Lecture #2: Implementing AI in Healthcare (part 1)

Data Sciences Institute
Topics in Deep Learning
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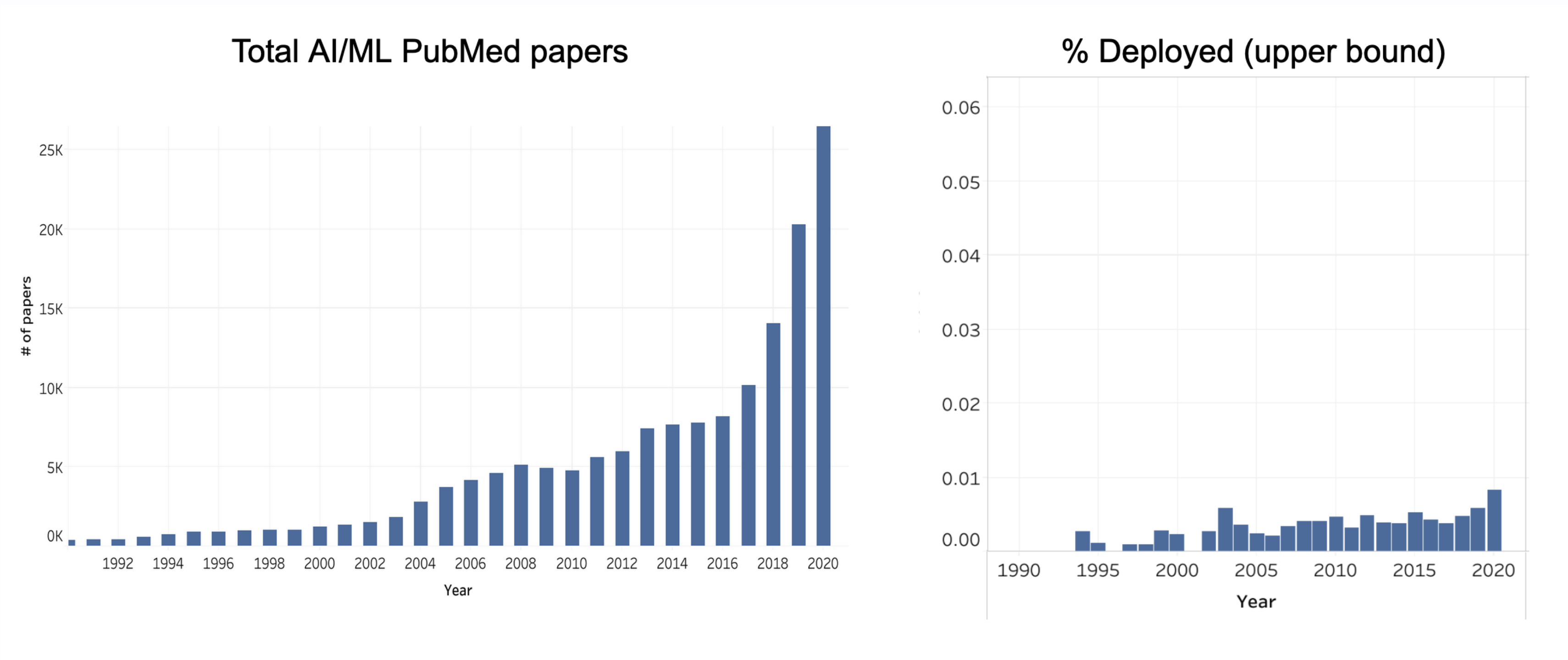
Lecture Outline

- The key difficulty (recap)
- The roadmap
- Choosing the right problem
- Developing a useful solution
- Considering ethical implications
- Rigorous evaluation (silent trial)
- Deploying the AI/ML

Recap: technology adoption in HC is hard

We've got publications figured out



Source: MLHC 2021 (Anna Goldenberg)

Talk is cheap

How AI could change the future of our health care

CBC News: The National

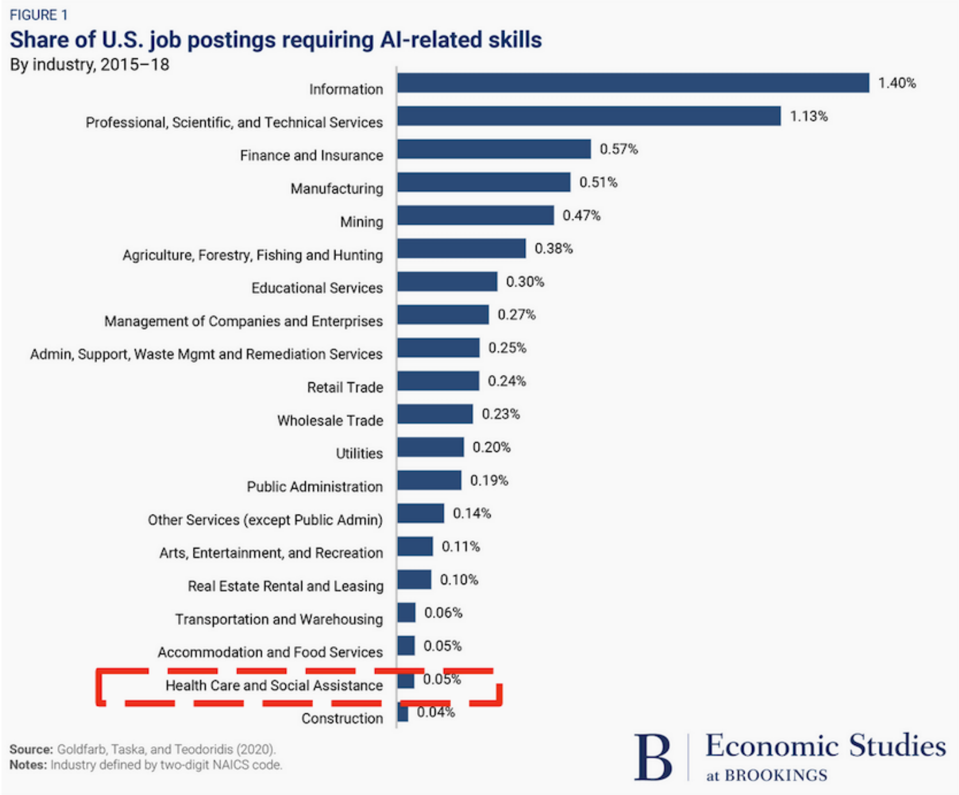
14K views • 4 years ago

RESEARCH

Why is AI adoption in health care lagging?

Avi Goldfarb, Florenta Teodoridis

March 9, 2022



Beware, beware ....

- "The reality is that most failures of AI projects are failures in strategy and in execution."
  - *Source: Why AI investments fail to deliver*
- "Validation of the performance of an algorithm in terms of its accuracy is not equivalent to demonstrating clinical efficacy. This is ... the 'AI chasm'—that is, an algorithm with an AUC of 0.99 is not worth very much if it is not proven to improve clinical outcomes."
  - *Source: High Performance Medicine*

Where many fear to tread

future tense

How IBM's Watson Went From the Future of Health Care to Sold Off for Parts

BY LIZZIE O'LEARY JAN 31, 2022 • 9:00 AM

HEALTH TECH

Epic's widely used sepsis prediction model falls short among Michigan Medicine patients

By Dave Muoio • Jun 22, 2021 03:35pm

ARTIFICIAL INTELLIGENCE

Google's medical AI was super accurate in a lab. Real life was a different story.

If AI is really going to make a difference to patients we need to know how it works when real humans get their hands on it, in real situations.

By Will Douglas Heaven April 27, 2020

NICOLE KOBIE BUSINESS 23.08.2022 12:00 PM

Babylon Disrupted the UK's Health System. Then It Left

A lot of upside

The Potential Impact of Artificial Intelligence on Healthcare Spending

Nikhil Sahni, George Stein, Rodney Zemmel & David M. Cutler

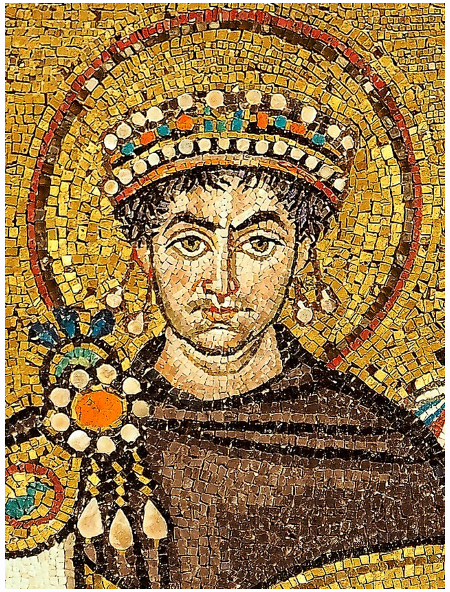
Figure 6. Breakdown of overall AI net savings opportunity within next five years using today's technology without sacrificing quality or access

Stakeholder group	Total costs (2019), $ billions	Net savings opportunity (2019), $ billions	Net savings opportunity as percent of stakeholder group's total costs	Percent of net savings opportunity focused on administrative costs
Hospitals	$1,096	$60–$120	5–11%	~40%
Physician groups	$711	$20–$60	3–8%	~50%
Private payers	$1,135	$80–$110	7–10%	~20%
Public payers	$511	$30–$40	5–7%	~20%
Other sites of care	$817	$10–$30	1–4%	~50%
Total		**$200–$360**	**5–10%[1]**	**~35%**

1. This represents the percent of total national health spending in 2019.

Source: National Health Expenditures data; authors' analysis

History's bumpy road of technological adoption



Justinian I

Emperor Hongxi

Sultan Bayezid II

Roadmap

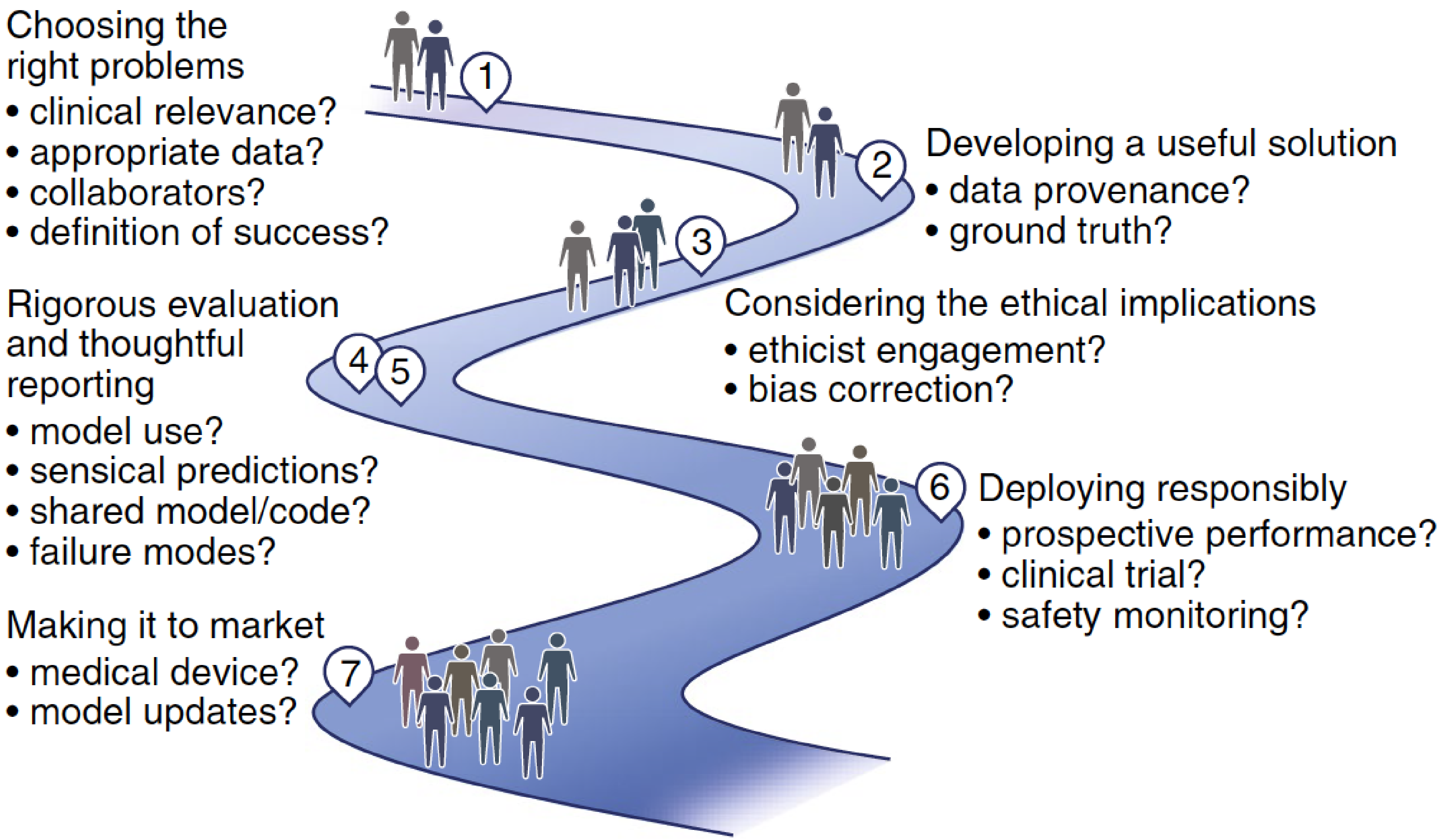
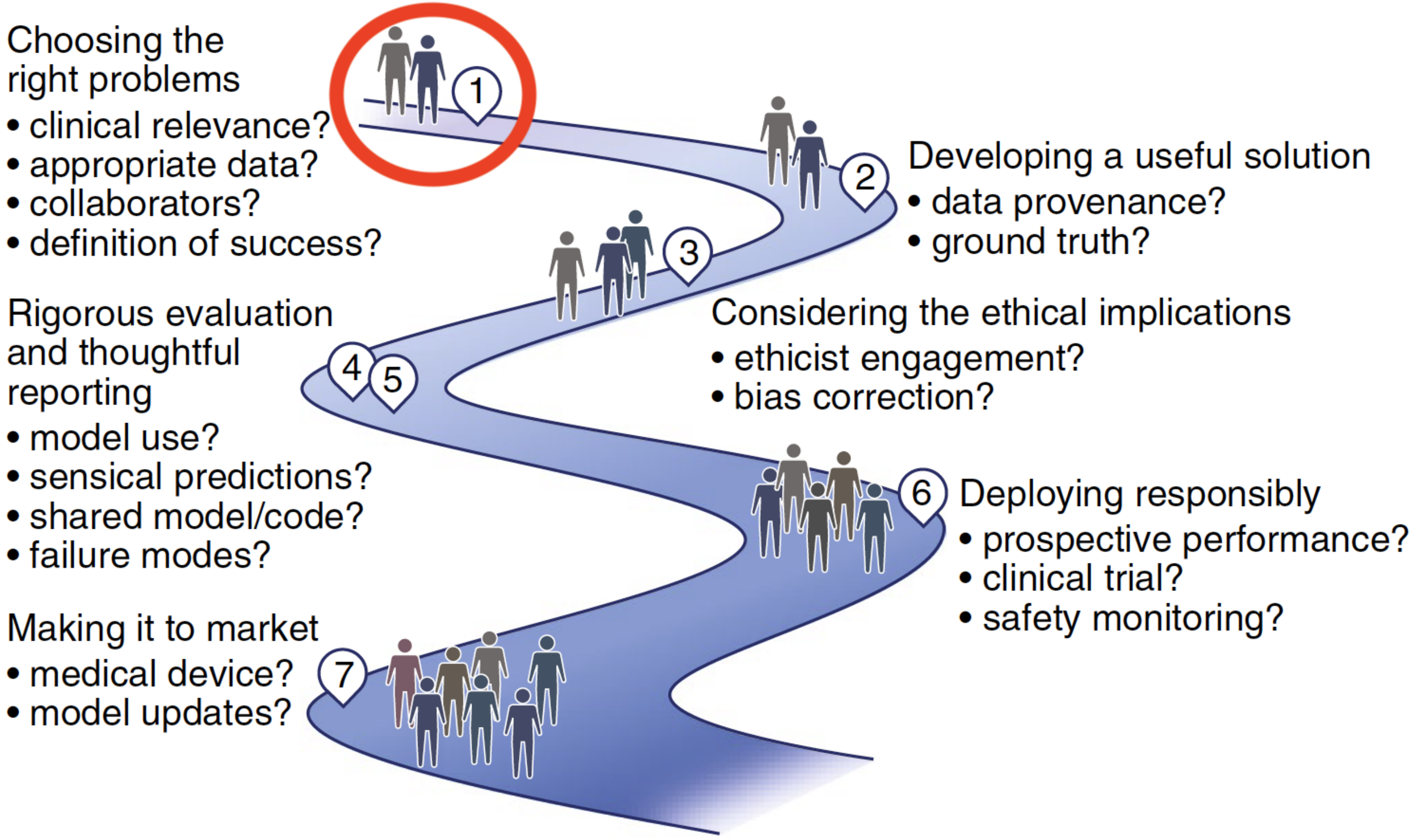


Fig. 1 | A roadmap for deploying effective ML systems in health care.
By following these steps and engaging relevant stakeholders early in the process, many issues stemming from the complexity of adopting ML in practice can be successfully avoided.

Choosing the right problem



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Unclear problem formulations

- The human body can be thought of as a "*black box*" - the root causes and mechanisms of illnesses are often not known.
- How does a prediction from a ML model actually help us solve a healthcare problem?
- How do we predict a "label" when there is no clear consensus among professionals on diagnosis or when there is significant inter- and intra-operator variability?
- **What problem are we trying to solve, and how does AI/ML help us solve it?**

Understanding the problem

- Understanding the specific problem being addressed is crucial.
- Researchers often focus on readily available datasets without questioning the clinical relevance of the problems they address.
- A high-performing model doesn't guarantee clinical utility if the model simply confirms existing knowledge without new insights.

Contextualization

- AI/ML tools in healthcare must align with existing ways of working.
  - Understanding the current workflow is therefore crucial.
- For example, before developing an AI-based sepsis model you need to know:
  - How is Sepsis defined in the hospital? Does this vary between institutions
  - How is Sepsis currently detected? Which staff often spot it first? What point along the patient journey does this happen?
  - What actions are currently taken after a diagnosis?

Remember the contextualization Mad Lib

As a [decision maker],

If I knew [information],

I would do [intervention],

to improve [measurable outcome]

Stakeholder engagement for problem definition

- Early stakeholder engagement identifies clinically relevant problems and ensures support throughout development.
  - *Note:* stakeholders can include healthcare providers, administrators, patients, and ethicists.
- Prioritizing clinically relevant and stakeholder-supported problems helps helps ensure diverse perspective and leads to impactful AI/ML solutions.
- **Rigorous problem definition** aligns solutions with stakeholder needs.

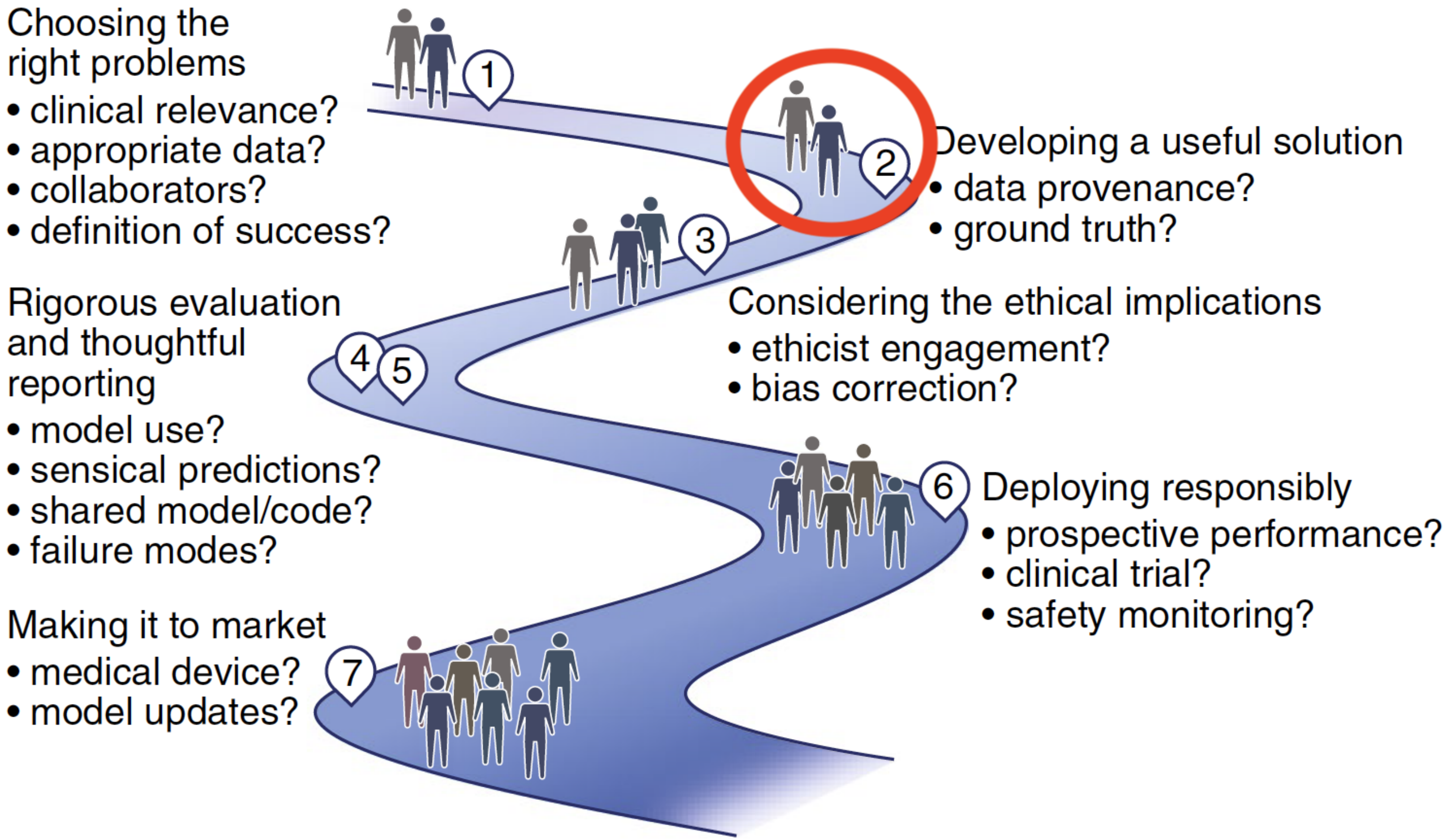
Stakeholder engagement: frontline health professionals

- Recognizing the expertise of frontline healthcare professionals is crucial.
- AI/ML tools should **augment clinical judgment, not replace it.**
- Involving clinicians in the development process is essential.
- Incorporating their feedback and providing necessary training and support enhances AI/ML effectiveness in practice.

Breakout #1

Suppose we wanted to reduce the rate of unplanned hospital re-admission (24H), what model would you build to do this, how would the model be acted on, and how would evaluate if it worked after deployment?

Developing a useful solution



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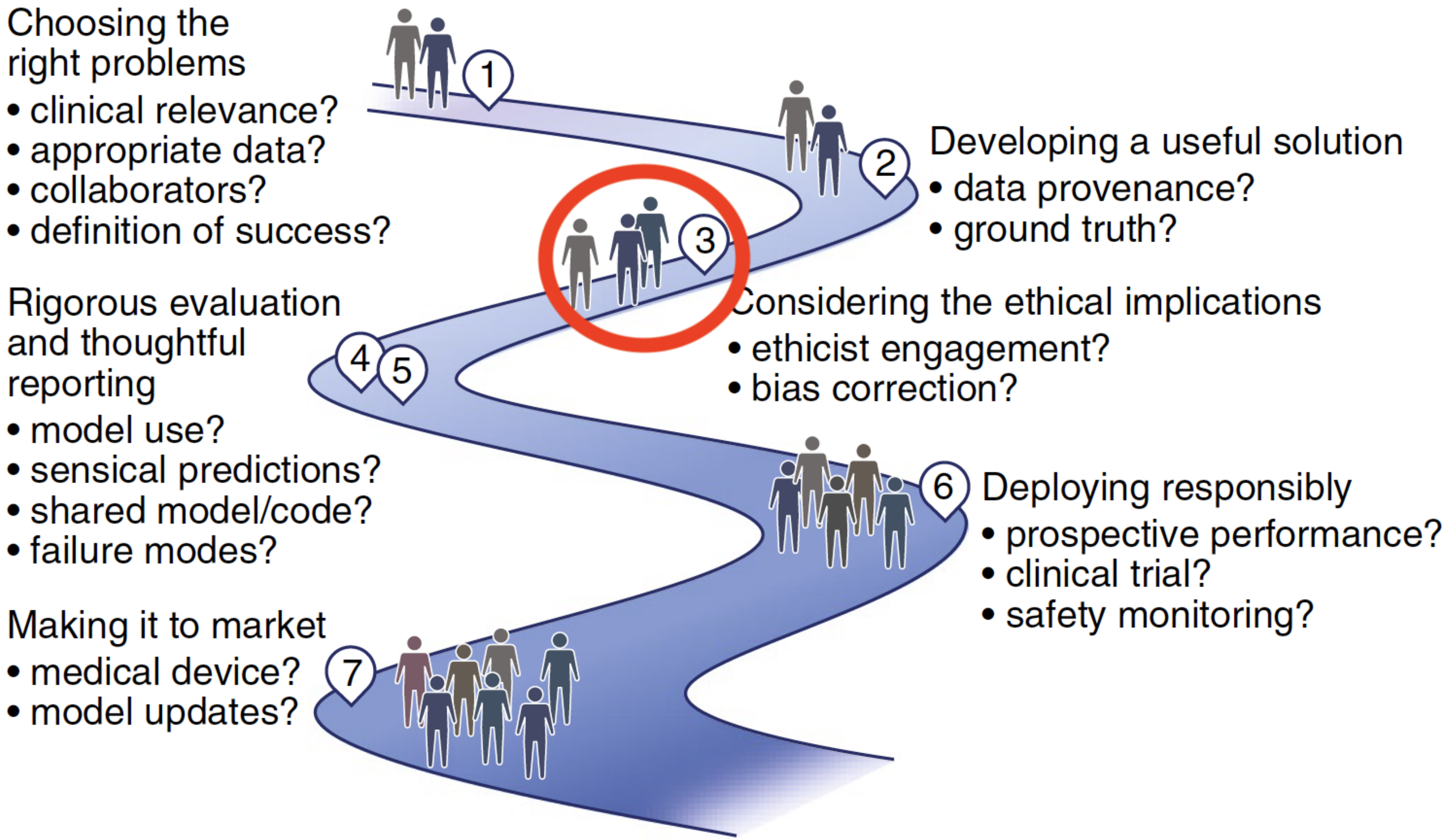
Solution design

- AI/ML models and tools are developed based on the insights gained during the exploration phase.
- Emphasis is placed on designing solutions that are effective, interpretable, and usable by end-users.

Data evaluation

- Before developing a solution, data must be thoroughly evaluated to ensure suitability for the problem at hand.
- Questions about data collection methods, purposes, and representativeness are crucial.
    - Ensure training data represent the environment where the model will be used.
    - Subtle biases in data can reduce model reliability and must be addressed during development.
    - Identifying and correcting biases upfront is crucial for model correctness.

Considering ethical implications



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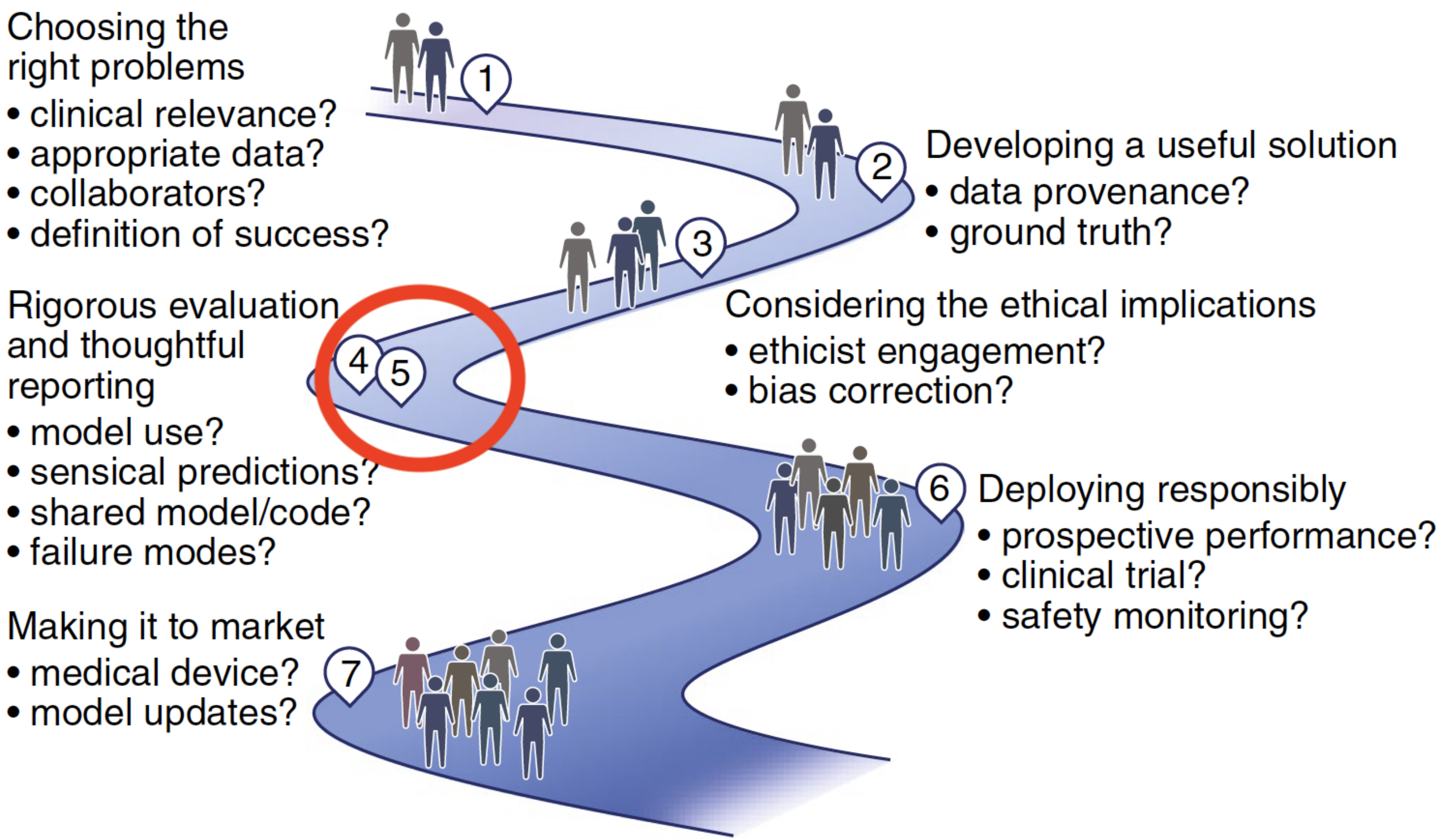
Health equity and disparities

- Health care data used for ML algorithms may be influenced by social inequalities (e.g., race, sex and other factors)
- Ethical questions may arise regarding the use of certain predictors, e.g., smoking status or HIV status
- Collaboration between ethicists, social scientists, regulatory scholars, AI/ML experts, and stakeholders is essential to address bias and ethical concerns.

Ethical considerations

- Ethical considerations must be prioritized to ensure the privacy, safety, and fair treatment of patients and affected parties when deploying AI/ML tools in clinical practice.
- AI/ML algorithms focused on fairness can help mitigate biases and promote equitable healthcare delivery.

Rigorous evaluation and reporting



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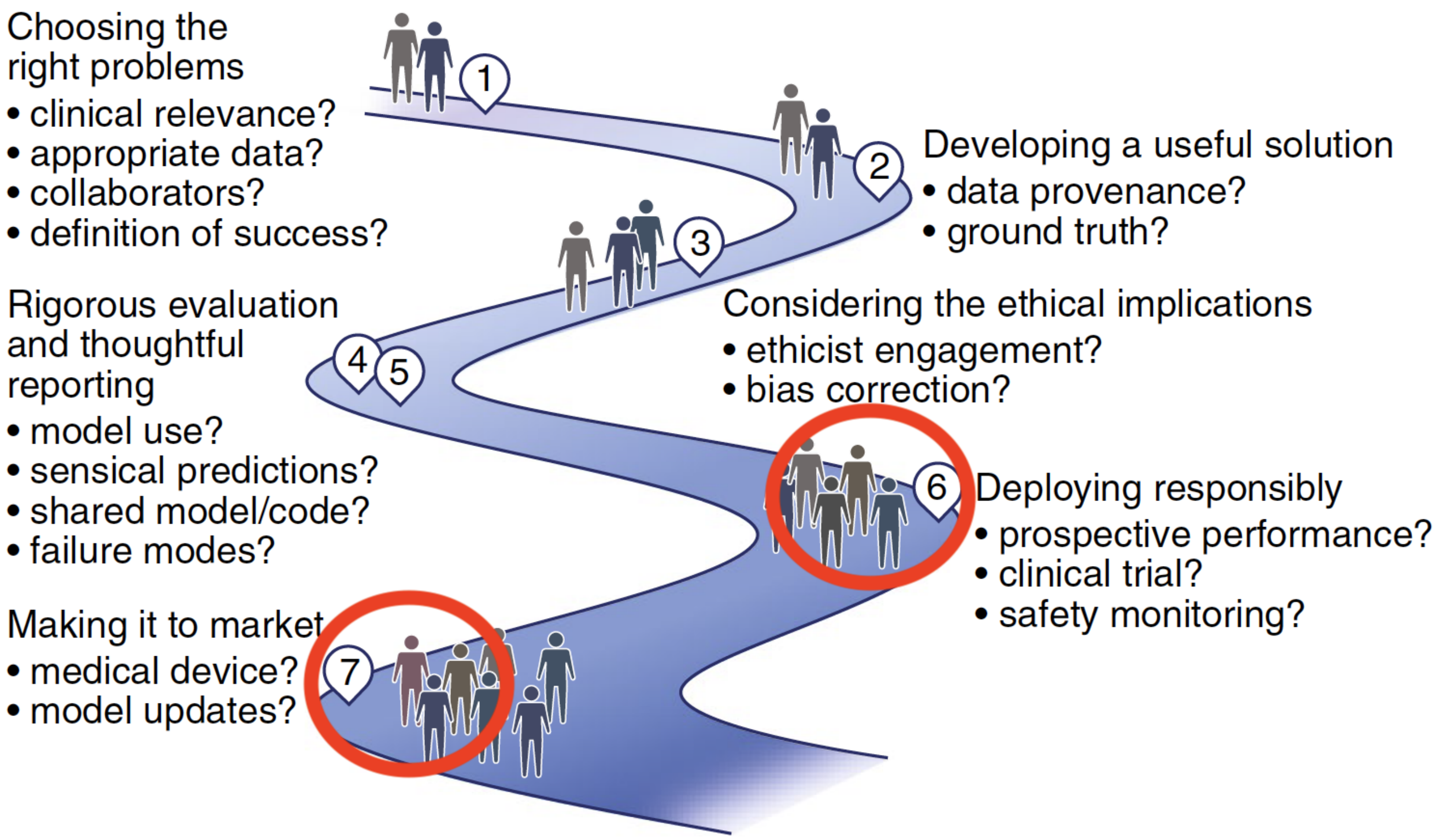
Proper model evaluation

- Focus on **clinically relevant evaluation metrics** over commonly used ones.
- Use qualitative approaches to uncover concerns missed by quantitative measures.
- Report results and share code and documentation for transparency.

Recall the Sepsis Model

- **Epic Sepsis Model Issues → Lack of reproducibility:**
  - Peer-reviewed data questioned the effectiveness of Epic's sepsis prediction algorithm.
  - University of Michigan Medical School study with over 27,000 patients found its performance "substantially worse" than reported.
- **Study Concerns:**
  - Lack of *external validation* for proprietary models and a call for transparency and validation before widespread clinical use.

Prospective evaluation



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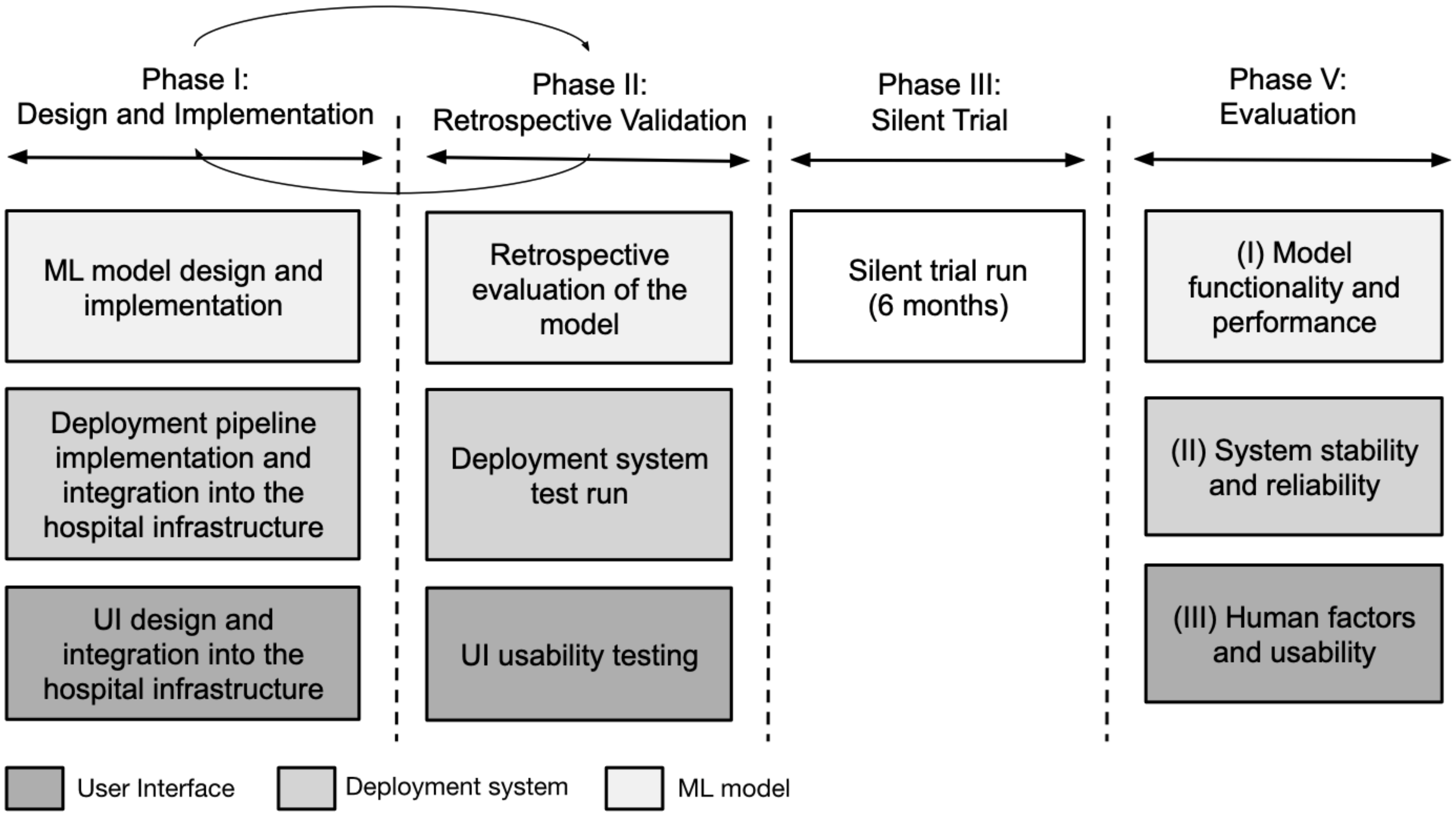
Silent trial

- ML models should have a real-time prospective evaluation to assess performance, failure points, ans biases



Source

Silent trial

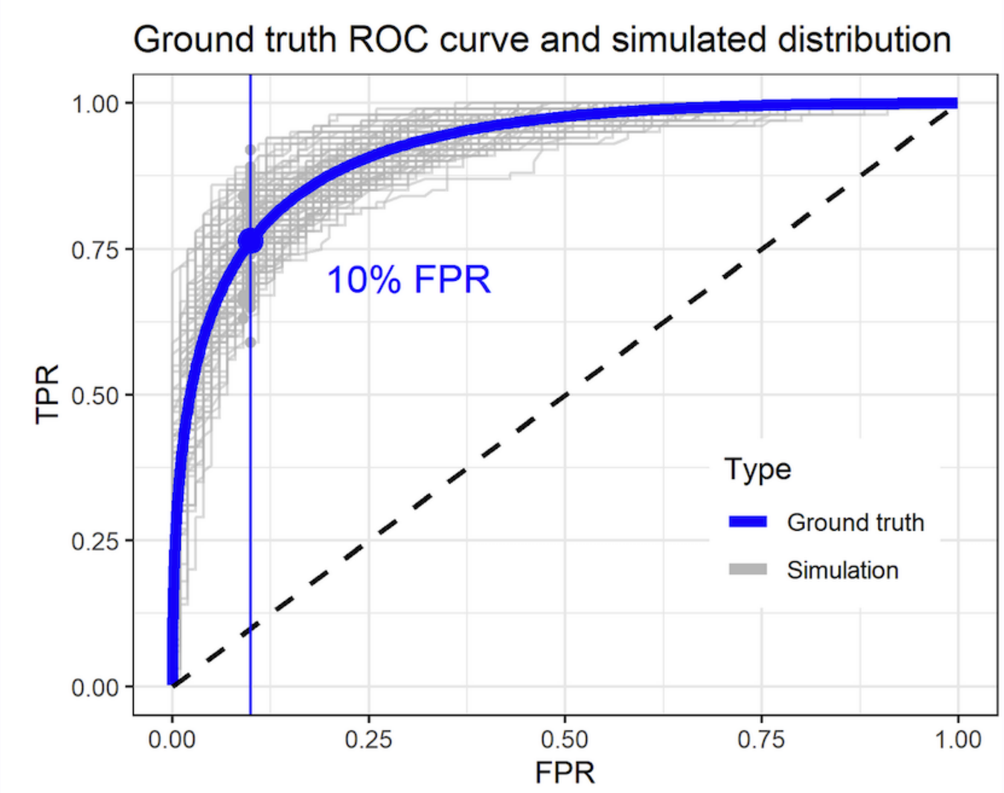
- A prospective trial let's us make one of two (statistical) claims rigorously:
  - This algorithm has at least [X] [accuracy measure]
  - This algorithm has at most [Y] [loss measure]
- How do we do this?
  - "Calibrate" model to have E[X] > X_hypothesis
  - ... or E[Y] < Y_hypothesis

Breakout #X

Suppose we wanted to run a silent trial to demonstrate a model has 80% sensitivity, how would we "calibrate" the model so that the trial would likely be successful?

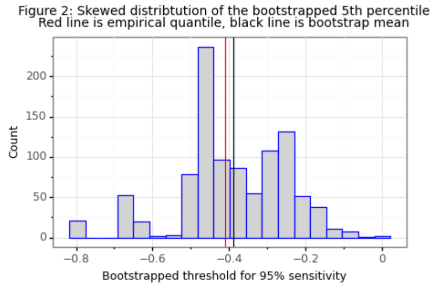
Silent trial

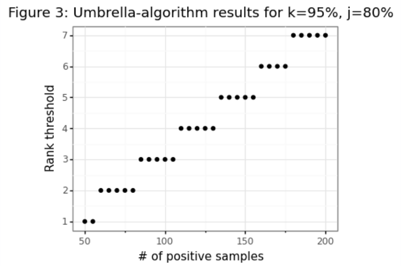
- In the case of a binary classifier, you need to pick an operating threshold to target a performance measure (e.g. sensitivity)
- But the operating performance=f(threshold) is a random variable



Silent trial (calibration)

- You can increase the likelihood of success by picking a "conservative" operating threshold
  - Bootstrap or order statistic theory (see Tong et. al (2018))





Empirical bootstrap

Rank order approach

Implementation and evaluation

- **Continuous monitoring and feedback** mechanisms allow for iterative improvements to the tool over time.
- Ongoing evaluation helps identify and address any unintended consequences or disparities in healthcare deliver

Summary

Considerations for successful translation of AI/ML into clinical care

- **Clear problem definition** is crucial for effective AI/ML deployment in healthcare.
- **Engaging stakeholders** early and into all stages of development ensures identification of clinically relevant problems.
- **Thorough data evaluation** is necessary to address biases and ensure alignment with existing workflows.
- **Continuous monitoring and feedback** in real-world settings are essential for successful AI/ML deployment.

Case Studies

- Deployment of a deep learning system for diabetic retinopathy screening in Thai clinics.
- Key findings reveal the challenges of integrating AI into clinical workflows, such as issues with system gradability, internet connectivity, and the necessity of obtaining patient consent.

Electronic Health Record (EHR) Data

- Challenges and barriers to achieving economies of scale in analyzing EHR data.
- Challenges in scaling EHR data analytics due to non-standardized systems.
- Importance of policy reforms and technology adoption for improved healthcare analysis and outcomes.

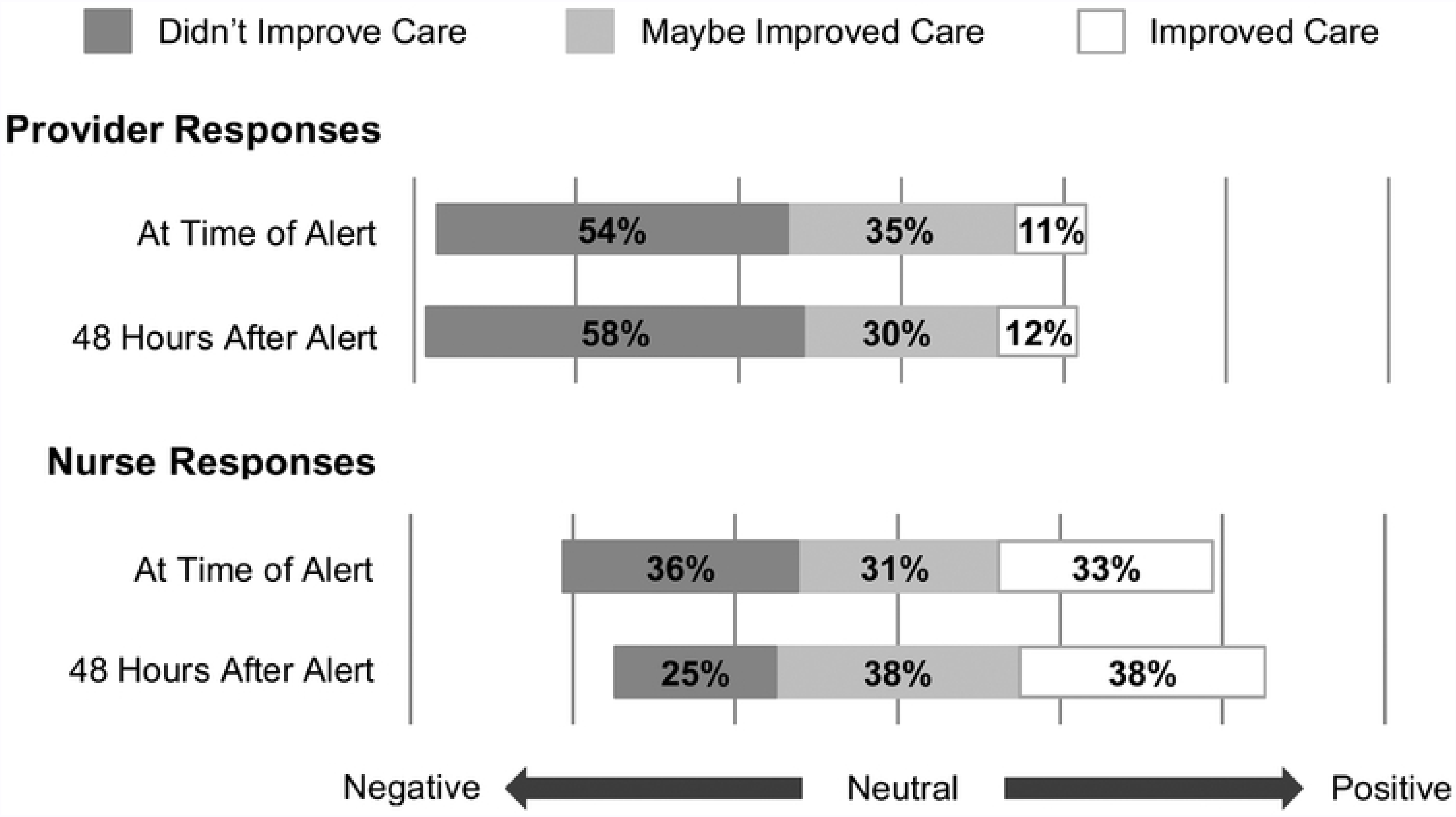
Alert Fatigue

- Healthcare professionals receive an overwhelming number of alerts, which often leads to crucial warnings being ignored.
- Current approach to alerts does not consider human factors or user-centered design.
- Solutions could include leveraging big data and enhancing device communication to minimize unnecessary alerts, focusing on a more advanced system for better patient safety.

UPenn's Sepsis Model

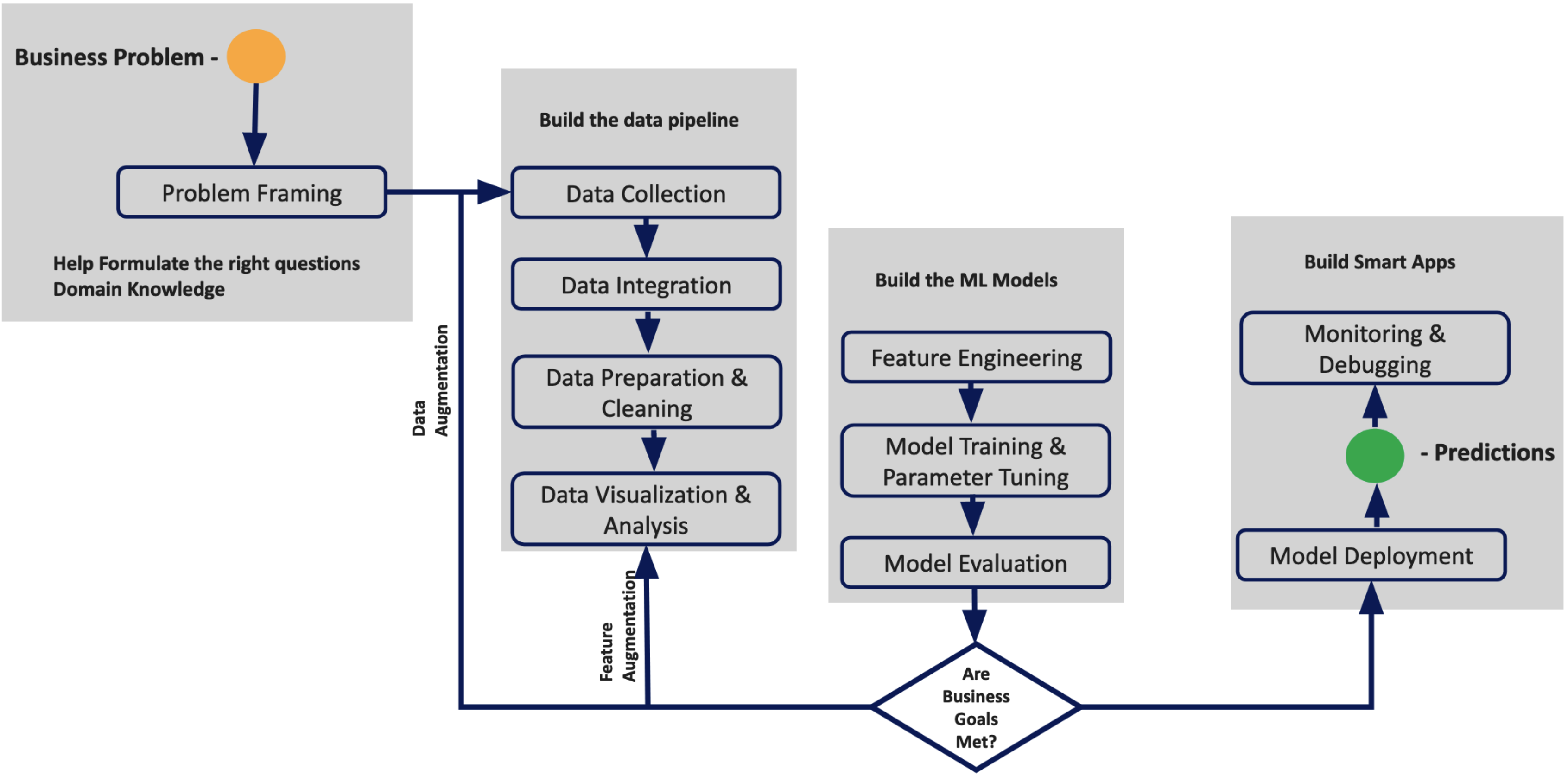
- Developed and evaluated a machine learning algorithm aimed at predicting severe sepsis and septic shock within a tertiary teaching hospital system.
- Algorithm, based on a random-forest classifier and electronic health record data, showed a sensitivity of 26% and specificity of 98%.

- Implementation led to a modest increase in lactate testing and IV fluid administration but no significant change in mortality or ICU transfer rates, though it did reduce the time-to-ICU transfer.



Clinician perceived impact on patient care (https://doi.org/10.1097/ccm.0000000000003803).

Think about how model fits within organization



Source: Great Learning (AI Project Life Cycle and Setting up AI Team)

Figure adapted from:

> Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., Jung, K., Heller, K., Kale, D., Saeed, M., Ossorio, P. N., Thadaney-Israni, S., & Goldenberg, A. (2022). Do No Harm: A Roadmap for Responsible Machine Learning in Healthcare. Nature Medicine

Ideas adapted from:

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>
> Drysdale, E., Dolatabadi, E., Chivers, C., Liu, V., Saria, S., Sendak, M., Wiens, J., Brudno, M., Hoyt, A., Mazwi, M., Mamdani, M., Singh, D., Allen, V., McGregor, C., Ross, H., Szeto, A., Anand, A., Verma, A., Wang, B., Paprica, P. A., & Goldenberg, A. (2020). Implementing AI in healthcare. Vector-SickKids Health AI Deployment Symposium, Toronto, Ontario, Canada.

Sendak, M., Elish, M. C., Gao, M., Futoma, J., Ratliff, W., Nichols, M., Bedoya, A., Balu, S., & O'Brien, C. (2020). "The human body is a black box": supporting clinical decision-making with deep learning. FAT* '20: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency

Verma, A. A., Murray, J., Greiner, R., Cohen, J. P., Shojania, K. G., Ghassemi, M., Straus, S. E., Pou-Prom, C., & Mamdani, M. (2021). Implementing machine learning in medicine. CMAJ.