



# Can an Algorithm support Safe Practice?

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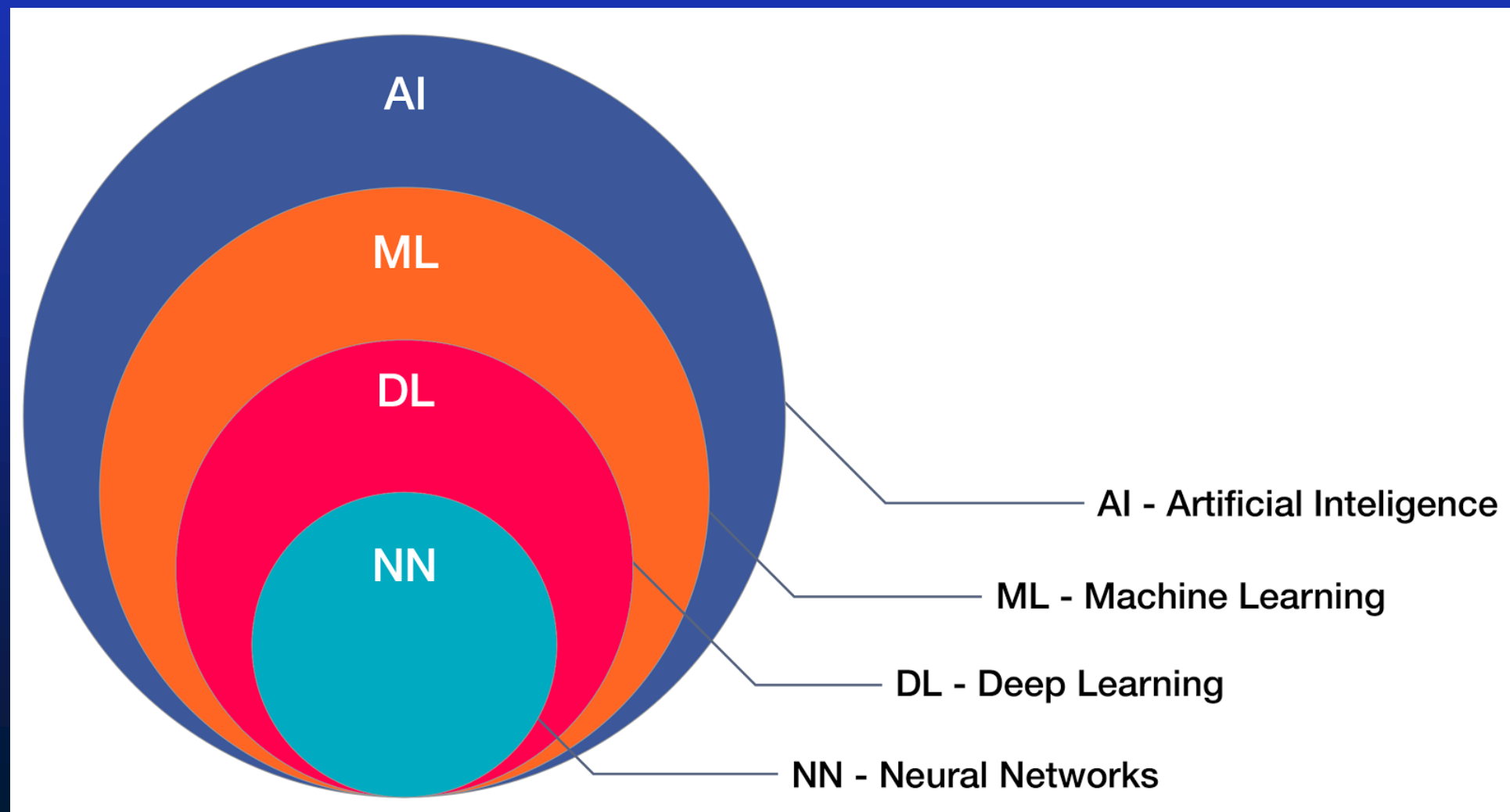
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# Disclaimers

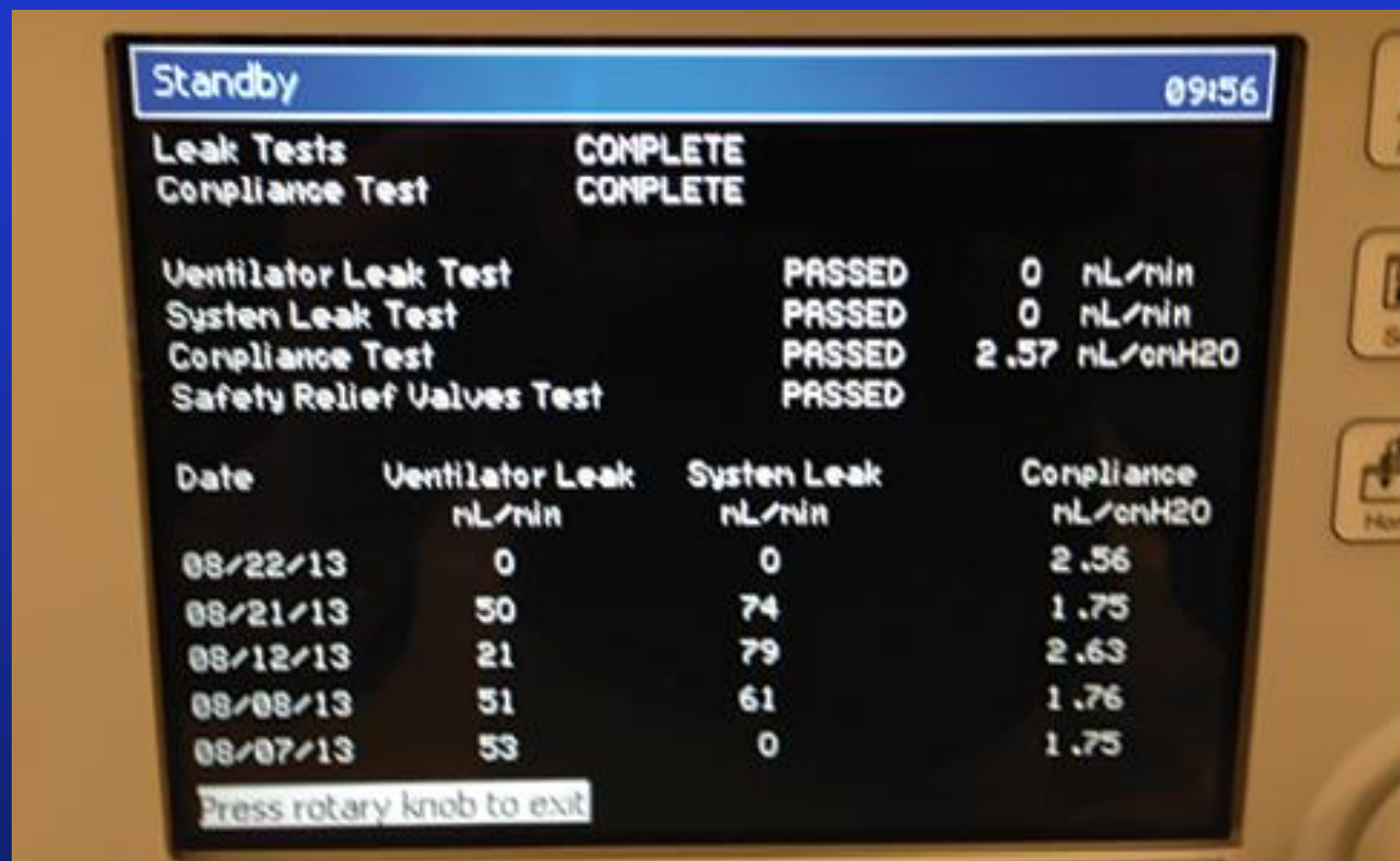
- Founder, BrainX,LLC.
- Founder, BrainX Community,LLC.
- I am a physician

# Algorithms, Artificial Intelligence and deeper

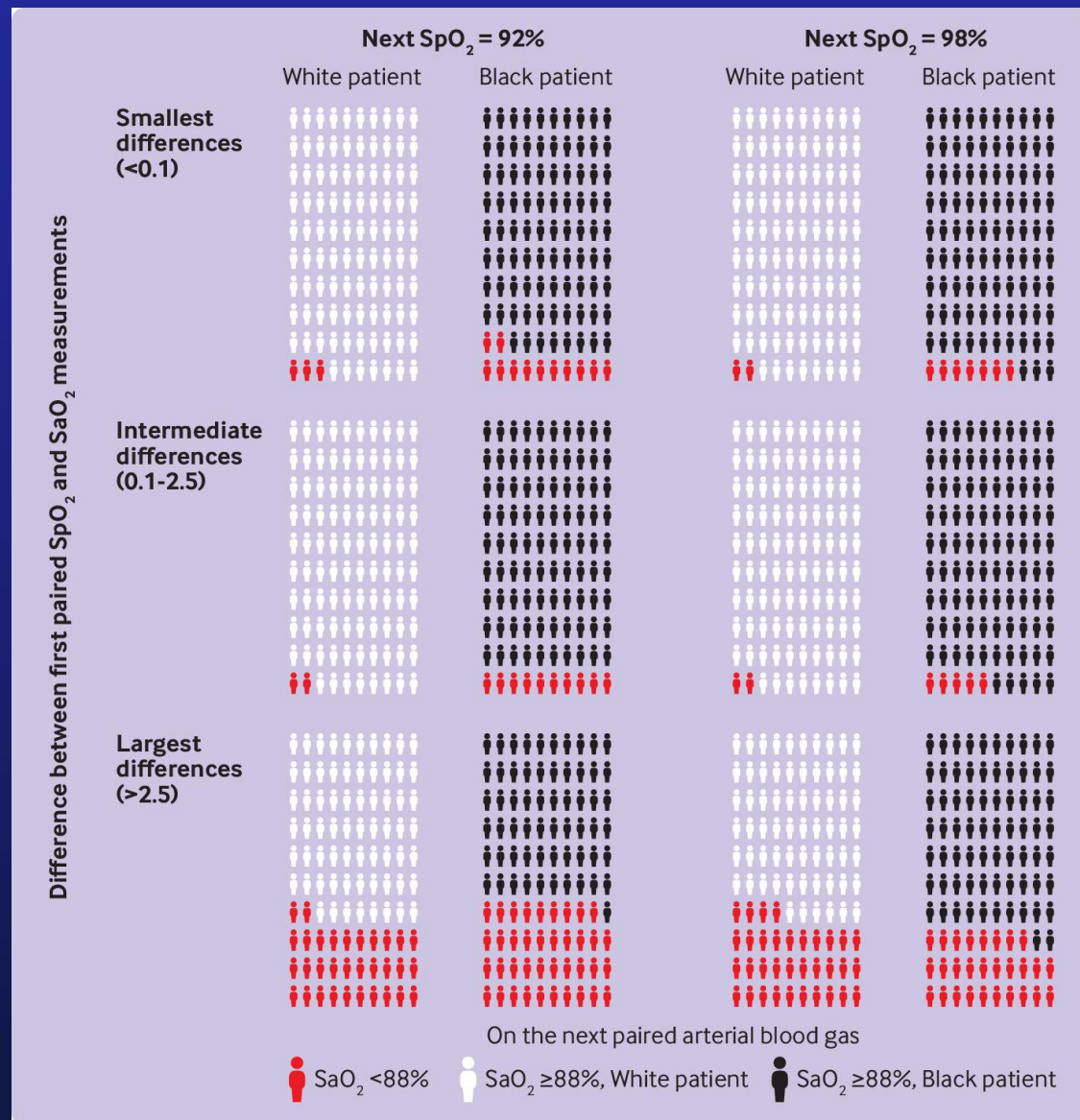
**Algorithm definition:** *“a procedure for solving a mathematical problem (as of finding the greatest common divisor) in a finite number of steps that frequently involves repetition of an operation”*



# Algorithms are not new to us...



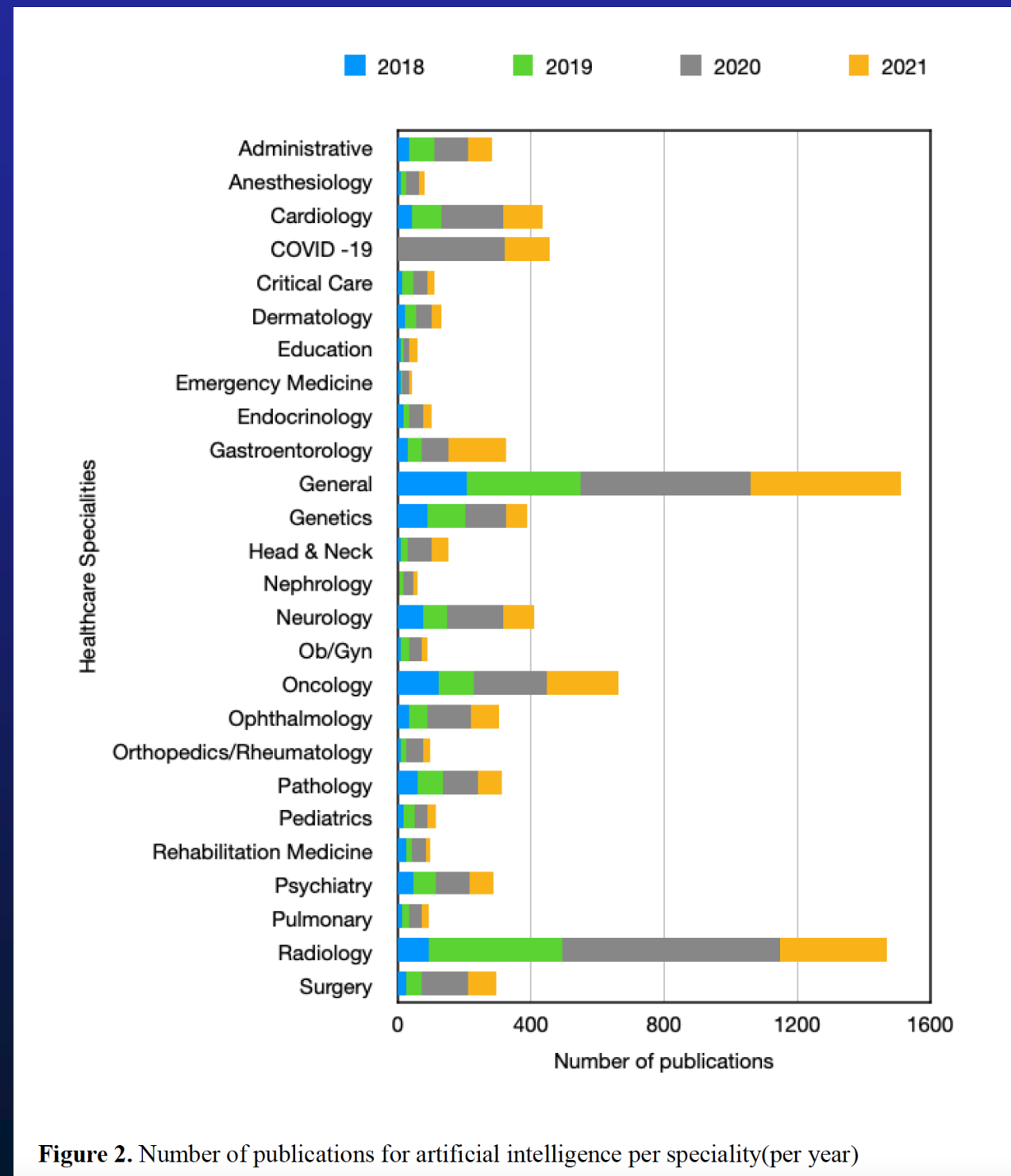
# Have algorithms been safe?



\* The algorithms employed within software of pulse oximeters are trade secrets and not open to scrutiny.

\* We recommended that manufacturers collect data in Black patients to develop better calibration algorithms.

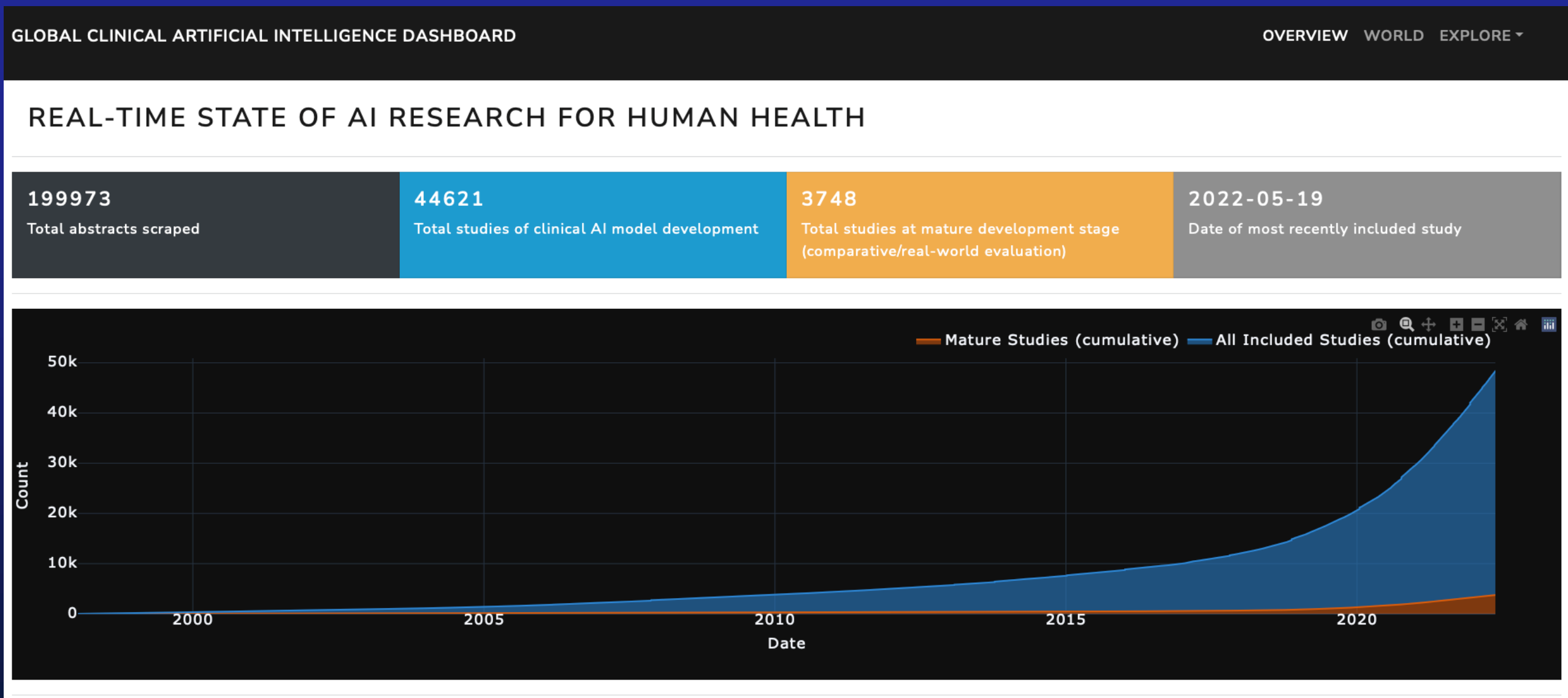
# AI publications per speciality





# Qualitative assessment

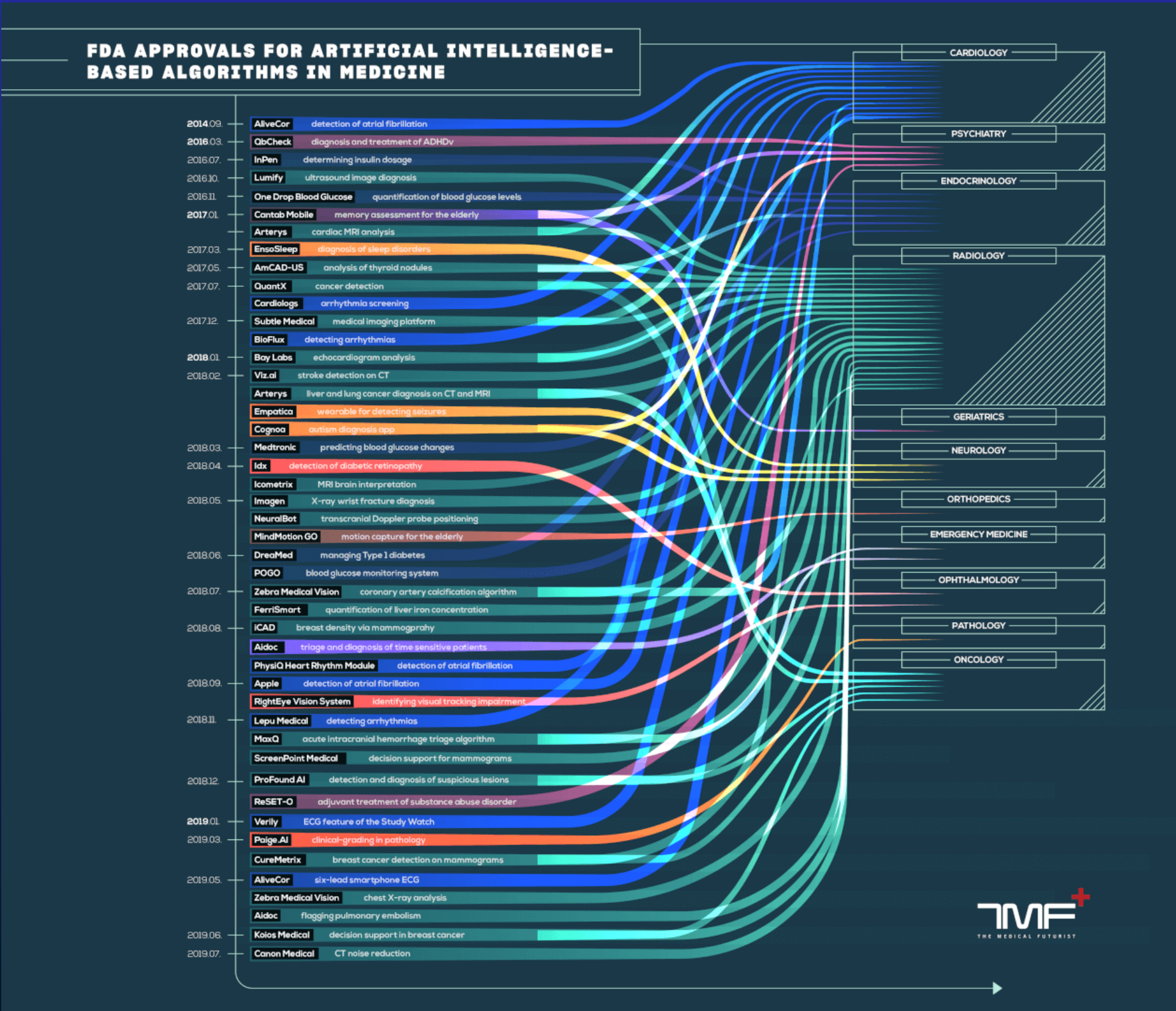
## Maturity of publications



<https://aiforhealth.app>

Zhang J, et al. An interactive dashboard to track themes, development maturity, and global equity in clinical artificial intelligence

# FDA approved AI algorithms





# Can Algorithms guide safe clinician decision making?

The screenshot displays the TREWS Severe Sepsis alert interface. It includes a 'Summary' section with a 'More Detail' link, a 'Nursing Assessment' section with an 'Expand' link, and a 'Severe Sepsis Evaluation' section. The evaluation section contains a step-by-step process for indicating infection and listing organ dysfunction criteria. Callouts highlight key features: 'Nursing assessment questions (automatically expands in nurse view)', 'Provider confirms if there is evidence of organ dysfunction', 'Organ dysfunctions that are not attributed to sepsis are grayed out and remembered to prevent future false alerts based on the same criteria', 'More Detail expands alert explanation to show factors behind the alert', and 'Provider indicates whether the patient has a suspected source of infection'.

**Nursing assessment questions (automatically expands in nurse view)**

**Provider confirms if there is evidence of organ dysfunction**

**Organ dysfunctions that are not attributed to sepsis are grayed out and remembered to prevent future false alerts based on the same criteria**

**"More Detail" expands alert explanation to show factors behind the alert**

**Provider indicates whether the patient has a suspected source of infection**

\*Timely alert confirmation by the provider was associated with:

- lower mortality ( $P < 0.001$ )
- improved SOFA progression ( $P = 0.001$ )
- lower median length of stay among survivors ( $P = 0.001$ ).

\*Adams, R., Henry, K.E., Sridharan, A. *et al.* Prospective, multi-site study of patient outcomes after implementation of the TREWS machine learning-based early warning system for sepsis. *Nat Med* **28**, 1455–1460 (2022). <https://doi.org/10.1038/s41591-022-01894-0>

Henry, K.E., Adams, R., Parent, C. *et al.* Factors driving provider adoption of the TREWS machine learning-based early warning system and its effects on sepsis treatment timing. *Nat Med* **28**, 1447–1454 (2022). <https://doi.org/10.1038/s41591-022-01895-z>

# 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., Jacek B. Cywinski, 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

# Can algorithms help with high skill decision making: Automated echocardiography

Accuracy

~92-97% for AI

VS

70-84% for board-certified echocardiographers

npj | Digital Medicine

[www.nature.com/npjdigitalmed](http://www.nature.com/npjdigitalmed)

ARTICLE OPEN

## Fast and accurate view classification of echocardiograms using deep learning

Ali Madani<sup>1</sup>, Ramy Arnaout<sup>2</sup>, Mohammad Mofrad<sup>1</sup> and Rima Arnaout<sup>3</sup>

Echocardiography is essential to cardiology. However, the need for human interpretation has limited echocardiography's full potential for precision medicine. Deep learning is an emerging tool for analyzing images but has not yet been widely applied to echocardiograms, partly due to their complex multi-view format. The essential first step toward comprehensive computer-assisted echocardiographic interpretation is determining whether computers can learn to recognize these views. We trained a convolutional neural network to simultaneously classify 15 standard views (12 video, 3 still), based on labeled still images and videos from 267 transthoracic echocardiograms that captured a range of real-world clinical variation. Our model classified among 12 video views with 97.8% overall test accuracy without overfitting. Even on single low-resolution images, accuracy among 15 views was 91.7% vs. 70.2–84.0% for board-certified echocardiographers. Data visualization experiments showed that the model recognizes similarities among related views and classifies using clinically relevant image features. Our results provide a foundation for artificial intelligence-assisted echocardiographic interpretation.

*npj Digital Medicine* (2018)1:6; doi:10.1038/s41746-017-0013-1



# Can algorithms democratize key skills?

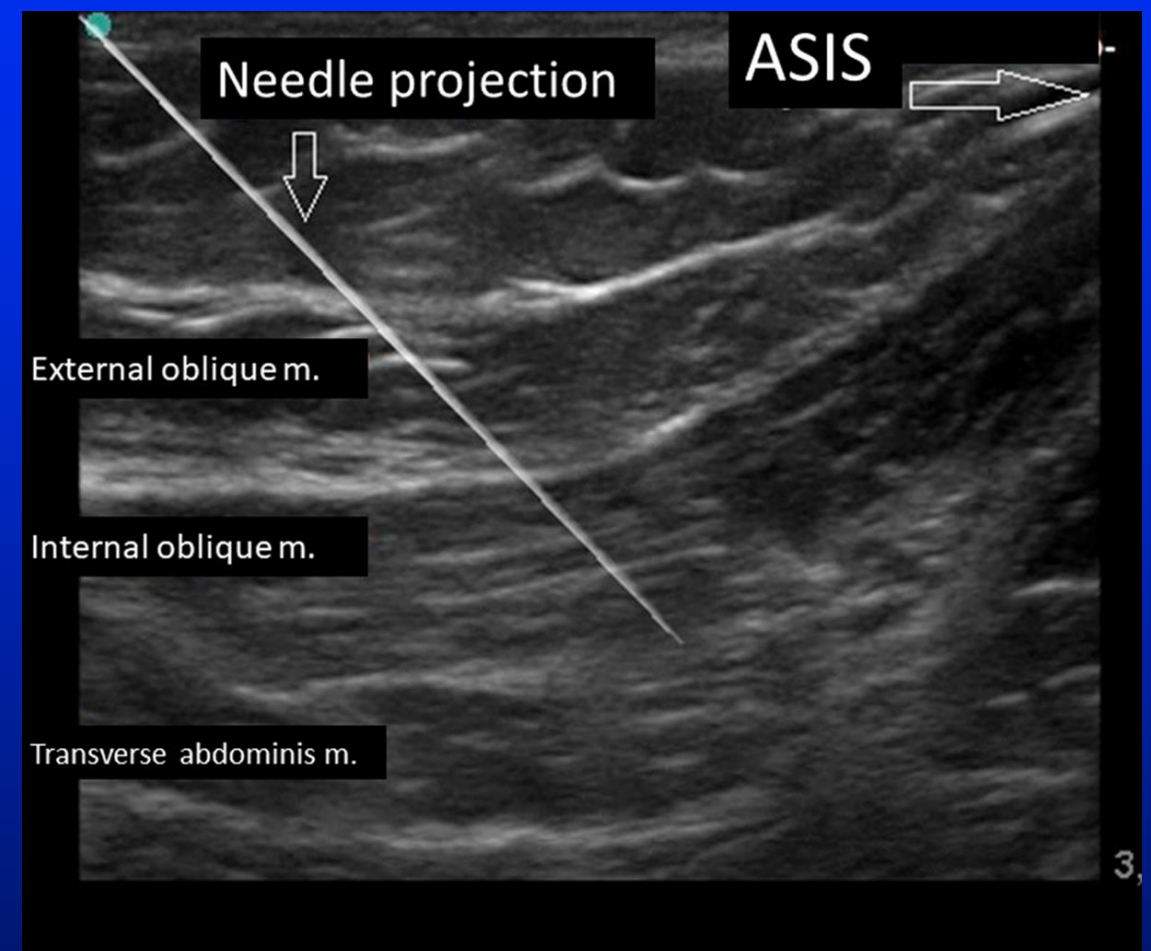
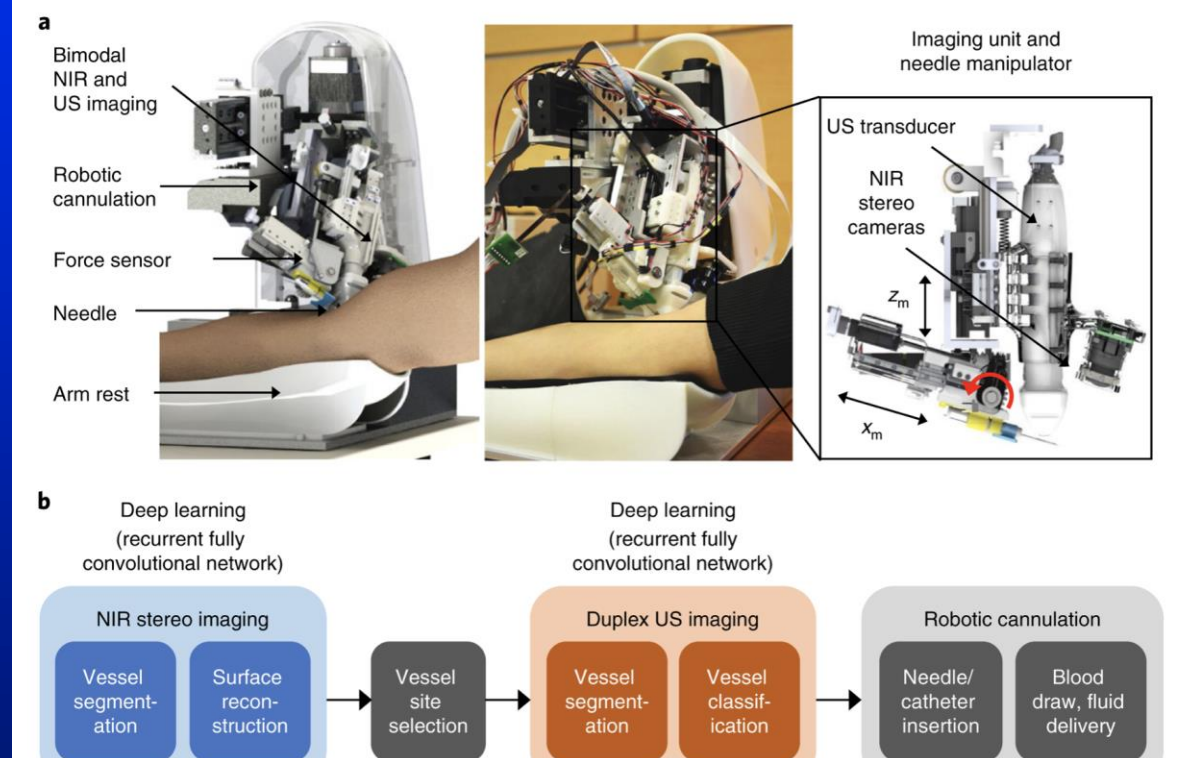
**Table 2. Comparison of Nurse-Acquired and Sonographer-Acquired Studies for Primary and Secondary Clinical Parameters<sup>a</sup>**

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

# Can algorithms help do procedures more safely and effectively?

Fig. 1: Autonomous image-guided robotic vascular access, blood drawing and fluid delivery.

From: [Deep learning robotic guidance for autonomous vascular access](#)



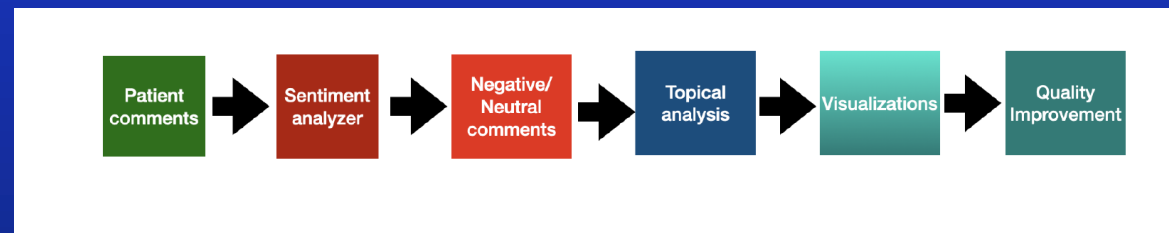
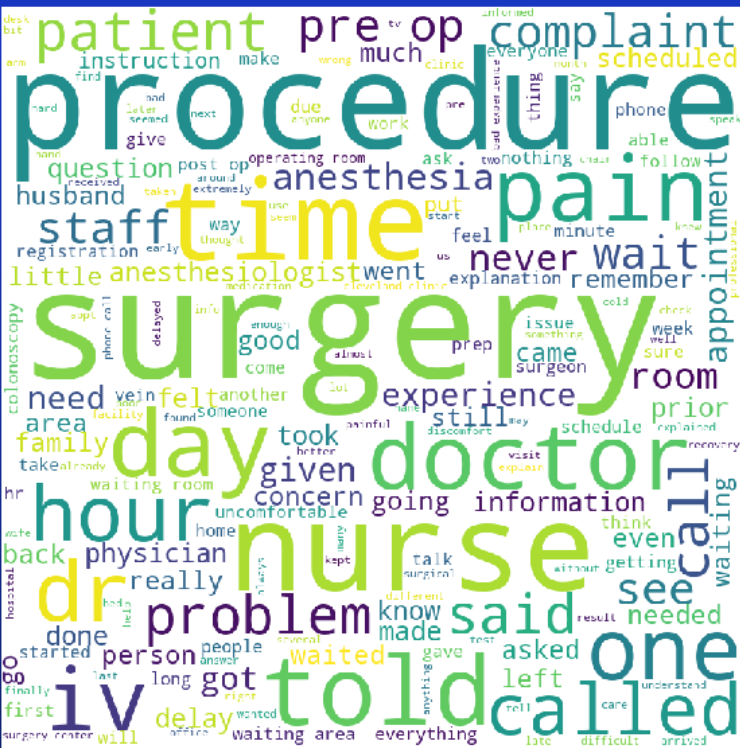
[Nature Machine Intelligence](#) volume2, pages 104–115 (2020)

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/10.1117/1.JMI.6.4.047001>



# Can algorithms help us listen to our patients better?

(15000+ comments analysis in less than one minute)



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

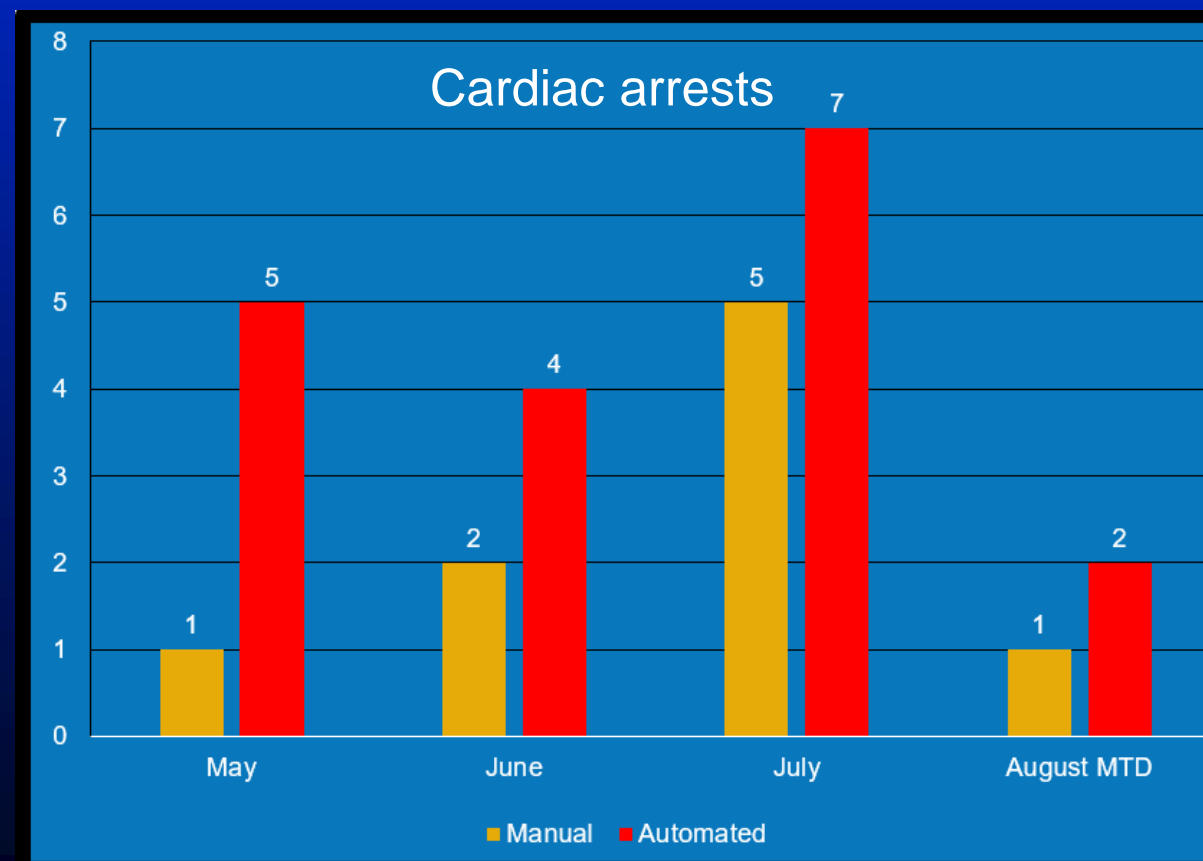
Mathur, Piyush, et al. "Automated analysis of ambulatory surgery patient experience comments using artificial intelligence for quality improvement: A patient centered approach." *Intelligence-Based Medicine* (2021): 100043.

# Can algorithms help improve safety event reporting?

## Algorithms

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

## Results

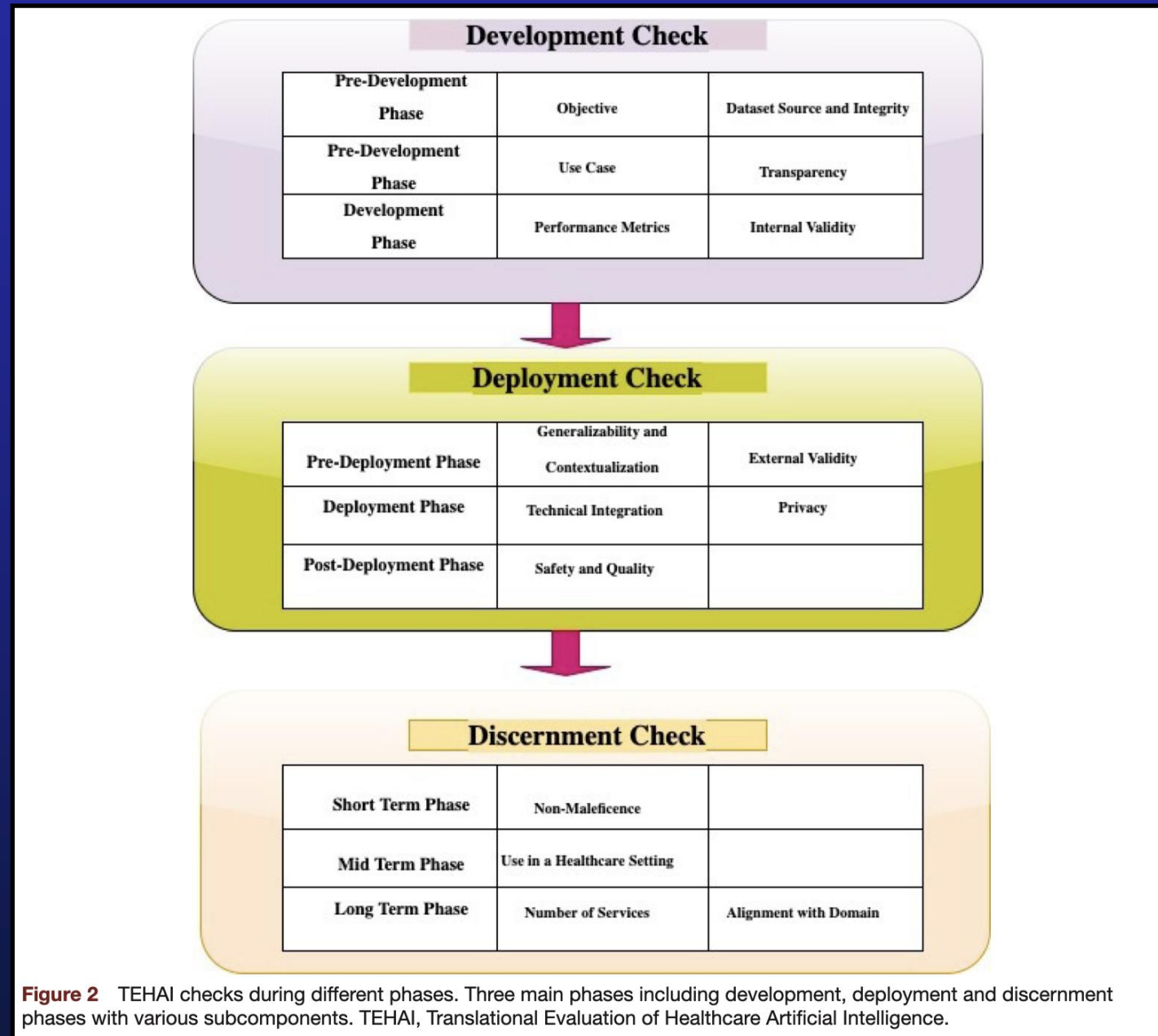


# Vision and Leadership

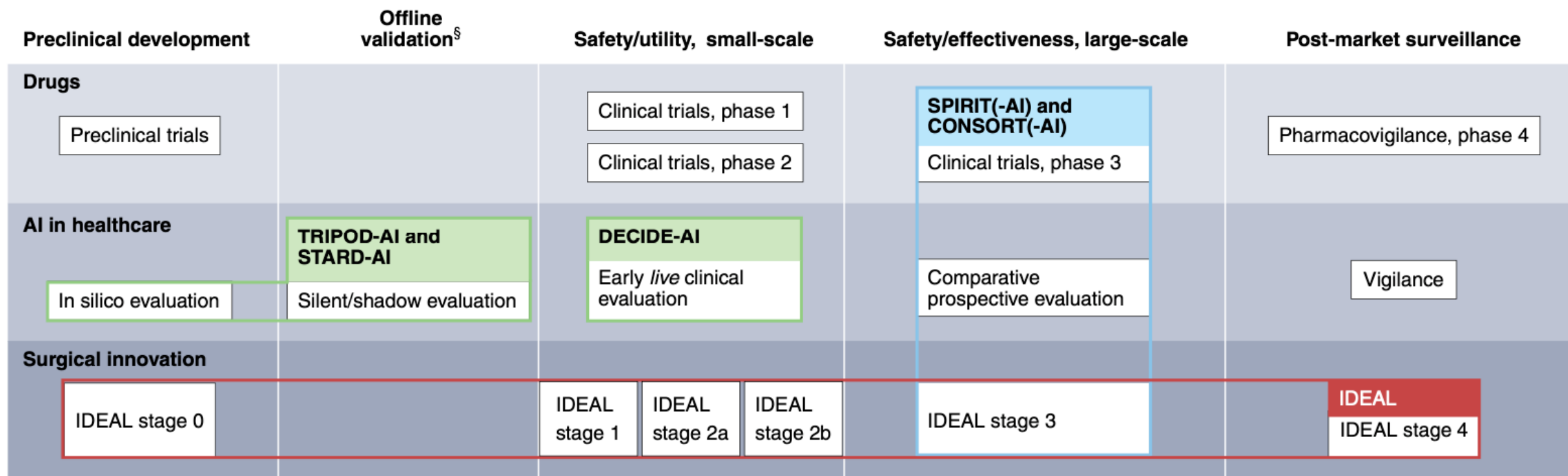
Table 1: Solutions for Effective Deployment of AI in Health Care

Patient- and care-provider-centric—first do no harm
Clinician leadership
Rigorous model development and testing
Explainable or Interpretable solutions—avoidance of black box
Clinical validation for generalizability and scalability
Cost-effective solutions

# Evaluation framework - TEHAI



# DECIDE - AI

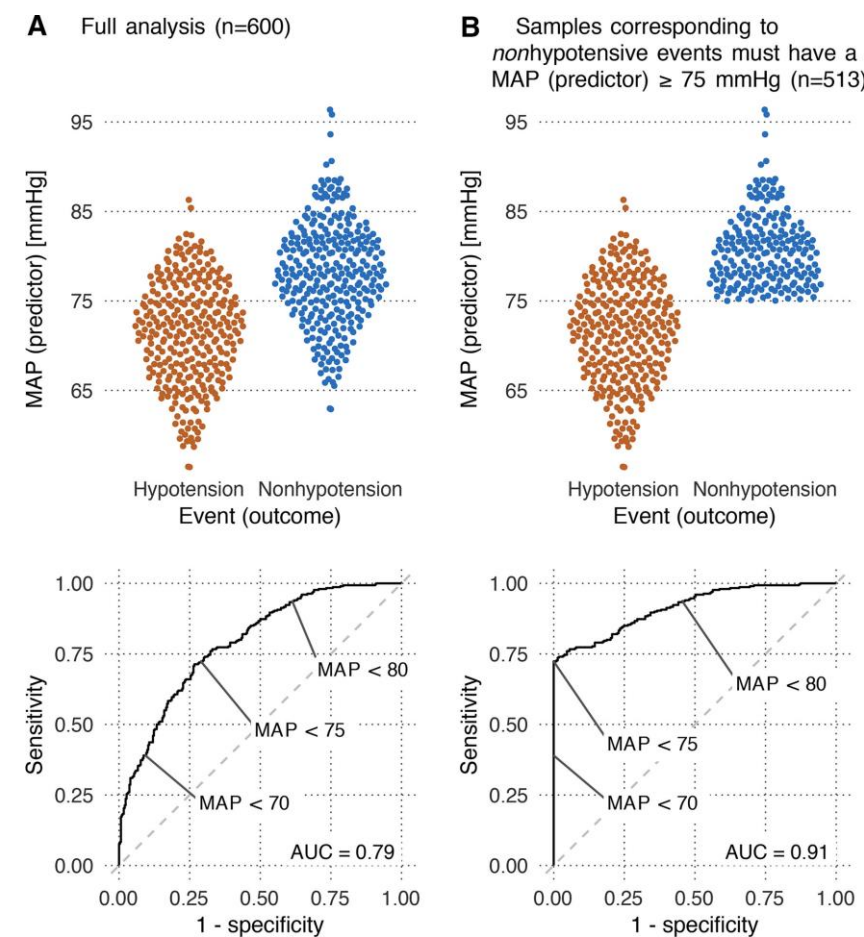


**Fig. 1 | Comparison of development pathways for drug therapies, AI in healthcare and surgical innovation.** The colored lines represent reporting guidelines, some of which are study design specific (TRIPOD-AI, STARD-AI, SPIRIT/CONSORT and SPIRIT/CONSORT-AI); others are stage specific (DECIDE-AI and IDEAL). Depending on the context, more than one study design can be appropriate for each stage. <sup>§</sup>Apply only to AI in healthcare.



## 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.

# Conclusion

- Algorithms in anesthesiology or perioperative medicine are not new and are growing in use.
- Validation is important.
- Clinician leadership and collaboration with engineers is key.
- Evaluation frameworks are essential for successful and safe clinical implementation.
- Can algorithms help clinicians deliver safe care?

# Can AI/algorithms save lives?



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