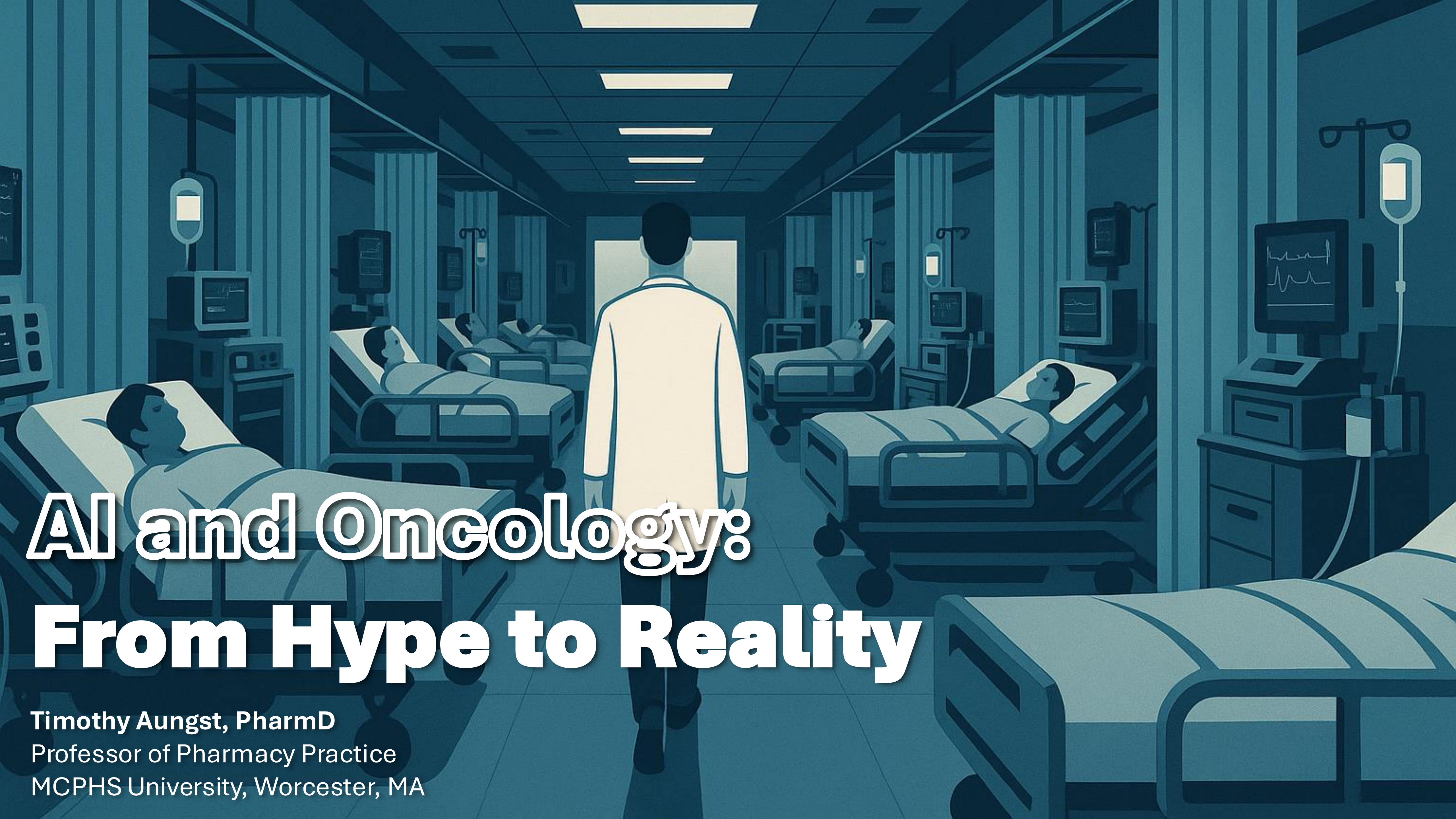


AI and Oncology: From Hype to Reality

Timothy Aungst, PharmD
Professor of Pharmacy Practice
MCPHS University, Worcester, MA

OBJECTIVES

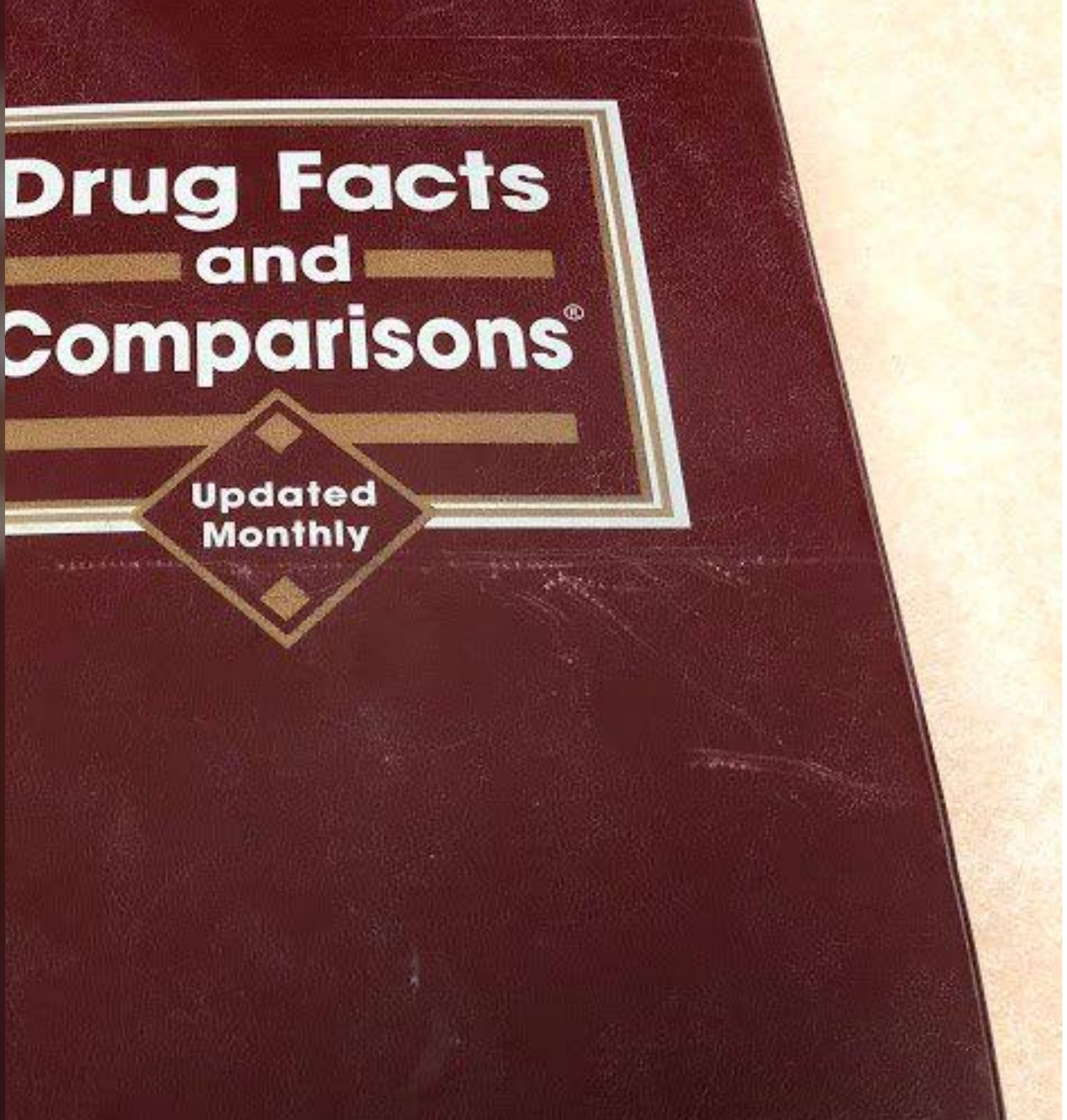
- Describe the technological principles of artificial intelligence (AI) in relationship to healthcare practices
- Identify the application of artificial intelligence (AI) to healthcare and pharmacy practice
- Describe real-world examples of AI technologies in pharmacy oncology practice
- Evaluate the limitations of AI applications in healthcare and how to navigate these barriers within oncology practice

WHY USE AI?

- Saves time from monotonous work and redundant activities
- Allows further scalability and improvement on labor from ‘self-learning’
- Leverage of automation in certain activities with limited oversight

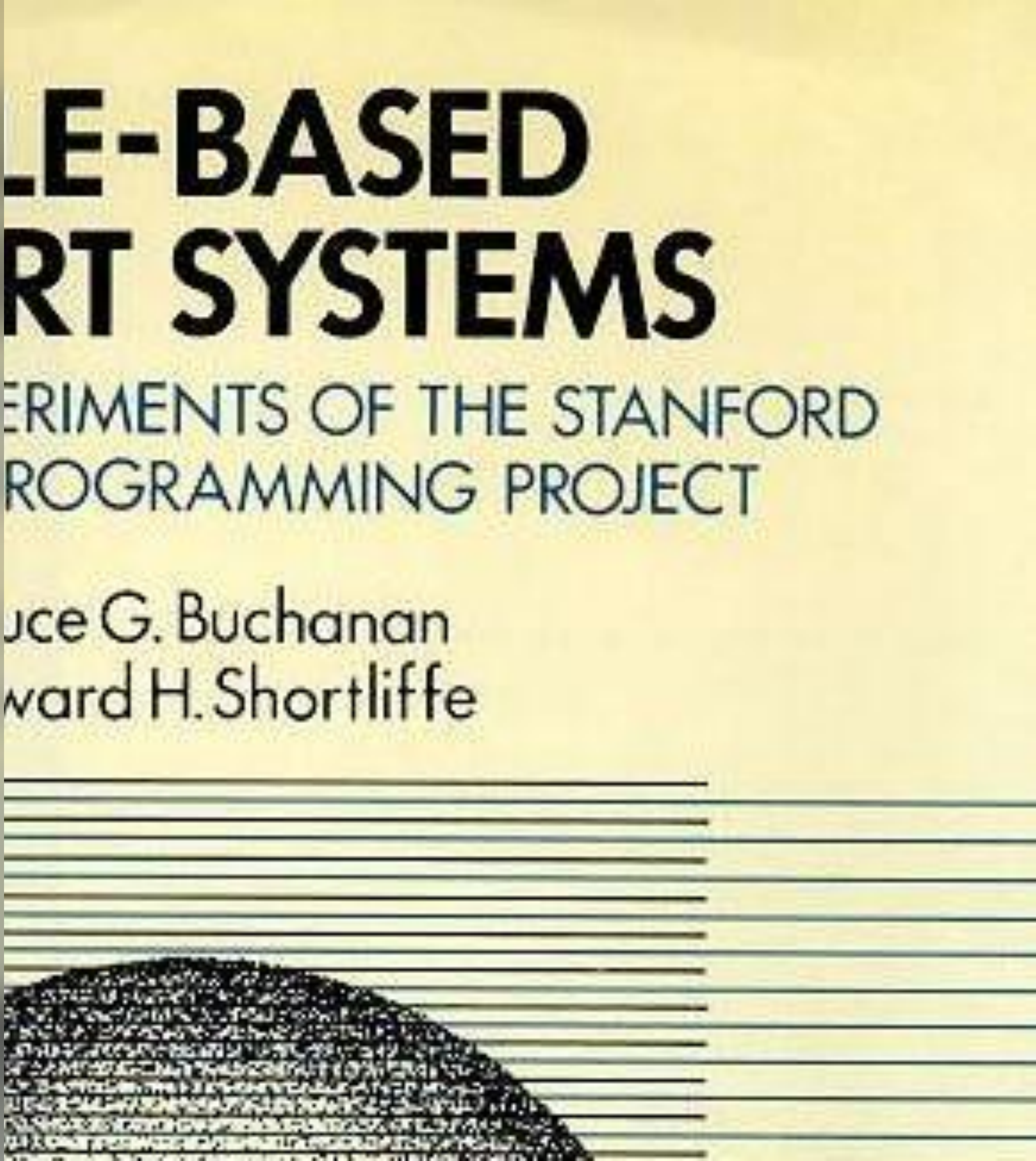
THINGS CHANGE…

- Tools and devices cause an upheaval each time they are introduced
- Pharmacy has seen vast changes in the use of technology to facilitate our services

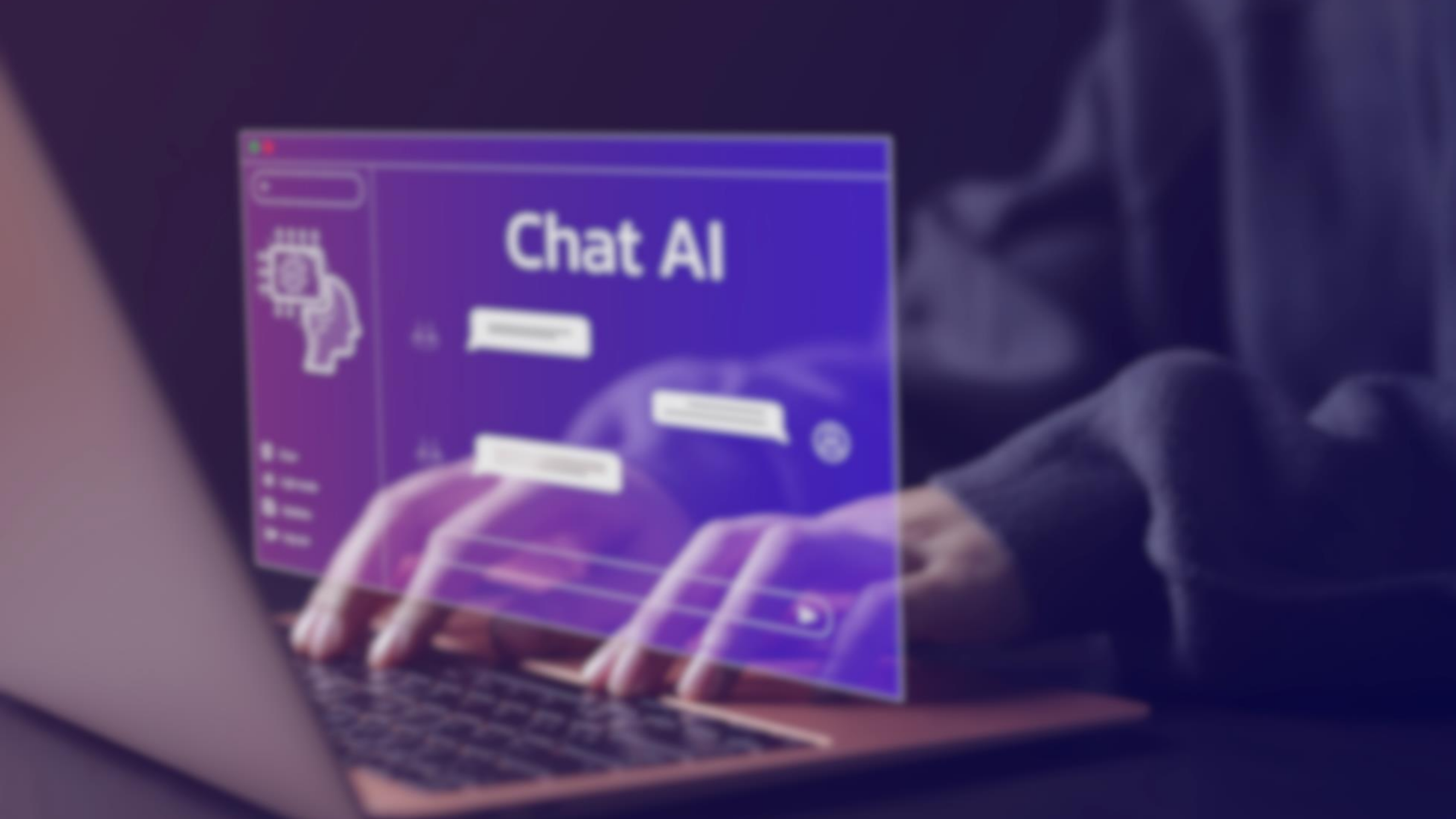


…BUT ALSO REMAIN

- Utilization of AI systems have been attempted in the past to mixed results
- Pharmacy Expert Systems targeted:
  - Drug interactions,
  - Drug therapy monitoring, and
  - Drug formulary selection



Nash D, et al. Pharmacoeconomics. 1994 Nov;6(5):478-9.
Morrell R, et al. Am J Hosp Pharm. 1994.
Dasta JF. Hosp Pharm. 1992 Apr;27(4):312-5, 319-22.


Chat AI


HOW DID WE GET HERE?
HOW DID WE GET HERE?
HOW DID WE GET HERE?
HOW DID WE GET HERE?
HOW DID WE GET HERE?
HOW DID WE GET HERE?
HOW DID WE GET HERE?

The Evolution of Health AI Through the Decades

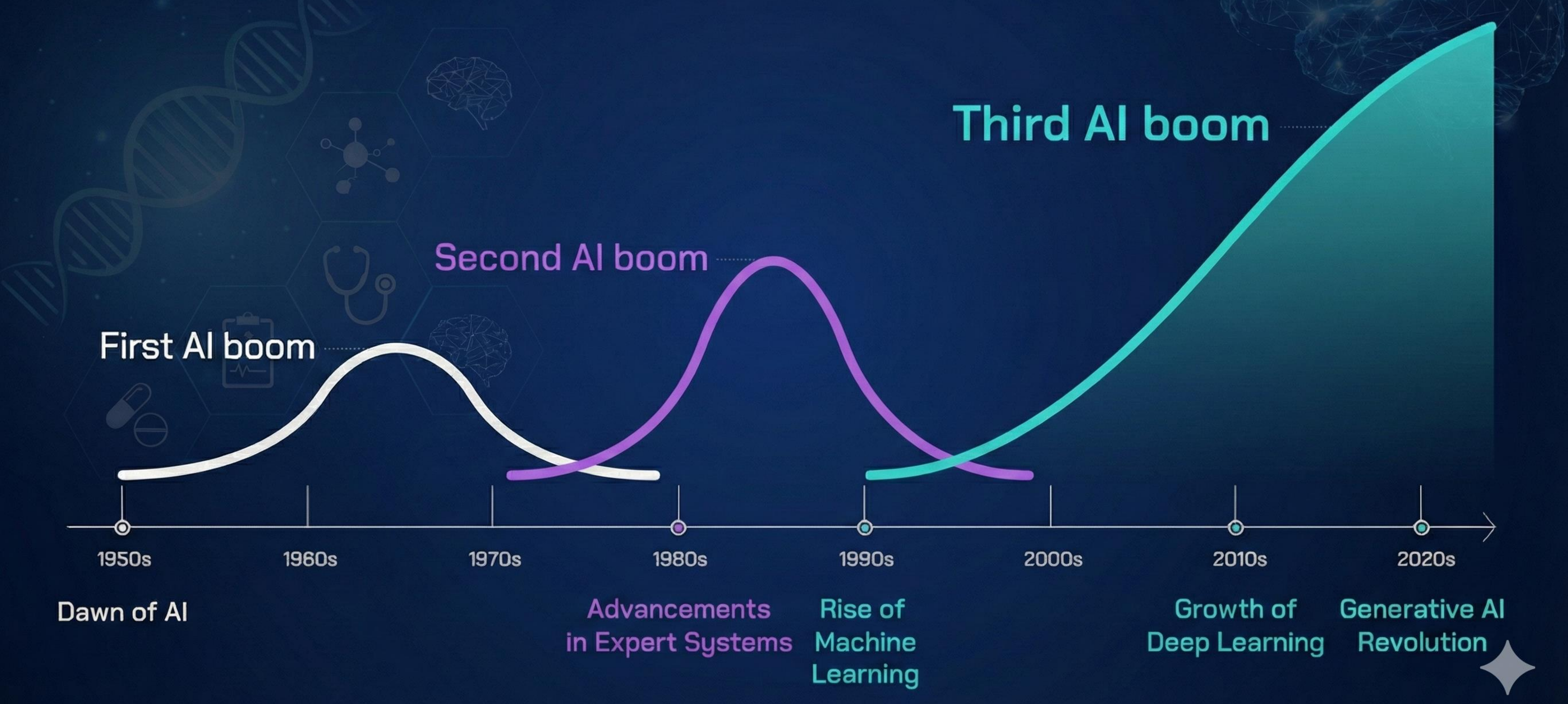


Image created with Gemini

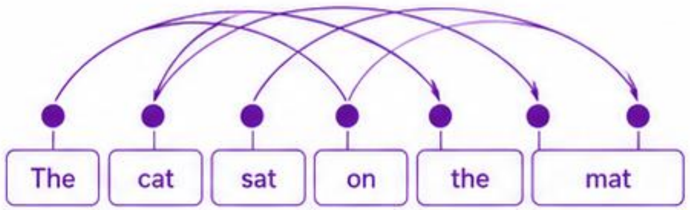
How 'Attention Is All You Need' Changed AI

1 Before Transformers

- Processed text step-by-step.
- Harder to capture long-range context.
- Slower to train and scale.
- Usually built for narrower tasks.

Older approaches: rule-based NLP, bag-of-words models, RNNs, LSTMs, seq2seq models.

2 2017 Breakthrough: Attention Is All You Need



- Introduced the Transformer architecture.
- Used self-attention to capture relationships across a sequence.
- Enabled parallelization and better scaling.

Seminal paper by Vaswani et al., 2017.

3 After: The Transformer Era

- Models learn from large-scale pretraining.
- Led to foundation models and LLMs.
- Improved language understanding and generation.
- Expanded into chatbots, copilots, search, summarization, coding, and multimodal tools.

Examples: BERT, GPT, chat-based assistants, multimodal AI.

Sequence-by-sequence	→	Parallel processing
Limited context	→	Rich context awareness
Task-specific models	→	Foundation models
Mostly analysis/classification	→	Generation and multimodal tools

Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need. In: Advances in Neural Information Processing Systems 30 (NIPS 2017). Curran Associates, Inc.; 2017:5998-6008.
Infographic created with ChatGPT 5.5, May 8, 2026

What is ChatGPT?

ChatGPT can make mistakes. Consider checking important information.

ChatGPT

ChatGPT is an advanced language model developed by OpenAI. It is part of the GPT (Generative Pre-trained Transformer) architecture. ChatGPT is designed to understand and generate human-like text based on the input it receives. It has been trained on diverse internet data, enabling it to comprehend and respond to a wide range of topics and questions. Users can interact with ChatGPT by providing prompts or questions, and the model generates responses based on its understanding of the context and patterns learned during training. While powerful, it's important to note that ChatGPT may not always be perfectly accurate or contextually precise.

Image captured from chatgpt.com on August 20, 2024

Helpful Definitions for AI

1 Generative AI

AI that generates new content based on patterns learned from existing data.

Oncology example: Drafting personalized patient education or visit summaries for a patient starting chemotherapy.

2 Predictive AI

AI that makes predictions about new data based on patterns learned from existing data.

Oncology example: Predicting which patients receiving chemotherapy are at highest risk for febrile neutropenia or hospital admission.

3 Large language model

AI that understands and generates human-like text by analyzing vast amounts of written-language data.

Oncology example: A clinical AI assistant that summarizes oncology notes, answers medication questions, or helps draft prior authorization language.

4 Explainable AI

AI that allows humans to understand and trust how the model makes its predictions or decisions.

Oncology example: A model that predicts treatment toxicity risk and shows which factors—such as age, renal function, lab values, or regimen—most influenced the prediction.

National Cancer Institute. Artificial intelligence. National Cancer Institute. Accessed May 11, 2026. https://www.cancer.gov/research/infrastructure/artificial-intelligence

Infographic created with ChatGPT 5.5, May 8, 2026

HOW DO WE MAKE AI TOOLS?

AI tools follow a product lifecycle, just like a medication.

DEFINE

What problem is being solved? (ex: Help identify patients at risk of ADRs from oral oncolytics)

DEVELOP

Build a model using data (e.g., labs, meds, diagnoses, outcomes, relevant health information)

VALIDATE

Test performance on new data to see if it works as intended (ex: ePROs)

IMPLEMENT

Embed into real workflows (e.g., EHR, PMS, DTx)

MONITOR

Track real-world performance, safety, and unintended effects (e.g., model drift, bias, overfitting) and user feedback metrics

EVALUATING AI

AI Evaluation Term	What It Means
AUROC / Discrimination *(Area Under the Receiver Operating Characteristic curve)*	Measures how well an AI model separates patients with an outcome from those without it. A high AUROC means the model ranks risk well, but it does not prove the model is clinically useful or safe.
Sensitivity and Specificity	Sensitivity shows how well the model catches true cases. Specificity shows how well it avoids false alarms. The ideal balance depends on the clinical scenario.
Positive Predictive Value and Negative Predictive Value	Positive predictive value tells clinicians how often an AI alert is correct. Negative predictive value tells clinicians how often a low-risk or negative result is reliable. These values depend heavily on how common the condition is.
Calibration	Shows whether the model's predicted risk matches real-world risk. If a model predicts 20% risk, about 20 out of 100 similar patients should experience the outcome.
External and Prospective Validation	External validation tests whether the model works in different hospitals, populations, or EHR systems. Prospective validation tests the model forward in time on new patients.

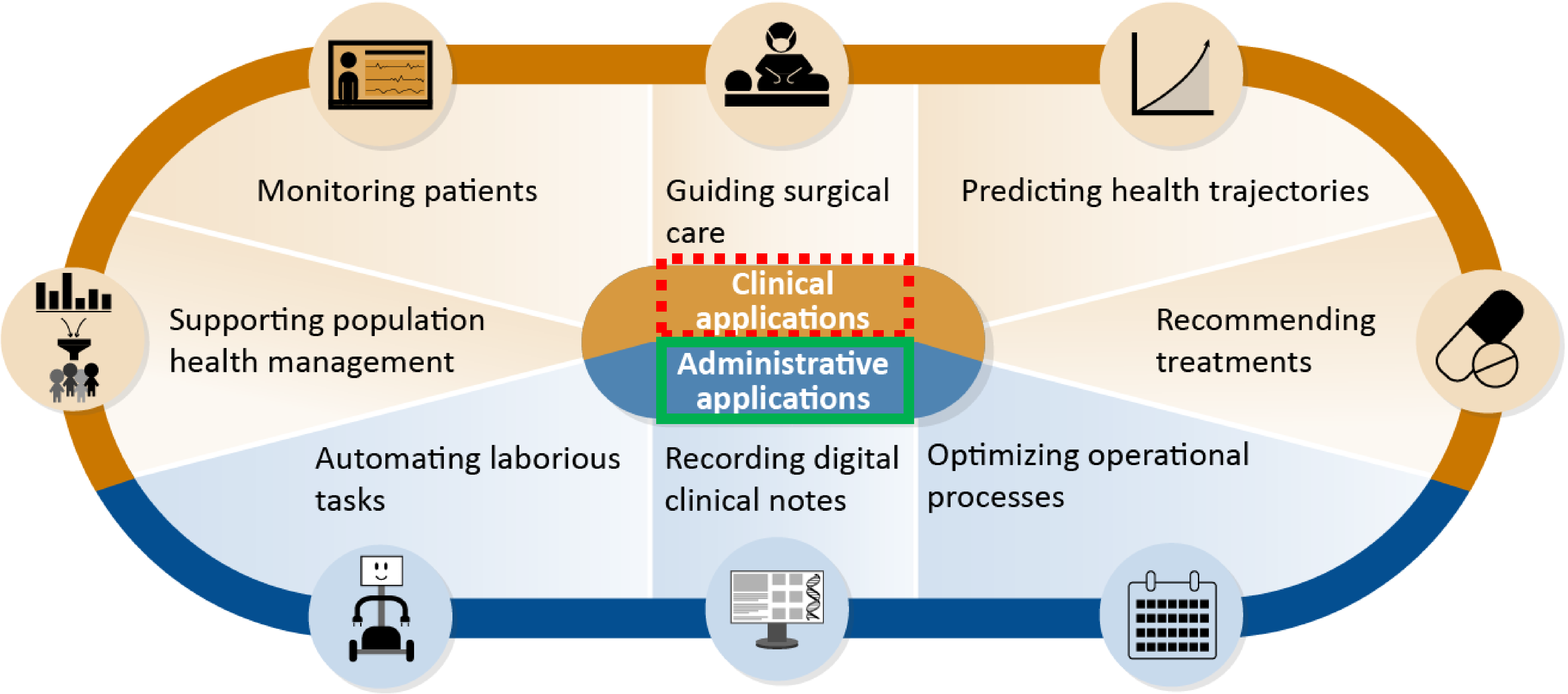
Deng J, Elghobashy ME, Zang K, Patel SK, Guo E, Heybati K. So you've got a high AUC, now what? An overview of important considerations when bringing machine-learning models from computer to bedside. *Med Decis Making*. 2025;45(6):640-653. doi:10.1177/0272989X251343082.

EVALUATING AI

AI Evaluation Term	Example in Oncology
AUROC / Discrimination *(Area Under the Receiver Operating Characteristic curve)*	An AI model predicts which patients with lung nodules are more likely to have cancer. A high AUROC suggests the model generally assigns higher risk scores to malignant nodules than benign ones.
Sensitivity and Specificity	For an AI mammography tool, high sensitivity helps detect more breast cancers, while high specificity helps reduce unnecessary callbacks, imaging, or biopsies.
Positive Predictive Value and Negative Predictive Value	If an AI flags patients as high risk for chemotherapy-related neutropenia, the positive predictive value indicates how often those flagged patients actually develop neutropenia.
Calibration	An AI tool estimates a patient has a 30% risk of cancer recurrence after treatment. Calibration checks whether patients given a 30% risk score actually recur about 30% of the time.
External and Prospective Validation	An AI model developed at one cancer center to predict immunotherapy response is tested at other oncology clinics and then evaluated prospectively in newly treated patients before routine use.

Deng J, Elghobashy ME, Zang K, Patel SK, Guo E, Heybati K. So you've got a high AUC, now what? An overview of important considerations when bringing machine-learning models from computer to bedside. *Med Decis Making*. 2025;45(6):640-653. doi:10.1177/0272989X251343082.

WHERE ARE WE GOING TO USE AI?



U.S. Government Accountability Office. *Artificial Intelligence in Health Care: Benefits and Challenges of Technologies to Augment Patient Care*. GAO-21-7SP. U.S. Government Accountability Office; November 30, 2020. Accessed December 3, 2025. https://www.gao.gov/products/gao-21-7sp

WHAT IS THE GOAL?

1. Reduce Administrative Burden & Cost
2. Improve Margins & Financial Stability
3. Enhance Clinical Quality, Safety, & Outcomes
4. Personalize Care & Patient Experience
5. Leverage Data & Remain Competitive

Poon EG, Lemak CH, Rojas JC, Guptill J, Classen D. Adoption of artificial intelligence in healthcare: survey of health system priorities, successes, and challenges. J Am Med Inform Assoc. 2025 Jul 1;32(7):1093-1100.

EHR + AI POWERHOUSES

Role of EHR for AI	Short Description	Example Focus / Resources
Data Backbone	Main source of structured and unstructured clinical data for AI models.	HL7 FHIR / SMART-on-FHIR access to diagnoses, labs, meds, notes.
Integration Hub	Connects EHR data with wearables, patient-reported data, and other systems.	Multimodal AI using EHR plus patient-generated health data.
Workflow & UI Surface	Where clinicians see AI insights inside normal workflows.	In-chart risk scores, alerts, summaries, and suggestions.
Automation Endpoint	Destination for AI-generated notes, orders, and messages.	Ambient scribing and order suggestions writing directly into the chart.
Safety & Governance Anchor	System of record for logging, access control, and provenance of AI outputs.	Audit trails, bias monitoring, and compliance tied to EHR governance.
Monitoring And Evaluation	Source for measuring AI performance and impact over time.	EHR-based dashboards tracking outcomes and alert behavior.
AI-native Platform	EHRs redesigned around embedded AI agents and copilots.	AI-driven EHRs from Epic, Oracle Health, eClinicalWorks.
Conversational Interface	Enables “chat with the chart” using LLMs.	Stanford ChatEHR and vendor copilots answering free-text queries.

Ye J, Woods D, Jordan N, Starren J. The role of artificial intelligence for the application of integrating electronic health records and patient-generated data in clinical decision support. AMIA Jt Summits Transl Sci Proc. 2024 May 31;2024:459-467.; Fernandes Prabhu D, Gurupur V, Stone A, Trader E. Integrating Artificial Intelligence, Electronic Health Records, and Wearables for Predictive, Patient-Centered Decision Support in Healthcare. Healthcare (Basel). 2025 Oct 30;13(21):2753.

EXAMPLE: AI SCRIBES

THEORY

- Ambient AI scribes in the background can help reduce the time spent on documenting and reduce workload on staff

REALITY

- Several large studies have come out in the past year
- Results demonstrating time saved on notes ranging from ~30s-130s.
- Burnout results vary, with some identifying a reduction of burnout and work exhaustion
- **Why?**
  - Perceived benefit (Placebo)
  - Indirect benefits (more F2F time with patients) increasing job satisfaction

Trang B. AI scribe clinical trial results are here. What do they actually reveal? *STAT*. December 3, 2025. Accessed December 4, 2025. https://www.statnews.com/2025/12/03/ambient-scribe-trial-doctor-burnout-ai-prognosis-newsletter/

Kim E, Liu VX, Singh K. AI scribes are not productivity tools (yet). NEJM AI. 2025;2(12).

Slim time savings but provider burnout relief

Results of ambient AI scribe studies

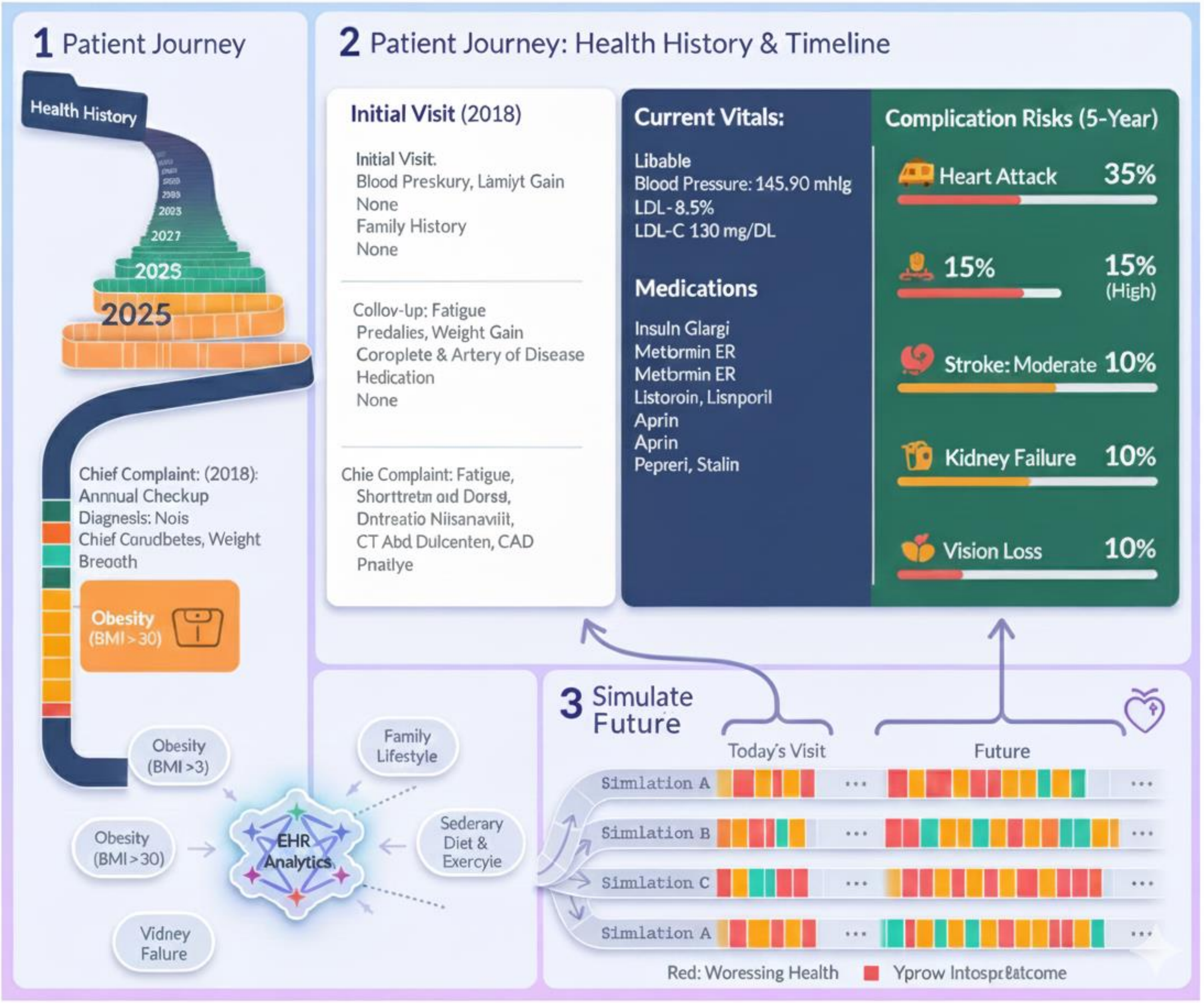
Study	Vendor	Start date and duration	Pajama time saved per day	Time saved per note	Burnout findings
Sutter Health, JAMA Network Open, 2025	Abridge	April 2024, 3 months	1.6 minutes more (insignificant)	54 seconds	No statistical difference
Permanente Medical Group, NEJM Catalyst, 2025	Nabla, Abridge	October 2023 - December 2024, 15 months	1.03 minutes	24 seconds	Not measured (satisfaction measured)
University of Pennsylvania, JAMA Network Open, 2025	DAX Copilot	April - June 2024, 5 weeks	15.2 minutes	126 seconds	Clinicians less likely to report feeling mentally overloaded and “drained” by the burden of clinical documentation
University of Iowa, Applied Clinical Informatics, 2025	Nabla	Unknown, 5 weeks	Not measured	Not measured	Burnout rates decreased from 69% to 43%
Stanford Health Care, JAMIA, 2025	DAX Copilot	October 2023, 3 months	Not measured	Not measured	Statistically significant reduction in burnout
Atrium Health, NEJM AI, 2024	DAX Copilot	June - August 2023, 6 months	No significant difference compared to control	No significant difference compared to control	Not measured
UCLA Health, NEJM AI, 2025	DAX Copilot, Nabla	November 2024, 2 months	No significant difference compared to control	5 seconds compared to control (DAX; insignificant), 23 seconds compared to control (Nabla; significant)	Improvement in burnout, cognitive task load, and work exhaustion
University of Wisconsin Health, NEJM AI, 2025	Abridge	August 2024, 6 months	30 minutes	Not measured	Clinically meaningful improvement in work exhaustion/interpersonal disengagement

Table: Brittany Trang, Mario Aguilar

EXAMPLE: Predicting Outcomes

Overview

- Curiosity is Epic's "medical intelligence" platform built on Cosmos, using transformer models trained on more than 100 billion de-identified medical events to predict future patient risks, outcomes, and trajectories.
- It simulates multiple possible care pathways and summarizes them into actionable insights that can be embedded into clinical workflows for anticipatory decision-making and operational planning.
- The platform runs within Epic's secure Cosmos environment and has shown strong performance across 78 evaluated tasks, with broader testing planned through a virtual lab in 2026.

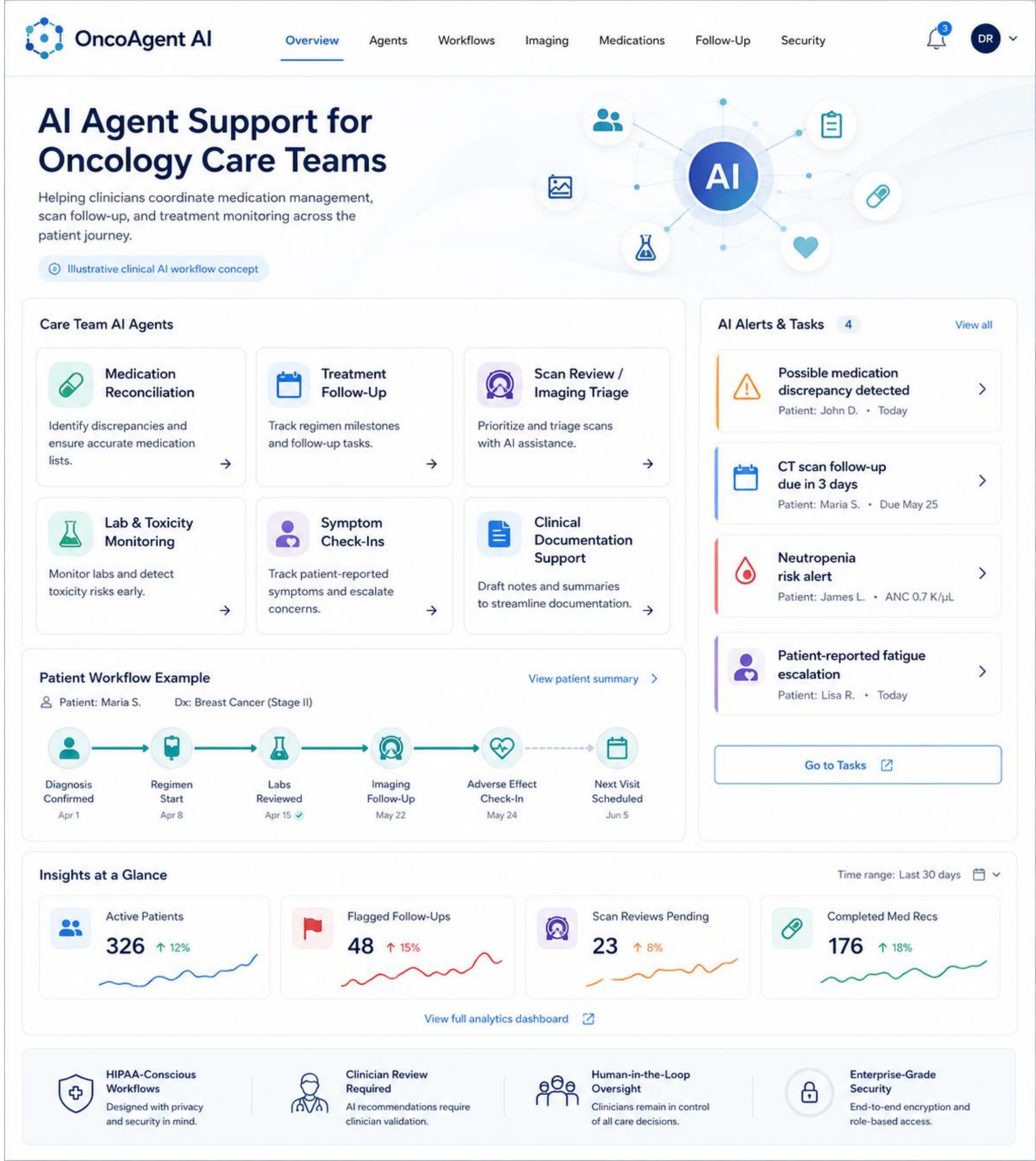


Waxler S, Blazek P, White D, et al. Generative medical event models improve with scale. arXiv. 2025. doi:10.48550/arXiv.2508.12104.; Curiosity: a new medical intelligence for clinical and operational insights. Epic. September 3, 2025. Accessed December 4, 2025. https://www.epic.com/epic/post/curiosity-a-new-medical-intelligence-for-clinical-and-operational-insights/

EXAMPLE: AI Agents

THEORY

- What if we could leverage Generative AI tools to create a virtual tool that could conduct a singular task with human oversight on what the process would be?
- Essentially Chatbots 2.0
    - Can communicate via voice or text based conversations
    - Memory of previous conversations
    - Focused on singular task oriented activities
    - Embedded into business operations



AI Generated Mockup

Gorenshtein A, Omar M, Glicksberg BS, Nadkarni GN, Klang E. AI Agents in Clinical Medicine: A Systematic Review. medRxiv [Preprint]. 2025 Aug 26:2025.08.22.25334232.

How AI Is Being Used in Pharmacy

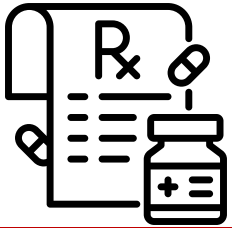
1. Medication Adherence Tracking
2. Prescription Refill Management
3. Chronic Disease Management
4. Inventory Management
5. Drug Interactions
6. Payments & Billing
7. Medication Reconciliation
8. Prescription Transfer
9. Adverse Drug Reaction Monitoring
10. Personalized Medication Management
11. Drug Shortages Management
12. Patient Education & Screening
13. Patient Scheduling & Triage
14. Drug Formulary Management
15. Drug Acquisition
16. Prior Authorizations

Khan O, et al. Intelligent Pharmacy J (2023)32-40
Infographic created with ChatGPT 5.5, May 8, 2026

THE MEDICATION-USE PROCESS

PRESCRIBING

- CPOE
- CDSS
- EMR



TRANSCRIBING

- Pharmacy Management & Information System

DISPENSING

- Automation & Robotics
- Vision AI

ADMINISTRATION

- Barcode Administration
- Intelligent Pumps
- Automated Cabinets

MONITORING

- Real-Time Patient Status
- RPM/RTM

Pharmacy is no stranger to leveraging technology to help with the medication use process, but with more data and assigning human capital labor to leverage it has led to the argument for AI augmentation for the workforce.

Bubalo J et al. J Oncol Pharm Pract. 2014 Dec;20(6):445-60.; Graafsma J et al. J Am Med Inform Assoc. 2024 May 20;31(6):1411-1422.

AUTONOMOUS PHARMACY

Level 1

Non-Autonomous Pharmacy

- Minimal to no automation
- Data primarily managed on paper or in disparate spreadsheets
- Pharmacists heavily engaged in distribution with little direct patient interaction. Technicians and nurses spend time on manual drug management (purchasing, locating, counting)

Level 2

Limited Autonomous Pharmacy

- Some automation, including some barcode tracking
- Data managed disparately across sites with some visibility
- Pharmacists largely focused on distribution and verification. Technicians and nurses manually responsible for most drug management with light automated support

Level 3

Intermediate Autonomous Pharmacy

- Majority of processes automated, with barcode tracking applied widely
- Data integrated across enterprise and mostly visible
- Pharmacists somewhat focused on medication distribution, with some direct patient care. Technicians focus on manual procurement and controlled substances, and nurses rely on automated dispensing

Level 4

Highly Autonomous Pharmacy

- Extensive automation with few gaps across processes
- Near complete data visibility, offering workflow optimization and real-time insights
- Pharmacists routinely involved in direct patient care, population health initiatives, and clinical programs. Technicians maintain automation and use workflow app, and nurses focus most of their time on patient care

Level 5

Fully Autonomous Pharmacy

- Complete process automation, tracking each dose as a node on the network
- Complete data visibility, real-time workflow optimization, and predictive intelligence
- Pharmacists realize full scope of their role in direct patient care and clinical program optimization. Technicians ensure optimal function of automation and use workflow app, and nurses focus on direct patient care

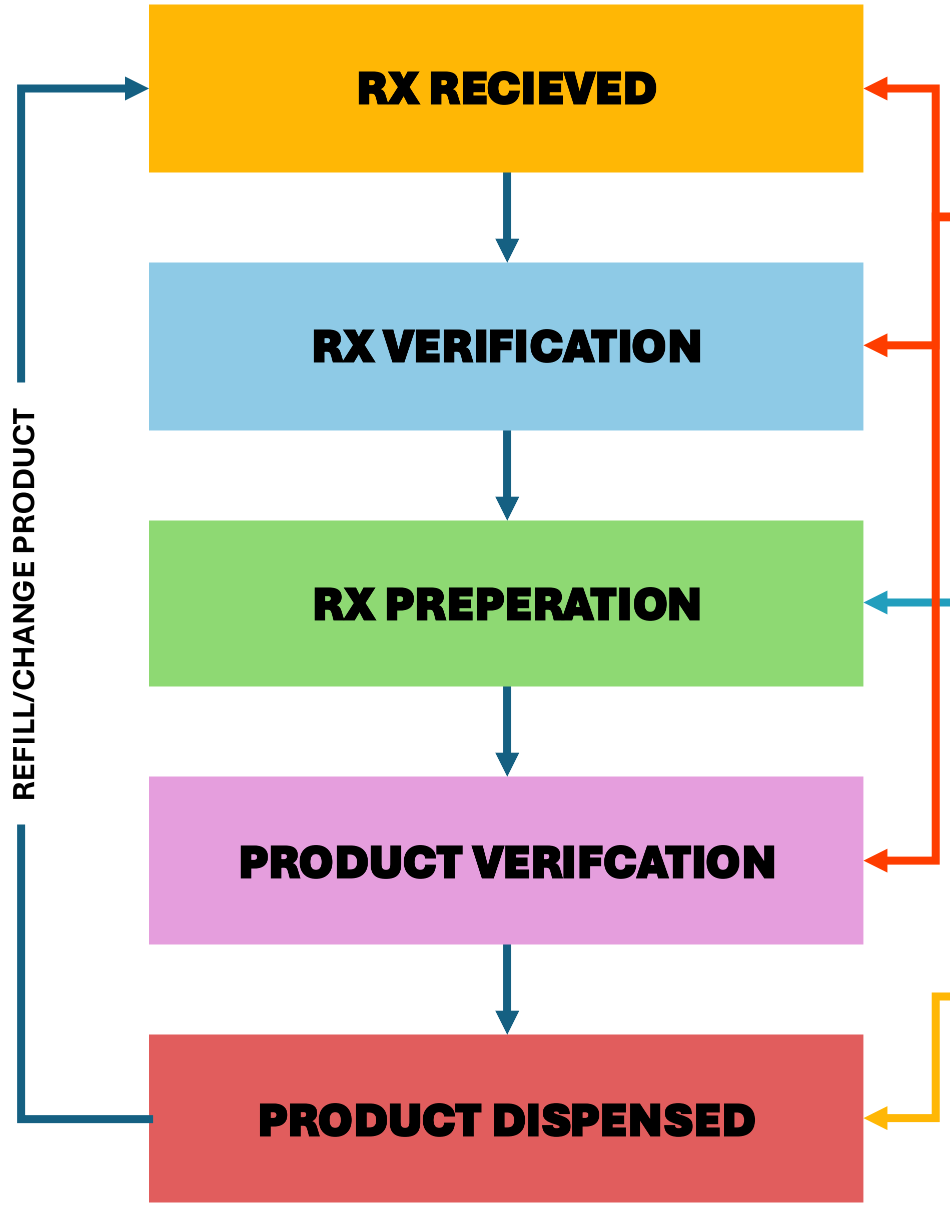
Outcomes

0	100%
✓ Medication Errors	✓ Data Visibility
✓ Medication Waste	✓ Time Spent on Clinical Activity
✓ Human Touches Pre-administration To Patient	✓ Regulatory Compliance

Performance Elements: Safety, Financials, Efficiency, Compliance, People

https://www.autonomouspharmacy.com/wp-content/uploads/2020/12/AutonomousPharmacyFramework.pdf

PHARMACEUTICAL DISPENSING



PMS AI INTEGRATION:
Vendors will seek to integrate AI tools that assist in the processing of Rx received, improving communication with payers, inventory control, billing, record keeping, helping with the verification process, and the final check prior to dispensing the product to the patient.

AUTOMATION:
Expansion on AI integration of automation/robotics for the preparation of medications across multiple settings.

PATIENT PORTAL & FOLLOW-UP TOOLS:
Engagement strategies expand with AI tools (e.g., agents, avatars) to be integrated into the pharmacy experience to ensure continued consumer engagement with the pharmacy and ensure adherence and maximize related services offered by the business (e.g., vaccinations).

BALANCING AI IN PHARMACY CARE

Rx SAFETY

- AI-Optimized Drug-Drug Interaction Alerts
- Computer Vision for Pill Identification
- Error Prevention during Verification
- Prescription Standardization
- Automated Alert Triage

Rx EFFICACY

- Predictive Dosing via Pharmacogenomics
- Smart Medication Adherence Tools
- AI-Guided Therapy Optimization
- Trends from Time-Series Data
- AI Personalizing Complex Regimens

Areas AI Is Being Explored in Oncology

- Cancer Prevention & Risk Stratification
- Early Screening
- AI-Assisted Diagnosis
- Intelligent Radiation Oncology
- AI and Teleoncology
- Prediction of Treatment Outcome

Lin B et al. *J Natl Cancer Cent*. 2022;3(1):83-91.
Infographic created with ChatGPT 5.5, May 8, 2026

Wang J, Zeng Z, Li Z, et al. The clinical application of artificial intelligence in cancer precision treatment. *J Transl Med*. 2025;23(1):120.

Using AI to Individualize Interventions

Surgery

Preoperative planning
Intraoperative guidance
Postoperative management

Chemo-Therapy

Therapy decision-making
Drug potentiation

Radio-Therapy

Tumor contouring
Dose optimizing

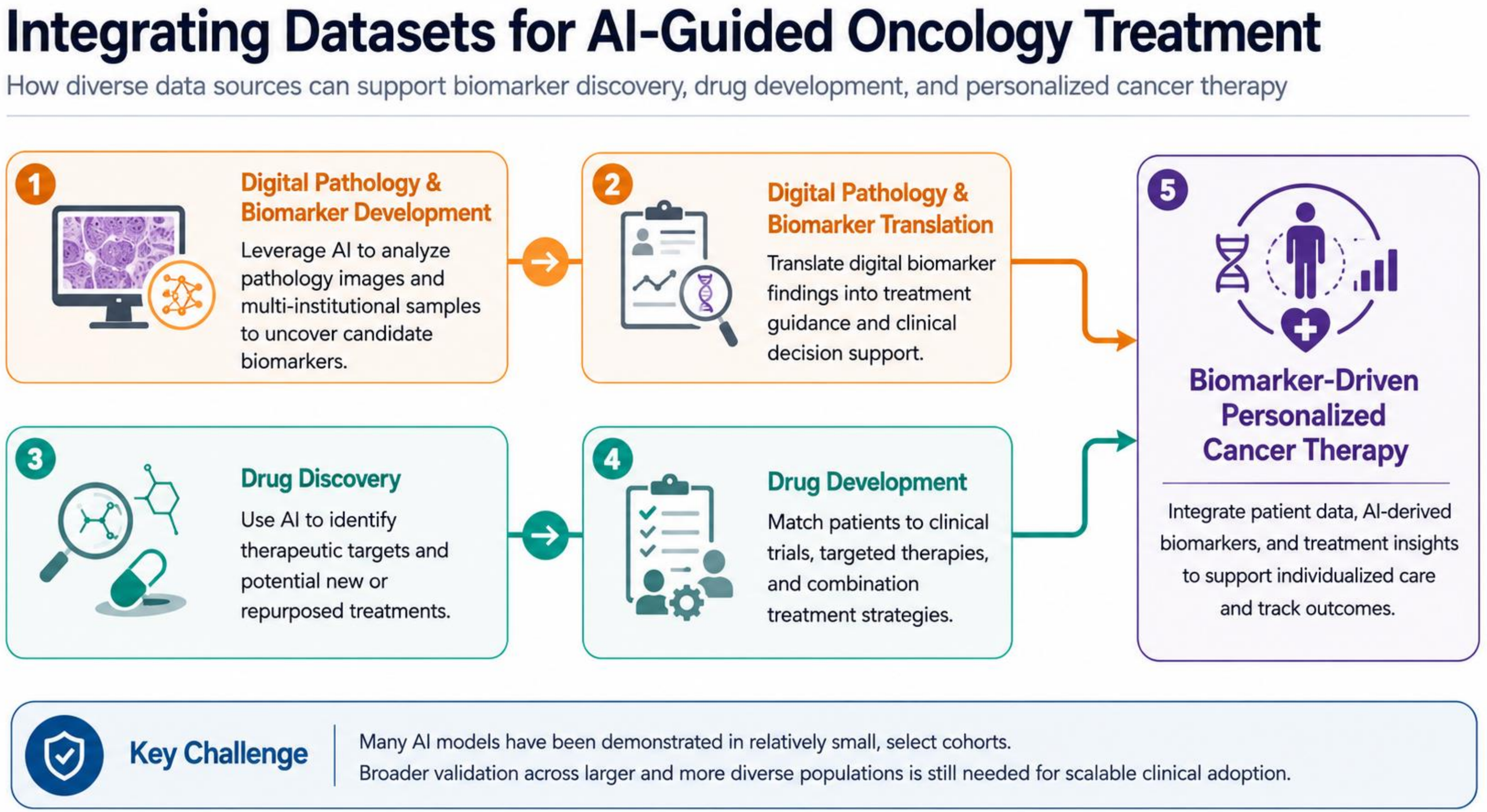
Available Datasets for AI Integration in Oncology

IMAGE DATA
- PET/CT Scans
- MRI Sans
- Dermoscopic Images
- Mammograms

OMICS DATA
- Genomics
- Transcriptomics
- Proteomics
- Epigenomics
- T-cell receptor sequencing

CLINICAL DATA
- Electronic Health Records
- Patient response to therapy
- Electronic patient-reported outcomes (ePROs)

Bhinder B et al. *Cancer Discov*. 2021;11(4):900-915.



Senthil Kumar K et al. Am Soc Clin Oncol Educ Book. 2023;43:e390084.; Infographic created with ChatGPT 5.5, May 8, 2026

AI For Cancer Detection & Screening

Early use of computer-aided design (CAD) for breast cancers had little impact on diagnostic accuracy despite 20+ years of investment. As hardware and processing speeds increased, there was more opportunity to leverage the massive amount of data available.

Early CAD Adoption

Petabytes of Imaging Data

Rise of ML/AI Tools

20+ AI Tools FDA Cleared for Breast Cancer

Expanded Tools Finding Role in Oncology

AI vs Traditional Imaging
AI being used in risk assessment, decision support, density quantification, workflow optimization, and chemotherapy response in order to augment health care teams

Taylor CR et al. Diagnostics (Basel). 2023;13(12):2041; Silva HECD et al. PLoS One. 2023;18(10):e0292063.

Deep Learning Algorithm for Pancreatic Cancer Trajectory

1 Large-Scale Clinical Data

AI analyzed clinical data from **>9 million patients**, including **27,900 pancreatic cancer cases**, using data from the Danish National Patient Registry (DNPR) and the US Veterans Affairs (US-VA).

2 Model Training

Deep learning models were trained on sequences of disease codes from patient histories to predict pancreatic cancer across multiple time windows.

Danish model AUROC = **0.88** for prediction within **36 months.**

3 External Validation

When applied to US-VA data, performance decreased (AUROC = 0.71), prompting retraining that improved performance to AUROC = 0.78.

AUROC 0.71 → AUROC 0.78

4 Clinical Implication

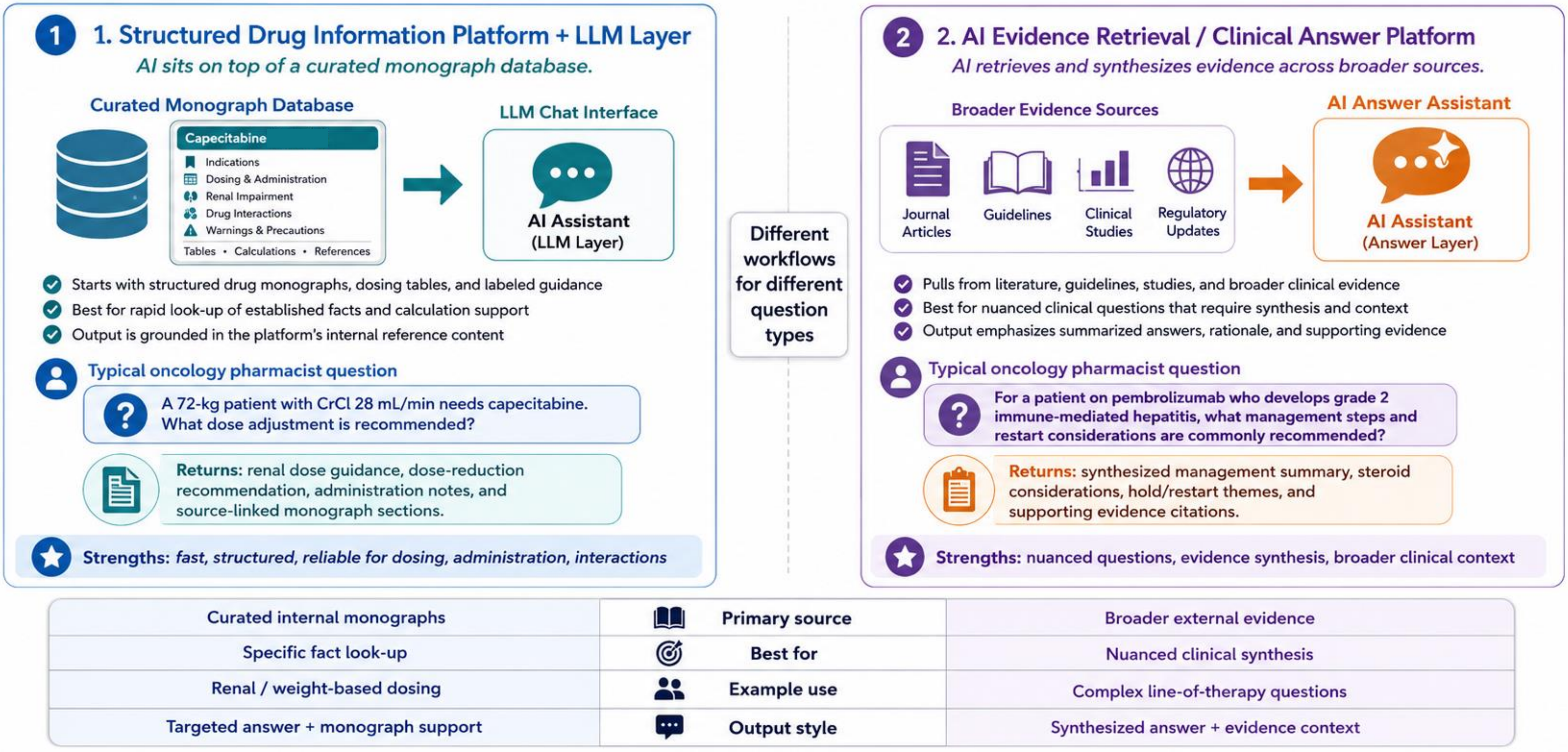
Findings suggest AI could strengthen surveillance strategies for high-risk patients, supporting earlier detection and improved outcomes in pancreatic cancer.

Key Takeaway

Population-scale clinical data and deep learning may help identify patients at elevated risk for pancreatic cancer earlier, but model generalizability across populations remains important.

Placido D et al. Nat Med. 2023;29(5):1113-1122.; Infographic created with ChatGPT 5.5, May 8, 2026

AI for Medical and Drug Information



Infographic created with ChatGPT 5.5, May 8, 2026

AI For Chemotherapy and Precision Medicines

Clinical Trial Enrollment

Using embedded AI tools to identify patients that may benefit from being enrolled in clinical trials using data to identify inclusion and exclusion criteria, and due to cancer progression sending alerts to care teams to suggest possible enrollments through the course of disease management.

Mazor T, Farhat KS, Trukhanov P, et al. Clinical Trial Notifications Triggered by Artificial Intelligence-Detected Cancer Progression: A Randomized Trial. JAMA Netw Open. 2025;8(4):e252013.

Predicting Neutropenia

Using clinical and genetic data from pediatric patients with B-cell acute lymphoblastic leukemia to develop ML models that accurately predicted high-dose methotrexate–related neutropenia and fever, with random forest plus adaptive synthetic resampling performing best and potentially supporting faster oncology decision-making.

Zhan M, Chen ZB, Ding CC, et al. Machine learning to predict high-dose methotrexate-related neutropenia and fever in children with B-cell acute lymphoblastic leukemia. *Leuk Lymphoma*. 2021;62(10):2502-2513.

Limiting Cardiotoxity

Using SEER-Medicare data from colorectal cancer patients receiving fluoropyrimidine-based chemotherapy to develop machine learning models predicting 30-day cardiotoxicity, with XGBoost performing best and identifying pre-existing cardiac conditions, surgery, and older age as key risk factors.

Li C, Chen L, Chou C, Ngorsuraches S, Qian J. Using Machine Learning Approaches to Predict Short-Term Risk of Cardiotoxicity Among Patients with Colorectal Cancer After Starting Fluoropyrimidine-Based Chemotherapy. *Cardiovasc Toxicol*. 2022;22(2):130-140.

EXAMPLE: AI For Medication Dosing

01 AI-Driven Precision in Medication Dosing

- Personalizes dosing using real-time patient data.
- Optimizes drug combinations and adapts to patient-specific responses.
- Goals: improve efficacy, reduce adverse effects, and extend progression-free survival (PFS).

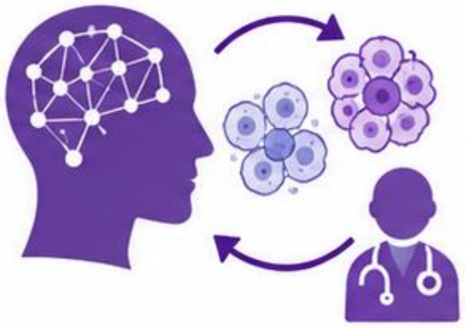
02 Personalized Drug Combination Design (QPOP)

- Quadratic Phenotypic Optimization Platform (QPOP).
- Combines lab experimentation with optimization analysis.
- Creates patient-specific drug combinations.
- Reduces the number of data points needed for testing and may improve treatment efficacy in chemotherapy-resistant cancers.

03 scFPM for Single-Cell Drug Profiling

- Single-cell Functional Precision Medicine (scFPM).
- Uses high-content microscopy to profile drug efficacy at the single-cell level.
- Prospective trial: improved PFS in 54% of 143 patients with advanced cancer.
- Results available within 5 days of sampling.

04 AI + Evolutionary Game Theory



- Models cancer cell resistance and physician treatment strategies.
- Supports dynamic treatment protocols that adapt to tumor evolution.
- May increase time to progression.
- Can reduce standard dosing by 47%.

Senthil Kumar K et al. Am Soc Clin Oncol Educ Book. 2023;43:e390084; Goh J et al. Sci Transl Med. 2022;14(667):eabn7824; Kornauth C et al. Cancer Discov. 2022;12:372-387.; Infographic created with ChatGPT 5.5, May 8, 2026

AI For Supportive Care Needs

Why this matters

AI tools could help make high-quality care accessible to more patients, including those who live far from cancer specialists or in low-resource settings, potentially helping reduce cancer health disparities.

Chatbots Across Oncology Care

- Narrative review of 21 studies across prevention, education, treatment, monitoring, and survivorship.
- Common uses included screening, risk stratification, symptom management, and patient education.
- Patients generally reported high satisfaction.
- In 9 of 12 efficacy studies, chatbots improved outcomes versus standard care.

Patient Education: PROSCA

- AI chatbot designed to educate patients about prostate disease, testing, cancer stages, and treatment options.
- In a proof-of-concept group, most users found it easy to use.
- 89% reported a clear to moderate increase in knowledge.
- All users supported future use of medical chatbots in care.

Drafting Patient-Facing Responses

- Study compared physician responses with ChatGPT-generated answers to 195 patient questions.
- Blinded licensed evaluators preferred chatbot responses 78.6% of the time.
- Chatbot responses were rated higher for both quality and empathy.
- Best framed as AI helping draft patient responses for clinician review, not replacing clinical judgment.

Supportive care opportunities

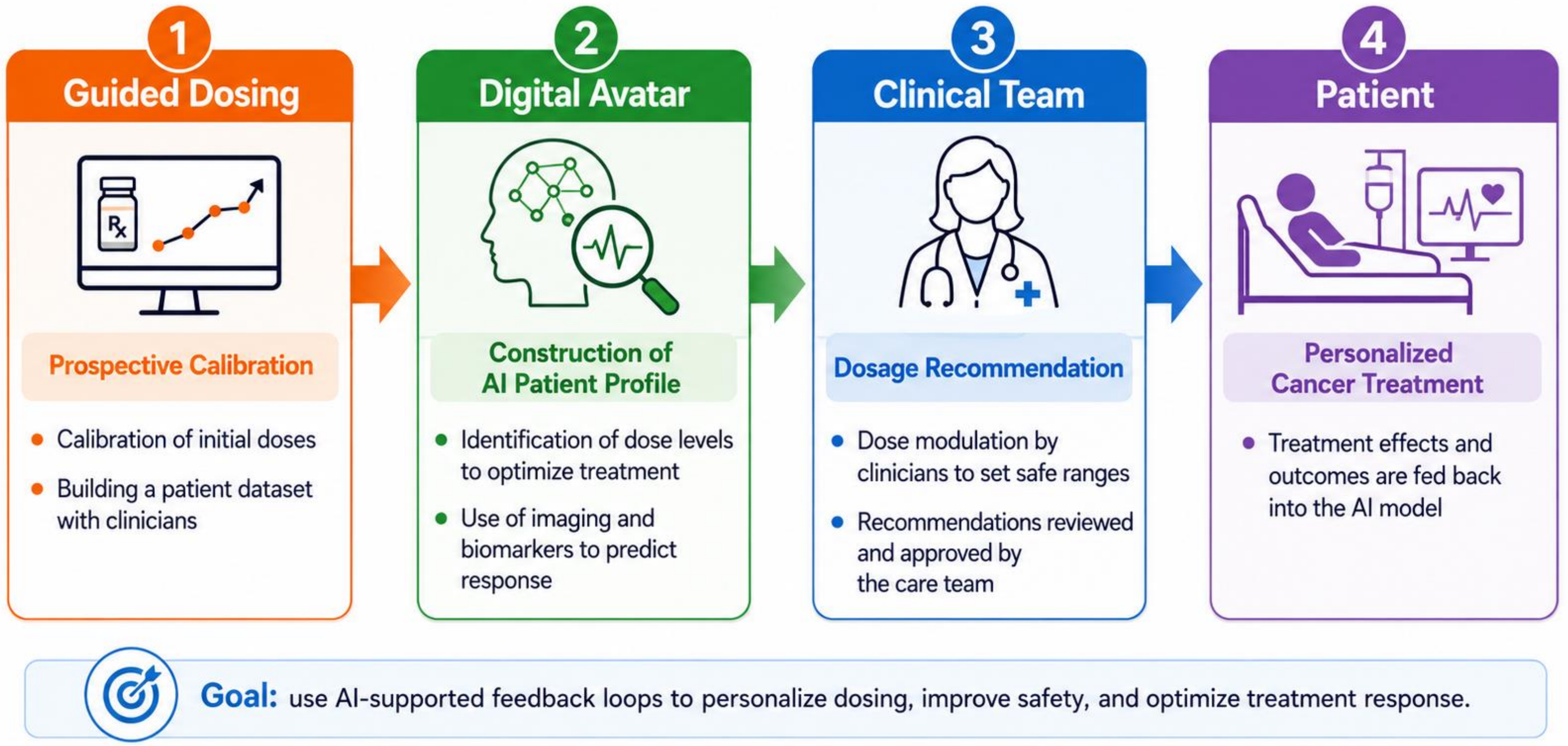
- Patient education
- Symptom monitoring
- Follow-up communication
- Improved access to care

Key message

AI may strengthen supportive oncology care by expanding education, communication, and monitoring—especially when paired with clinician oversight.

Wang A, et al. *Int J Gen Med*. 2023;16:1591-1602.; Görtz M, et al. Digit Health. 2023;9:20552076231173304.; Ayers JW, et al. JAMA Intern Med. 2023;183(6):589-596.; National Cancer Institute. Artificial intelligence (AI) and cancer. National Cancer Institute. Published May 30, 2024. Accessed May 12, 2026. https://www.cancer.gov/research/infrastructure/artificial-intelligence ; Infographic created with ChatGPT 5.5, May 8, 2026

Sample AI Workflow: CURATE.AI



Senthil Kumar K et al. Am Soc Clin Oncol Educ Book. 2023;43:e390084.
Infographic created with ChatGPT 5.5, May 8, 2026


How Do We Prepare
To Practice In The
Age Of AI?

01
Accuracy & Explainability

02
Governance & Regulatory Landscape

03
Ethical Concerns

04
Data & Patient Privacy

05
Education & Training

Issues to Be Resolved Prior to Widespread AI Adoption

THINGS TO CONSIDER

How do we think?

Important to understand how humans learn and process information through data they encounter on an everyday basis.

How does AI work?

AI was developed to mimic similar processes that humans utilize to process information.

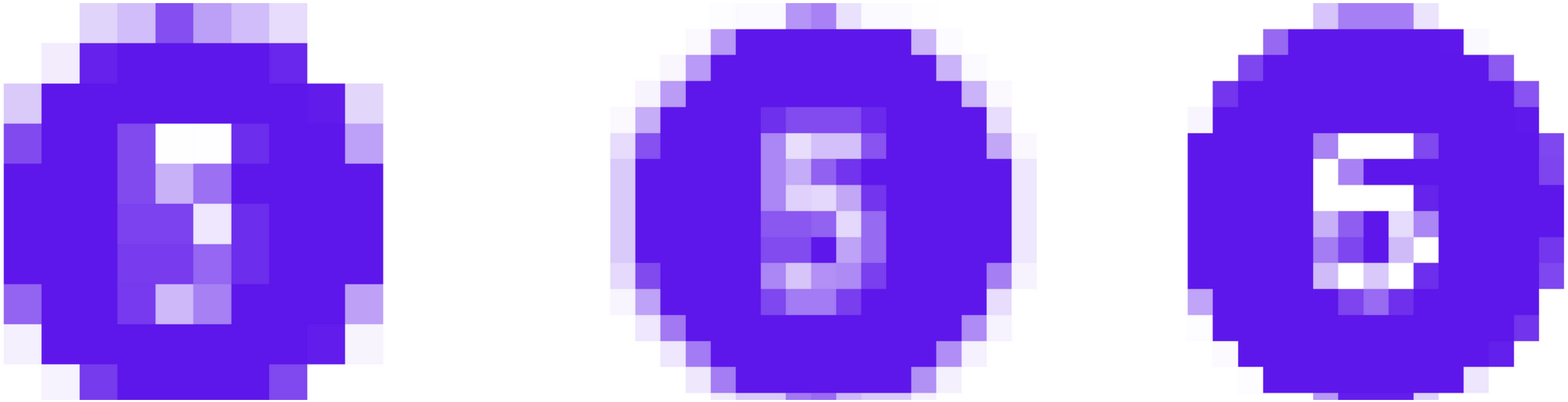
How can these factors impact AI utilization?

Considering that AI inherits limitations from processing data can determine situations where AI may be at risk for clinical practice.

LEARNING THROUGH EXPERIENCE

THINKING / LEARNING STYLE	DESCRIPTION IN CLINICAL DECISION-MAKING	WHEN THIS SKILL TYPICALLY DEVELOPS (SCHOOL → CLINICALS → RESIDENCY)		
1. System 1 thinking (intuitive / pattern recognition)	Fast, automatic, instinctive thinking that uses pattern recognition to generate a quick diagnosis when the presentation matches familiar cases and contextual cues (environment, resources, typical cases). Efficient but vulnerable to bias and early anchoring.	**School:** Early templates built from lectures, cases, and simulation (e.g., classic presentations).	**Clinicals:** Strengthens as learners repeatedly see common patterns at the bedside.	**Residency:** Becomes more sophisticated and faster as case volume and acuity increases, especially in high-throughput settings (ED, ICU).
2. System 2 thinking (analytic / deliberative)	Slow, effortful, logical thinking used when no clear pattern is recognized or when the case is complex or uncertain. Involves iterative data gathering, analysis, and reasoning to build and narrow a differential diagnosis using training and critical thinking.	**School:** Explicitly taught via pathophysiology, pharmacology, and structured reasoning (SOAP notes, differential diagnosis exercises, problem-based learning).	**Clinicals:** Applied under supervision on rounds and in case presentations.	**Residency:** Refined under time pressure and complexity; residents learn when to deliberate slow down and engage System 2.
3. Heuristic thinking (rules of thumb)	Shortcuts or mental rules derived from experience that help clinicians rapidly link presenting features to likely diagnoses or actions (e.g., young + pleuritic chest pain does not always equal PE). Useful for speed under pressure but can oversimplify and miss atypical presentations.	**School:** Introduced as simple pearls or rules of thumb in teaching.	**Clinicals:** Begins to form as learners repeatedly encounter similar presentations.	**Residency:** Heuristics become robust and highly influential; requires coaching to recognize when a heuristic might mislead and when to pause for Systerm 2.
4. Experience-based learning (pattern building over time)	Learning through repeated exposure to clinical situations, where past cases gradually form internal templates for recognizing patterns. Strengthens System 1's library of cases but reinforces biased or incomplete mental models if not critically examined.	**School:** Starts in simulation labs, standardized patient encounters, and early patient contact.	**Clinicals:** Accelerates as learners see real patients with supervision and feedback.	**Residency:** Deepens rapidly due to volume and diversity of cases; reflection, feedback, and quality improvement activities help shape higher-quality patterns libraries.

Woodford P. The decision is yours. *Journal of Paramedic Practice*. 2015;7(2):90-94.
Infographic created with ChatGPT 5.5, May 1, 2026



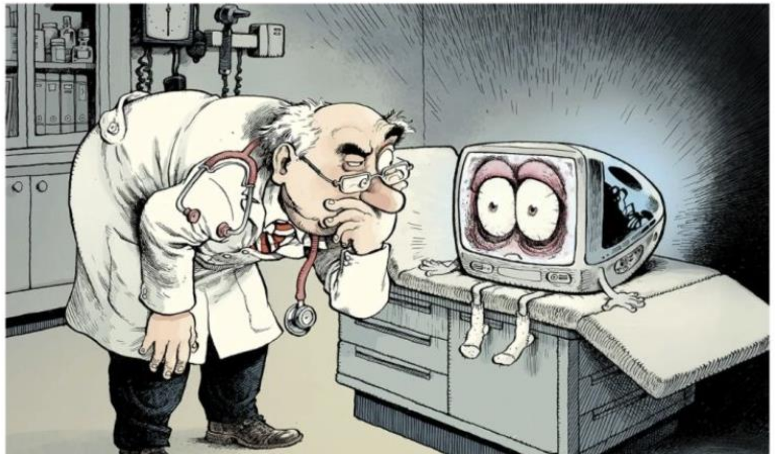
WHAT DO YOU SEE?

NEWS FEATURE | 07 April 2026

Scientists invented a fake disease. AI told people it was real

Bixonimania doesn't exist except in a clutch of obviously bogus academic papers. So why did AI chatbots warn people about this fictional illness?

By Chris Stokel-Walker



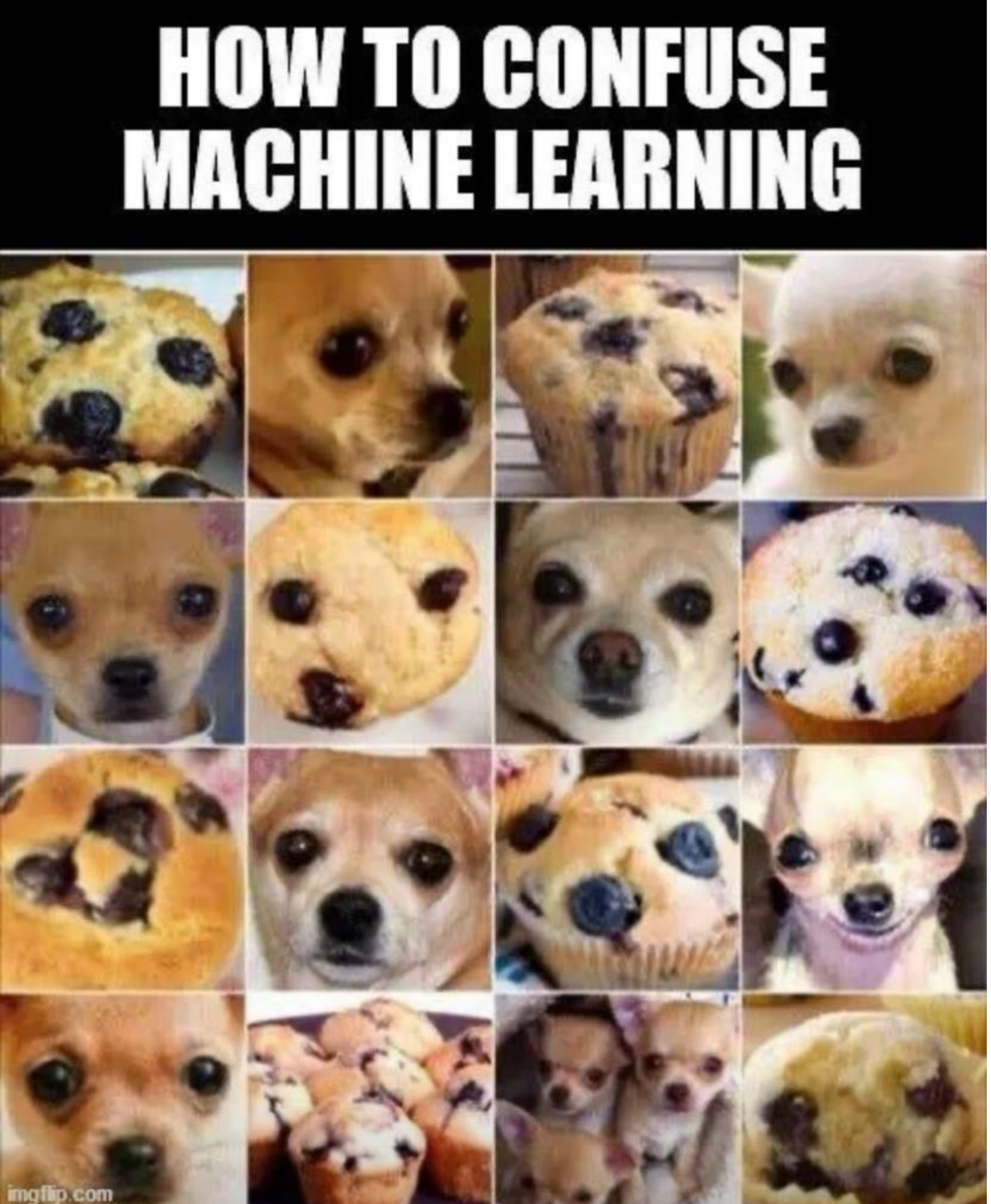
AI DATA ISSUES

- **AI bases much of its analysis on public databases**
  - *May include public forums such as Reddit*
- **Models must be trained to adjust how to weigh credence on certain resources**
  - *Traditional peer reviewed literature and medical guidelines*
- **Weaknesses exist for models, which can increase risk of hallucinations or inaccuracy**
  - *Recognize what models use for data resource*
  - *May utilize RAG (retrieval augmented generation) to alleviate issues or other model deployment to reduce risk of errors*

"BLACKBOX" AI

- **Greater potential harm from misdiagnosis:** Even if black-box medical AI is more accurate on average than clinicians, its errors can be more serious because users cannot understand or anticipate when and why the system fails, making it harder to detect and correct unsafe recommendations.
- **Threats to patient autonomy and informed consent:** Because black-box AI cannot adequately explain the reasoning behind its recommendations, physicians struggle to give patients the clear, comprehensible information they need to participate meaningfully in decisions, undermining shared decision-making and patient-centered care.
- **Psychological and financial burdens:** The opacity of black-box systems can create anxiety, distrust, and confusion for patients and clinicians, and may lead to unnecessary tests or treatments driven by uncertainty, increasing emotional stress and health care costs.

Xu H, Shuttleworth KMJ. Medical artificial intelligence and the black box problem: a view based on the ethical principle of "do no harm." *Intelligent Medicine*. 2024;4(1):52-57.



ACCURACY & EXPLAINABILITY

Accuracy Concerns

There have been many concerns related to the use of AI tools due to several limitations:

- **Bias** – Models outputs reflect limited data that may not represent a wider population
- **Hallucinations** – Models produce outputs that are incorrect
- **Drift** – Models become divergent on their responses

What is Explainability?

Understood as a characteristic of an AI-driven system allowing a person to reconstruct why a certain AI came up with the presented predictions

- Essentially, do you understand the MOA of the AI model?

Issues:

- **Legal** – How much has to be exposed on MOA?
- **Regulatory** – What is governance and rules?
- **Medical** – Training and knowledge

Amann J, Blasimme A, Vayena E, Frey D, Madai VI; Precise4Q consortium. BMC Med Inform Decis Mak. 2020;20(1):310.; Sahiner B, Chen W, Samala RK, Petrick N. Data drift in medical machine learning: implications and potential remedies. *Br J Radiol*. 2023;96(1150):20220878.


THE PROBLEM WITH AI AND WORKFORCE

The more that a user off-loads tasks onto AI tools creates opportunities that can impact their training and skillset through lack of experience and internal data gathering and processing. The biggest concern in medical education is the impact on critical thinking, which will be more important in the era of AI.

Automation Bias	• **Overreliance on automated systems and risk of error** • Ex. CDSS makes dosing recommendation, provider defaults to EHR suggestions
Deskilling	• **Loss of previously acquired skill** • Ex. AI tool interprets EKG, provider losses ability to interpret
Never Skilling	• **Failure to develop essential competencies** • Ex. Student relies on Scribe for documentation, never develops skills to write documentation
Mis-Skilling	• **Reinforcement of incorrect behavior due to AI errors or bias** • Ex. AI tool triage system incorrectly flags patients for opioid abuse, putting select populations at risk for denial of care or lower health services

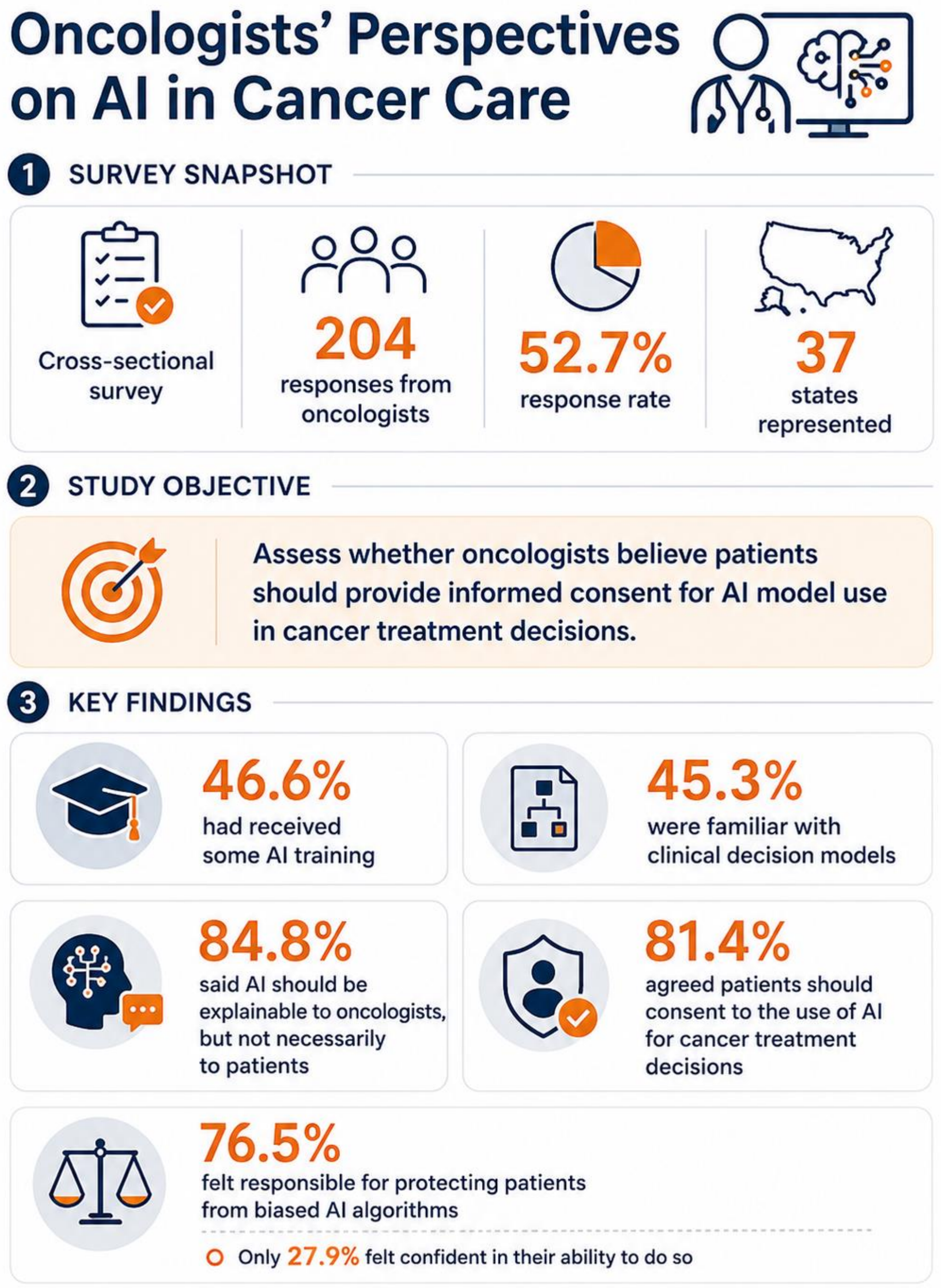
Abdulnour RE, Gin B, Boscardin CK. Educational Strategies for Clinical Supervision of Artificial Intelligence Use. N Engl J Med. 2025 Aug 21;393(8):786-797.

ETHICAL CONCERNS OF AI

Concerns Related to AI and Health Care:

- Data bias and model development
- Informed consent and transparency
- Patient privacy and data protection
- Allocation and fairness of use
- Liability and accountability
- Explainability

Currently, there is limited training on AI health ethics for health professionals.



Weidener L et al. JMIR Med Educ. 2024;10:e55368; Weidener L et al. Perspect Med Educ. 2023;12(1):399-410; Hasan HE et al. BMC Med Ethics. 2024;25(1):55.
Hantel A et al. JAMA Netw Open. 2024;7(3):e244077. -- Infographic created with ChatGPT 5.5, May 8, 2026

WE NEED TO KEEP THE HUMAN IN THE LOOP.

Governance of AI | Oversight of AI | Training and Deployment of AI Tools | Vendor Relationship and Product Management | AI Health Educators | And many more!

Jotterand F, Bosco C. Keeping the "Human in the Loop" in the Age of Artificial Intelligence : Accompanying Commentary for "Correcting the Brain?" by Rainey and Erden. Sci Eng Ethics. 2020 Oct;26(5):2455-2460. ; Bakken S. AI in health: keeping the human in the loop. J Am Med Inform Assoc. 2023 Jun 20;30(7):1225-1226.; For trustworthy AI, keep the human in the loop. Nat Med. 2025 Oct;31(10):3207.

FURTHER OPPURTUNIES FOR AI YOUR TRAINING

Setting the Bar with Learners
- Do you have a syllabus or learning statement regarding AI?
- Have you established what AI tools are appropriate to use?

Prompt Engineering
- Consider the creation of workshops or scenarios where learners can practice using AI tools

Librarians
- Consider working with your medical librarian on building AI knowledge banks or helping to create programs for staff and learners

AI Tool Onboarding
- If your organization uses AI tools who will onboard learners on how to use such tools?
- What are additional training that learners need with AI tools at your system?
- Are learners aware of PHI issues with any AI tools?
- Have you demonstrated how to use any AI tools or relevance to your training?

Promote AI Literacy
- Courses and teaching moments on evidence based evaluation of AI-tools and AI outputs with learners
- Create discussions regarding the regulatory concerns of AI tools and governance
- Evaluate ethical concerns related to AI, especially in ways to help mitigate bias that may harm a patient

ETHICAL CONCERNS
Data Privacy and Security
Algorithmic Bias and Fairness
Transparency and Explainability
Informed Consent
Liability and Accountability
Data Ownership

Abdulnour RE, Gin B, Boscardin CK. Educational Strategies for Clinical Supervision of Artificial Intelligence Use. N Engl J Med. 2025 Aug 21;393(8):786-797.

QUESTIONS?