

AMBOSS Cross Talk

AI-ENABLED MEDICAL DEVICES

***P r o g r e s s •
P o t e n t i a l • C h a l l e n g e s***

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OPEN DISCUSSION



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50 Responses

Medical Editor - Emergency Medicine

Coach

user researcher

User researcher

Engineering manager in the
knowledge access team (aka Search)

Product software search

Copy editor

Managing engineering teams

De student content, e.g exams

CRM marketing manager

Market & User Research

Operation reps

Quantitative researcher

Business/data analyst

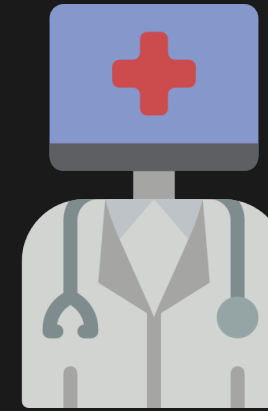


Source:

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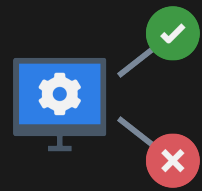
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Edit



***Use cases for artificial
intelligence in healthcare***

USE CASES FOR ARTIFICIAL INTELLIGENCE IN HEALTHCARE



CLINICAL DECISION SUPPORT

- Assisting clinicians in making decisions
- Using algorithms to analyze medical data
- Providing evidence-based treatment options, or alerts



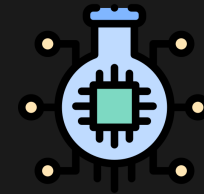
ADMINISTRATIVE TASKS

- Appointment scheduling
- Processing patient information
- Supply chain management



TRAINING AND EDUCATION

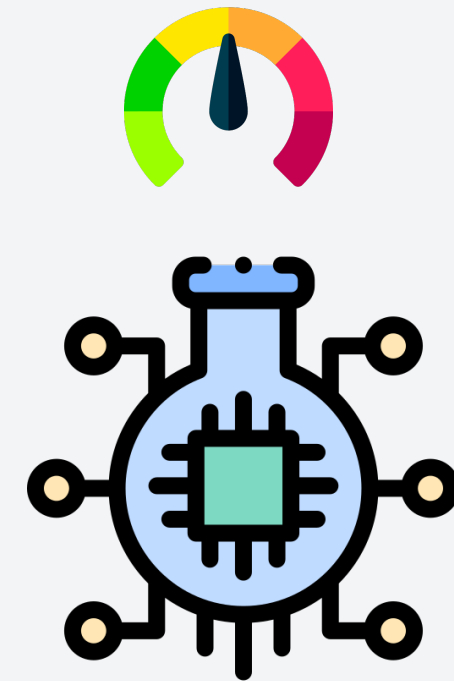
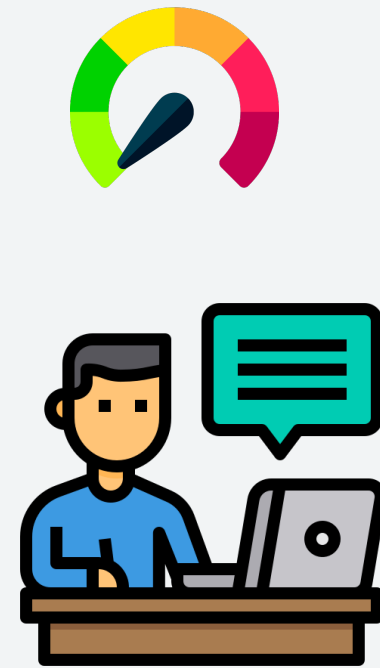
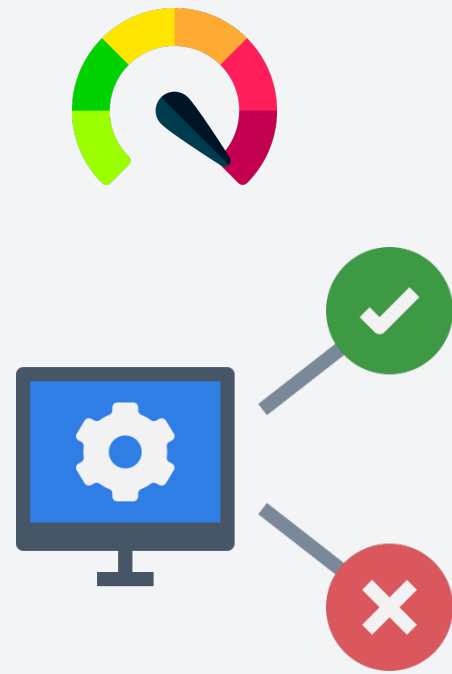
- Automated feedback systems
- Simulation of medical conditions

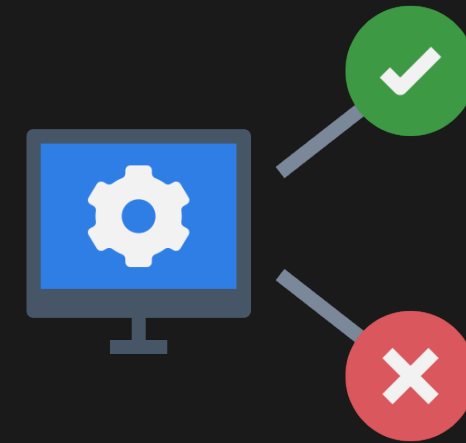


RESEARCH

- New drug discovery
- New technologies and technological features
- Genetic profiles

ARTIFICIAL INTELLIGENCE IN THE HEALTHCARE CONTEXT: PERCEIVED RISK





***AI-enabled clinical decision
support in different medical
fields***

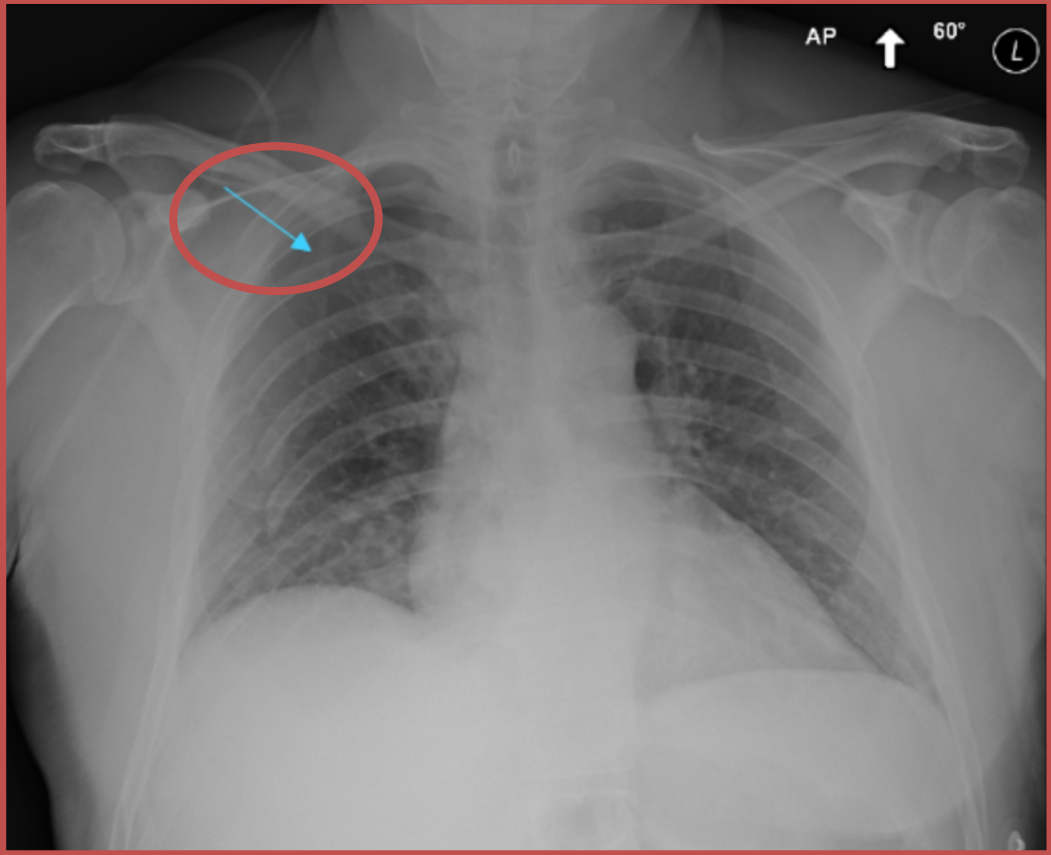
AI in radiology

Diagnosis: Right Pneumothorax

Edit Mode



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Patient Information: A 57 year old male with shortness of breath.

Findings:

- Mild cardiomegaly
- Visceral pleural edge at right apex
- Right basilar atelectasis
- Small right pleural effusion
- Right rib fractures

Render Time: 0 ms
Image #1/1

Zoom: 0.18
WW/WL: 4096/2048

Source: OWN

A I in cardiology



Zio XT Final Report for Patient #16

1

iRhythm Technologies
Tel: (888) 693-2401
www.zioreports.com

Date of Birth 12/12/67 (51 yrs)	Patient ID	Gender Female	Primary Indication (R94.31) Abnormal electrocardiogram
Prescribing Clinician Dr. E. Physician	Managing Location San Francisco		

Ventricular Tachycardia (4 beats or more)

▼ Fastest VT (HR Range 135-150 bpm, Avg 142 bpm)

2

Episodes
5

HR Range
116-150 bpm

Avg
132 bpm

Pauses (3 secs or longer)

▼ Longest Pause (4.9 s, 12 bpm)

3

Episodes
3

Range
3.9-4.9 s

Atrial Fibrillation

▼ Fastest AF (HR Range 61-154 bpm, Avg 100 bpm)

3

AF Burden
37%

Longest Duration
1 d 19 h

HR Range
50-154 bpm

Avg
97 bpm

AV Block (2nd° Mobitz II, 3rd°)

None found

4

Supraventricular Tachycardia (4 beats or more)

Preliminary Findings

Patient had a min HR of 50 bpm, max HR of 154 bpm, and avg HR of 78 bpm. Predominant underlying rhythm was Sinus Rhythm. 5 Ventricular Tachycardia runs occurred, the run with the fastest interval lasting 4 beats with a max rate of 150 bpm, the longest lasting 4 beats with an avg rate of 127 bpm. Episodes of Ventricular Tachycardia may be possible Atrial Fibrillation with aberrancy. Atrial Fibrillation occurred (37% burden), ranging from 50-154 bpm (avg of longest lasting 1 day 19 hours with an avg rate of 97 bpm). 3 Pauses (longest lasting 4.9 secs (12 bpm). Atrial Fibrillation and Pause were detected within +/- 45 seconds of symptomatic patient event(s). Isolated SVEs were rare (<1.0%, 6723), SVE Couplets were rare (<1.0%, 141), and SVE Triplets were rare (<1.0%, 9). Isolated VEs were rare (<1.0%, 1716), VE Couplets were rare (<1.0%, 192), and VE Triplets were rare (<1.0%, 26).

4

Preliminary Findings

Patient had a min HR of 50 bpm, max HR of 154 bpm, and avg HR of 78 bpm. Predominant underlying rhythm was Sinus Rhythm. 5 Ventricular Tachycardia runs occurred, the run with the fastest interval lasting 4 beats with a max rate of 150 bpm, the longest lasting 4 beats with an avg rate of 127 bpm. Episodes of Ventricular Tachycardia may be possible Atrial Fibrillation with aberrancy. Atrial Fibrillation occurred (37% burden), ranging from 50-154 bpm (avg of longest lasting 1 day 19 hours with an avg rate of 97 bpm). 3 Pauses (longest lasting 4.9 secs (12 bpm). Atrial Fibrillation and Pause were detected within +/- 45 seconds of symptomatic patient event(s). Isolated SVEs were rare (<1.0%, 6723), SVE Couplets were rare (<1.0%, 141), and SVE Triplets were rare (<1.0%, 9). Isolated VEs were rare (<1.0%, 1716), VE Couplets were rare (<1.0%, 192), and VE Triplets were rare (<1.0%, 26).

Heart Rate

Overall

Max	154 bpm	09:49am, 03/25
Min	50 bpm	11:59pm, 03/22
Avg	78 bpm	

Sinus

Max	96 bpm	11:14am, 03/24
Min	50 bpm	11:59pm, 03/22
Avg	66 bpm	

3

Patient Events

Total Triggers: 2 Total Diaries: 1

Findings within ± 45 sec of triggered events or diary entries:

	Range	Trigger	Diary
AF	59-126 bpm	✓	✓
Pause(s)	3.9 s	✓	
Sinus	56-73 bpm	✓	
SVE(s)		✓	
VE(s)		✓	

Ectopics

Rare	Occasional	Frequent
<1%	1% - 5%	>5%

4

Preliminary Findings

Patient had a min HR of 50 bpm, max HR of 154 bpm, and avg HR of 78 bpm. Predominant underlying rhythm was Sinus Rhythm. 5 Ventricular Tachycardia runs occurred, the run with the fastest interval lasting 4 beats with a max rate of 150 bpm, the longest lasting 4 beats with an avg rate of 127 bpm. Episodes of Ventricular Tachycardia may be possible Atrial Fibrillation with aberrancy. Atrial Fibrillation occurred (37% burden), ranging from 50-154 bpm (avg of longest lasting 1 day 19 hours with an avg rate of 97 bpm). 3 Pauses (longest lasting 4.9 secs (12 bpm). Atrial Fibrillation and Pause were detected within +/- 45 seconds of symptomatic patient event(s). Isolated SVEs were rare (<1.0%, 6723), SVE Couplets were rare (<1.0%, 141), and SVE Triplets were rare (<1.0%, 9). Isolated VEs were rare (<1.0%, 1716), VE Couplets were rare (<1.0%, 192), and VE Triplets were rare (<1.0%, 26).

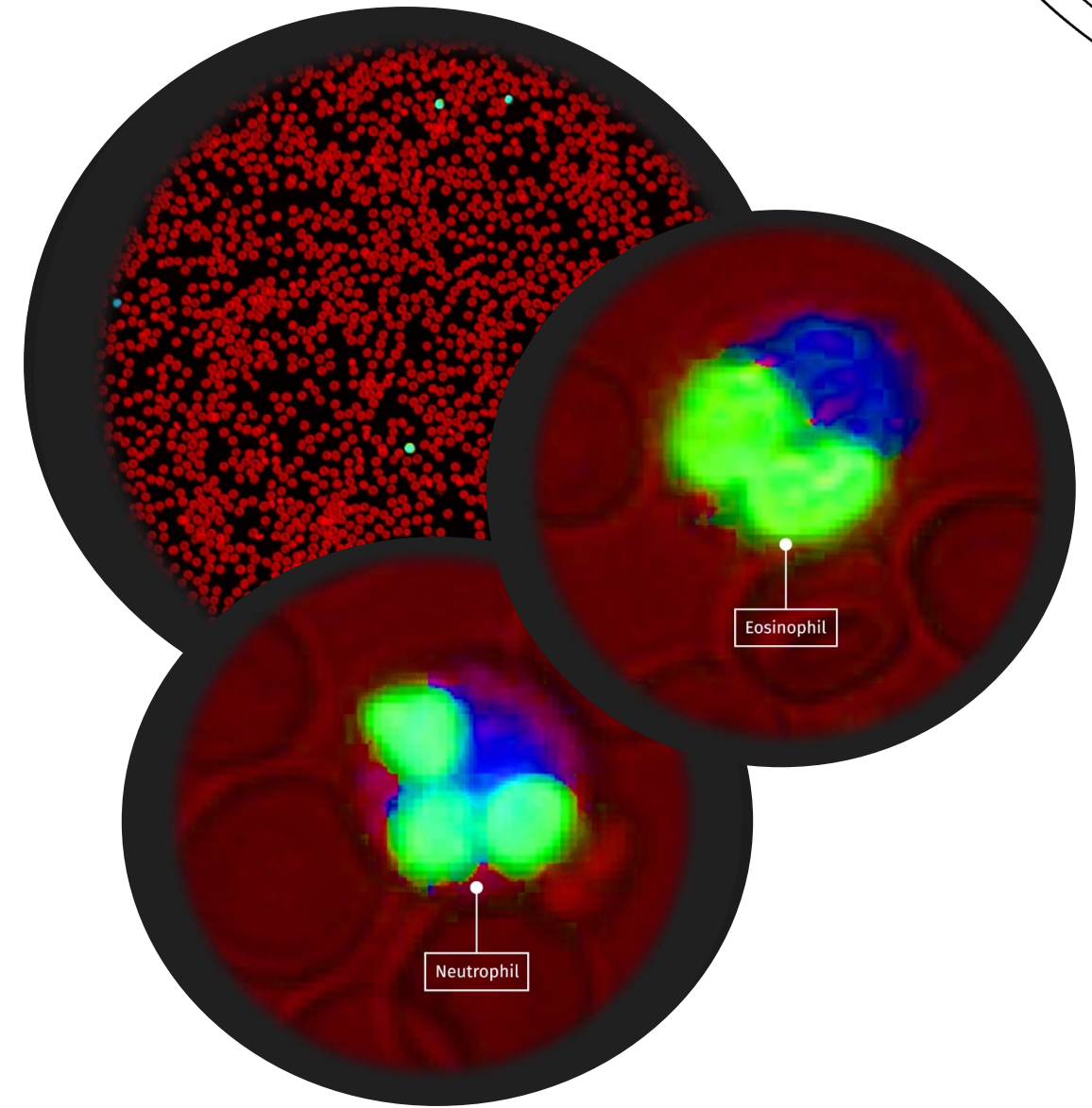
Final Interpretation

1. Agree with above interpretation
2. Underlying Sinus rhythm with normal rates average =78/min
3. 5 runs of VT some of which could be AF with aberrancy
4. Atrial fibrillation with 37% burden and longest run of 42 hours
5. Pauses of up to 4.9 seconds likely post conversion related
6. Triggered events consistent with AF, Pauses

Electronically signed by Dr. Example Physician 04/12/19 06:18 PM (CT)

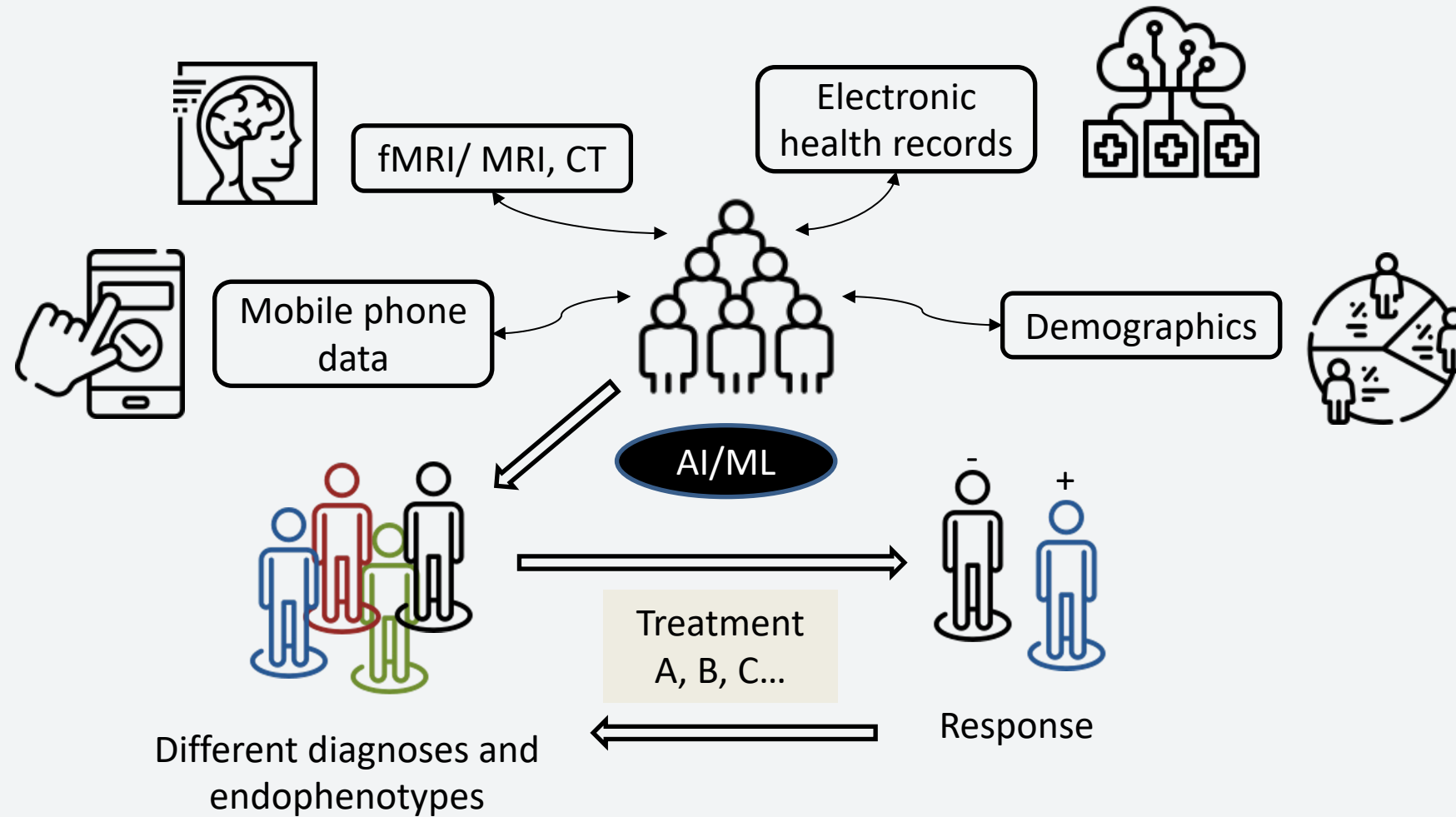
SIGNATURE

AI in hematology



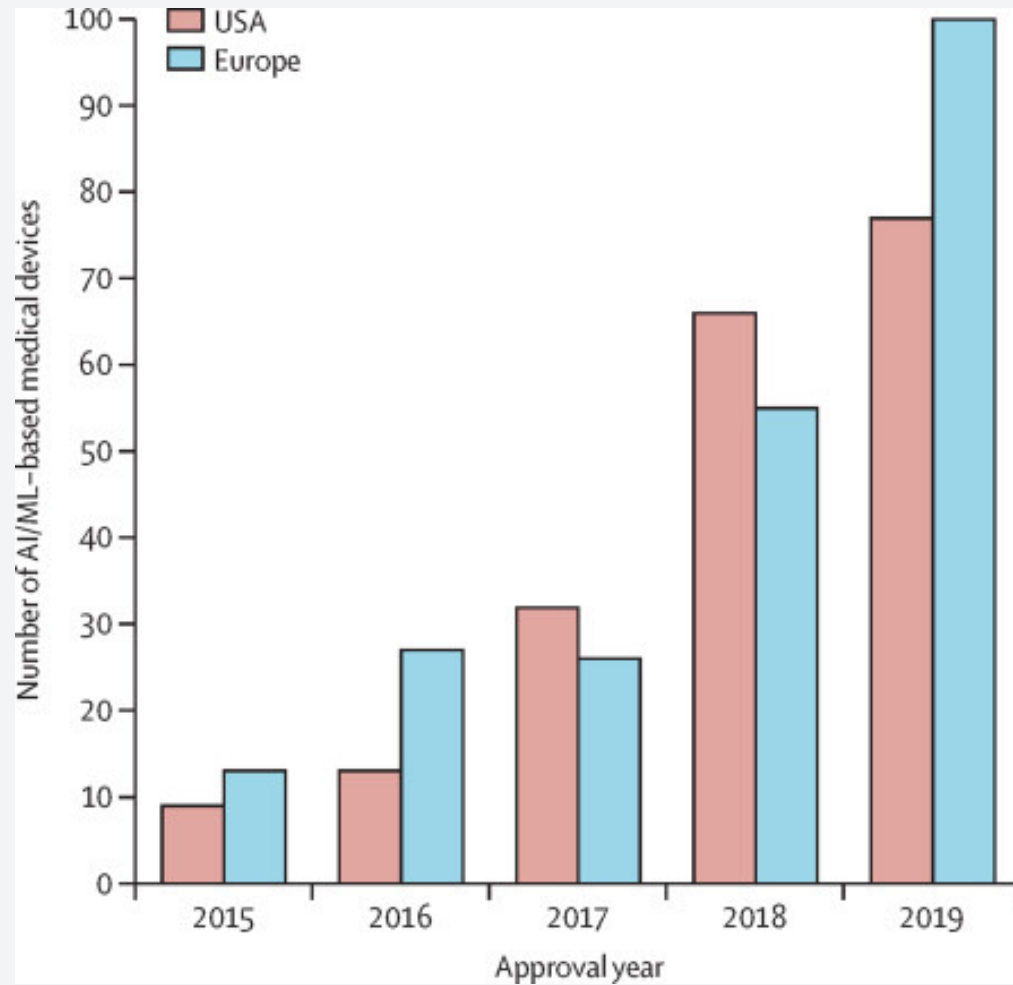
Source: Sight OLO, <https://sightdx.com/en/product>

AI in mental health: Dreams of the future

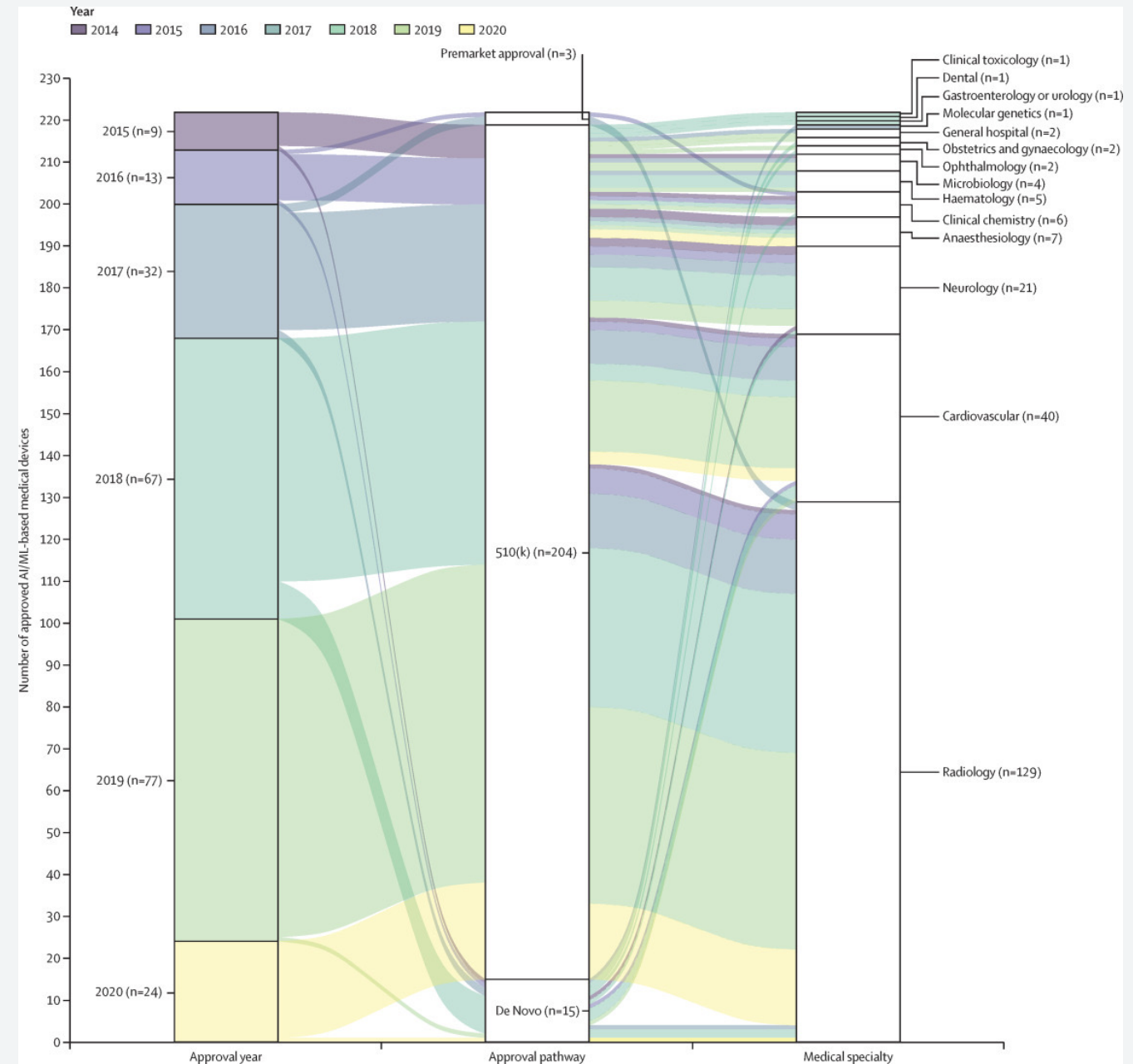


Fernandes et al., 2017

Regulated AI-CDSS in different medical fields



Source: Muehlematter et al. (2021). Approval of artificial intelligence and machine learning-based medical devices in the USA and Europe (2015–20): a comparative analysis.





***Reasons for the lack of
implementation of AI-CDSS into
clinical practice***

Reasons for the non-adoption of AI-CDSS in clinical practice



Data privacy and security



High costs, unclear gains



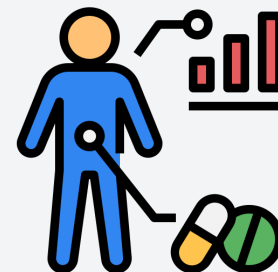
Interpretability and transparency



Integration issues



Regulatory challenges



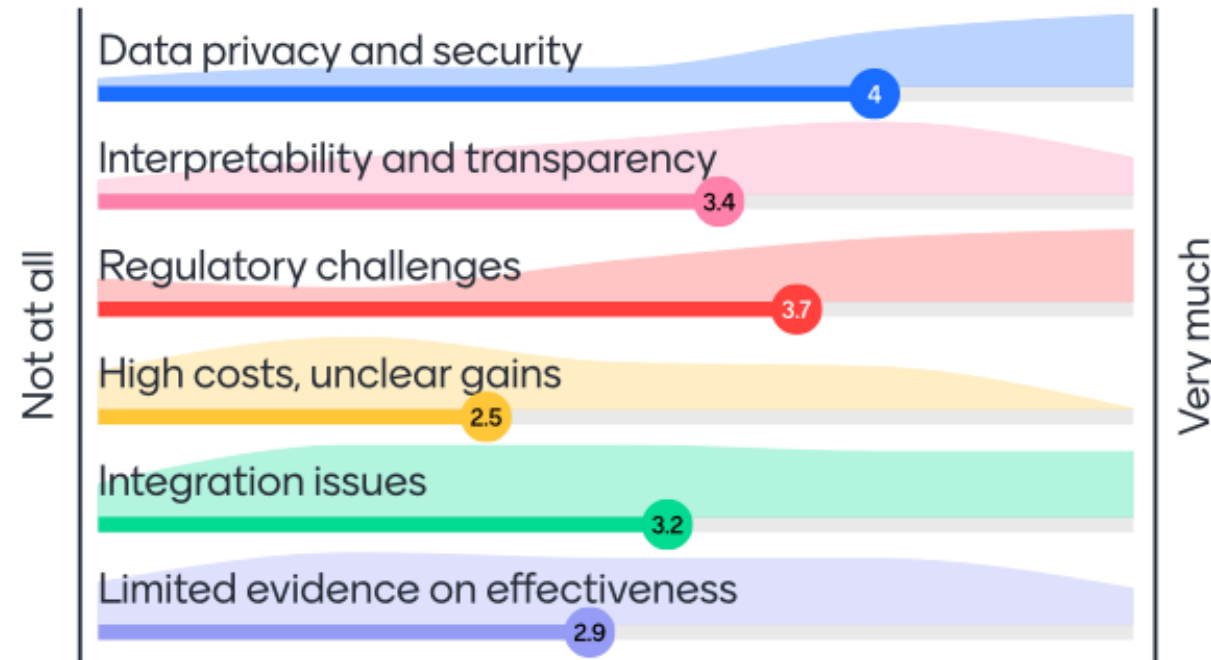
Limited evidence on effectiveness

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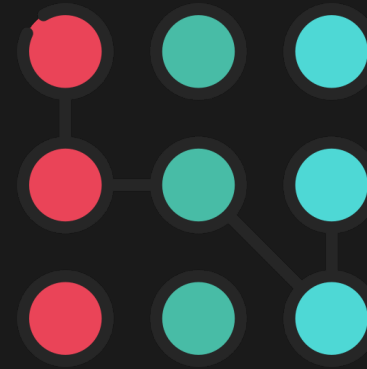
How much do you think do the following issues hamper the adoption of AI-CDSS in your field?



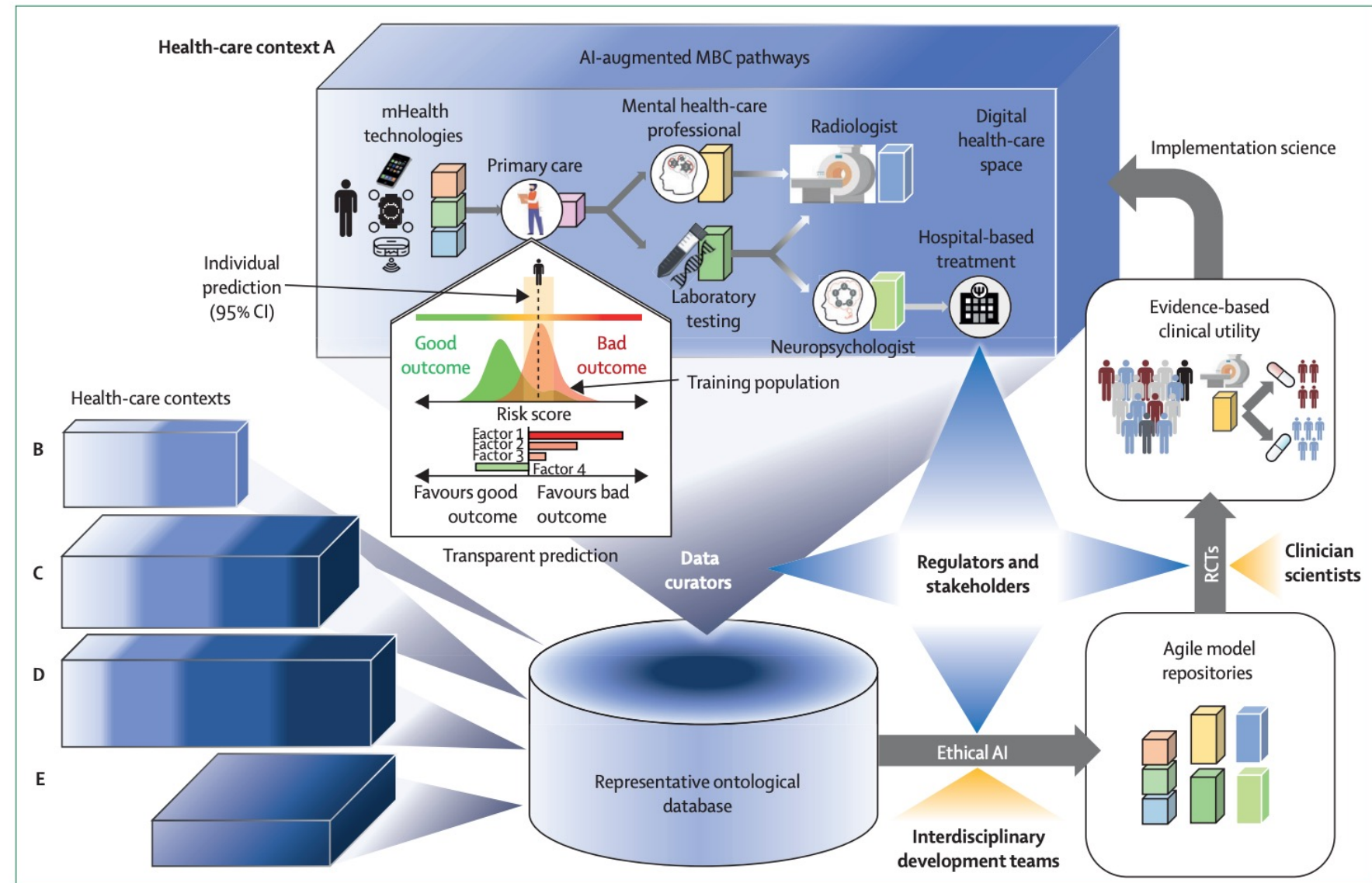
How much do you think do the following issues hamper the adoption of AI-CDSS in your field?



***AI-informed healthcare: A system
view***

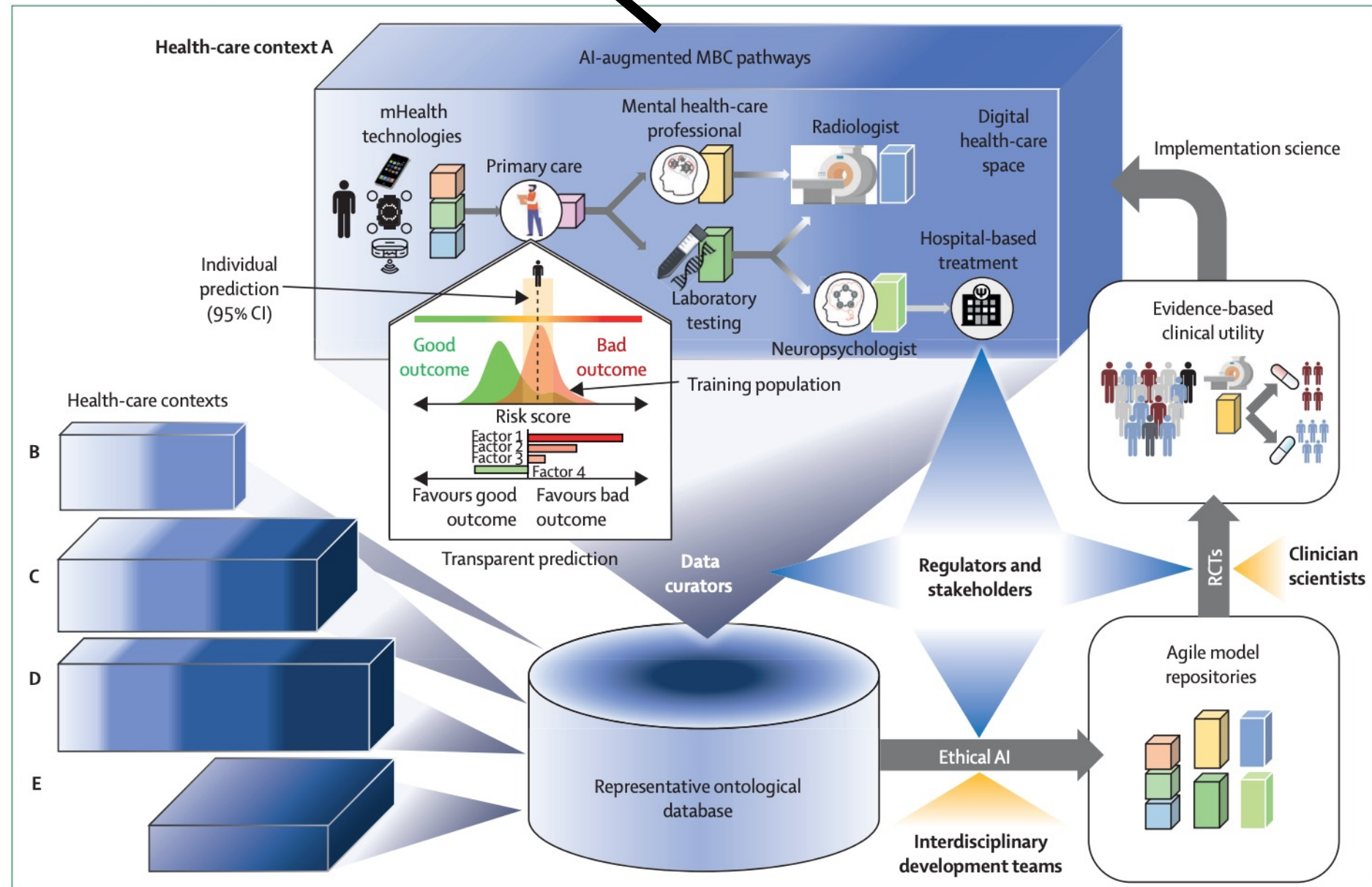


Koutsouleris et al. (2022). From promise to practice: Towards the realisation of AI-informed mental health care

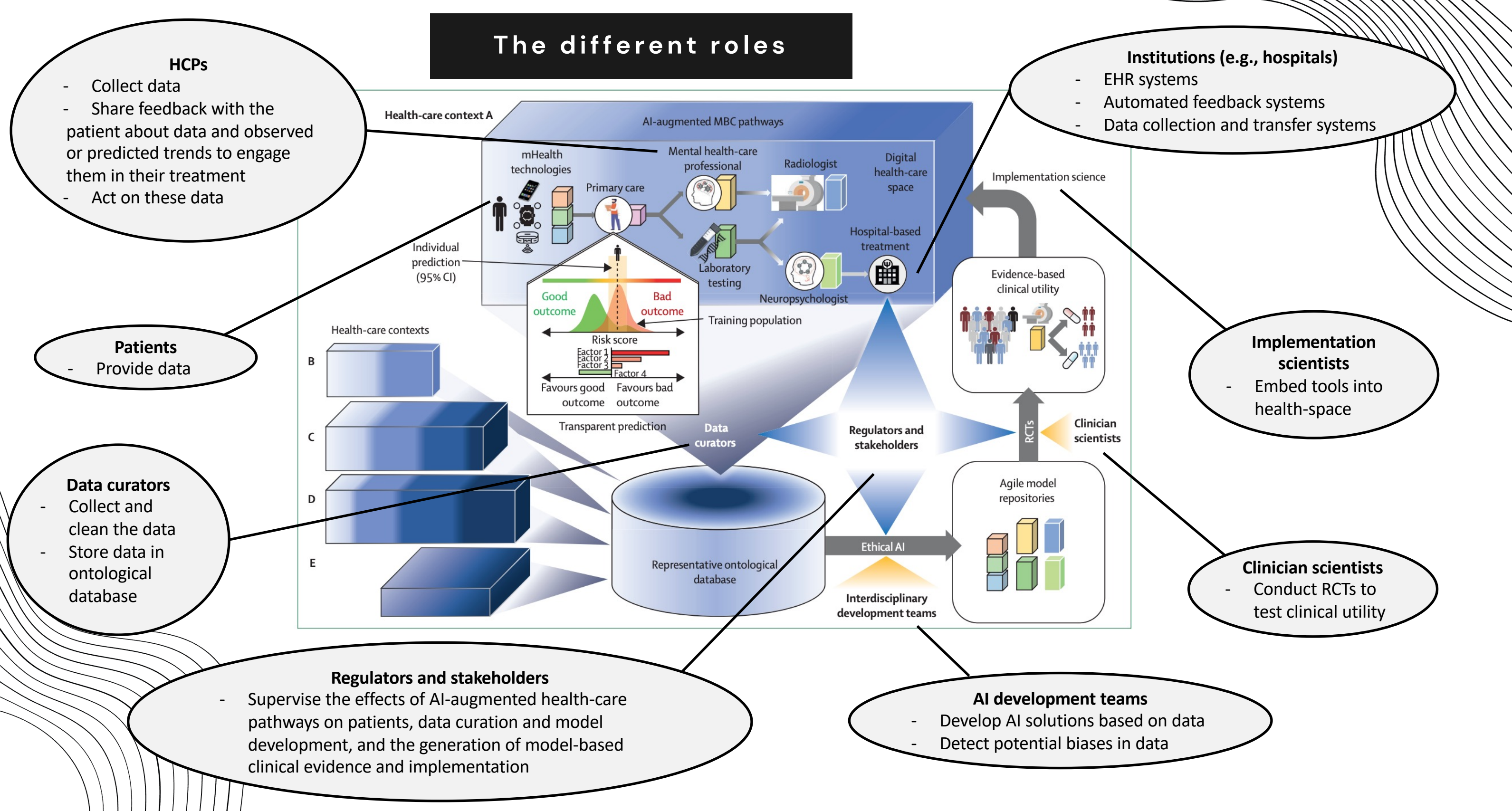


Measurement-based care (MBC)

- Evidence-based practice where care providers systematically assess patient symptoms and use that information to inform treatment decisions



The different roles



HCPs

- Collect data
- Share feedback with the patient about data and observed or predicted trends to engage them in their treatment
- Act on these data

Institutions (e.g., hospitals)

- EHR systems
- Automated feedback systems
- Data collection and transfer systems

Patients

- Provide data

Implementation scientists

- Embed tools into health-space

Data curators

- Collect and clean the data
- Store data in ontological database

Clinician scientists

- Conduct RCTs to test clinical utility

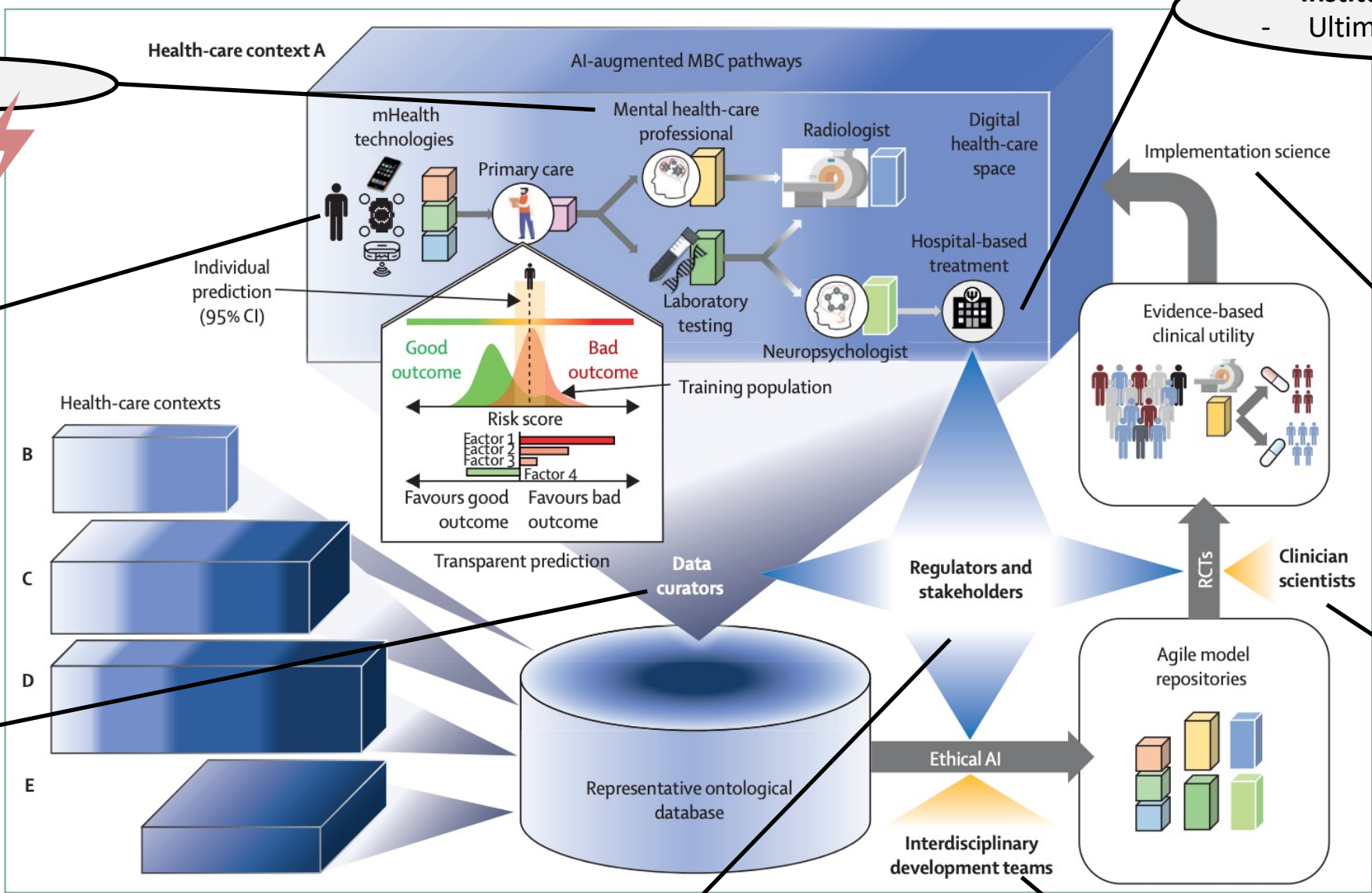
Regulators and stakeholders

- Supervise the effects of AI-augmented health-care pathways on patients, data curation and model development, and the generation of model-based clinical evidence and implementation

AI development teams

- Develop AI solutions based on data
- Detect potential biases in data

Data privacy and security



HCPs

Patients

Institutions (e.g., hospitals)
- Ultimately responsible!

Implementation scientists

Data curators
- Anonymize data
- Monitor access

Clinician scientists
- Ensure data privacy and security in clinical trials

Regulators and stakeholders
- Define standards and protocols
- Inspection of clinics
- Can put pressure on healthcare institutions and AI developers to ensure patient data privacy and security

AI development teams
- Create secure AI models
- AI systems that comply with data privacy standards

THANK YOU!

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<https://www.clinaid-lab.com>
<https://www.annekathrinkleine.com>

RESOURCES

Blanken, T. F., Benjamins, J. S., Borsboom, D., Vermunt, J. K., & Van Someren, E. J. W. (2020). Insomnia disorder subtypes and the role of hyperarousal. *Journal of Sleep Research*, 29(SUPPL 1). Embase. <https://doi.org/10.1111/jsr.13181>

Boswell, J. F., Hepner, K. A., Lysell, K., Rothrock, N. E., Bott, N., Childs, A. W., Douglas, S., Owings-Fonner, N., Wright, C. V., Stephens, K. A., Bard, D. E., Aajmain, S., & Bobbitt, B. L. (2023). The need for a measurement-based care professional practice guideline. *Psychotherapy*, 60(1), 1–16. <https://doi.org/10.1037/pst0000439>

Fernandes, B. S., Williams, L. M., Steiner, J., Leboyer, M., Carvalho, A. F., & Berk, M. (2017). The new field of ‘precision psychiatry.’ *BMC Medicine*, 15(1), 80. <https://doi.org/10.1186/s12916-017-0849-x>

Kleine, A.-K., Kokje, E., Lermer, E., & Gaube, S. (2023). Attitudes Toward the Adoption of 2 Artificial Intelligence–Enabled Mental Health Tools Among Prospective Psychotherapists: Cross-sectional Study. *JMIR Human Factors*, 10(1), e46859. <https://doi.org/10.2196/46859>

Kleine, A.-K., Lermer, E., Cecil, J., Heinrich, A., & Gaube, S. (2023). *Advancing Mental Health Care with AI-Enabled Precision Psychiatry Tools: A Patent Review*. PsyArXiv. <https://doi.org/10.31234/osf.io/wmr38>

Koutsouleris, N., Hauser, T. U., Skvortsova, V., & Choudhury, M. D. (2022). From promise to practice: Towards the realisation of AI-informed mental health care. *The Lancet Digital Health*, 4(11), e829–e840. [https://doi.org/10.1016/S2589-7500\(22\)00153-4](https://doi.org/10.1016/S2589-7500(22)00153-4)

Lewis, C. C., Boyd, M., Puspitasari, A., Navarro, E., Howard, J., Kassab, H., Hoffman, M., Scott, K., Lyon, A., Douglas, S., Simon, G., & Kroenke, K. (2018). Implementing Measurement-Based Care in Behavioral Health: A Review. *JAMA Psychiatry*, 10.1001/jamapsychiatry.2018.3329. <https://doi.org/10.1001/jamapsychiatry.2018.3329>

Research and Markets, Inc. (2022). *Precision Psychiatry Market—Global Industry Size, Share, Trends, Opportunity, and Forecast, 2017-2027*. TechSci Research. <https://www.researchandmarkets.com/reports/5689413/precision-psychiatry-market-global-industry>