Implementing AI in Healthcare #1

Data Sciences Institute
Topics in Deep Learning

Outline

- Choosing the right problem
- Developing a useful solution
- Considering ethical implications
- Rigorous evaluation and reporting
- Deploying the AI/ML

Choosing the right problem

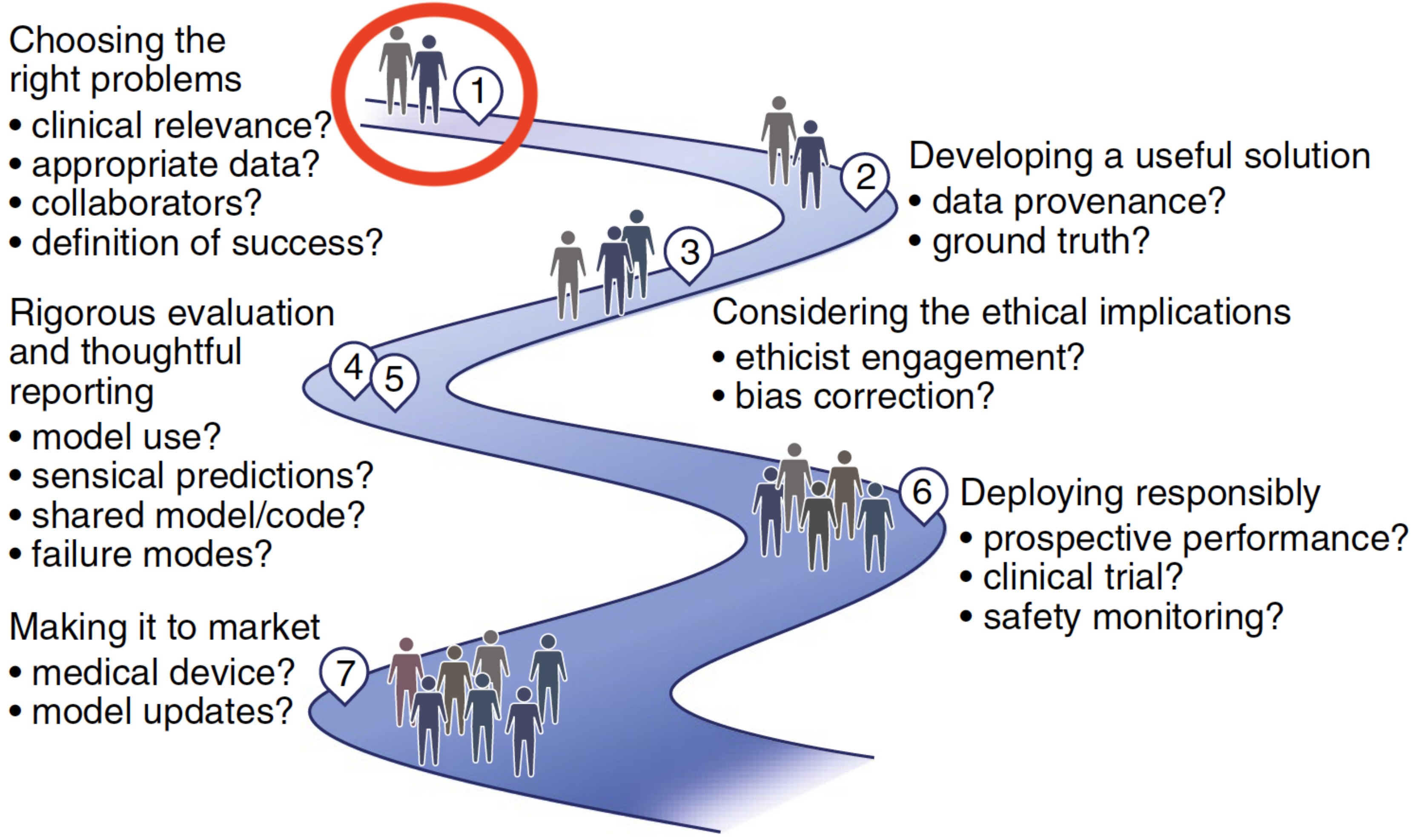


Fig. 1 | A roadmap for deploying effective ML systems in health care. By following these steps and engaging relevant stakeholders early in the process, many issues stemming from the complexity of adopting ML in practice can be successfully avoided.

Unclear problem definitions

- The human body is thought of as a **"black box"** - the root causes and mechanisms of illnesses are often not known.
- In situations where there is no clear consensus among professionals on diagnosis, how do we determine what constitutes an explainable algorithm for clinical use, especially when the underlying pathophysiology of the condition is not fully understood?
- Progress in AI/ML for healthcare has been hindered by unclear problem definitions.

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 workflows and practices.
- Understanding current detection methods for diseases is crucial.
- For example,
    - If an institution effectively detects a specific disease, AI could help in streamlining the process.
    - If there are systematic diagnostic gaps, AI could focus on addressing these challenges.

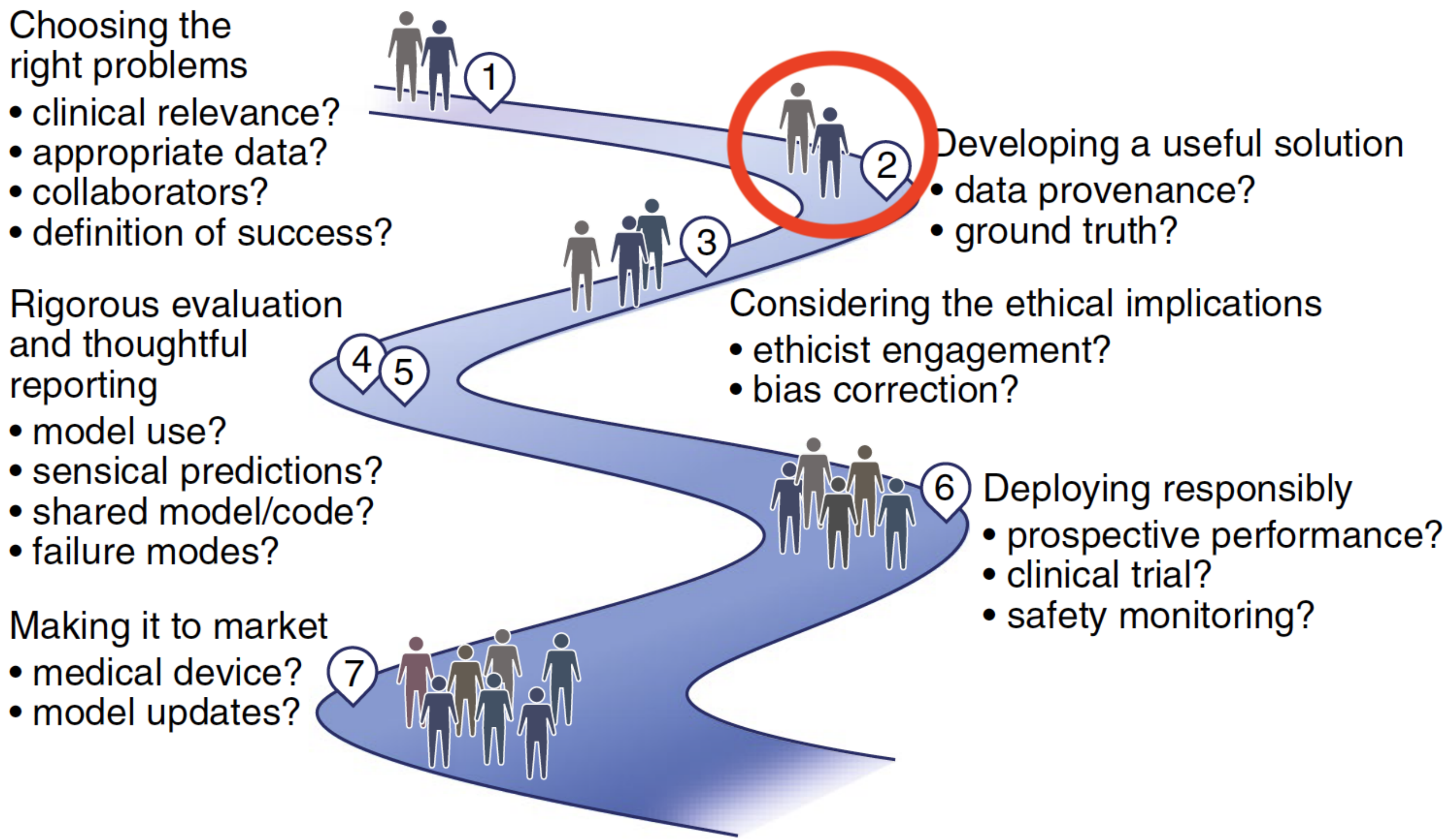
Stakeholder engagement for problem definition

- 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.

Developing a useful solution



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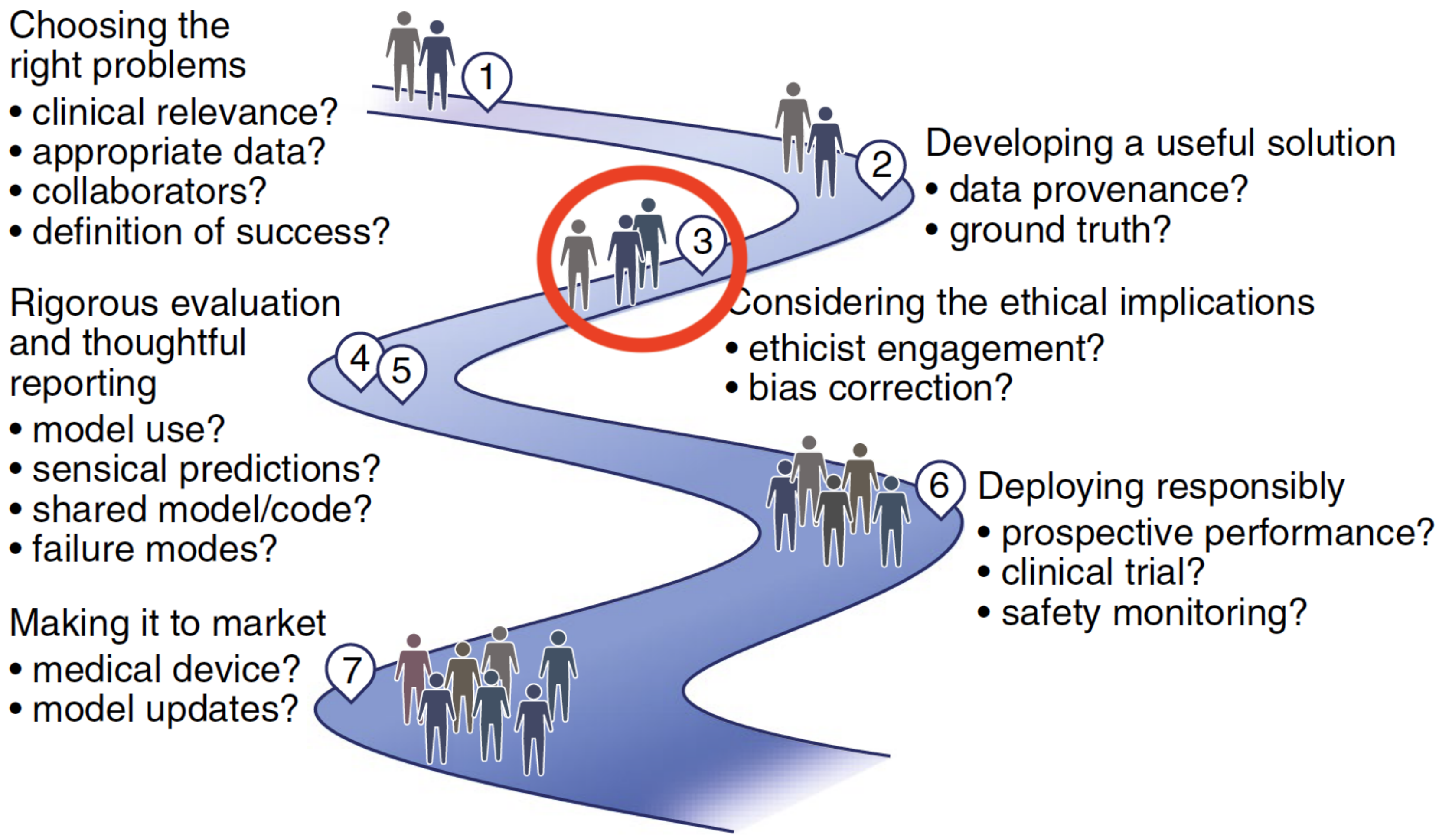
Solution design

- 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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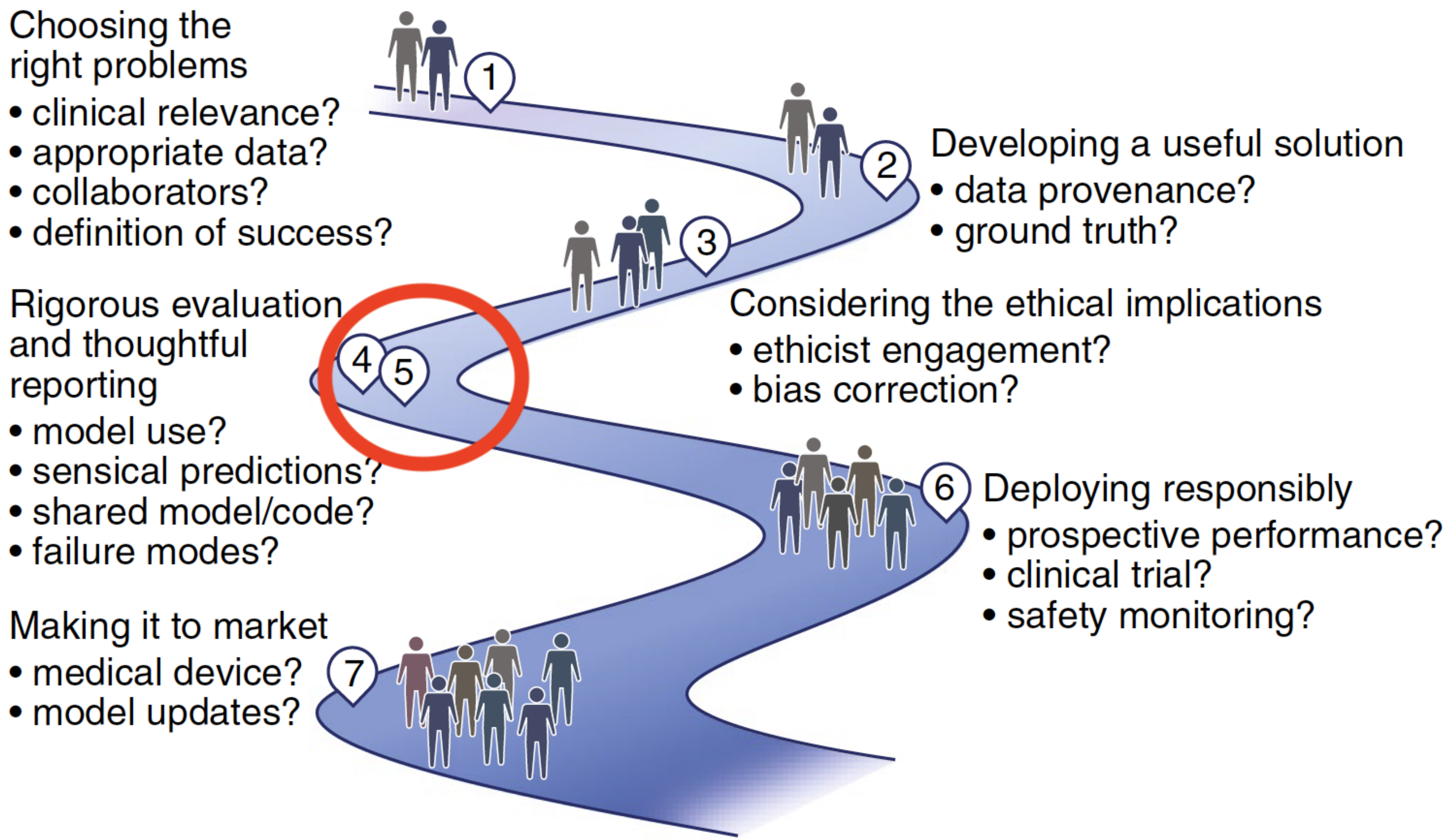
Health equity and disparities

- 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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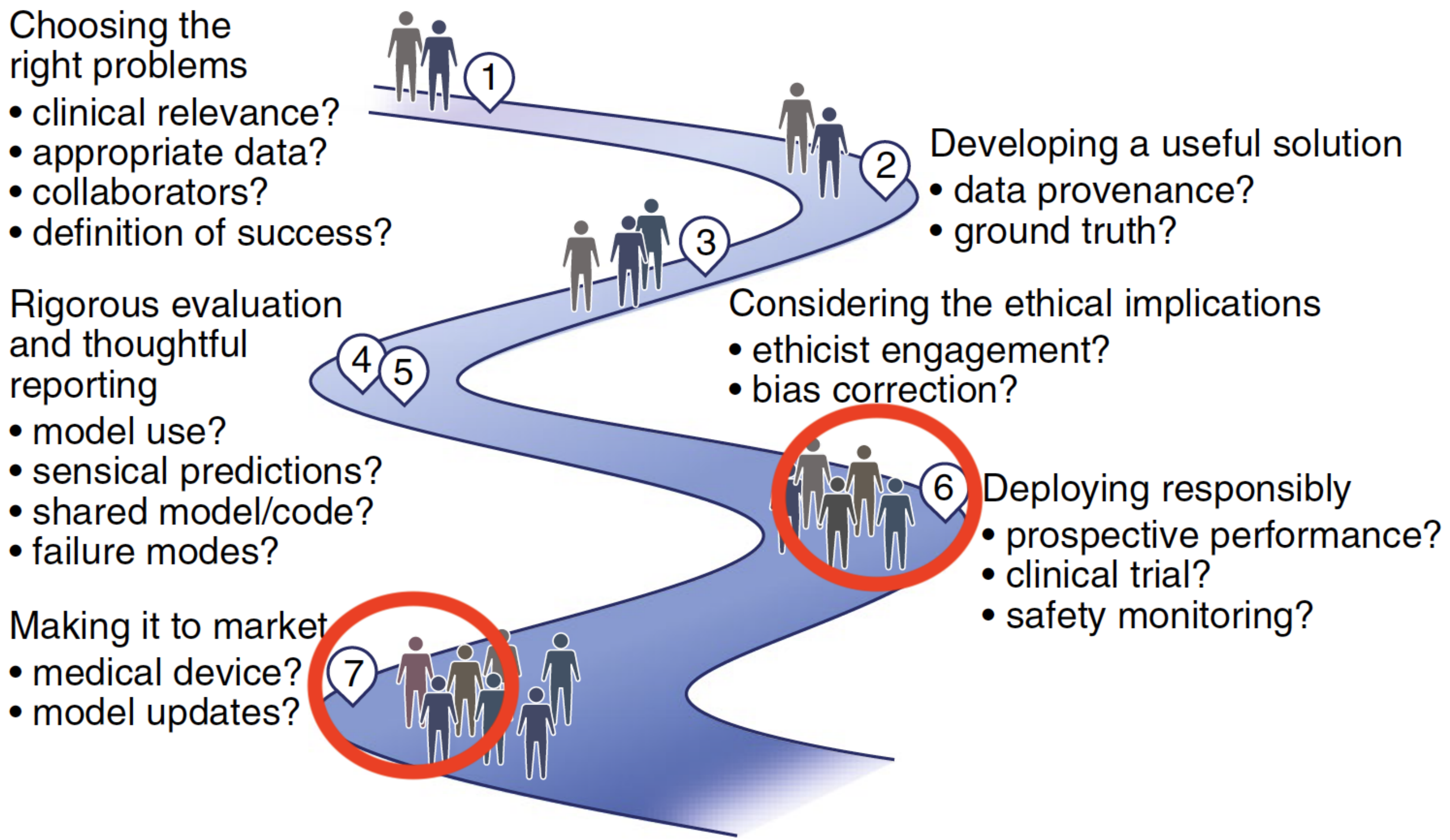
Proper model evaluation

- 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.

Deploying the AI/ML



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Implementation and evaluation

- ML models should undergo rigorous evaluation in real-world clinical settings to assess their performance, impact, and potential biases.
- **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.

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

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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.