



# **Automation to Augmentation: AI in Oncology Care**

**Janeesh Sekkath Veedu, MD, FACP**

Assistant Professor of Medicine

Division of Medical Oncology

**University of Kentucky Markey Cancer Center**

# Disclosure



## **Financial Relationships**

The presenter has no relevant financial relationships with companies to disclose.



## **AI Transparency Statement**

Artificial intelligence tools assisted in organizing content and developing graphics.

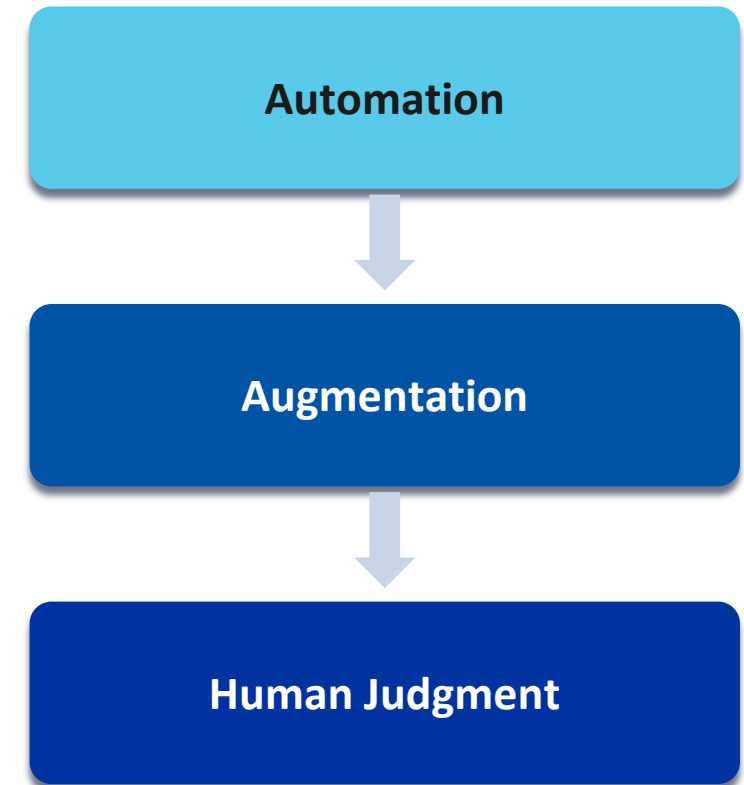
All clinical recommendations, literature review, interpretation, and final content were independently reviewed and verified by the presenter.

# Learning Objectives

*By the end of this session, participants should be able to:*

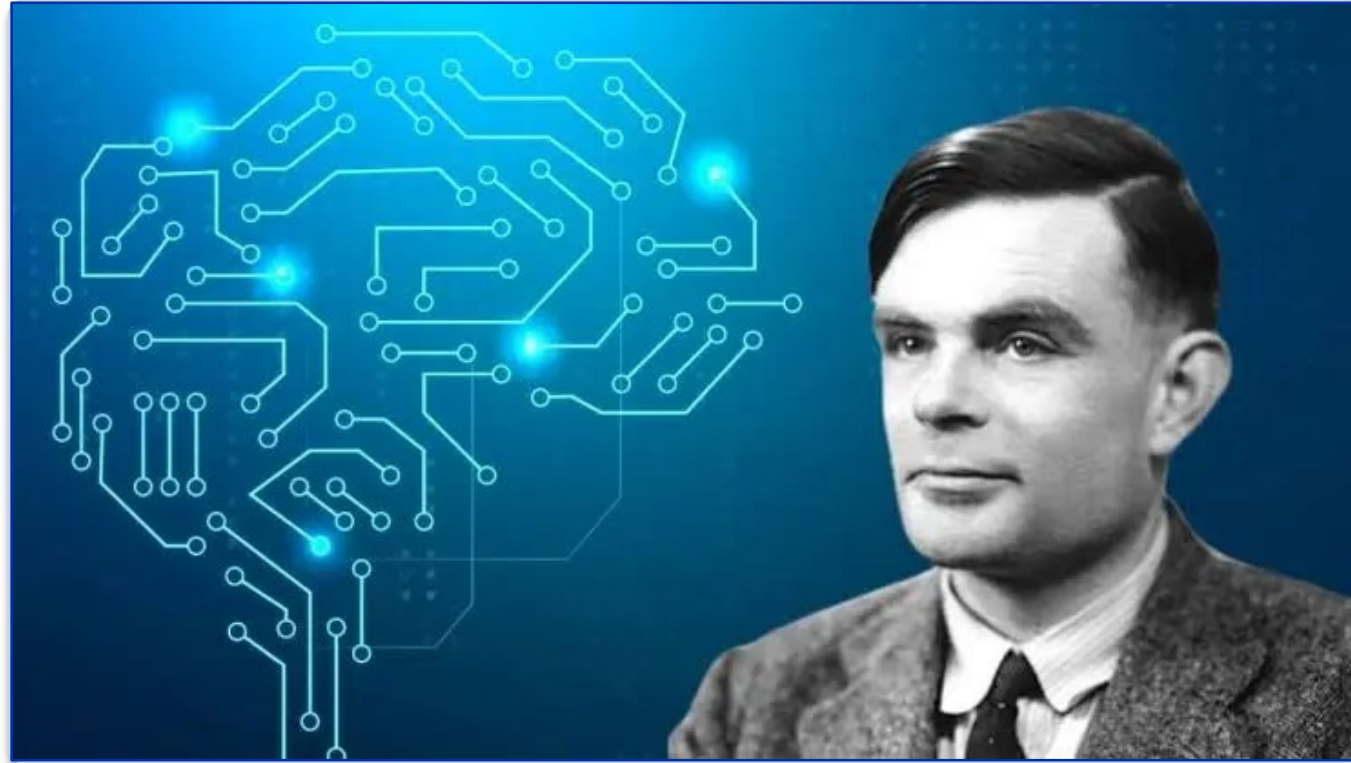
- ✓ Differentiate automation, augmentation, and agentic AI
- ✓ Recognize current AI applications throughout oncology care
- ✓ Evaluate opportunities and limitations of AI for oncology pharmacists
- ✓ Apply principles for safe implementation of AI in clinical practice

## THE THROUGH-LINE



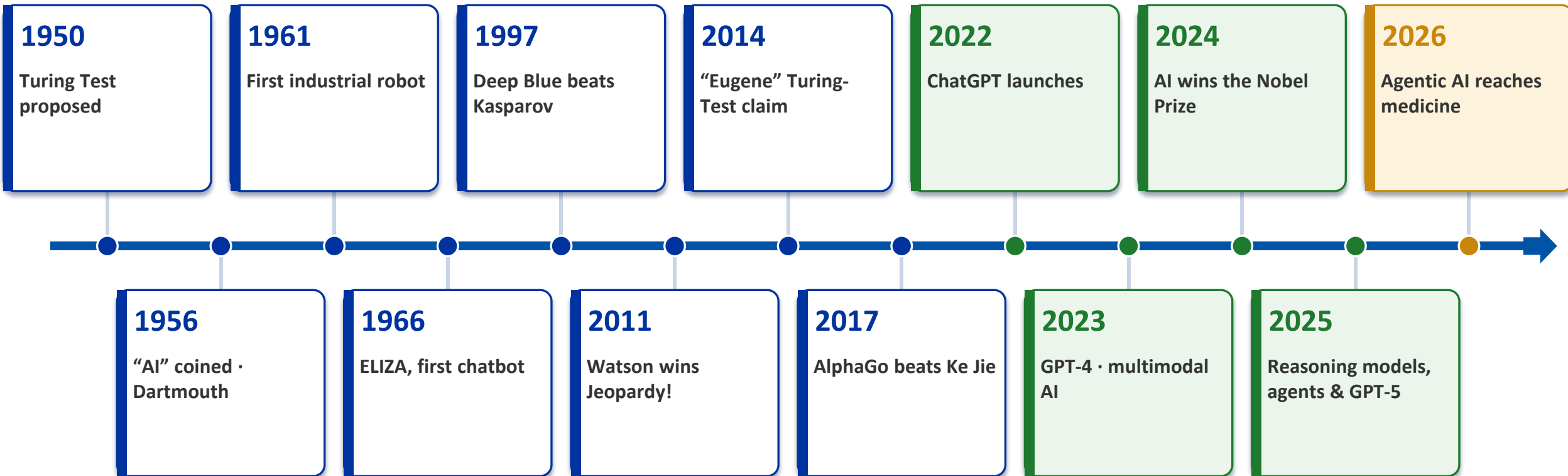
# It Started with a Question: Can Machines Think?

*Long before today's tools, Alan Turing framed the question we're still answering.*



*Alan Turing (1912–1954) — mathematician, WWII codebreaker, and a founding figure of computer science and AI.*

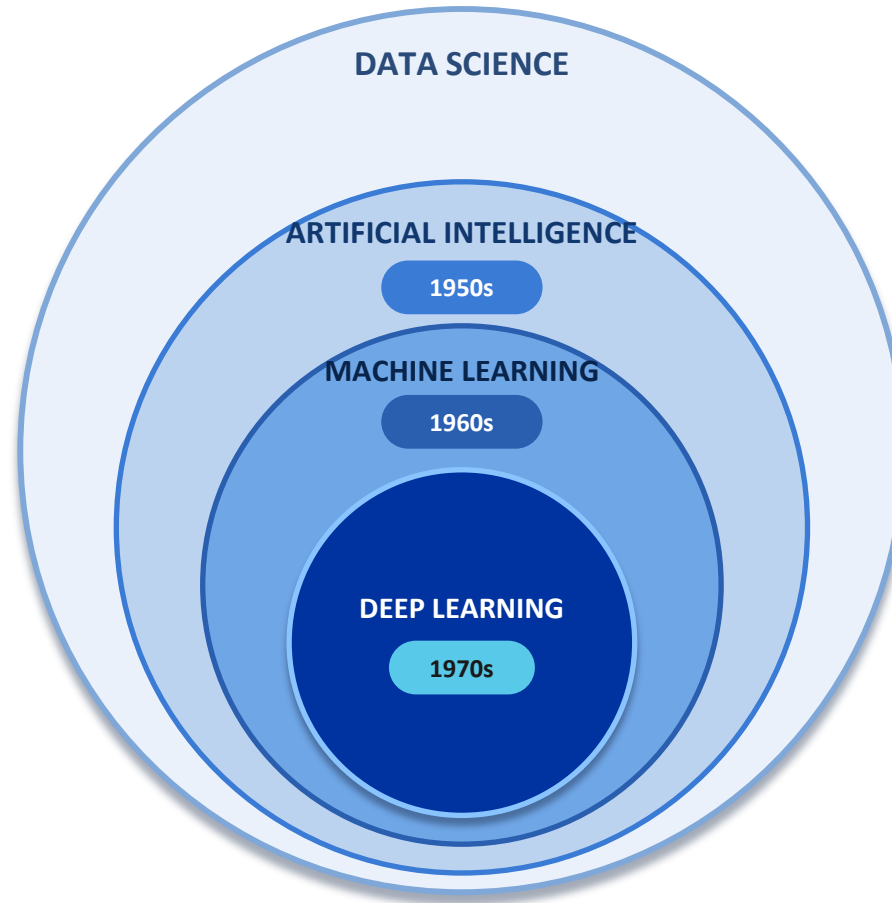
# From Turing to ChatGPT: A Brief History of AI



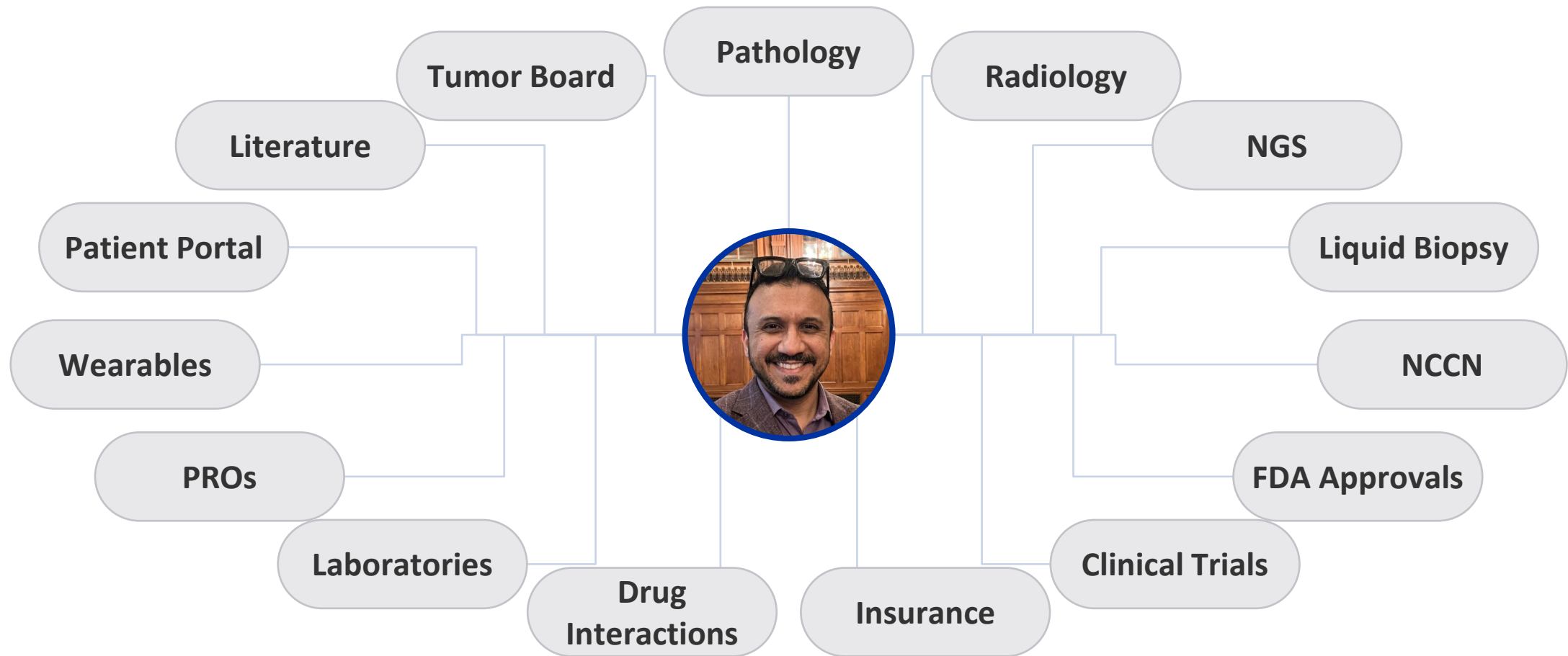
"Eugene" (2014) claim is disputed. 2024: AI Nobel Prizes (Hinton & Hopfield; AlphaFold). GPT-5 (2025).

# Data Science, AI, Machine Learning & Deep Learning

*The Russian-doll model — each field nests inside the next*



# The Oncology Information Explosion



# The Explosion Explodes



Behind every data point is a life shaped by place, income, and literacy — and these barriers compound one another.

Selected figures: Appalachia +12.8% cancer mortality vs. the rest of the U.S. (ACS/ACoS 2025) · ~50% of patients report financial hardship · 36% of U.S. adults have limited health literacy (NAAL) · ~1 in 5 rural Americans lack broadband · Kentucky ranks #1 in U.S. lung cancer.



# Live Poll Everywhere Question

## How frequently do you use AI?

[▶ Open in Poll Everywhere \(presenter\)](#)

*Scan the QR code to join the live poll — be honest, any AI, at work or at home.*



Scan to vote

Live results appear here  
Poll Everywhere response chart

1 Every hour

2 Once a day

3 Once a week

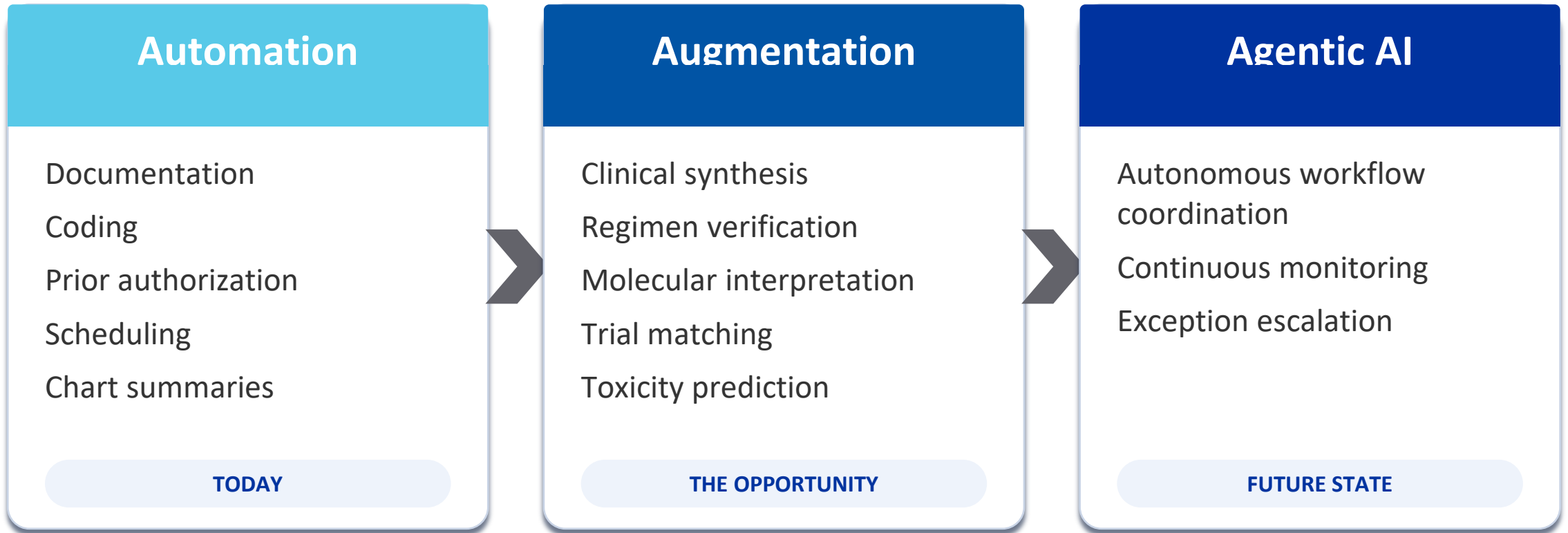
4 Once a month

5 A few times a year

6 Never

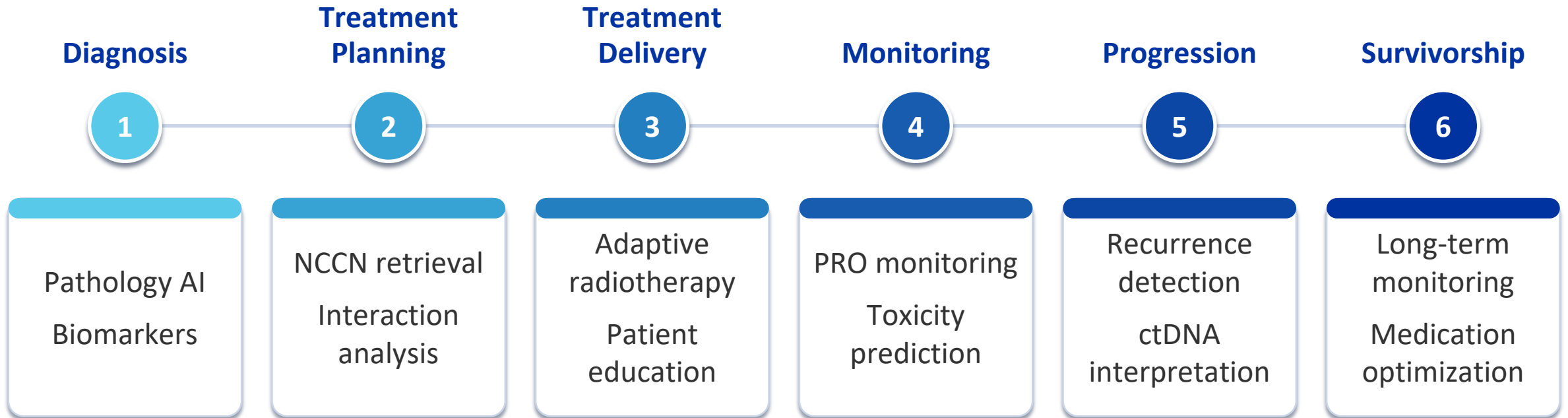
**Discussion:** where does AI already fit into your day — and where hasn't it yet?

# From Automation to Augmentation



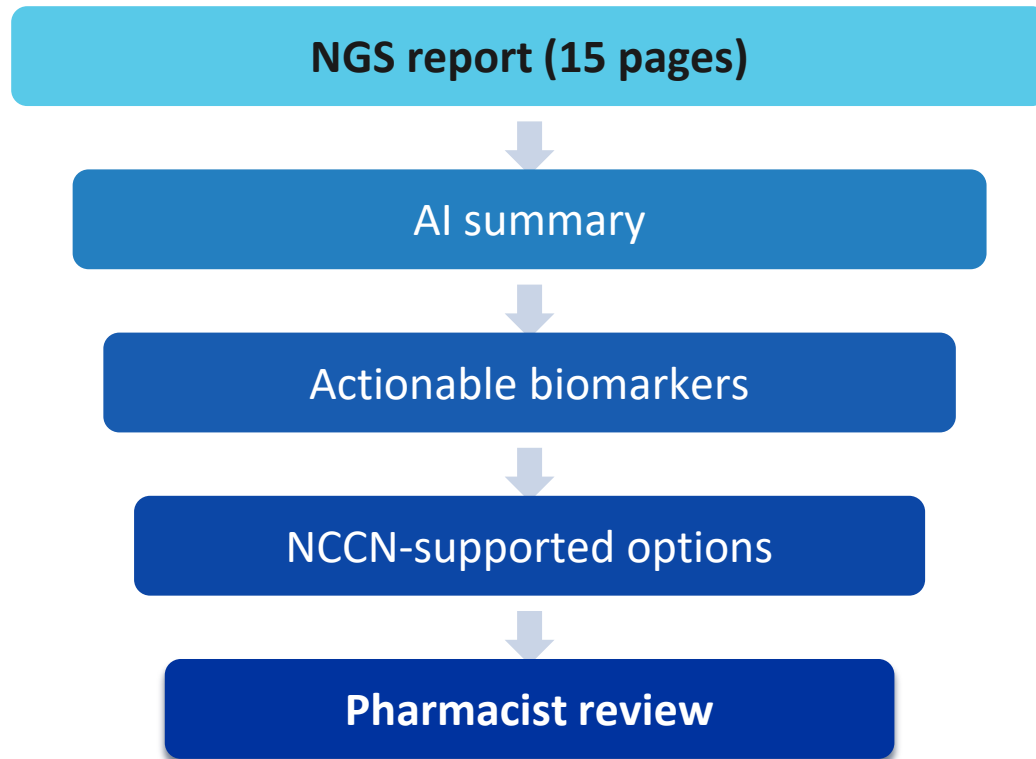
*Automation replaces tasks. **Augmentation enhances expertise.***

# AI Across the Oncology Care Continuum



# Diagnosis — Biomarkers & Molecular Profiling

*From 15-page reports to actionable summaries*



## The pharmacist's role

- ✓ Confirm companion diagnostics
- ✓ Review biomarker–drug concordance
- ✓ Identify resistance mutations
- ✓ Verify guideline alignment

# Evidence: AI in Prostate Pathology

High performance ≠ better outcomes — **AI augments the pathologist.**

1

## Foundational AI model

*Arvaniti et al., Mod Pathol 2018*

~1.36M patches · 549 slides

External test: 1,627 slides

**0.991**

AUC

**98%**

Sensitivity

**97%**

Specificity

**99.1%**

NPV

*Exceptional diagnostic accuracy*

2

## AI assists pathologists

*Steiner et al., JAMA Netw Open 2020*

20 pathologists · 240 biopsies · vs. subspecialists

Agreement with subspecialists

69.7% → **75.3%**

↑ +5.6

Tumor-detection accuracy

92.7% → **94.2%**

↑ +1.5

Review time

**decreased ~13.5%**

↓ time

*Better accuracy, agreement & speed*

3

## AI raises sensitivity

*Bulten et al., Mod Pathol 2022*

13 pathologists · 50 biopsies · Paige Prostate AI

PATHOLOGIST SENSITIVITY

**74% → 90%**



Without AI



With AI

↑ +16 points

*Higher cancer detection*

# 2024 Nobel Prize in Chemistry

*Protein structure prediction & computational protein design*



**David Baker**

Professor of Biochemistry, University of Washington · Director, Institute for Protein Design · HHMI Investigator

Computational protein design ( $\frac{1}{2}$  of the prize)



**Demis Hassabis**

CEO & co-founder, Google DeepMind

Protein structure prediction — AlphaFold ( $\frac{1}{4}$ )



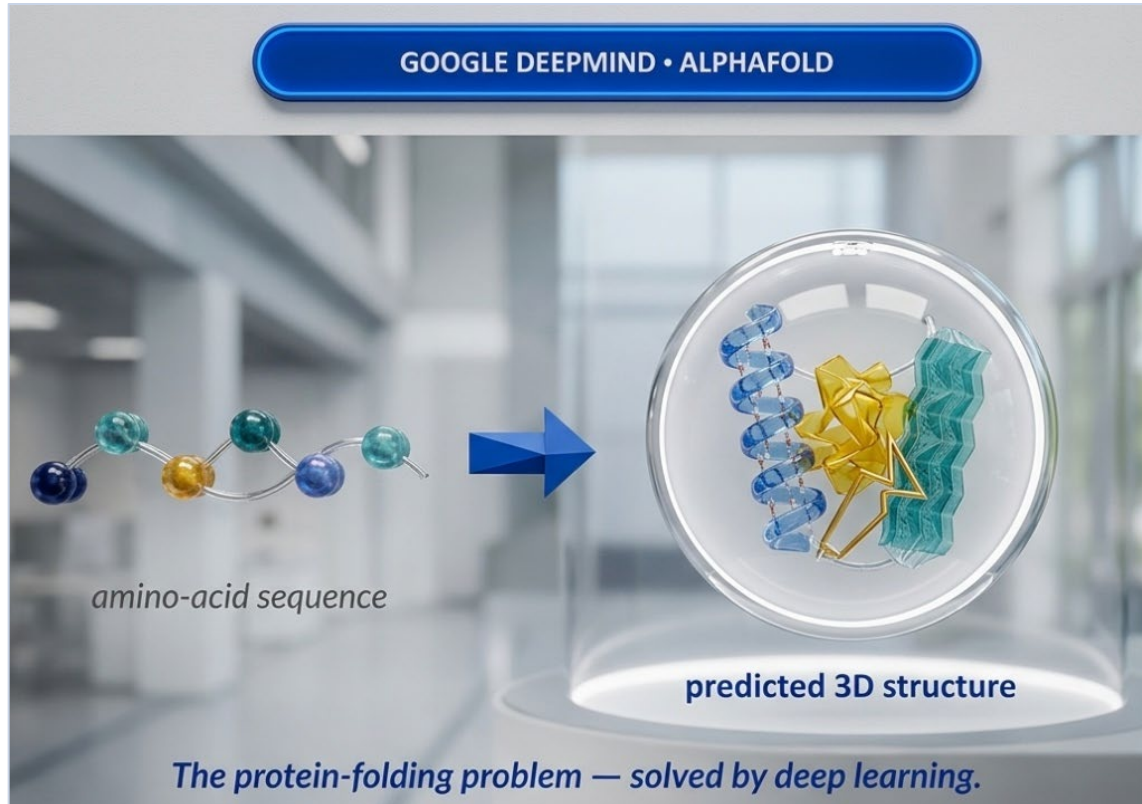
**John M. Jumper**

Director & Senior Research Scientist, Google DeepMind

Protein structure prediction — AlphaFold ( $\frac{1}{4}$ )

# Spotlight: AlphaFold — AI Solves Protein Folding

*Google DeepMind's landmark — and why it matters for cancer drug discovery*



1

## The breakthrough

Predicts a protein's 3-D shape from its amino-acid sequence — now solved.

2

## The scale

200M+ predicted structures — nearly every known protein, free to all.

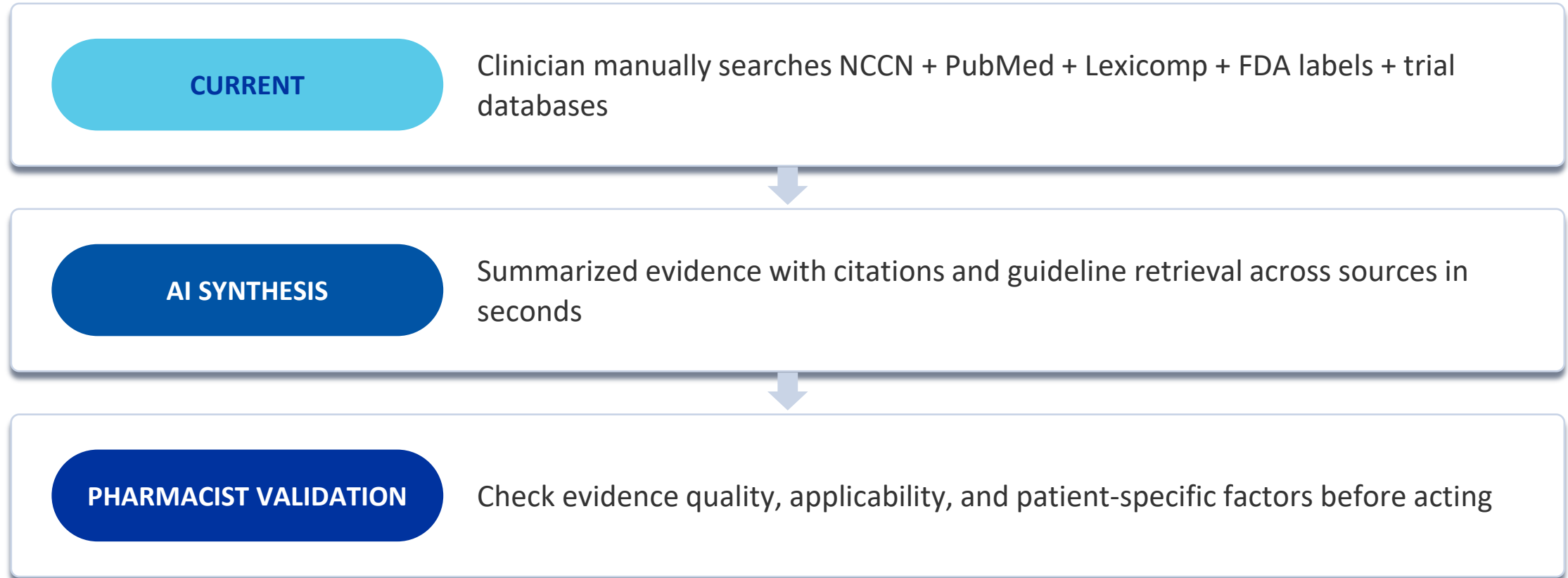
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## AlphaFold 3 (2024)

Now models how proteins interact with DNA, RNA and drug molecules.

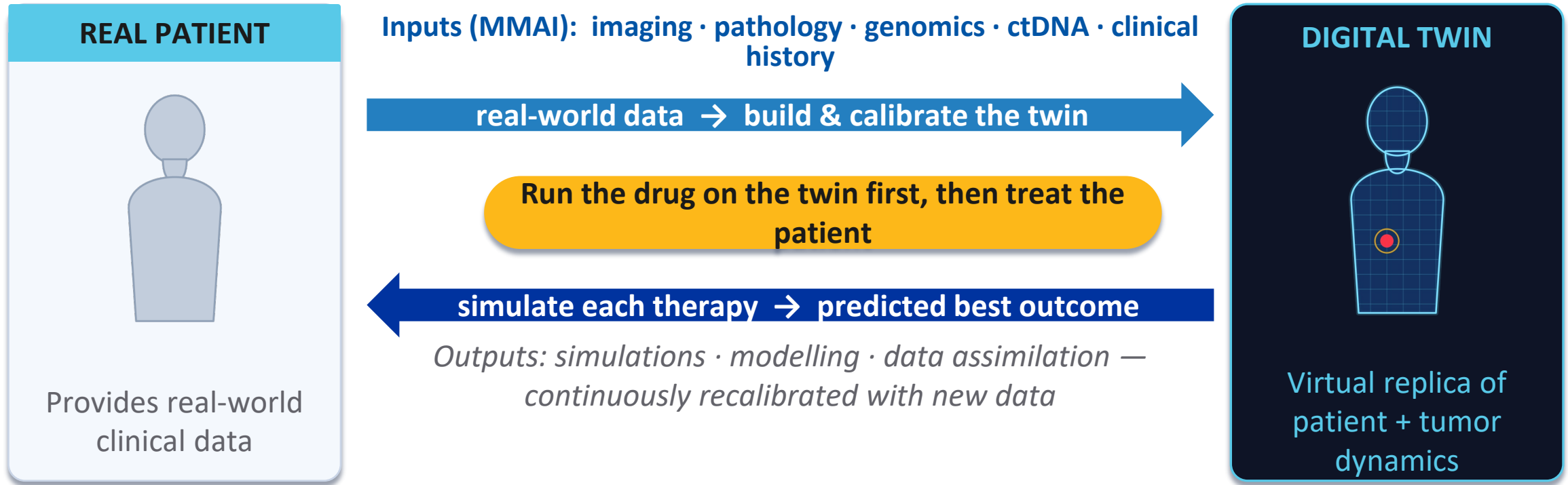
# Treatment Planning — Evidence Synthesis

## *AI-assisted evidence synthesis*



# Oncology Digital Twins

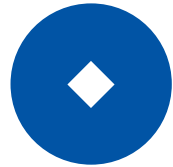
*Like testing a self-driving car in simulation before the road — we simulate treatments on the twin before the patient.*



**Oncology goal: better prediction, monitoring, treatment selection, and timing of intervention.**

# Progression & Survivorship

*AI after progression and beyond active treatment*



## Progression

- ctDNA interpretation
- Resistance mutation review
- Emerging evidence summaries



## Survivorship

- Long-term toxicity tracking
- Medication optimization
- Patient education & follow-up

# Evidence: Ambient AI Can Give Clinicians Back Time

Ambient AI scribes consistently reduce documentation burden — **and early randomized evidence suggests clinician workload and burnout can improve.**

## 1 Randomized trial *NEJM AI 2025 · Lukac et al.*

238 physicians · 3-arm RCT

Time in the note (vs usual care)

↓ **9.5%** with Nabla

✓ ↓ 0.27 work exhaustion

✓ Time-in-note reduced

## 2 Embedded pharmacists *AJHP 2026 · Olson AW et al.*

30 pharmacists · pre–post

Documentation ↓ **50%**

38.8 → 19.2

Time in notes ↓ **86 sec**

/encounter

Patient time ↑ **25%**

P=0.0001

## 3 Real-world, multicenter *JAMA Netw Open 2025*

263 clinicians · 6 health systems

BURNOUT PREVALENCE

51.9% → **38.8%**

↓ **13.1 points**

↓ 0.90 h/day after-hours

# Practical Oncology Pharmacy Workflows

*Where AI augments the day-to-day operations of oncology pharmacy*



## **Regimen Verification**

Exception-based  
order review



## **Oral Chemotherapy & Adherence**

Education and  
follow-up loops



## **Prior Authorization**

Faster access to  
therapy



## **Pharmacovigilance**

Earlier ADR signal  
detection



## **Clinical Trial Matching**

Screening at the  
point of care

# Regimen Verification in Practice

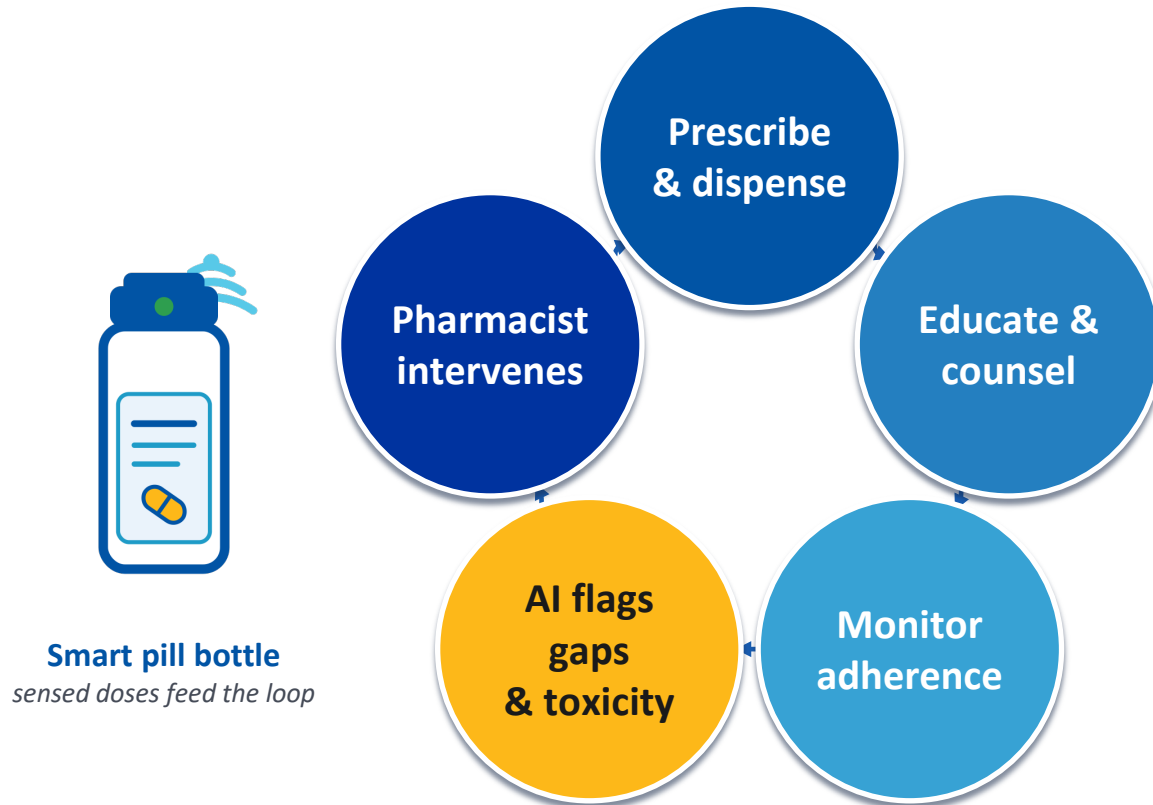
*Exception-based review — attention spent on judgment, not screening*



**Only exceptions reach the pharmacist — AI narrows the field, the pharmacist makes the call.**

# Oral Chemotherapy & Adherence

*Extending pharmacy oversight beyond the infusion center*



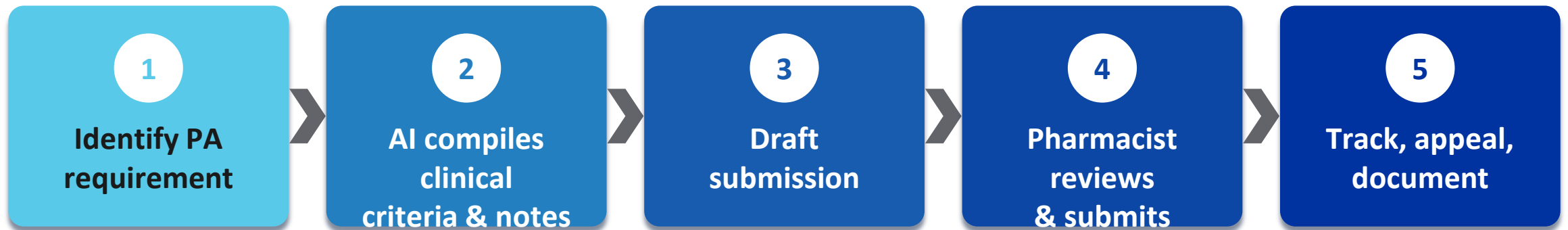
## How AI supports the loop

- Refill-gap and missed-dose detection from pharmacy data
- Symptom and toxicity check-ins via patient-reported outcomes
- Interaction screening as new medications are added
- Prioritized worklist so pharmacists reach the right patients first

**Adherence and toxicity are continuous — AI keeps the loop from going unwatched between visits.**

# Prior Authorization

*Compressing the administrative path between decision and treatment*

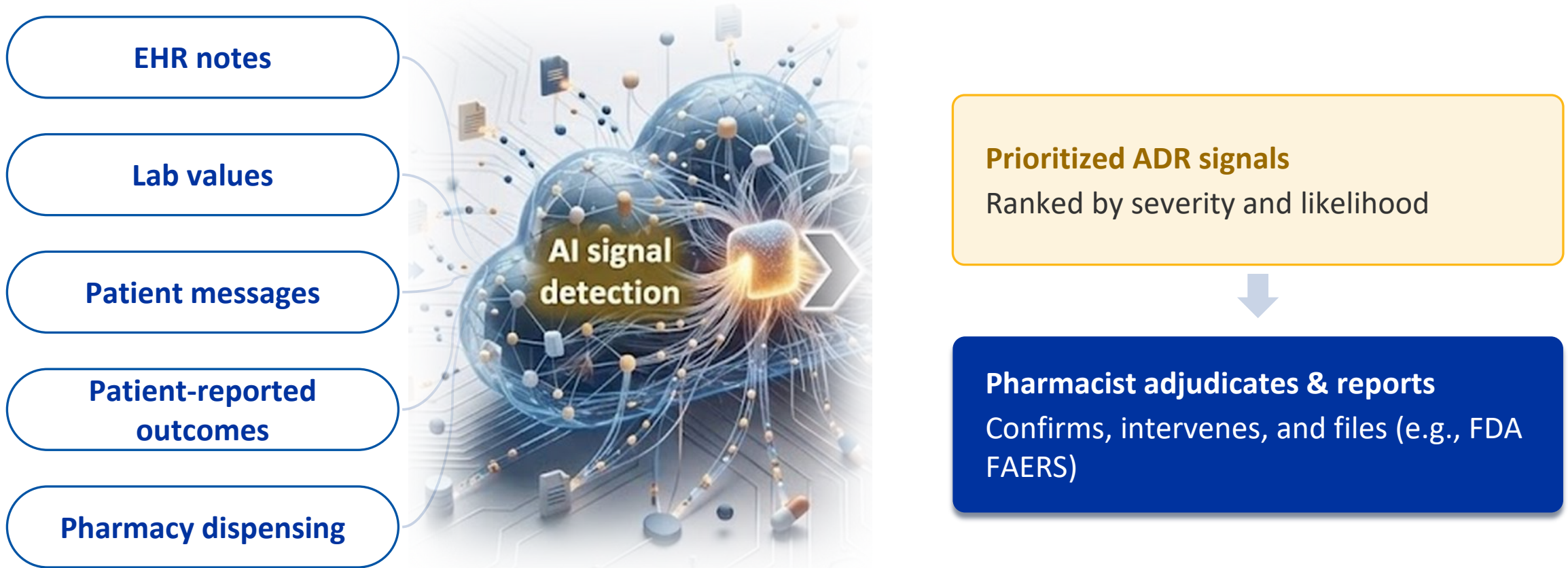


## **Fewer delays to therapy**

Criteria and supporting notes assembled in minutes, not hours.

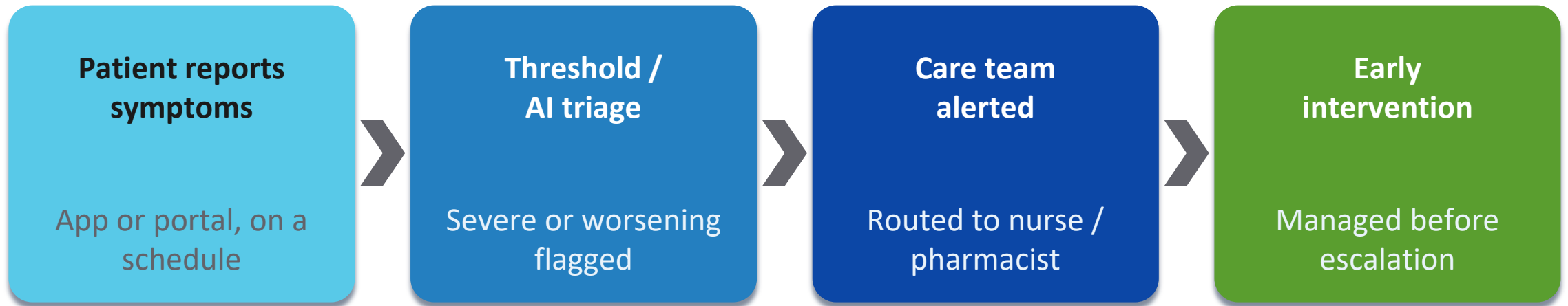
# Pharmacovigilance & Medication Safety

*Turning scattered signals into earlier, actionable safety alerts*



**AI connects signals no single chart review would catch; the pharmacist confirms and acts.**

# Patient-Reported Outcomes (PROs)



## Why PROs matter most

Randomized trials of electronic PRO monitoring (Basch et al.) have been associated with better symptom control, fewer emergency visits, and — in some studies — improved survival.

# Monitoring — From Reactive to Proactive Care

## Today · Reactive

Patient becomes symptomatic

Calls clinic

Labs obtained

Assessment performed

**Hospitalization may occur**

## Future · Proactive

PROs collected continuously

Wearable data integrated

Lab trends analyzed

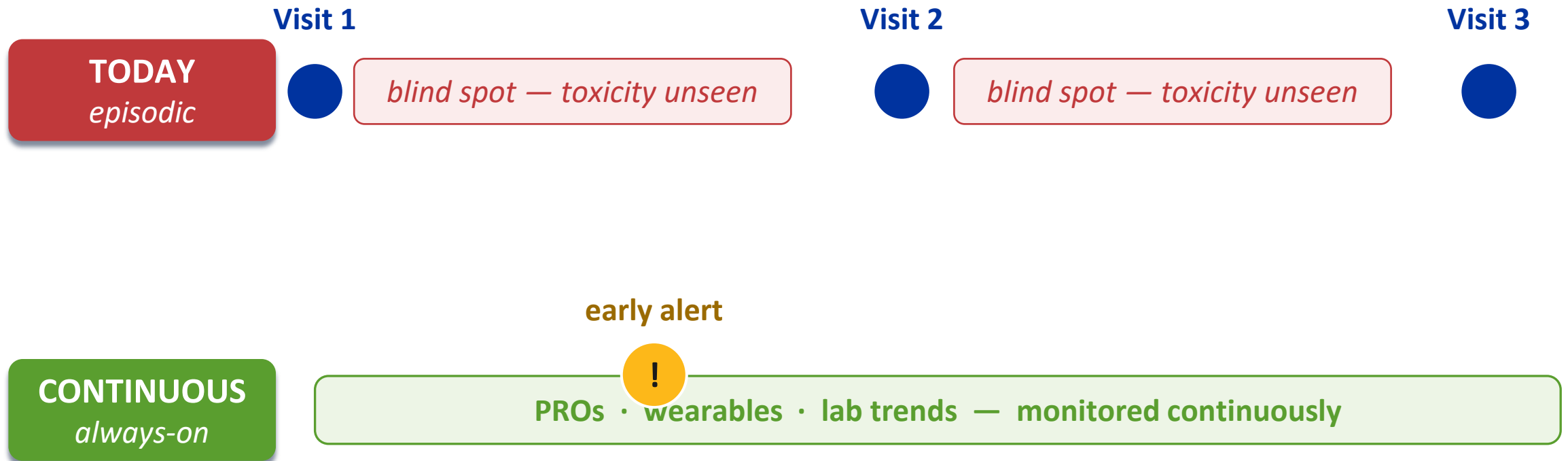
AI predicts deterioration

**Pharmacist intervenes early**

***Prediction is not diagnosis — it is earlier recognition of risk.***

# Predictive Toxicity Monitoring

*Most toxicity develops at home — between clinic visits*



*The clinic visit is a snapshot; continuous data lets us intervene before a problem becomes an emergency.*

# Risk-Stratification Dashboards

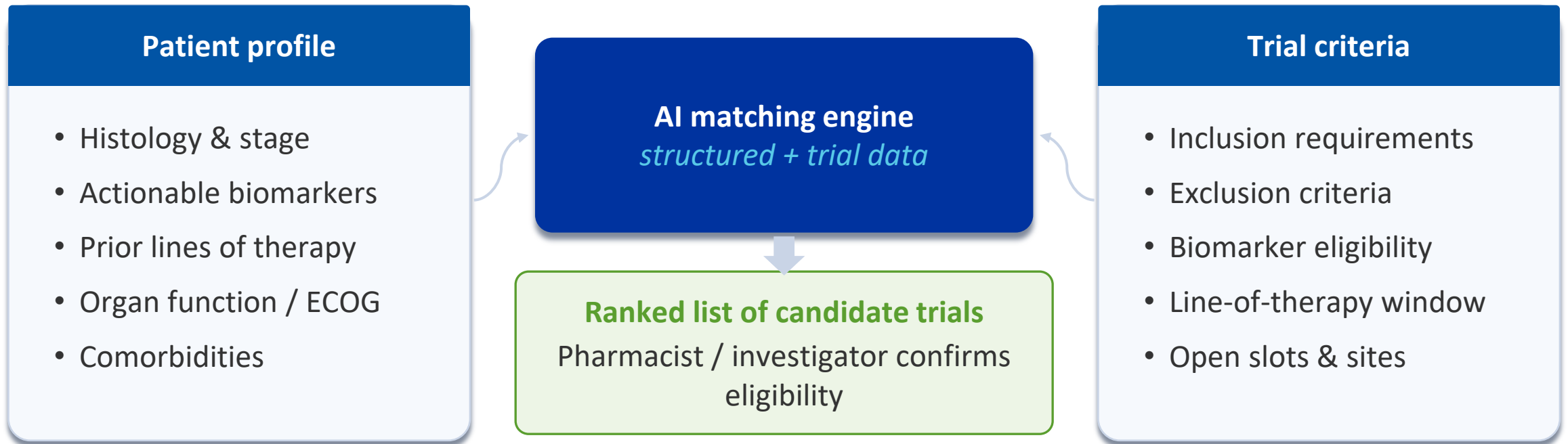
*One screen that turns continuous monitoring into a prioritized workload*



| Patient | Regimen       | Risk   | Key driver                   | Suggested action                |
|---------|---------------|--------|------------------------------|---------------------------------|
| J.M.    | FOLFOX        | High   | ANC falling + fever reported | Call today; assess neutropenia  |
| S.P.    | Pembrolizumab | High   | Diarrhea grade rising        | Rule out colitis; consider hold |
| R.K.    | Osimertinib   | Medium | New cough; PRO score up      | Nurse check-in within 48h       |
| T.W.    | AC-T          | Medium | Missed doses + fatigue       | Adherence outreach              |
| A.L.    | Capecitabine  | Low    | Stable, adherent             | Routine follow-up               |

Guardrails: a flag prompts assessment (not diagnosis) · validate locally · design against alarm fatigue · watch for inequities

# Clinical Trial Matching



**AI screens every patient against every open trial — the team confirms the true matches.**

# Governance & Regulation

*Every benefit so far assumes the tool is accurate, fair, and safe*

## The trust gap

*Adoption is easy to imagine. Trust has to be earned.*

Safe, accurate, equitable  
— before and after care.



Hallucinations & accuracy



Bias & inequity



Privacy & security



Model drift



Accountability

None of these are reasons to avoid AI — they are the reasons we govern it.

# Hallucinations & Accuracy

*The failure mode that matters most: confident, fluent, and wrong*



## The problem

- Fluent and confident text can be factually wrong
- Fabricated citations & doses look authoritative
- A wrong dose or interaction → real harm



## Mitigations

- Ground answers in trusted sources
- Require citations a human can verify
- Keep a clinician in the loop
- Scope tools to validated tasks

**Treat AI output as a well-read draft — never as a verified source.**

# Bias & Equity

*AI learns from the past — including its gaps and its inequities*



## Where bias starts

- Under-represented training data
- Historical disparities in records
- Sensors less accurate for some
- Access gaps



## What can go wrong

- Lower accuracy for some patients
- Missed toxicity or eligibility signals
- Disparities widen
- False reassurance



## How we protect

- Diverse training and test data
- Validate by subgroup
- Monitor real-world outcomes
- Equitable access

**Equity is a design requirement — not an afterthought**

# The Regulatory & Guidance Landscape



## U.S. — FDA

- Some tools exempt from device rules (Cures Act)
- Jan 2026 guidance broadened it
- Higher-risk AI stays regulated
- Updates via change-control plans



## Professional societies

- ASCO (2024): six AI principles
- ESMO (2025): LLM-use guidance
- ESMO EBAI: biomarker standards



## Data Protection

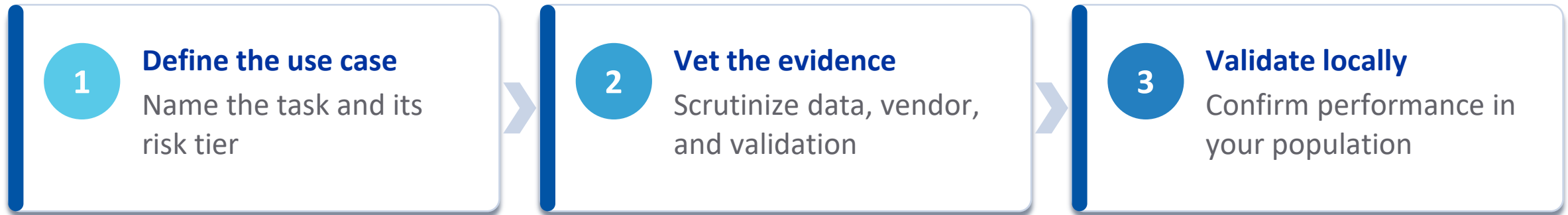
- HIPAA: PHI privacy (U.S.)
- EU AI Act: health AI is high-risk
- GDPR: data protection (EU)

Oversight is layered — federal, professional, and data law

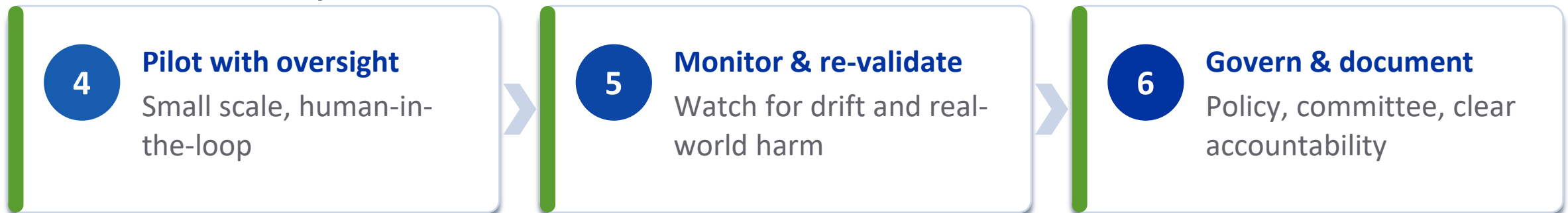
# A Practical Implementation Roadmap

*How a hematology/oncology pharmacy team adopts AI without losing control*

## BEFORE GO-LIVE — prove it



## IN PRODUCTION — keep it safe



**Adoption is not a purchase — it is a program: validate, pilot, monitor, and stay accountable.**

# Key Takeaways

1

**AUGMENTATION,  
NOT REPLACEMENT**

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2

**PHARMACISTS ARE  
CENTRAL**

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3

**START WHERE  
EVIDENCE IS  
STRONGEST**

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4

**KEEP A HUMAN  
ACCOUNTABLE**

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5

**GOVERN ADOPTION  
AS A PROGRAM**

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# Thank you

## Questions & Discussion

**Janeesh Sekkath Veedu, MD, FACP**

Assistant Professor of Medicine · Division of Medical Oncology

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