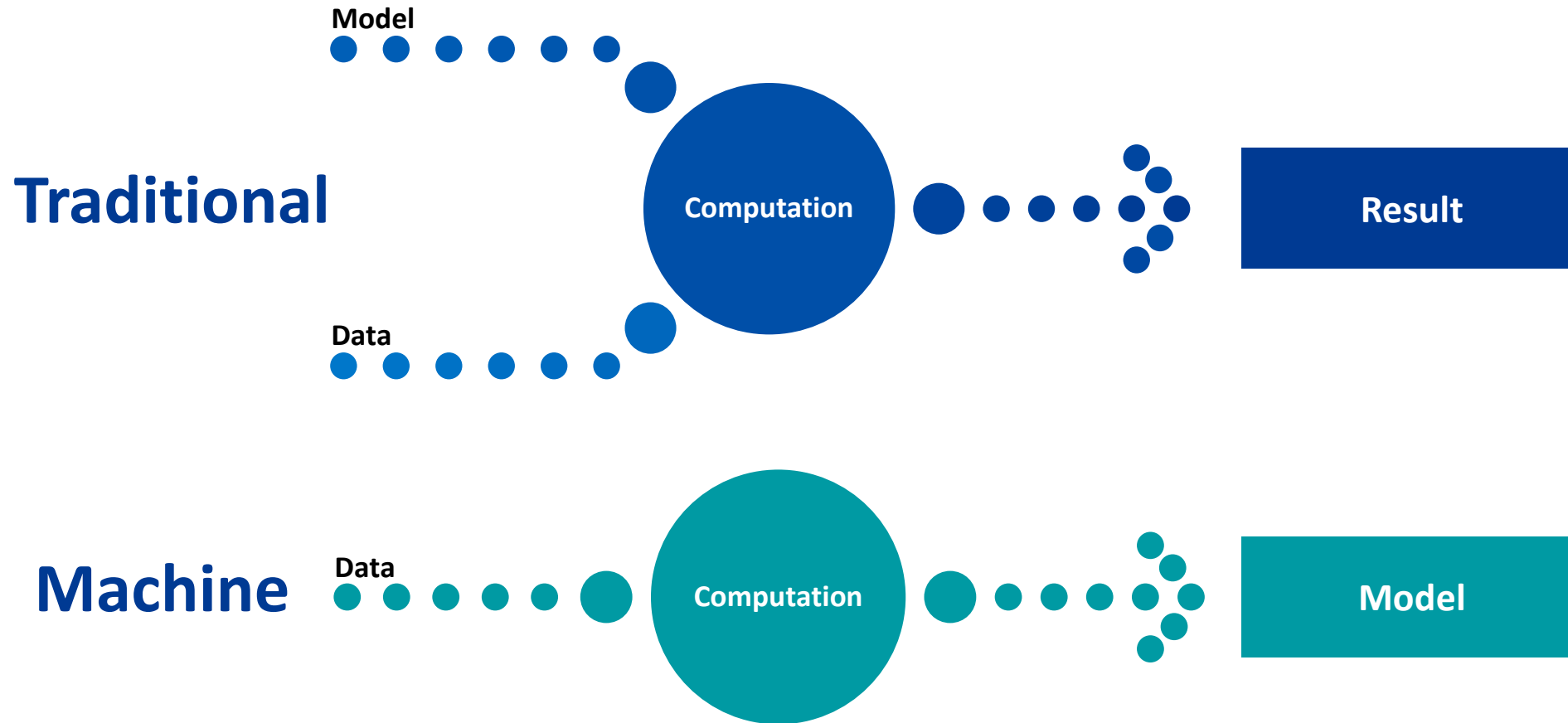
Common Parlance



10.1056/NEJMs2503956. Epub 2025 Apr 10. PMID: 40208922; Wiens J, Shenoy ES. Machine Learning for Healthcare: On the Verge of a Major Shift in Healthcare Epidemiology. Clin Infect Dis. 2018 Jan 6;66(1):149-153. doi: 10.1093/cid/cix731. PMID: 29020316; PMCID: PMC5850539; Bajwa J, Munir U, Nori A, Williams B. Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthc J. 2021 Jul;8(2):e188-e194. doi: 10.7861/fhj.2021-0095. PMID: 34286183; PMCID: PMC8285156; GPT-5 Plus, Accessed 8/30/2025.



Traditional vs Machine Learning

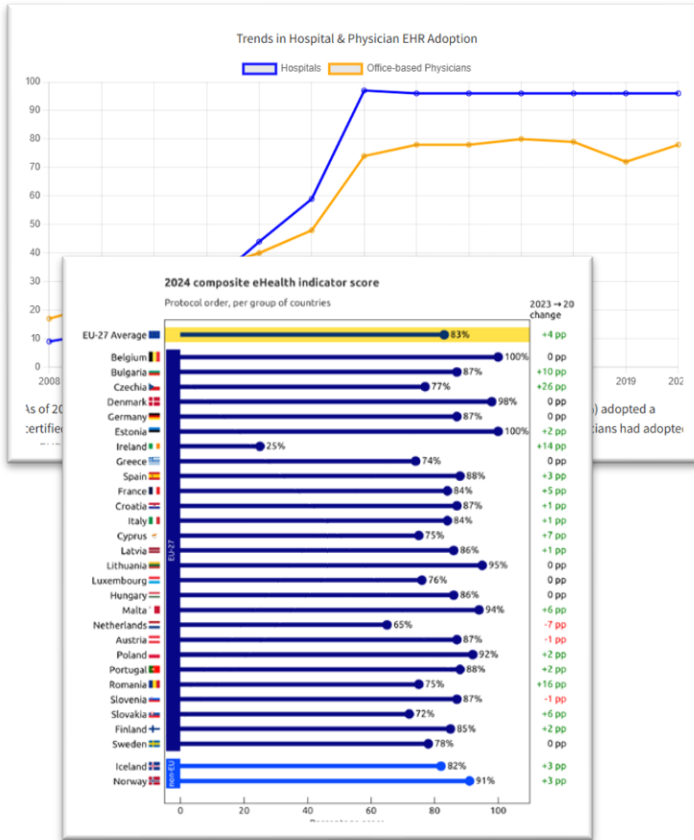


Wiens J, Shenoy ES. Machine Learning for Healthcare: On the Verge of a Major Shift in Healthcare Epidemiology. Clin Infect Dis. 2018 Jan 6;66(1):149-153. doi: 10.1093/cid/cix731. PMID: 29020316; PMCID: PMC5850539.

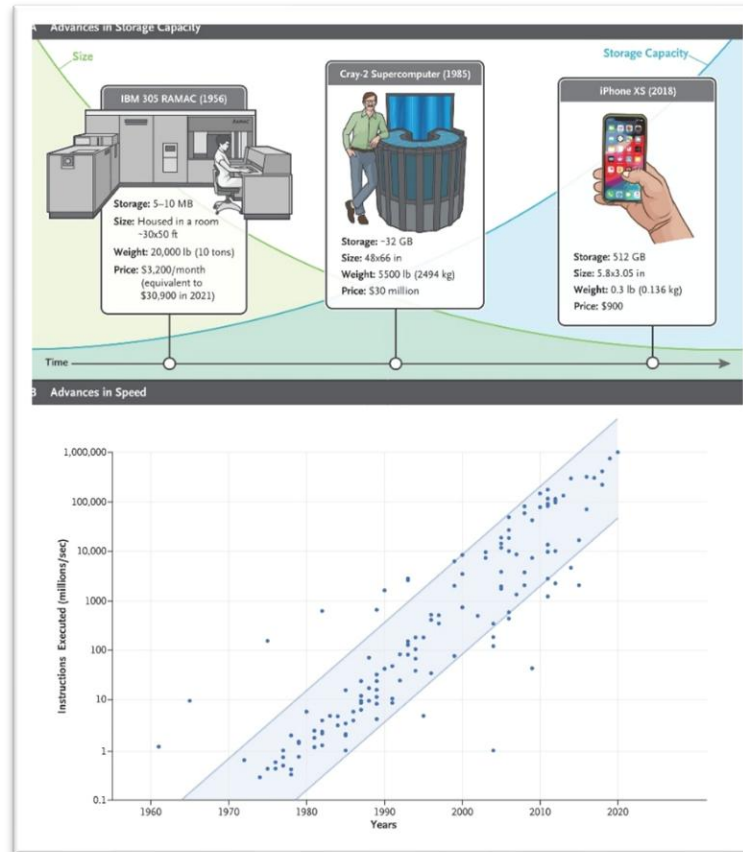


Why Now?

Availability of so so much data



Computing storage and speed



Bringing models to end users

Use Case	Example Tools
Clinical Decision Support & Diagnostics	Aidoc • Zebra Medical Vision • IDx-DR • Viz.ai • Ask Avo • PEACH
Documentation & Administrative Support	Nuance DAX • Heidi Health • Suki • Sully.ai
Remote Monitoring & Wearables	Eko Health • Empatica • Current Health • Apple Watch ECG/AFib detection
Patient Engagement & Chatbots	Babylon Health • Ada Health • ChatGPT (adapted) • Buoy Health
Research & Knowledge Support	OpenEvidence • PubMed/LitCovid NLP • Trial-matching AI • DeepMind AlphaFold
Administrative / Workflow Optimization	Olive AI • Notable Health • Qventus • Epic Cognitive Computing

Office of the National Coordinator for Health Information Technology. 'National Trends in Hospital and Physician Adoption of Electronic Health Records,' *Health IT Quick-Stat #61*; European Commission: Directorate-General for Communications Networks, Content and Technology, Capgemini Invent, Page, M. and de Waal, P., 2025 *digital decade ehealth indicator study – Final report*, Publications Office of the European Union, 2025, <https://data.europa.eu/doi/10.2759/2737039>; Haug CJ, Drazen JM. Artificial Intelligence and Machine Learning in Clinical Medicine, 2023. *N Engl J Med*. 2023 Mar 30;388(13):1201-1208. doi: 10.1056/NEJMra2302038. PMID: 36988595; GPT-5 Plus, Accessed 8/30/2025.



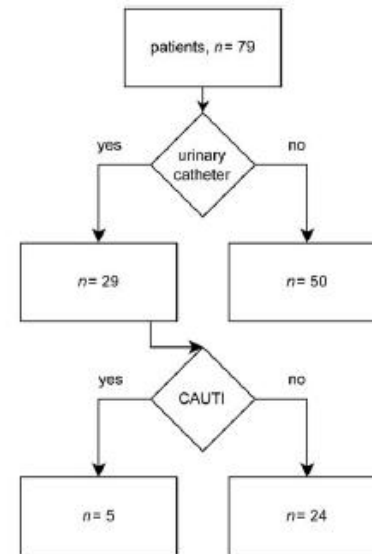
Some Use Cases



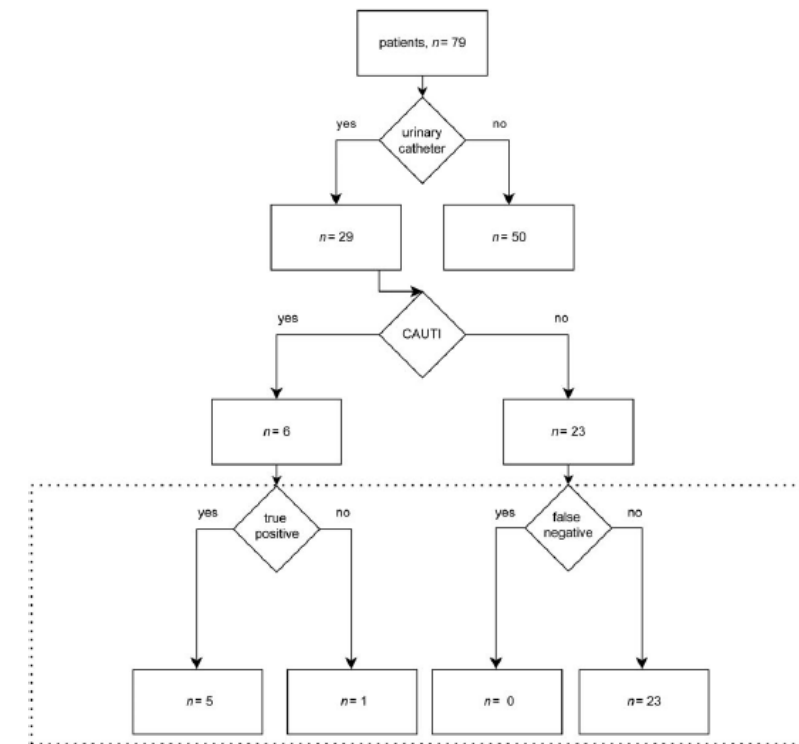
1. Detection/Surveillance of Healthcare Associated Infections: CAUTI

- Problem:
 - HAI surveillance is time-consuming and relies on humans; some HAIs are more manual than others due to how they are defined.
 - Could we use GAI to data sets to detect CAUTI, increasing efficiency and accuracy?
- Methods:
 - Synthetic data sets created
 - GPT-4 applied to both data sets and asked to analyze the data to identify CAUTI using NHSN criteria, retrieve catheter days, and calculate the device utilization ratio
 - Sensitivity, specificity, and predictive values calculated initially and after repeated prompts, compared to “gold standard” IP and infectious disease MD

Gold Standard Surveillance

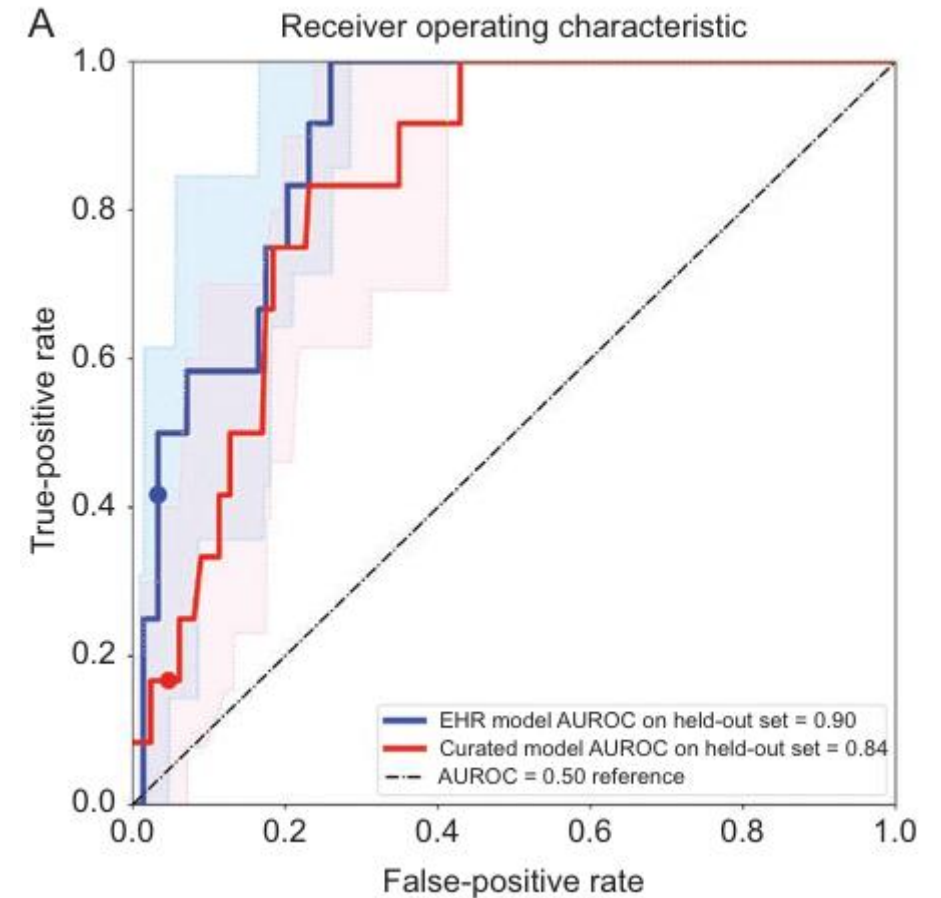


GPT-4 with comparison to gold standard



2. Prediction of Healthcare Associated Infections

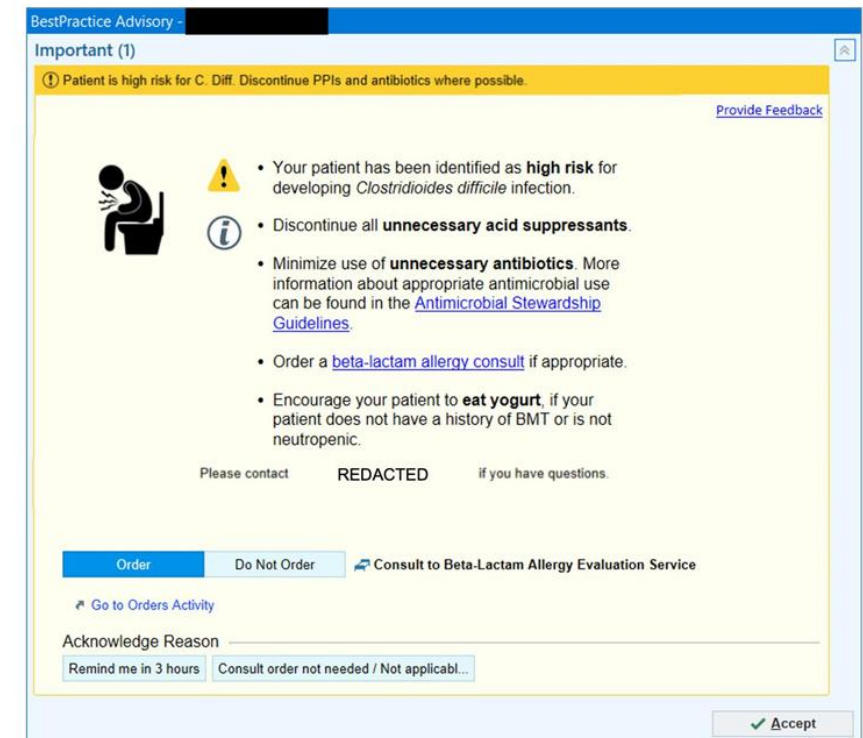
- Problem:
 - How can we identify patients at highest risk of C diff complications (e.g., ICU admission, toxic megacolon, need for colectomy, death)?
- Methods:
 - ML model applied to historical, labeled data of adult patients diagnosed with C diff
 - Trained on 894 cases to predict development of complications on day 1, 2, 3 after C diff diagnosis
 - Evaluated on a held out validation data set of 224 cases
 - Compared to curated model (23 features) vs EHR model (100s to 1000s of features)
- Results:
 - EHR model outperformed curated model
 - AUROC shown for prediction of complications 2 days after diagnosis



3. Prevention of Healthcare Associated Infections

- Problem:
 - Can AI be utilized to guide infection prevention efforts targeted to patients at high risk of developing C diff infection?
- Methods:
 - Previously validated model to predict risk of C diff infection was integrated into daily workflows
 - Model score was used to guide interventions related to hand hygiene (adding hand washing upon entry) and antimicrobial stewardship (beta-lactam allergy consult, antimicrobial de-escalation, and yogurt recommendation) from Jan – December 2023
 - CDI incidence, antimicrobial use, and qualitative assessments of bundle implementation were reported

eFigure 7. Screenshot of BPA #2 for recommendations for reducing CDI risk.



Tang S, Shepard S, Clark R, Ötles E, Udegbunam C, Tran J, Seiler M, Ortwine J, Waljee AK, Nagel J, Krein SL, Kurlander JE, Grant PJ, Baang J, Wasylshyn A, Rao K, Wiens J. Guiding Clostridioides difficile Infection Prevention Efforts in a Hospital Setting With AI. JAMA Netw Open. 2025 Jun 2;8(6):e2515213. doi: 10.1001/jamanetworkopen.2025.15213. PMID: 40504526; PMCID: PMC12163649.



No impact on CDI but...decreased antimicrobial use!

Table 2. Primary and Secondary Outcomes Comparison Between Adjusted Pre-AI and Post-AI Samples

Outcome	Estimate (95% CI)		Change (95% CI)	P value ^a	
	Pre-AI (adjusted)	Post-AI			
Primary outcome					
Antibiotic use, days of therapy per 1000 d present					
Ampicillin-sulbactam		20.45 (19.22 to 21.73)	17.63 (16.42 to 18.87)	-2.82 (-4.59 to -1.03)	.03
Piperacillin-tazobactam		59.21 (56.76 to 61.50)	49.58 (47.28 to 52.00)	-9.64 (-12.93 to -6.28)	<.001
Ceftriaxone		19.20 (17.61 to 20.84)	18.01 (16.65 to 19.41)	-1.19 (-3.28 to 1.03)	>.99
Cefepime, concurrent with metronidazole		9.00 (8.16 to 9.94)	10.98 (9.82 to 12.15)	1.98 (0.52 to 3.43)	.24
Carbapenems ^b		16.05 (14.48 to 17.73)	16.90 (15.27 to 18.56)	0.85 (-1.43 to 3.13)	>.99
Clindamycin		3.38 (2.97 to 3.85)	2.34 (1.98 to 2.73)	-1.04 (-1.60 to -0.47)	.03
Fluoroquinolones ^f		26.44 (24.57 to 28.43)	28.32 (26.44 to 30.17)	1.88 (-0.90 to 4.43)	>.99
Acid suppressant use, days of therapy per 1000 d present					
Proton pump inhibitors ^g	255.69 (250.21 to 261.71)	249.94 (244.20 to 255.43)	-5.74 (-14.36 to 2.28)	>.99	
Histamine ₂ -blockers ^h	114.49 (109.95 to 118.91)	110.49 (106.12 to 114.83)	-4.01 (-10.24 to 2.58)	>.99	



Abbreviations: AI, artificial intelligence; CDI, *Clostridioides difficile* infection; PCR, polymerase chain reaction.

^a P values for secondary outcomes are for 2-sided tests and corrected with a Bonferroni adjustment.

^b Laboratory-identified CDI.

^c Includes all tests with positive results for PCR regardless of enzyme immunoassay result (could be positive or negative).

^d Subset of laboratory-identified CDI that are hospital onset.

^e Carbapenems include meropenem, imipenem, and ertapenem.

^f Fluoroquinolones include ciprofloxacin, moxifloxacin, and levofloxacin.

^g Proton pump inhibitors include omeprazole, lansoprazole, pantoprazole, and esomeprazole.

^h Histamine₂-blockers include famotidine, cimetidine, and nizatidine.

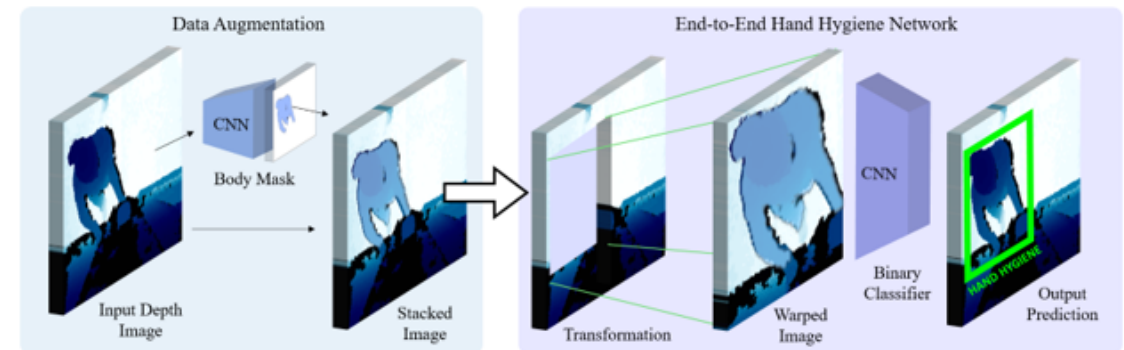
Tang S, Shepard S, Clark R, Ötles E, Udegbumam C, Tran J, Seiler M, Ortwine J, Waljee AK, Nagel J, Krein SL, Kurlander JE, Grant PJ, Baang J, Wasylshyn A, Rao K, Wiens J. Guiding *Clostridioides difficile* Infection Prevention Efforts in a Hospital Setting With AI. *JAMA Netw Open*. 2025 Jun 2;8(6):e2515213. doi: 10.1001/jamanetworkopen.2025.15213. PMID: 40504526; PMCID: PMC12163649.



4. Observation and Assessment: Hand Hygiene Monitoring

- Problem: Hand hygiene is an essential infection prevention intervention but real world performance remains sub-optimal
 - Direct observation is the gold standard to evaluate technique and can provide immediate feedback/correction; however, high risk for bias (Hawthorne Effect), is costly, and not feasible to deploy at a scale that can provide true measures of compliance
- Approach:
 - Use computer vision to observe hand hygiene dispenser use to determine if the computer vision algorithm could accurately identify dispenser usage from images collected, and compare to simultaneous human observation
 - Sensors placed in an acute care unit on the ceiling above hand hygiene dispensers; imaging data collected and analyzed using a deep learning algorithm

Figure B2. Layout of our deep neural network



Given a single depth image, our algorithm predicts whether a person is using a hand hygiene dispenser. The data augmentation stage consists of a convolutional network³² locating the person in the image. This is combined with the original depth image and is transformed (i.e., enlarged, rotated, cropped) by the neural network according to its understanding of hand hygiene from multiple hospital viewpoints. The final yes/no prediction is made by a 201-layer densely connected convolutional network (DenseNet).

Głowicz JB, Landon E, Sickbert-Bennett EE, Aiello AE, deKay K, Hoffmann KK, Maragakis L, Olmsted RN, Polgreen PM, Trexler PA, VanAmringe MA, Wood AR, Yokoe D, Ellingson KD. SHEA/IDSA/APIC Practice Recommendation: Strategies to prevent healthcare-associated infections through hand hygiene: 2022 Update. *Infect Control Hosp Epidemiol.* 2023 Mar;44(3):355-376. doi: 10.1017/ice.2022.304. Epub 2023 Feb 8. PMID: 36751708; PMCID: PMC10015275; Singh A, Haque A, Alahi A, Yeung S, Guo M, Glassman JR, Beninati W, Platchek T, Fei-Fei L, Milstein A. Automatic detection of hand hygiene using computer vision technology. *J Am Med Inform Assoc.* 2020 Aug 1;27(8):1316-1320. doi: 10.1093/jamia/ocaa115. PMID: 32712656; PMCID: PMC7481030.



Machine performed as well as humans

Table 1. Results of machine and human labeling

	Human observers	Machine	Ground truth
Dispenser used	79	92	88
Dispenser not used	639	626	630
Sensitivity, %	85.2 (95% CI, 76.1-91.1)	92.1 (95% CI, 84.3-96.7)	—
Specificity, %	99.4 (95% CI, 98.4-99.8)	98.3 (95% CI, 96.9-99.1)	—

“...we noted more events of dispenser nonuse, rather than use.”

Wow, this is seriously prediction!

Maine Med addressing bat problem in neonatal intensive care unit →

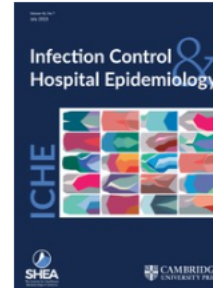
August 22, 2025

PORTLAND PRESS HERALD • August 22, 2025

MaineHealth Maine Medical Center in Portland has struggled in recent years to keep bats from getting into the hospital's neonatal intensive care unit, prompting a complaint last year to the federal Occupational Safety and Health Administration. Hospital officials said on Thursday they are currently addressing the "occasional incursions from bats." Despite efforts to control bats at the Coulombe Family Tower, where the NICU and the critical care nursery are located, hospital officials confirmed there have been seven bat sightings this year.

Source: <https://www.pressherald.com/2025/08/22/maine-med-add...>

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Infection Control & Hospital Epidemiology

Article contents

Abstract
Footnotes
References

Management of Rabies Prophylaxis for Potential Bat Exposures in a Level III Neonatal Intensive Care Unit

Published online by Cambridge University Press: 19 December 2016

Ann L. Bailey, Rachel D. Quick, Joanne Dixon and Sarmistha B. Hauger

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Abstract

This report describes the unique challenges of managing potential exposure to bats in a neonatal intensive care unit. The outcome demonstrates that rabies post-exposure prophylaxis can be safely administered to preterm infants with evidence that preterm infants are able to develop adequate titers post vaccination.

Infect Control Hosp Epidemiol 2017;38:483–485



GPT-4 for the win



Darker Grey=Worse; Darker Gold = Better

LLM (N=93)	Question Prompt Restrictions ^c	Acceptable Accuracy				Acceptable Completeness			
		Isolation Precautions (%)	HCP Exposure (%)	Patient Exposure (%)	Environmental Cleaning (%)	Isolation Precautions (%)	HCP Exposure (%)	Patient Exposure (%)	Environmental Cleaning (%)
OpenEvidence	Without CDC	82.4	87.5	77.8	88.9	66.7	83.3	77.8	66.7
	With CDC	72.6	79.2	88.9	66.7	62.8	79.2	88.9	55.6
GPT-3.5	Without CDC	80.4	95.8	100.0	100.0	60.8	70.8	77.8	88.9
	With CDC	86.3	91.7	100.0	100.0	64.7	58.3	77.8	88.9
GPT-4	Without CDC	98.0	100.0	100.0	100.0	88.2	95.8	88.9	88.9
	With CDC	98.0	95.8	100.0	100.0	92.2	95.8	100.0	100.0
Bing AI (Microsoft Copilot)	Without CDC	80.4	95.8	100.0	100.0	76.5	79.2	100.0	100.0
	With CDC	74.5	79.2	100.0	100.0	62.8	58.3	100.0	100.0

Abosi OJ, Kobayashi T, Ross N, Trannel A, Rodriguez Nava G, Salinas JL, Brust K. A head-to-head comparison of the accuracy of commercially available large language models for infection prevention and control inquiries, 2024. Infect Control Hosp Epidemiol. 2024 Dec 12;46(3):1-3. doi: 10.1017/ice.2024.205. Epub ahead of print. PMID: 39664019; PMCID: PMC11883648.



Are we there yet?



Success in applying AI in Healthcare remains elusive

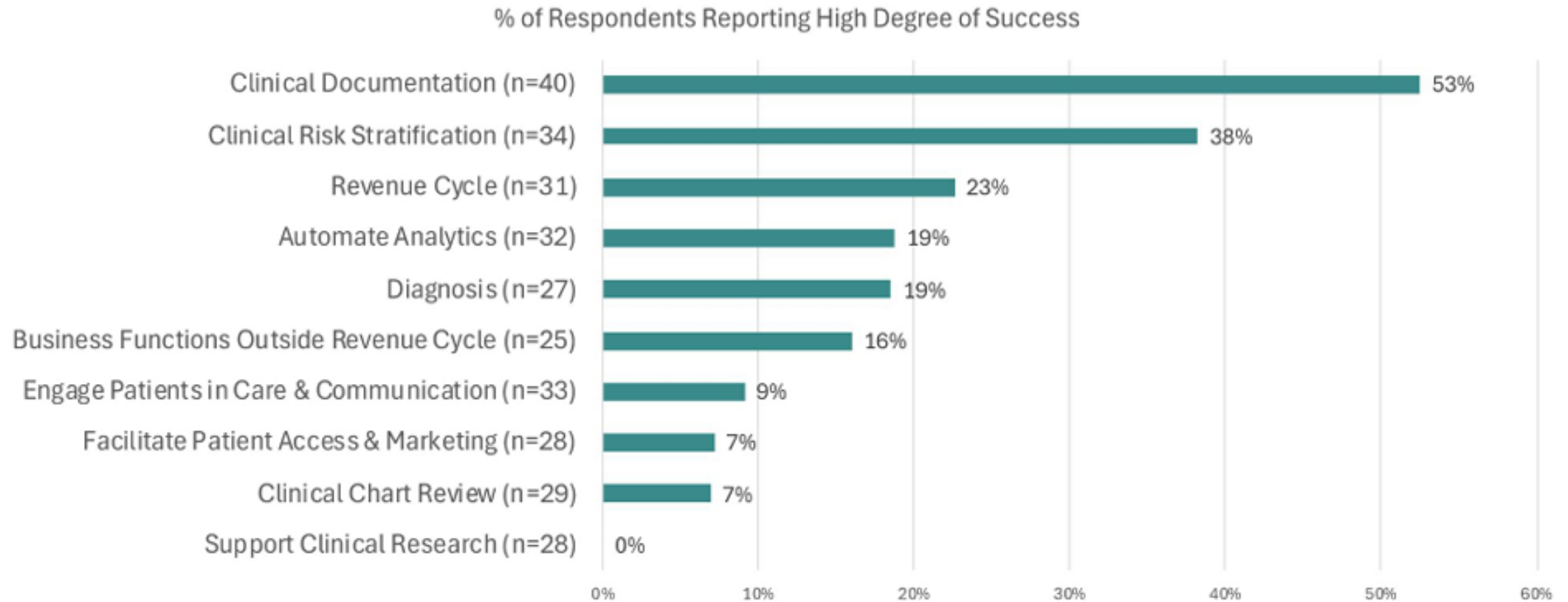


Figure 3. Successes reported among AI use case categories. Proportion of organizations reporting a high degree of success within each AI use case category, among those that have started developing, piloting, or deploying it.

Poon EG, Lemak CH, Rojas JC, Guptill J, Classen D. Adoption of artificial intelligence in healthcare: survey of health system priorities, successes, and challenges. *J Am Med Inform Assoc.* 2025 Jul 1;32(7):1093-1100. doi: 10.1093/jamia/ocaf065. PMID: 40323320; PMCID: PMC12202002.



Barriers to Developing or Deploying AI in Healthcare

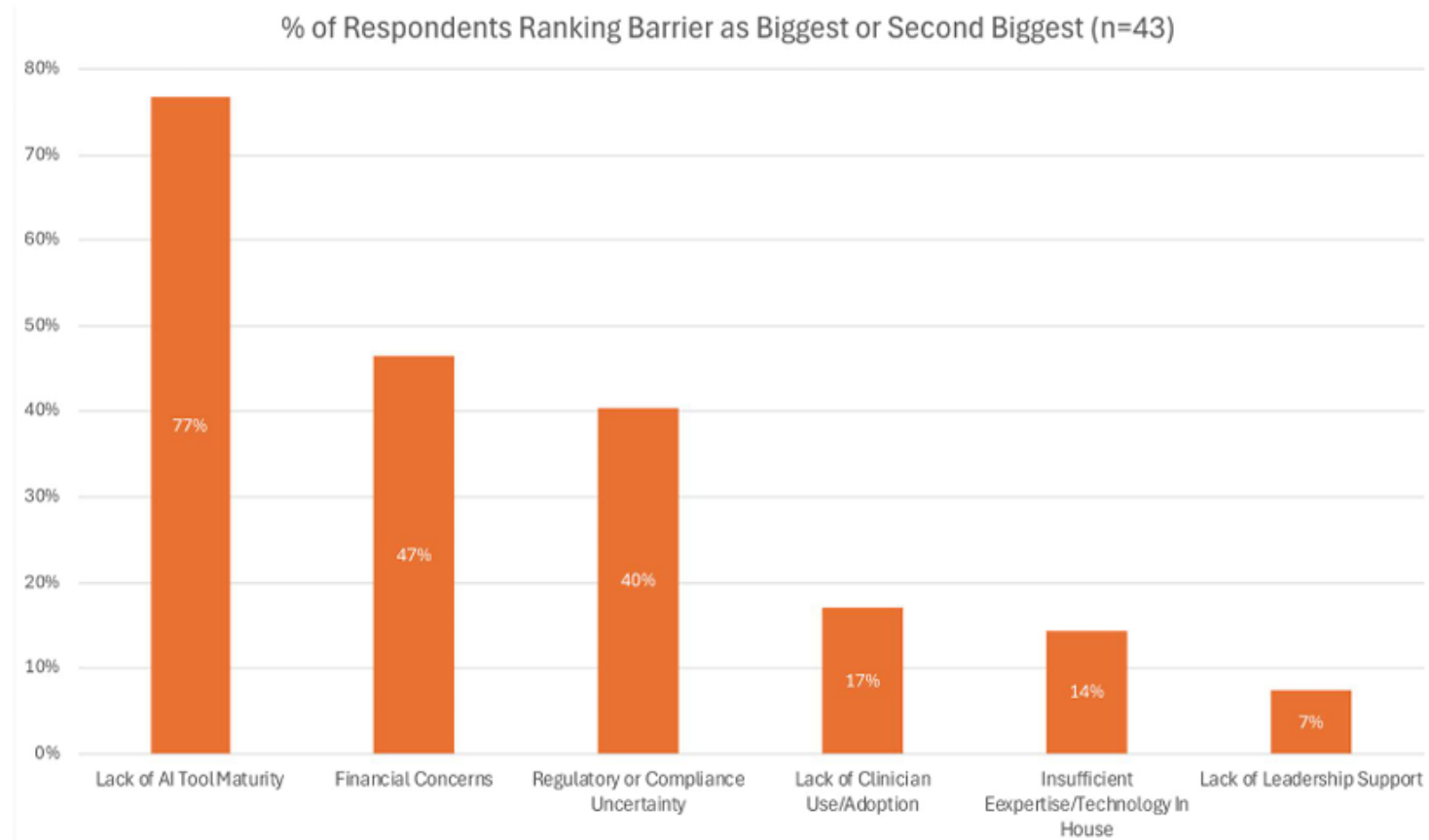
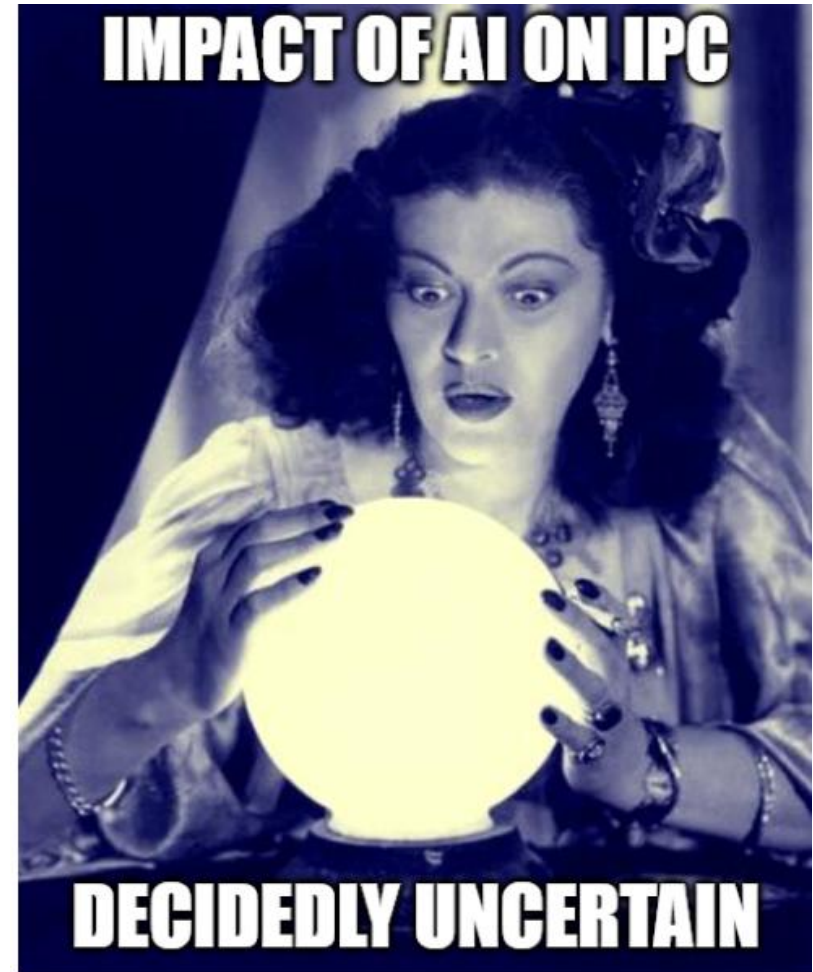


Figure 4. Key barriers to developing or deploying AI. Proportion of survey respondents ($n = 43$) who rated each barrier as the highest or second-biggest.

No crystal ball here...

- Real-time operational use not yet demonstrated
- Training, validation, ongoing maintenance and revalidation are time consuming and resource intensive
- If surveillance definitions for HAIs become fully discrete, then opens up large potential for automated surveillance as well as risk prediction advances
- Full integration into commercial electronic health records necessary
- Needs to account for lean/under-resourced IPC workforce (and ideally augment it)
- Disruptive



Thank you and now...questions!

