

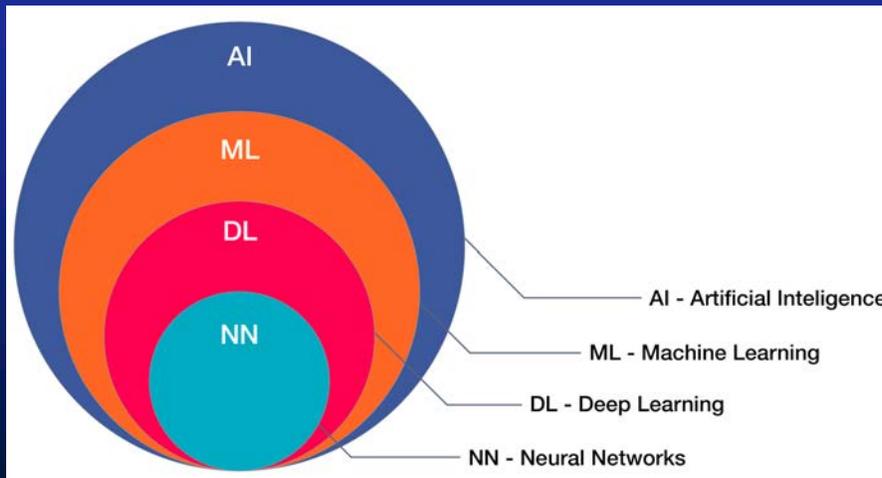
Getting Practical: How to go about Incorporating AI in your ASC Business?



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1

Artificial Intelligence and deeper



2

ChatGPT: What is Anesthesia?

P What is anesthesia?

G Anesthesia refers to the administration of drugs or techniques to induce a temporary state of unconsciousness, loss of sensation, or analgesia (pain relief) during medical procedures. Its primary goal is to ensure patient comfort and safety during surgical or diagnostic interventions. Anesthesia allows for painless surgery, minimizes patient movement, and helps control vital functions such as heart rate, blood pressure, and breathing.

Anesthesia can be administered in various forms, including:

1. General Anesthesia: This type of anesthesia renders the patient completely unconscious and eliminates all sensation and awareness. It involves the use of intravenous drugs and inhaled

Anesthesia is typically administered by an anesthesiologist, a medical doctor specializing in anesthesia, or by a certified registered nurse anesthetist (CRNA) under the supervision of a physician. These professionals carefully monitor the patient's vital signs and adjust the anesthesia dosage throughout the procedure to maintain the desired level of unconsciousness and pain control. After the procedure, the anesthesia is gradually discontinued, allowing the patient to wake up and recover.

spinal cord, numbing a larger area of the body. Epidurals are commonly used during childbirth to relieve pain in the lower body.

3

Instruct GPT: Reinforcement learning

Prompts Dataset

Sample many prompts

Initial Language Model

Train on (sample, reward) pairs

Generated text

Human Scoring

Reward (Preference) Model

Outputs are ranked (relative, FLO, etc.)

Reinforcement learning (RL). Once again following Stiennon et al. (2020), we fine-tune the SFT model on our environment using PPO (Schulman et al., 2017). The environment is a handful environment which presents a random customer prompt and expects a response to the prompt. Given the prompt and response, it produces a reward determined by the reward model and ends the episode. In addition, we add a per-token KL penalty from the SFT model at each token to mitigate over-optimization of the reward model. The value function is initialized from the RM. We call these models "PPO".

We also experiment with mixing the pretraining gradients into the PPO gradients, in order to fix the performance regressions on public NLP datasets. We call these models "PPO-ptx." We maximize the following combined objective function in RL training:

$$\text{objective}(\theta) = E_{(x,y) \sim D_{\text{ptx}}} [r(x,y) - \beta \log(\pi_{\theta}^{\text{RL}}(y|x)/\pi^{\text{SFT}}(y|x))] + \gamma E_{x \sim D_{\text{RM}}} [\log(\pi_{\theta}^{\text{RL}}(x))] \quad (2)$$

where π_{θ}^{RL} is the learned RL policy, π^{SFT} is the supervised trained model, and D_{RM} is the pretraining distribution. The KL reward coefficient, β , and the pretraining loss coefficient, γ , control the strength of the KL penalty and pretraining gradients respectively. For "PPO" models, γ is set to 0. Unless otherwise specified, in this paper InstructGPT refers to the PPO-ptx models.

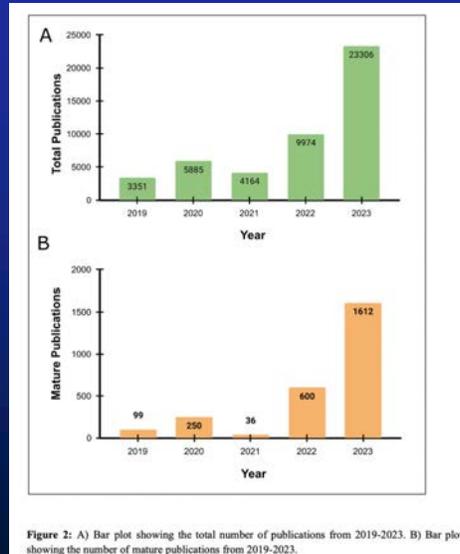
Baselines. We compare the performance of our PPO models to our SFT models and GPT-3. We also compare to GPT-3 when it is provided a few-shot prefix to "prompt" it into an instruction-following mode (GPT-3 prompts). This prefix is prepended to the user-specified instructions.

We additionally compare InstructGPT to fine-tuning 175B GPT-3 on the FLAN (Wei et al., 2021) and TO (Sanh et al., 2021) datasets, which both consist of a variety of NLP tasks, combined with natural language instructions for each task (the datasets differ in the NLP datasets included, and the style of instructions used). We fine-tune them on approximately 1 million examples respectively and choose the checkpoint which obtains the highest reward model score on the validation set. See Appendix C for more training details.

arXiv:2203.02155

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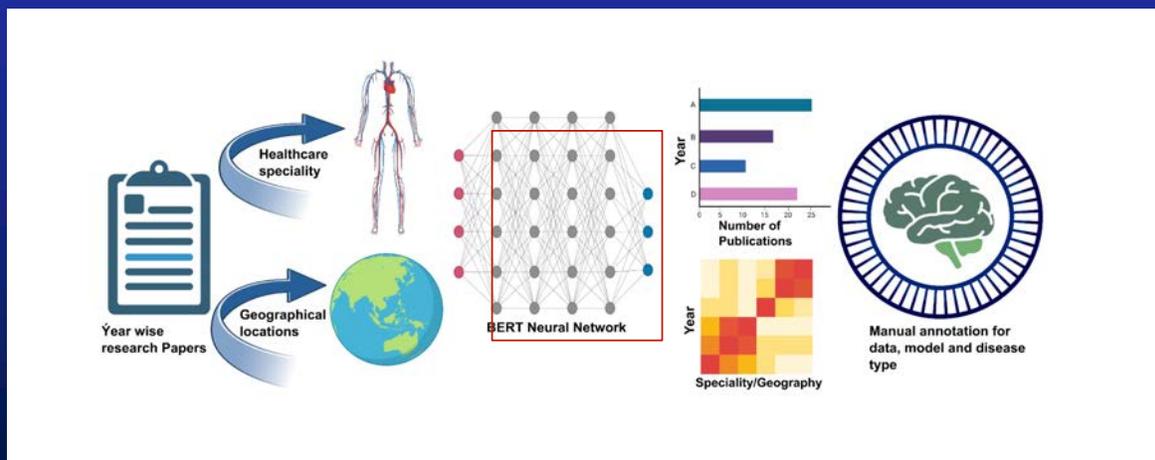
AI based research in healthcare



Awasthi, R., et al. (2024). "Artificial Intelligence in Healthcare: 2023 Year in Review." [medRxiv.2024.02.02.2028.24303482](https://doi.org/10.1101/2024.02.02.2028.24303482).

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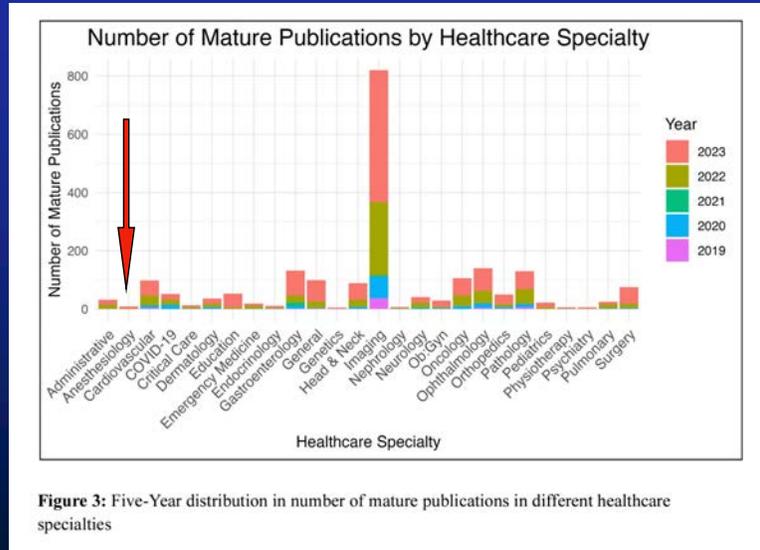
Using AI to assess AI based publications for maturity



Awasthi R, et al. Quantitative and Qualitative evaluation of the recent Artificial Intelligence in Healthcare publications using Deep-Learning. medRxiv. 2023:2022.12.31.22284092.

6

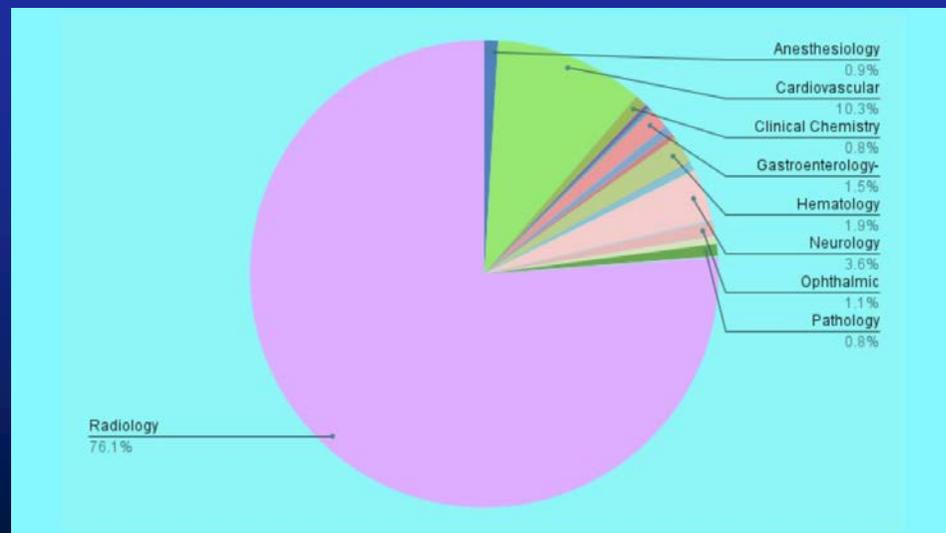
AI publications (mature) in healthcare per speciality



Awaathi, R., et al. (2024). "Artificial Intelligence in Healthcare: 2023 Year in Review." [medRxiv.2024.2002.2028.24303482](https://doi.org/10.2196/medRxiv.2024.2002.2028.24303482).

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950 FDA approved AI algorithms



Source: Margareta Colangelo and Lambert Leong

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AI examples from the real world

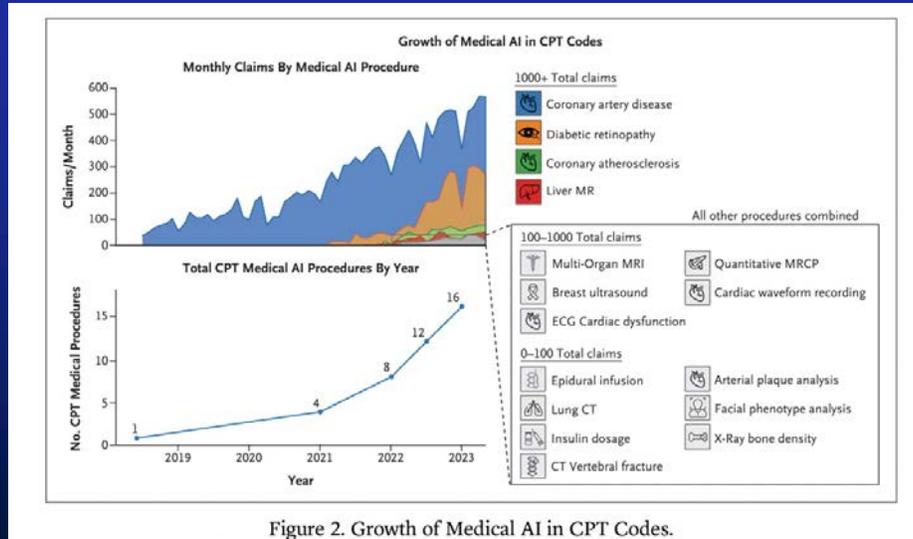


Figure 2. Growth of Medical AI in CPT Codes.

Characterizing the Clinical Adoption of Medical AI Devices through U.S. Insurance Claims. [Kevin Wu, M.S., NEJM AI 2023;1\(1\)](#)

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What are the patients asking for?

- **80%** Americans believe that AI had the potential to improve care
- **25%** Americans are more likely to talk to an AI chatbot instead of attending a therapy
- **25%** would not visit a healthcare provider who refuses to embrace AI

<https://www.medicaleconomics.com/view/ai-special-report-what-patients-and-doctors-really-think-about-ai-in-health-care>

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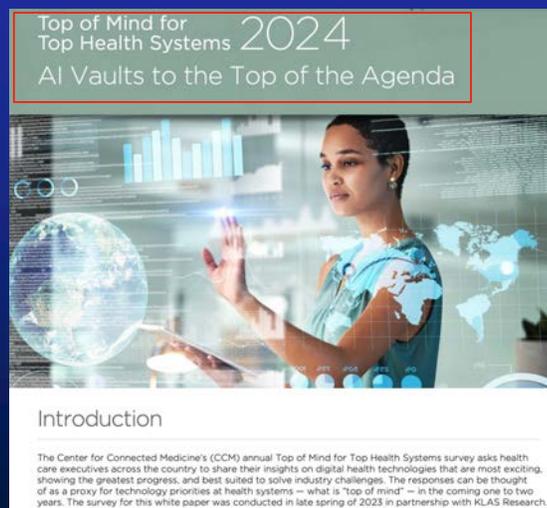
What are the clinicians asking for?

- **10%** healthcare professionals use AI technologies
- **50%** expressed interest to adopt it in future
- **95%** have a positive perspective

<https://www.medicaleconomics.com/view/ai-special-report-what-patients-and-doctors-really-think-about-ai-in-health-care>

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What are the healthcare executives planning for?



https://info.connectedmed.com/l/689353/2023-08-30/2ld521/689353/1693403930sCnDbt8/Top_Of_Mind_For_Top_Health_Systems_2024_CCM_Reports.pdf

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10 key opportunities for AI applications in an ASC



1. Schedule the appointment
2. Review of records
3. Assess the patient
4. Evaluate the options
5. Discuss the options with the patient
6. Order tests or assist with procedures
7. Generate diagnosis
8. Document the conversation
9. Provide patient with education
10. Communicate with all the teams

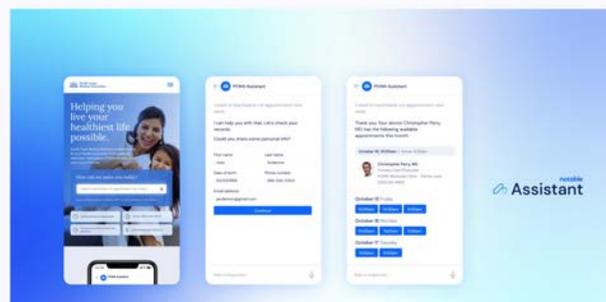
<https://www.aha.org/aha-center-health-innovation-market-scan/2024-01-16-5-ways-hospitals-can-integrate-ai-and-automation-surgical-care>

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AI assisted appointment scheduling

Introducing Notable Assistant, a ChatGPT-like innovation that patients can use to manage everything from appointment scheduling to bill payments

Notable Assistant makes it easy for health systems to rapidly deliver concierge care for every patient



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ChatGPT Diagnose: Tell me the ASA score

The screenshot shows a ChatGPT interface with the following content:

input

What is the ASA status of an 80 year old with severe COPD, hypertension and CKD3 coming for a lap cholecystectomy?

output 0

The ASA status of an 80 year old with severe COPD, hypertension, and CKD3 coming for a lap cholecystectomy would be ASA 4. This is because the patient has multiple comorbidities that increase the risk of complications during

Turan El, et al. Evaluating the accuracy of ChatGPT-4 in predicting ASA scores: A prospective multicentric study ChatGPT-4 in ASA score prediction. J Clin Anesth. 2024 PMID: 38657530.

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Review of literature or patient information

```

1 ## Llama QA for the first question
2 question = examples["input"][0]
3 print(question)
4 print("")
5 print("Correct answer:", examples["output"][0])
6 print("")
7 vectordb.max_marginal_relevance_search(question, k = CFG.k)

```

Q: A 23-year-old pregnant woman at 22 weeks gestation presents with burning upon urination. She states it started 1 day ago and has been worsening despite treatment with antibiotics. What is the most appropriate antibiotic to prescribe?

Correct answer: E: Nitrofurantoin

[Document(page_content="by progesterational effects on ureteral and bladder smooth muscle and later in pregnancy due to compression effects of the enlarging uterus. In itself, this condition is not associated with an adverse outcome of pregnancy. However, if asymptomatic bacteriuria is left untreated, symptomatic pyelonephritis may occur. Indeed, ~75% of pregnancy-associated pyelonephritis cases are the result of untreated asymptomatic bacteriuria. All pregnant women should be screened with a urine culture for asymptomatic bacteriuria at the first prenatal visit. Subsequent screening with nitrite/leukocyte esterase strips is indicated for high-risk women, such as those with sickle cell trait or a history of urinary tract infections. All women with positive screens should be treated. Pregnant women who develop pyelonephritis need careful monitoring, including inpatient IV antibiotic administration due to the elevated risk of urosepsis and acute respiratory distress syndrome in pregnancy. Abdominal pain and fever during pregnancy create a clinical dilemma. The diagnosis of greatest concern is intrauterine amniotic infection. While amniotic infection most commonly follows rupture of the membranes, this is not always the case. In general, antibiotic therapy is not recommended as a temporizing measure in these circumstances. If intrauterine infection is suspected, induced delivery with concomitant antibiotic therapy is generally indicated. Intrauterine amniotic infection is most often caused by pathogens such as Escherichia coli and group B Streptococcus (GBS). In high-risk patients at term or in preterm patients, routine intrapartum prophylaxis of GBS disease is recommended. Penicillin G and ampicillin are the drugs of choice. In penicillin-allergic patients with a low risk of anaphylaxis, cefazolin is recommended. If the patient is at high risk of anaphylaxis, vancomycin is recommended. If the organism is known to be sensitive to clindamycin, this antibiotic may be used. For the reduction of neonatal morbidity due to GBS, universal screening of pregnant women for GBS between 35 and 37 weeks of gestation, with intrapartum antibiotic treatment of infected women, is recommended. Postpartum infection is a significant cause of maternal morbidity and mortality. Postpartum endomyometritis is more common after cesarean delivery than vaginal delivery and develops in 2% of women after elective repeat cesarean section and in up to 10% after emergency cesarean section following prolonged labor. To reduce the risk of endomyometritis, prophylactic antibiotics should be given to all patients undergoing cesarean section, and administration 30-60 min prior to skin incision is preferable to administration at the time of umbilical cord clamping. As most cases of postpartum endomyometritis are polymicrobial, broad-spectrum antibiotic coverage with a penicillin, an aminoglycoside, and metronidazole is recommended (Chap. 201). Most cases resolve within 72 h. Women who do not respond to antibiotic treatment for postpartum endomyometritis should be evaluated for septic pelvic thrombophlebitis. Imaging studies may be helpful in establishing the diagnosis, which is primarily a clinical', metadata={'page': 139, 'source': '/content/drive/MyDrive/InternalMed_Harrison.pdf'})]

{'page': 139, 'source': '/content/drive/MyDrive/InternalMed_Harrison.pdf'}}

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Multimodal Machine Learning for Automated ICD Coding

Proceedings of Machine Learning Research 106:1-17, 2019

Keyang Xu¹, Mike Lam¹, Jingzhi Pang¹, Xin Gao¹, Charlotte Band¹,
 Piyush Mathur MD², Frank Papay MD², Ashish K. Khanna MD², Jacek B. Cywinski MD²,
 Kamal Maheshwari MD², Pengtao Xie¹, Eric Xing¹
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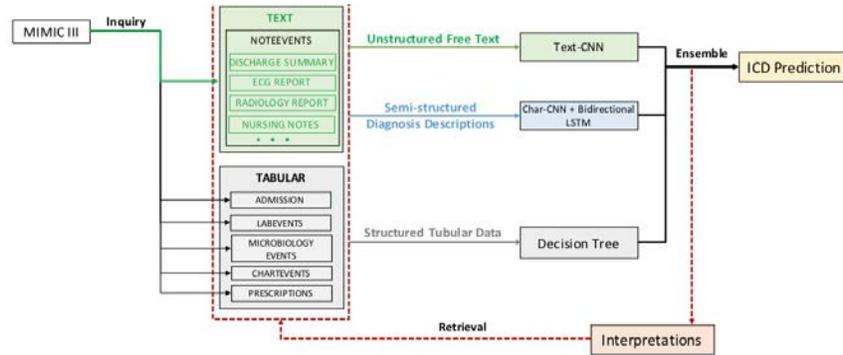


Fig. 1. Model architecture for ICD code prediction based on multimodal data, where each prediction is interpreted using retrieval-based methods.

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Automated echocardiography

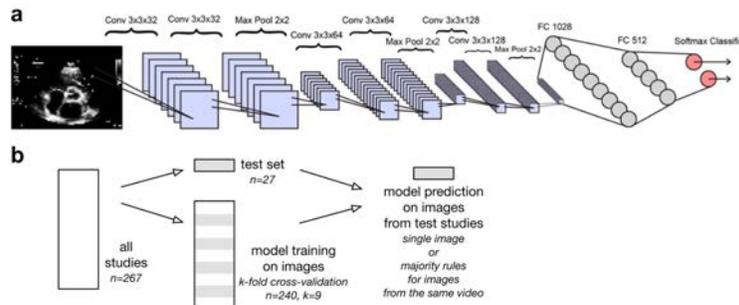


Fig. 1 Convolutional neural net architecture for image classification. **a** The neural network algorithm used for classification included six convolutional layers and two fully-connected layers of 1028 and 512 nodes, respectively. The softmax classifier (pink circles) consisted of up to 15 nodes, depending on the classification task at hand. **b** Training, validation, and test data were split by study, and test data was not used for training or validating the model. The model was trained to classify images, with video classification as a majority rules vote on related image frames. Conv convolutional layer, Max Pool max pooling layer, FC fully connected layer

npj Digital Medicine (2018) 6

Published in partnership with the Scripps Translational Science Institute

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Can algorithms democratize key skills?

Table 2. Comparison of Nurse-Acquired and Sonographer-Acquired Studies for Primary and Secondary Clinical Parameters^a

Image No.	Clinical parameter examined by qualitative visual assessment	No. (%) [95% CI]		Nurse-sonographer difference, percentage points
		Nurse examination	Sonographer examination	
1	Left ventricular size	232 (98.7) [96.3-99.7]	235 (100) [98.4-100.0]	-1.3
2	Global left ventricular function	232 (98.7) [96.3-99.7]	235 (100) [98.4-100.0]	-1.3
3	Right ventricular size	217 (92.3) [88.2-95.4]	226 (96.2) [92.9-98.2]	-3.9
4	Nontrivial pericardial effusion	232 (98.7) [96.3-99.7]	234 (99.6) [97.7-100.0]	-0.9
5	Right ventricular function	214 (91.1) [86.7-94.4]	226 (96.2) [92.9-98.2]	-5.1
6	Left atrial size	222 (94.5) [90.7-97.0]	234 (99.6) [97.7-100.0]	-5.1
7	Aortic valve	215 (91.5) [87.2-94.7]	228 (97.0) [94.0-98.8]	-5.5
8	Mitral valve	226 (96.2) [92.9-98.2]	233 (99.1) [97.0-99.9]	-2.9
9	Tricuspid valve	195 (83.0) [77.6-87.6]	217 (92.3) [88.2-95.4]	-9.3
10	Inferior vena cava size	135 (57.4) [50.9-63.9]	215 (91.5) [87.2-94.7]	-34.1

Narang A, Bae R, Hong H, et al. Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use. *JAMA Cardiol.* 2021;6(6):624–632

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ANESTHESIOLOGY

The Journal of the American Society of Anesthesiologists, Inc.

From: Machine-learning Algorithm to Predict Hypotension Based on High-fidelity Arterial Pressure Waveform Analysis
Anesthes. 2018;129(4):663-674. doi:10.1097/ALN.0000000000002300

**Hypotension prediction
 (minutes before event)**

**5 mins:0.95 AUC
 10 mins:0.95 AUC
 15 mins:0.97 AUC**



Machine-learning Algorithm to Predict Hypotension Based on High-fidelity Arterial Pressure Waveform Analysis

Hypotension Prediction Index – Development, Validation, and Performance

The machine-learning algorithm was developed with two different data sources from surgical and intensive care unit patients:

	Number of events	Number of hypotensive events
Training cohort	1,334	25,461
External validation cohort	33,236	1,923

- The algorithm relates a large set of features calculated from the high-fidelity arterial pressure waveform to the prediction of an upcoming hypotensive event.
- Receiver-operating characteristic curve analysis evaluated the algorithm's success in predicting hypotension.

Algorithm prediction of hypotension based on 3,022 features per cardiac cycle

Minutes before	Sensitivity	Specificity	Area under curve
15	0.95 (0.95-0.95)	0.95 (0.95-0.95)	0.95 (0.95-0.95)
10	0.95 (0.95-0.95)	0.95 (0.95-0.95)	0.95 (0.95-0.95)
5	0.97 (0.97-0.97)	0.97 (0.97-0.97)	0.97 (0.97-0.97)

A machine-learning algorithm can be trained with large data sets of high-fidelity arterial waveforms to predict hypotension in surgical patients' records.

Hartig F, et al. *ANESTHESIOLOGY*, October 2018.

ANESTHESIOLOGY
 The Journal of the American Society of Anesthesiologists, Inc. • www.anesthesiology.com

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Date of download: 12/1/2018

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From: Machine-learning Algorithm to Predict Hypotension Based on High-fidelity Arterial Pressure Waveform Analysis
Anesthes. 2018;129(4):663-674. doi:10.1097/ALN.0000000000002300

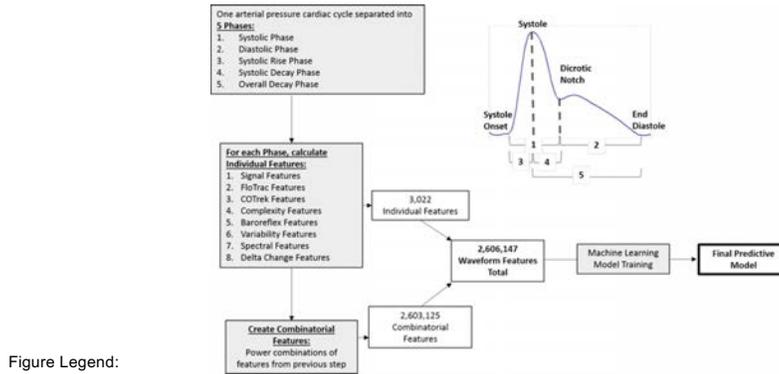


Figure Legend:

Summarizing arterial pressure waveform featurization and model training. Higher-level overview of the predictive model development.

Date of download: 12/1/2018

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Will clinicians follow algorithm's guidance?

ANESTHESIOLOGY

Hypotension Prediction Index for Prevention of Hypotension during Moderate- to High-risk Noncardiac Surgery

A Pilot Randomized Trial

Kamal Maheshwari, M.D., M.P.H., Tetsuya Shimada, M.D., Ph.D., Dongsheng Yang, M.S., Sandeep Khanna, M.D., Jack B. Dwyanski, M.D., Samuel A. Irefin, M.D., Sabry Ayad, M.D., Alparslan Turan, M.D., Kurt Ruetzler, M.D., Yuwei Qiu, M.D., Partha Saha, M.D., Edward J. Mascha, Ph.D., Daniel I. Sessler, M.D.

ANESTHESIOLOGY 2020; 133:1214-22

EDITOR'S PERSPECTIVE

What We Already Know about This Topic

- Hypotension prediction algorithms commonly use arterial waveform features derived from arterial blood pressure monitoring. Whether they reduce the duration and severity of hypotension, especially in noncardiac surgery, is unknown.

What This Article Tells Us That Is New

ABSTRACT

Background: The Hypotension Prediction Index is a commercially available algorithm, based on arterial waveform features, that predicts hypotension defined as mean arterial pressure less than 65 mmHg for at least 1 min. We therefore tested the primary hypothesis that index guidance reduces the duration and severity of hypotension during noncardiac surgery.

Methods: We enrolled adults having moderate- or high-risk noncardiac surgery with invasive arterial pressure monitoring. Participating patients were randomized to hemodynamic management with or without index guidance. Clinicians caring for patients assigned to guidance were alerted when the index exceeded 85 (range, 0 to 100) and a treatment algorithm based on advanced hemodynamic parameters suggested vasopressor administration, fluid administration, inotrope administration, or observation. Primary outcome was the amount of hypotension, defined as time-weighted average mean arterial pressure less than 65 mmHg. Secondary outcomes were time-weighted mean pressures less than 60 and 55 mmHg.

Results: Among 214 enrolled patients, guidance was provided for 105 (49%) patients randomly assigned to the index guidance group. The median (first quartile, third quartile) time-weighted average mean arterial pressure less than 65 mmHg was 0.14 (0.03, 0.37) in guided patients versus 0.14 (0.03, 0.39) mmHg in unguided patients; median difference (95% CI) of 0 (-0.03 to 0.04), $P = 0.757$. Index guidance therefore did not reduce amount of hypotension less than 65 mmHg, nor did it reduce hypotension less than 60 or 55 mmHg. Post hoc, guidance was associated with less hypotension when analysis was restricted to episodes during which clinicians intervened.

Conclusions: In this pilot trial, index guidance did not reduce the amount of intraoperative hypotension. Half of the alerts were not followed by treatment, presumably due to short warning time, complex treatment algorithm, or clinicians ignoring the alert. In the future we plan to use a lower index alert threshold and a simpler treatment algorithm that emphasizes prompt treatment.

(*ANESTHESIOLOGY* 2020; 133:1214-22)

- Half of alerts were not followed by clinicians
- When intervened by clinicians, guidance associated hypotension was decreased

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From: Performance of the Hypotension Prediction Index May Be Overestimated Due to Selection Bias
Anesthesiology. 2022;137(3):283-289. doi:10.1097/ALN.0000000000004320

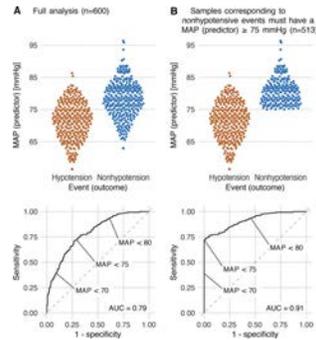


Figure Legend:

Simulation of the selection problem. Columns, A and B, illustrate different data selection strategies. Upper panels show simulated mean arterial pressure (MAP; mmHg) values for samples corresponding to hypotensive events and nonhypotensive events. Lower panels are receiver operating characteristics curves showing MAP's ability to discriminate hypotensive events from nonhypotensive events. The simulation is not an attempt to produce realistic data. It only serves to illustrate how the selection problem can result in a "skewed" receiver operating characteristics curve with very high specificity.

Date of download: 8/30/2022

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Evaluate the options

Journal of Clinical Monitoring and Computing
https://doi.org/10.1007/s10877-018-0200-x

ORIGINAL RESEARCH

Identify and monitor clinical variation using machine intelligence: a pilot in colorectal surgery

Kamal Maheshwari^{1,2} · Jacek Cywinski¹ · Piyush Mathur¹ · Kenneth C. Cummings III¹ · Rafi Avitsian¹ · Timothy Crone³ · David Liska⁴ · Francis X. Champion⁵ · Kurt Ruetzler^{1,2} · Andrea Kurz^{1,2}

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© Springer Nature B.V. 2018

Abstract
Standardized clinical pathways are useful tool to reduce variation in clinical management and may improve quality of care. However the evidence supporting a specific clinical pathway for a patient or patient population is often imperfect limiting adoption and efficacy of clinical pathway. Machine intelligence can potentially identify clinical variation and may provide useful insights to create and optimize clinical pathways. In this quality improvement project we analyzed the inpatient care of 1786 patients undergoing colorectal surgery from 2015 to 2016 across multiple Ohio hospitals in the Cleveland Clinic System. Data from four information subsystems was loaded in the Clinical Variation Management (CVM) application (Ayasdi, Inc., Menlo Park, CA). The CVM application uses machine intelligence and topological data analysis methods to identify groups of similar patients based on the treatment received. We defined "favorable performance" as groups with lower direct variable cost, lower length of stay, and lower 30-day readmissions. The software auto-generated 9 distinct groups of patients based on similarity analysis. Overall, favorable performance was seen with ketorolac use, lower intra-operative fluid use (< 2000 cc) and surgery for cancer. Multiple sub-groups were easily created and analyzed. Adherence reporting tools were easy to use enabling almost real time monitoring. Machine intelligence provided useful insights to create and monitor care pathways with several advantages over traditional analytic approaches including: (1) analysis across disparate data sets, (2) unsupervised discovery, (3) speed and auto-generation of clinical pathways, (4) ease of use by team members, and (5) adherence reporting.

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Cohort analysis



Fig. 3 Autogenerated subgroups. A Summary of a subgroup, B Each row depicts individual patient care event, C Details of patient care event

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AI Scribe



Radar Plot of Modified PDQI-9 (10 Domains) Based on Physicians' Review of Ambient Artificial Intelligence (AI) Scribe Transcripts and Notes

Our analysis of the quality of the ambient AI-generated summaries of the visit transcripts showed high levels of performance across all 10 of our metrics on a subsample of 35 randomly assessed notes across multiple clinical specialties. Our regional pilot phase suggests that using AI scribes resulted in high-quality — but not perfect — notes generated by the technology.



AI = artificial intelligence.
Source: The authors.
NEJM Catalyst (catalyst.nejm.org) © Massachusetts Medical Society

Ambient Artificial Intelligence Scribes to Alleviate the Burden of Clinical Documentation. <https://doi.org/10.1056/CAT.23.0404>

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Discuss options with the patient

Key Points

Question Can an artificial intelligence chatbot assistant, provide responses to patient questions that are of comparable quality and empathy to those written by physicians?

Findings In this cross-sectional study of 195 randomly drawn patient questions from a social media forum, a team of licensed health care professionals compared physician's and chatbot's responses to patient's questions asked publicly on a public social media forum. The chatbot responses were preferred over physician responses and rated significantly higher for both quality and empathy.

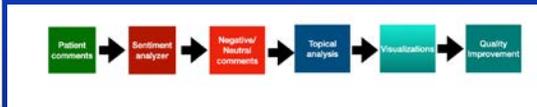
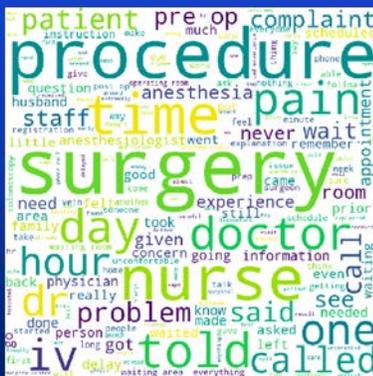
Meaning These results suggest that artificial intelligence assistants may be able to aid in drafting responses to patient questions.

liak A, Dredze M, et al. Comparing Physician and Artificial Intelligence Chatbot Responses to Patient Questions Posted to a Public Social Media Forum. *JAMA Intern Med.* 2023;18

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Can algorithms help us listen to our patients better? (15000+ comments analysis in less than one minute)



Topic	Related words*	Themes
1	room (0.029) surgery (0.025) hour (0.025) waiting (0.022) wait (0.019)	Wait times
2	area (0.046) waiting (0.030) staff (0.021) cold (0.019) professional (0.017)	Facilities
3	procedure (0.035) surgery (0.031) day (0.031) time (0.023) call (0.022)	Explanation
4	remember (0.029) surgery (0.019) am (0.014) dr (0.012) pm (0.012)	Doctor communication
5	desk (0.014) clinic (0.013) registration (0.012) experience (0.011) person (0.011)	Friendliness
6	nurse (0.034) iv (0.021) pain (0.020) procedure (0.016) surgery (0.012)	Pain control

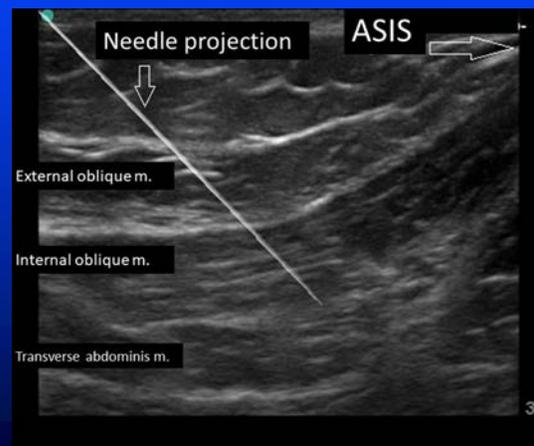
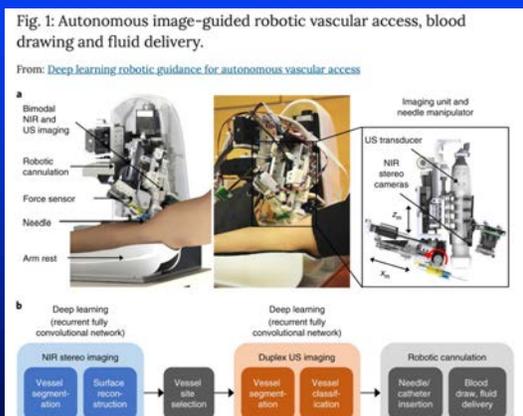
Mathur, Piyush, et al. "Automated analysis of ambulatory surgery patient experience comments using artificial intelligence for quality improvement: A patient centered approach." *Intelligence-Based Medicine* (2021): 100043.

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Communicate with all the teams

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Can AI help do procedures more safely and effectively?



[Dariusz Machuga, Publications, volume2, pages 104-115 \(2020\).](#)

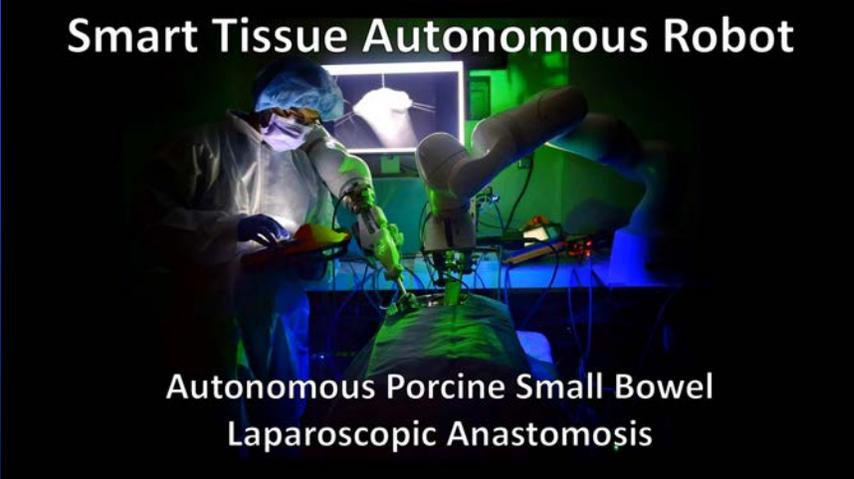
Jon D. Klingensmith, Asher L. Haggard, Jack T. Ralston, Beidi Qiang, Russell J. Fedewa, Hesham Elsharkawy, David G. Vince, "Tissue classification in intercostal and paravertebral ultrasound using spectral analysis of radiofrequency backscatter," *J. Med. Imag.* 6(4) 047001 (7 November 2019) <https://doi.org/10.1117/JMI.6.4.047001>

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Imagine the future...

Smart Tissue Autonomous Robot



Autonomous Porcine Small Bowel Laparoscopic Anastomosis

Courtesy: Axel Krieger, PhD, JHU
 Source: <https://brainxai.org/connect/brainx-community-live-february-2022artificial-intelligence-and-robotics-in-surgery/>

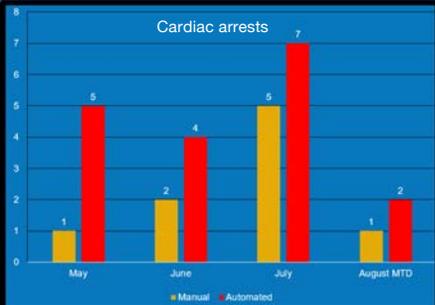
31

Can algorithms help improve safety event reporting?

Algorithms

Cardiac Arrest	Hypotension	Airway Event
<ul style="list-style-type: none"> 1mg epinephrine IV Text string search: ventricular fibrillation, V. fib, chest compressions, pulseless electrical activity, PEA, cardiac arrest 	<ul style="list-style-type: none"> Mean arterial pressure < 65mmHg for cumulative time >15 minutes for anesthetic time CMS QCDR approved metric 	<ul style="list-style-type: none"> Airway trauma Failed airway Esophageal intubation Laryngospasm Pneumothorax Bronchospasm Aspiration Unintended extubation

Results



Month	Manual	Automated
May	1	5
June	2	4
July	5	7
August MTD	1	2

Unpublished data

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Evaluation framework - TEHAI

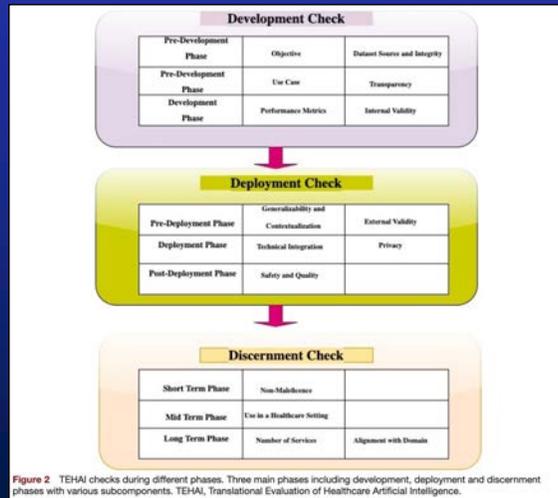


Figure 2 TEHAI checks during different phases. Three main phases including development, deployment and discernment phases with various subcomponents. TEHAI, Translational Evaluation of Healthcare Artificial Intelligence.

Reddy, Sandeep, et al. "Evaluation framework to guide implementation of AI systems into healthcare settings." *BMJ Health & Care Informatics* 28.1 (2021): e100444

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Beware of the hype

Hype Cycle for Emerging Technologies, 2023



gartner.com

Source: Gartner
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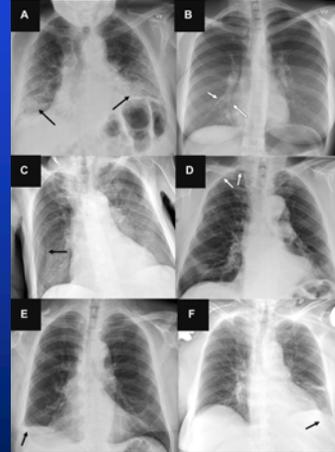
Gartner.

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Does AI outperform radiologists?

“Current-generation AI tools showed moderate to high sensitivity for detecting airspace disease, pneumothorax, and pleural effusion on chest radiographs.

However, they produced more false-positive findings than radiology reports, and their performance decreased for smaller-sized target findings and when multiple findings were present.”



[Commercially Available Chest Radiograph AI Tools for Detecting Airspace Disease, Pneumothorax, and Pleural Effusion](#)
Louis Lind Plesner, et al. Radiology 2023 308:3

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Will I lose my job?

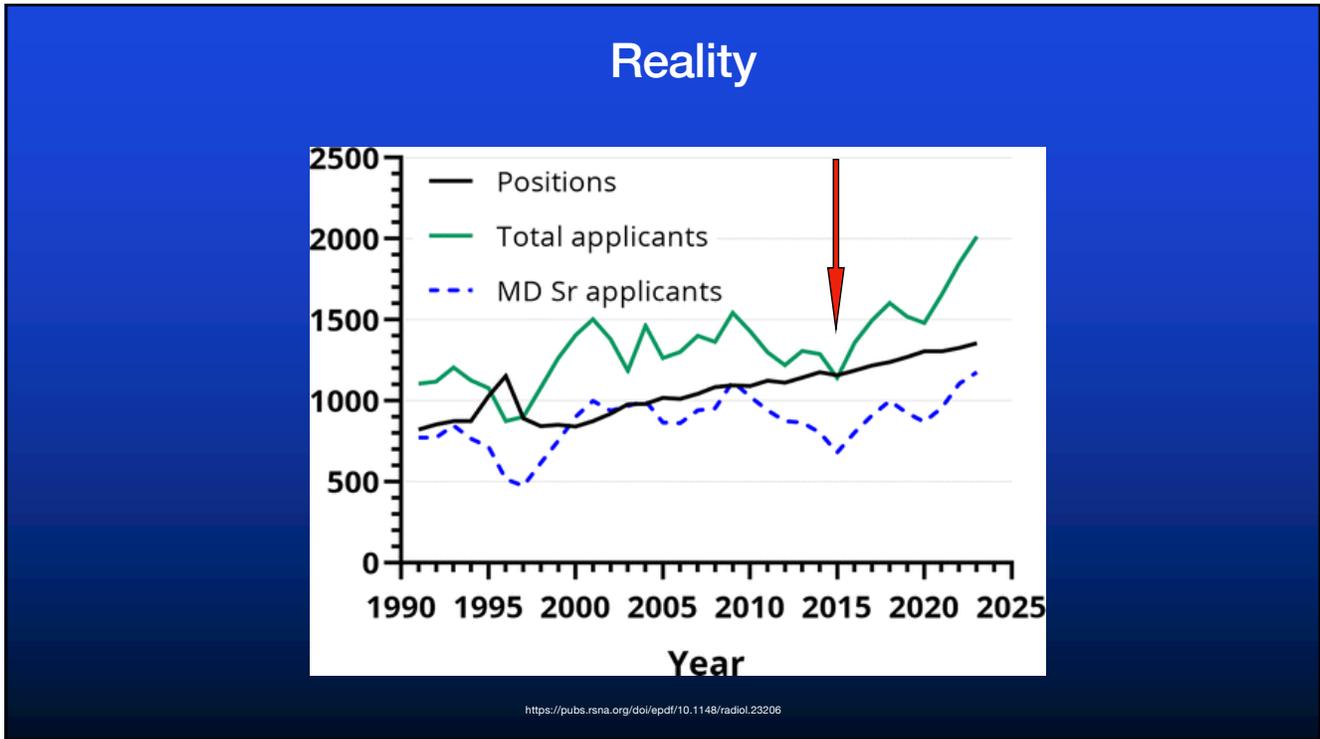
...ing radiologists now. It's just completely obvious that, within five years, deep learn

Geoffrey Hinton, British cognitive psychologist and “godfather” of AI (2016)



<https://www.politico.com/news/2022/08/15/artificial-intelligence-health-care-00051828>

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The opportunity

Research

“AI is the new electricity”
- Andrew Ng, Professor, Stanford

Market

“We need to build Energy companies” - Piyush Mathur

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Challenges

- Big data-segregated across hospitals
- Poor quality of data
- Regulatory concerns(HIPAA)
- Lack of knowledge
- Lack of unified approach
- Ethical and legal concerns



Nazer LH, Zatarah R, Waldrip S, et al. Bias in artificial intelligence algorithms and recommendations for mitigation. *PLOS Digit Health*. 2023;2(6):e0000278. Published 2023 Jun 22. doi:10.1371/journal.pdig.0000278

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Multimodal Future state

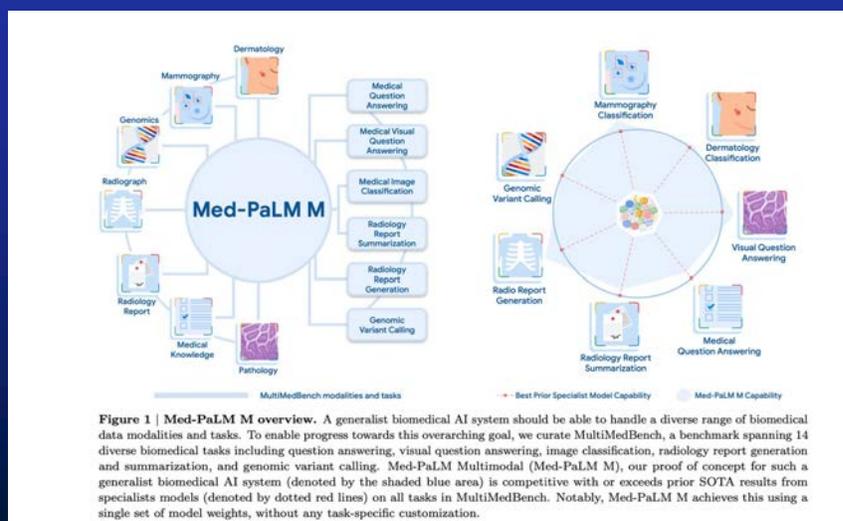
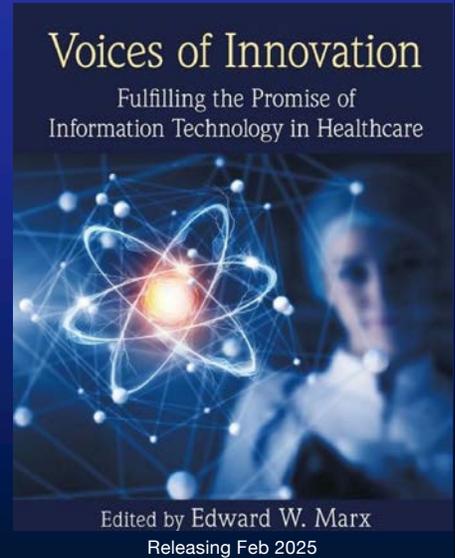
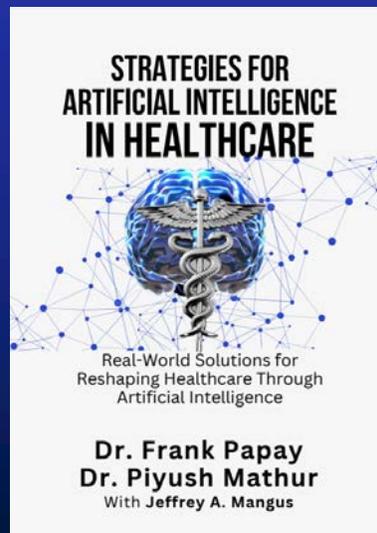
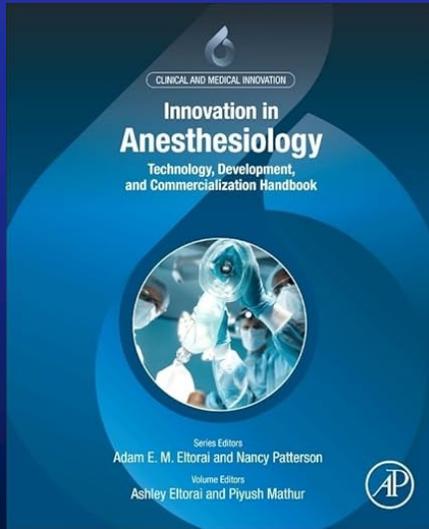


Figure 1 | Med-PaLM M overview. A generalist biomedical AI system should be able to handle a diverse range of biomedical data modalities and tasks. To enable progress towards this overarching goal, we curate MultiMedBench, a benchmark spanning 14 diverse biomedical tasks including question answering, visual question answering, image classification, radiology report generation and summarization, and genomic variant calling. Med-PaLM Multimodal (Med-PaLM M), our proof of concept for such a generalist biomedical AI system (denoted by the shaded blue area) is competitive with or exceeds prior SOTA results from specialists models (denoted by dotted red lines) on all tasks in MultiMedBench. Notably, Med-PaLM M achieves this using a single set of model weights, without any task-specific customization.

arXiv:2307.14334 (cs)

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What you need is a strategy



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Recommendations for adoption of AI

- Education
- Collaboration
- Data quality and access
- Algorithm validation
- AI Implementation
- Regulatory advocacy



Maheshwari, et al. Artificial Intelligence for Perioperative Medicine: Perioperative Intelligence. Anesthesia & Analgesia 136(4):p 637-645, April 2023.

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