



Achieving scale | Improving access & affordability | Improving quality

Use Case: Use of AI to Predict Donor Variability & Manufacturability for Ex-vivo CAR-T

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### Disclosures

The presenter has or had affiliations with the following entities related to this work:

Amazon Web Services (AWS)

OmniaBio Inc.

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### Leaning in with AI for personalized medicine

Since the CGT exuberant times of 2021, we now see 2025 funding tracking to the following

#### **Headwinds in CGT**

50% of start-up biotechs are failing to raise institutional seed funding, and then

50% of the seed funded start-ups are failing to raise a Series A

Running fast to get clinical data is showing many flaws in start-up's practices

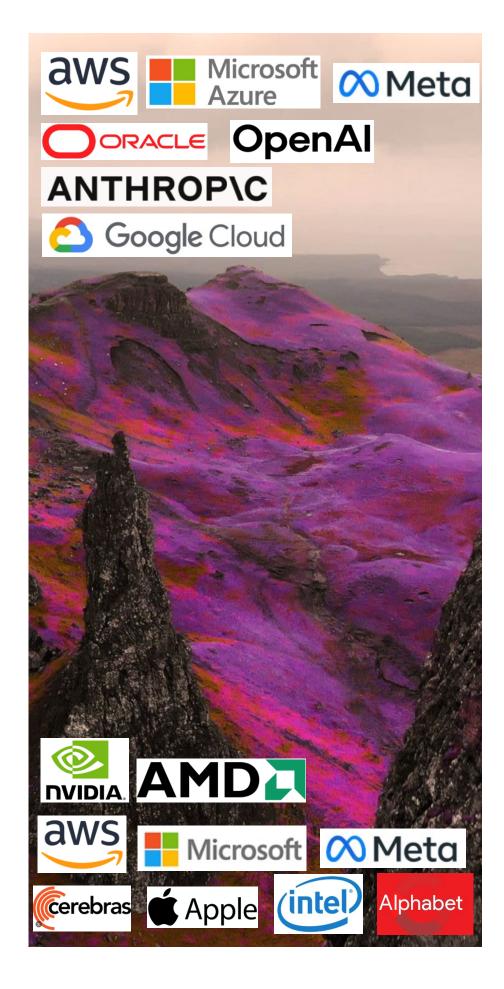
Prof. Dr. Wolfram Carius, EVP, Cell & Gene Therapy, Bayer

ARM, 2025 Meeting on the Mesa, Private Presentation

When approaching Bayer with a CGT therapy for investment, it is now fundamentally essential to **show the use** of artificial intelligence and data to drive prediction and analysis. Bayer will diligence this capability...... think about using AI with a few humans to do what 50 scientists would do 5 years ago.<sup>1</sup>



# The Allandscape



Follow the money not the naysayers

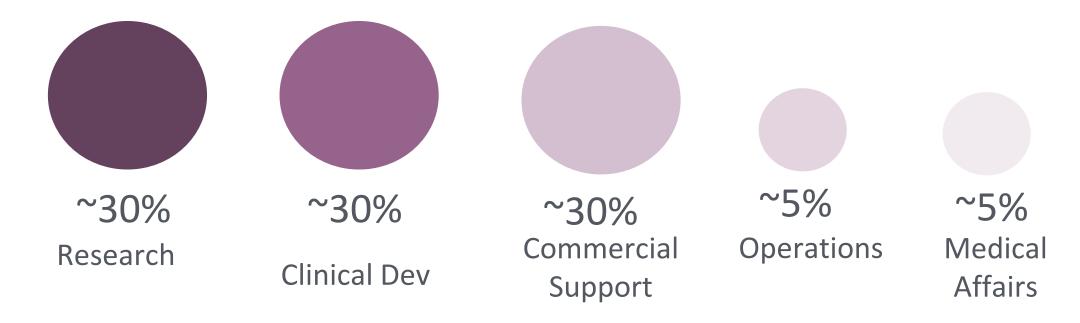
US\$ 1.2+ Trillion

US\$ 60-100 B

Non-exhaustive list; logos are Trademarks of the respective organizations

- Stargate \$500B
- Hyperscalers \$400B
- Sovereigns \$250B
- LLMs \$110B (excl. OpenAl which is Stargate)

#### Annual Value for AI in Pharma<sup>2</sup>





<sup>2025</sup> Committed Spend in Al Infrastructure<sup>1</sup>

<sup>&</sup>lt;sup>1</sup>Sources are SEC filings, press releases, public statements

<sup>&</sup>lt;sup>2</sup> McKinsey & Co 2024 White Paper, Generative AI in the pharmaceutical industry

### Focusing on autologous CAR-T

~11K Treatments in 2025



~3M Treatments by 2032 <sup>1</sup>



Total CAR-T Eligible Population	Approx Patients
North America	1,136,,000
EU + UK	1,385,000
Japan	370,000
Australia	77,000
TOTAL ESTIMATE	2,968,000

CAR-T Eligible by Indication Class	Approx Patients
Hem Onc	170,000
Solid Tumors	2,728,000
Autoimmune	70,000
TOTAL ESTIMATE	2,968,000

Access, Affordability, and Scale are Serious Blockers

Al Strategy Pro



# Autologous CAR-T Assessing Cost, Access, and Reimbursement

#### Patient Reimbursement & Hospital Burden

A Sankey graph helps visualize patient reimbursement buckets via DRGs

#### Identifying Barriers: Costs, Prescribing Rates, Reimbursement, Access, and Tx Toxicity

The visualization highlights major expense categories and barriers, revealing inefficiencies in resource allocation.

#### **Targeting Solutions using AI**

Mapping blockers by personas enables stakeholders to focus tools, systems, and processes that improve patient access (prescribing rates, cost, reimbursement, geography) and overall reduce healthcare costs.



Improve provider network so local geo therapy possible (toxicity, cost, training)



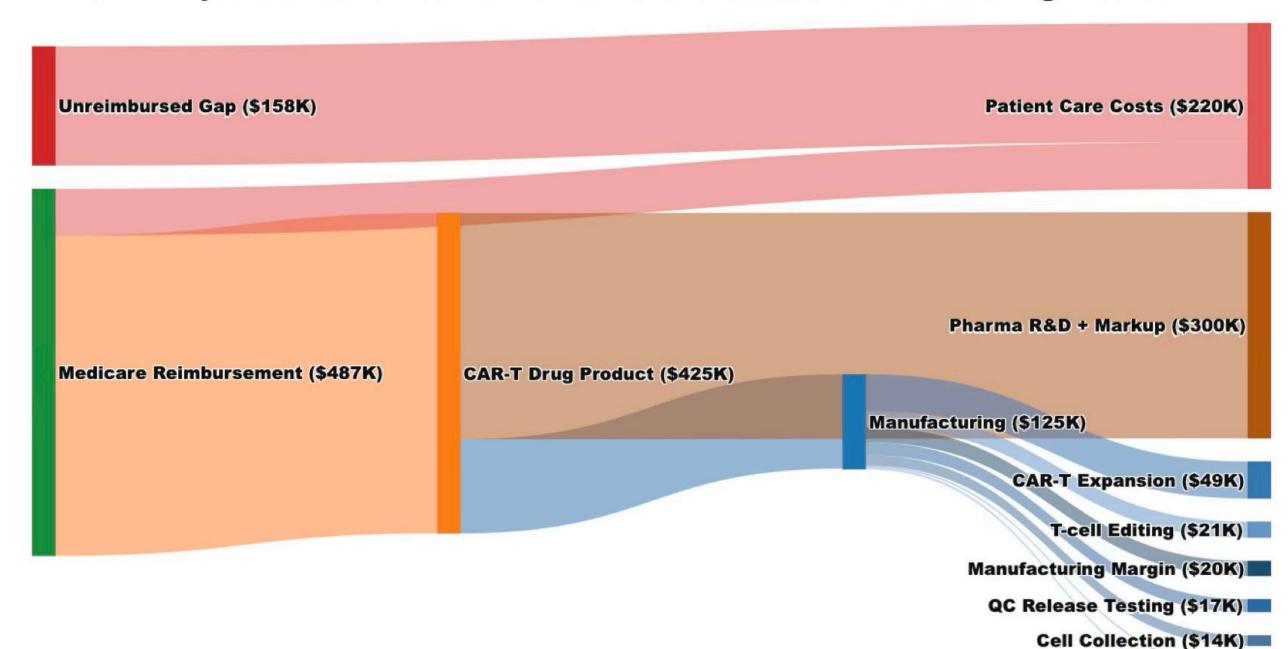
Reduce batch failure rates
Reduce cost and time to manufacture
Improve cold chain management
Improve manufacturing capacity



Improve predictive models in the EMR to aid in prescribing
Improve Care Pathways in EMR to handle Adverse Events
Improve batch failure rates
Reduce toxicity
Reduce cost/ Improve reimbursement / Reduce Pre-Authorization Burden

#### Patient Requiring Inpatient Management<sup>1</sup>

#### CAR-T Inpatient Economics: Reimbursement vs. Costs and Manufacturing Breakdown



#### <160 clinical sites in USA

<30% of eligible patients receive Rx



Fill & Finish (\$2K)

Drug Shipment (\$3K)

<sup>&</sup>lt;sup>1</sup> Internal modeling; published DRG; Hospitalization rates from multiple publications

### Focusing on autologous CAR-T

■ Solid Tumors

Autoimmune

~10K Treatments in 2025

~2.7M

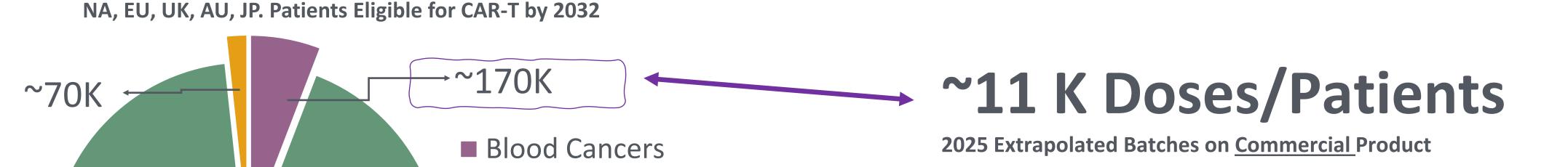


~3M Treatments by 2032



Up to 25% of cancer patients fail to produce an "in-spec" CAR-T drug product <sup>1</sup>

<sup>1</sup> Baguet et al, Early predictive factors of failure in autologous CAR T-cell manufacturing, Blood Advances, Jan 2024





### Focusing on autologous CAR-T

(1) ~10K Treatments in 2025

~3M Treatments by 2032

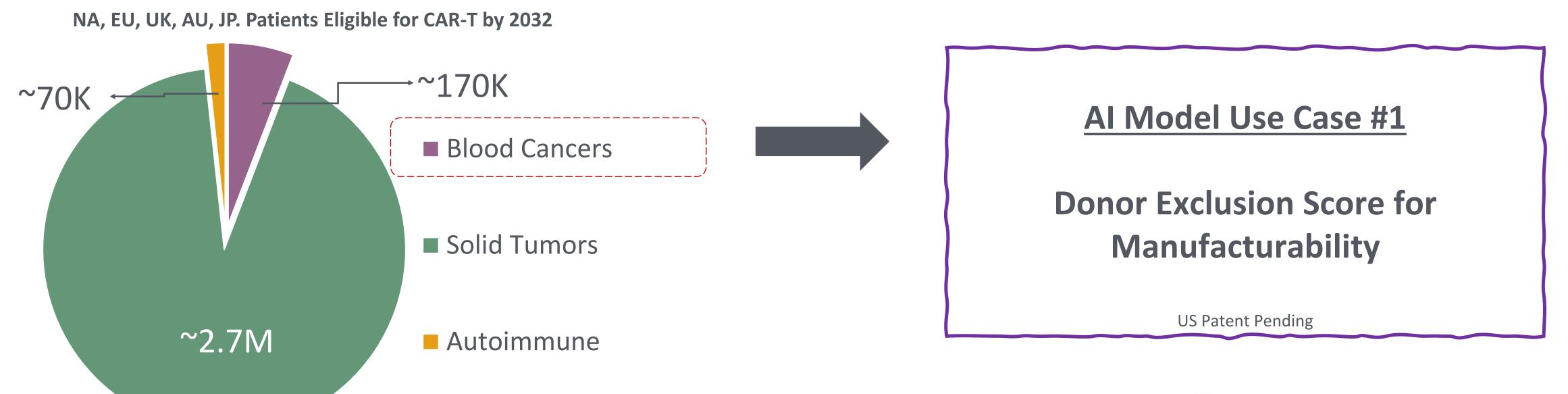


(2) Up to 20% of cancer patients fail to produce an "in-spec" CAR-T drug product



Failed batches consume manufacturing capacity, contribute to higher overall costs, and erode patient and clinician confidence







## Prediction of donor manufacturability

#### Autologous CAR-T: Assessing pre-apheresis/pre-lymphodepletion t-cells

#### **GOAL:**

To predict whether a patient's t-cell population (pre-apheresis/pre-lymphodepletion) can expand into an **in-specification** drug dose post CAR transduction. Goal is to achieve an AUC of 0.8.

#### **BENEFIT:**

Will aid the patient, clinician, and manufacturer in assessing the likelihood of a successful CAR-T manufactured dose to meet the IND/BLA specification criteria. (note, this does not predict efficacy)

#### METHOD:

Uses an **artificial intelligence modular platform** (machine learning algorithms and neural networks) based on molecular readouts and historical clinical responses to predict t-cell expansion capability.



1 DATA



Public Datasets (Hem Onc Pre infusion, Clinical)
Public Datasets (Human t-cell transcriptomes)
Confidential Datasets (Hem Onc Pre infusion, Clinical, Manufacturing Outcomes)



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2 PREPROCESSING



Data Cleaning
Feature Extraction
Annotation/Labeling



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2 PREPROCESSING



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MODEL DEVELOPMENT



Inferencing (Regression analysis, decision trees, random forest, etc)
Multimodal
Fine Tuning



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2 PREPROCESSING



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MODEL DEVELOPMENT



Inferencing (Regression analysis, decision trees, random forest, etc) Multimodal Fine Tuning

PREPARE for VALIDATION



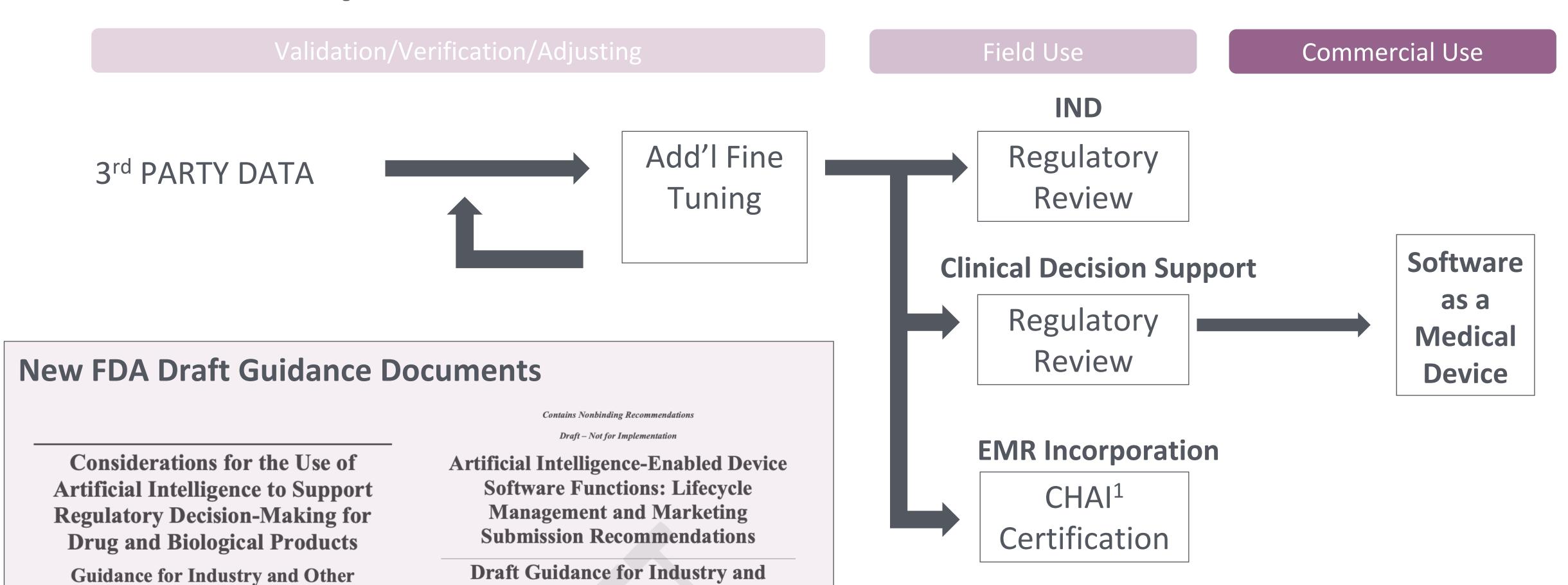
Preliminary prediction value is 0.88 [exceeds our goal]
Testing model with "wild type" data



### Next Steps

**Interested Parties** 

DRAFT GUIDANCE

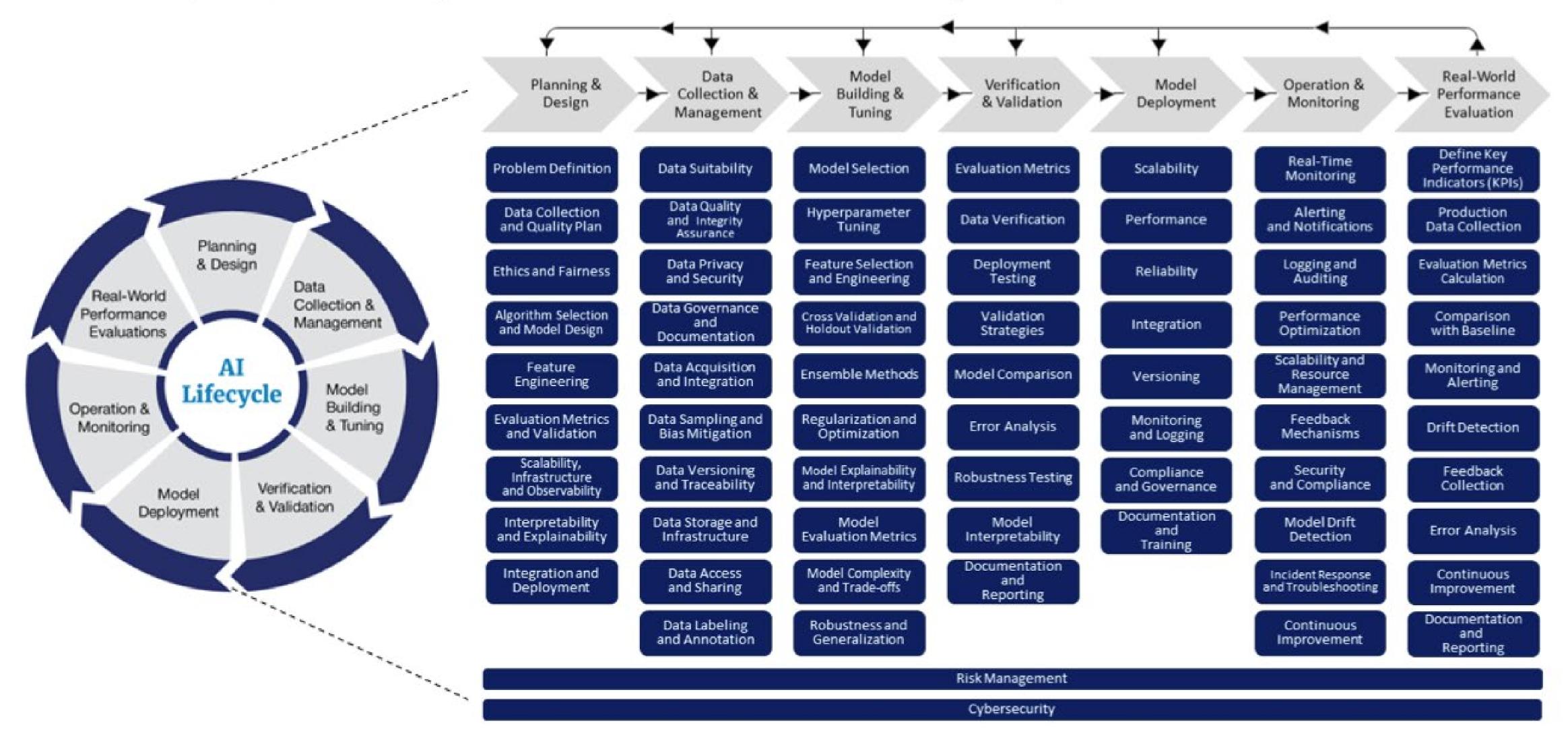


Food and Drug Administration Staff

DRAFT GUIDANCE

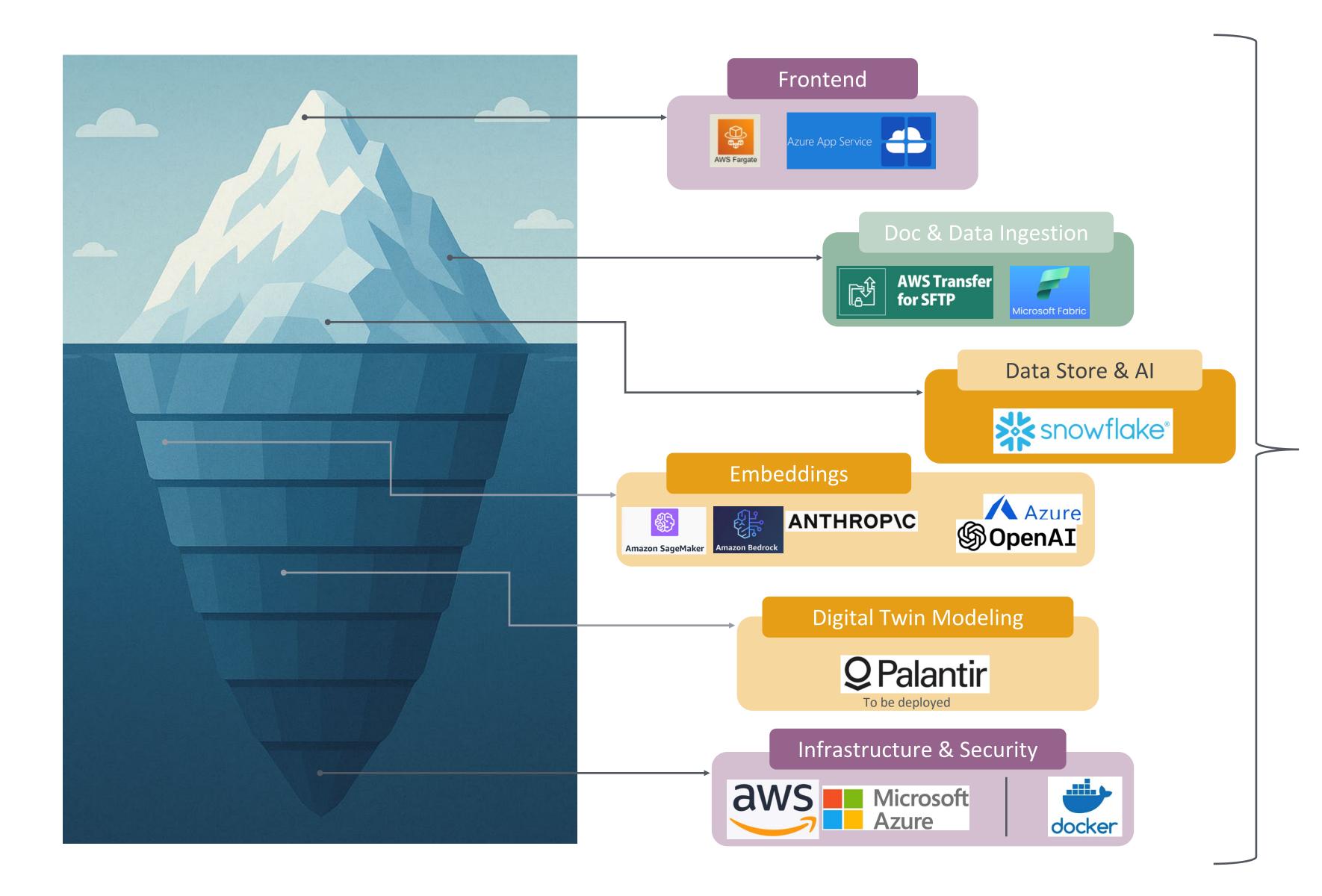
<sup>&</sup>lt;sup>1</sup> CHAI is the Coalition for Health AI offering Assurance Certification for health AI solutions. www.chai.org

#### The AI Lifecycle expanded to illustrate per-phase considerations



https://www.fda.gov/medical-devices/digital-health-center-excellence/blog-lifecycle-management-approach-toward-delivering-safe-effective-ai-enabled-health-care

### Overview of the IT infrastructure



Secured Cloud Infra.

Multicloud

**US HIPAA Compliant** 

IAM

### Thank You

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