Superintelligenz im Gesundheitswesen

Wie intelligente Daten die Patientenversorgung verändern

Dr. André Baumgart

November 04th, 2025

Handelskammer Deutschland Schweiz
Ihr Wirtschaftsnetzwerk D-CH

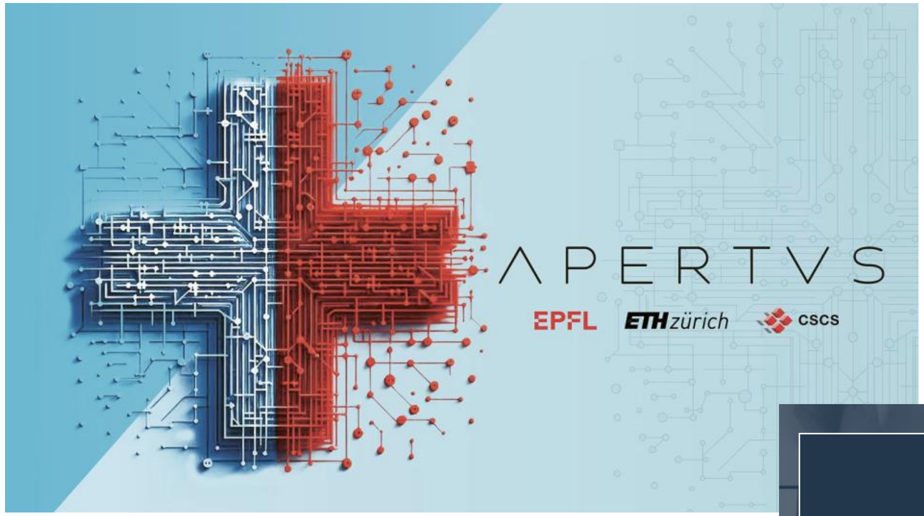
Fachsymposium Gesundheitswesen | Zürich

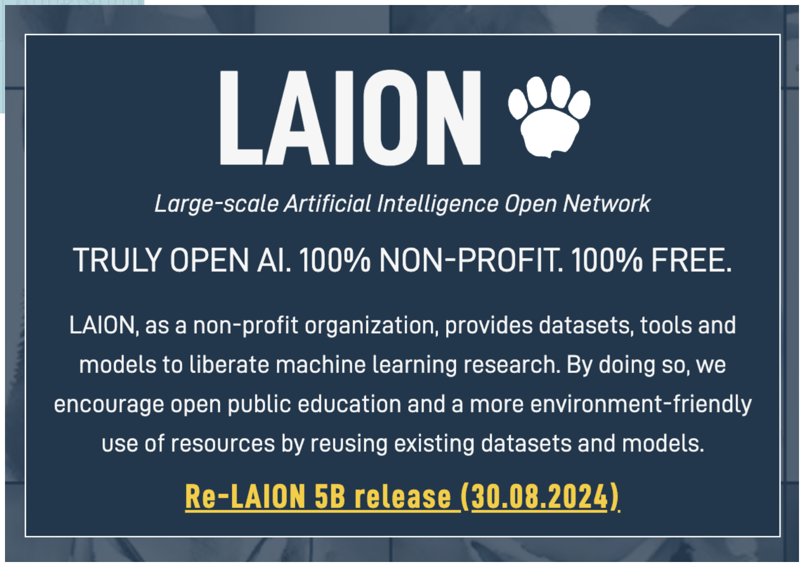
The AI Hype ...

Your Opinion.

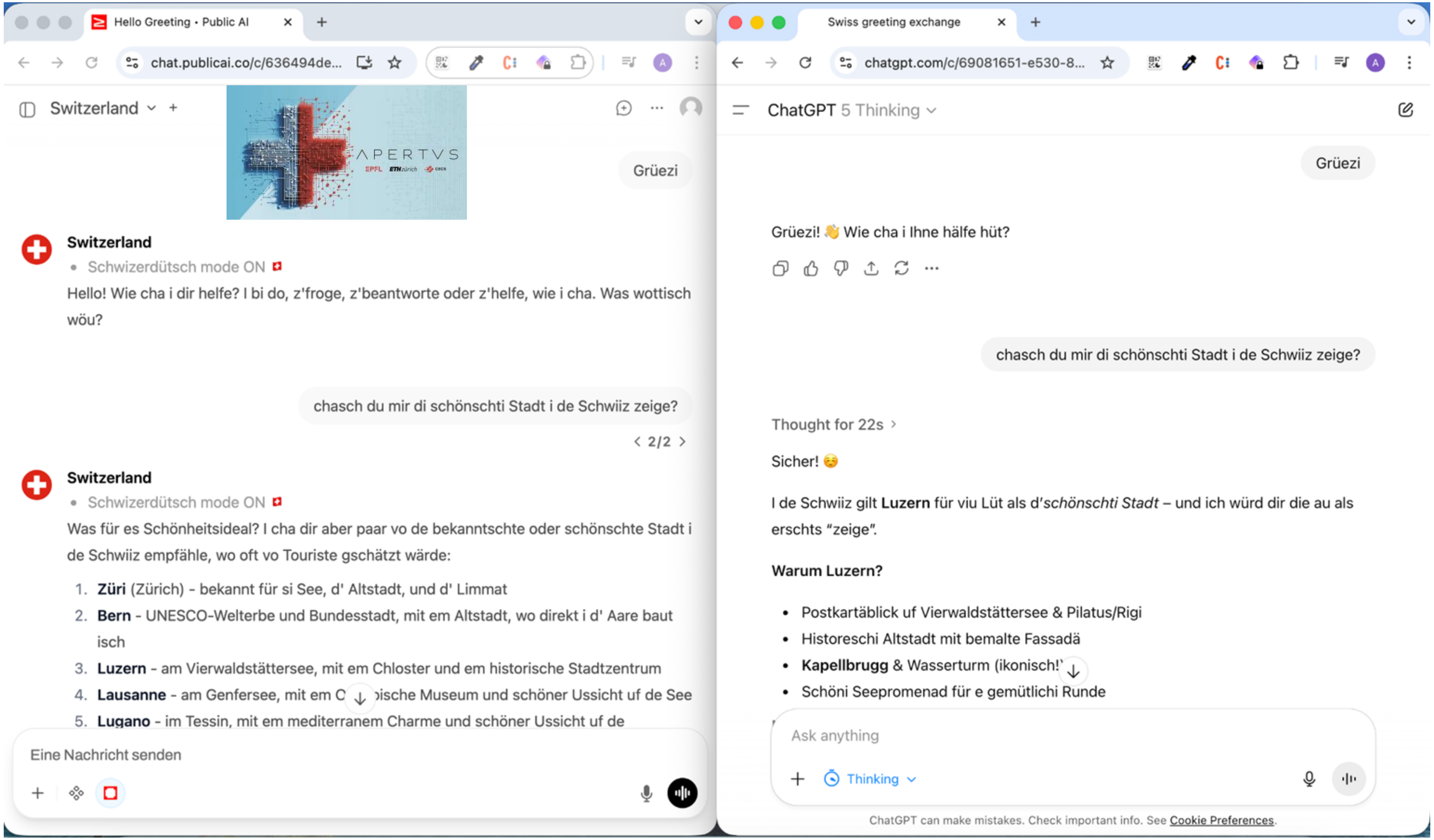
Superintelligence …

?

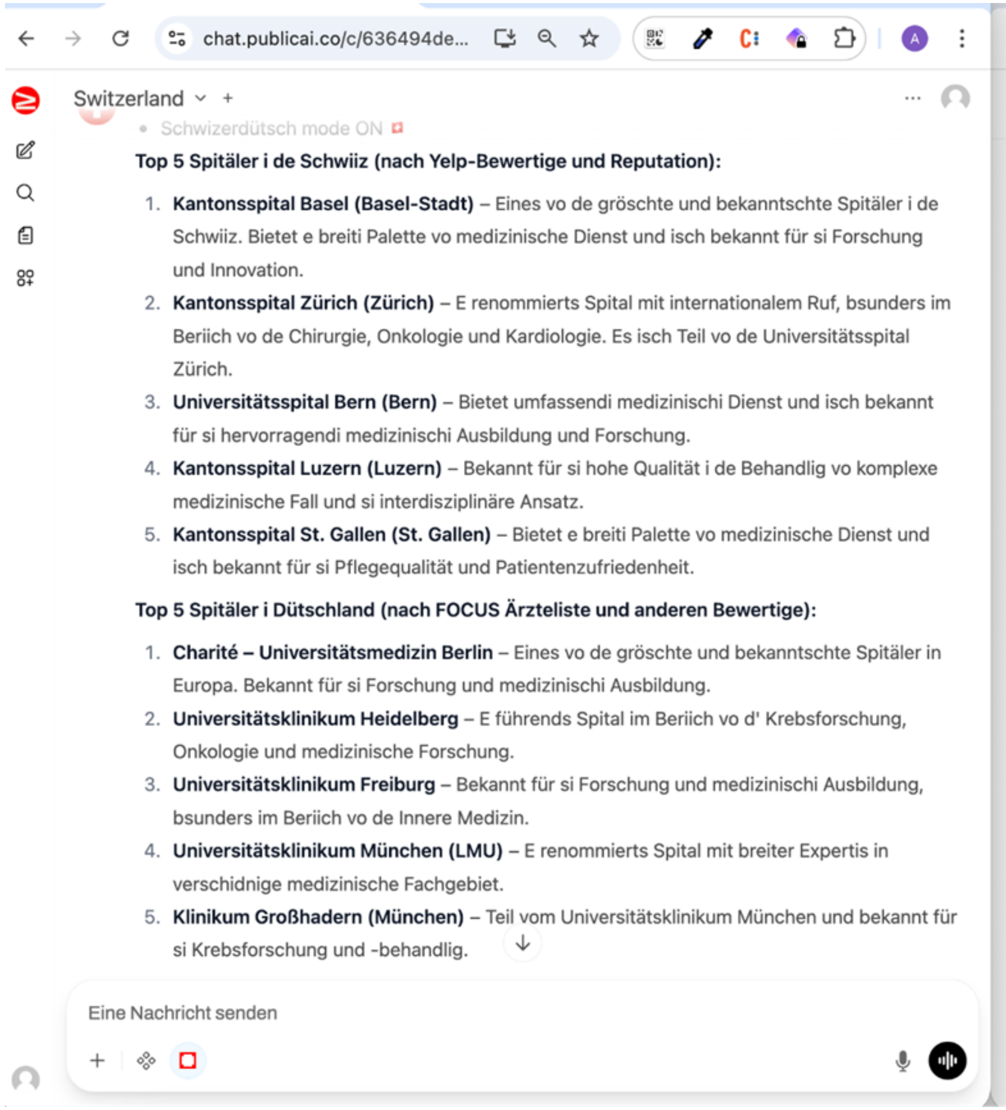


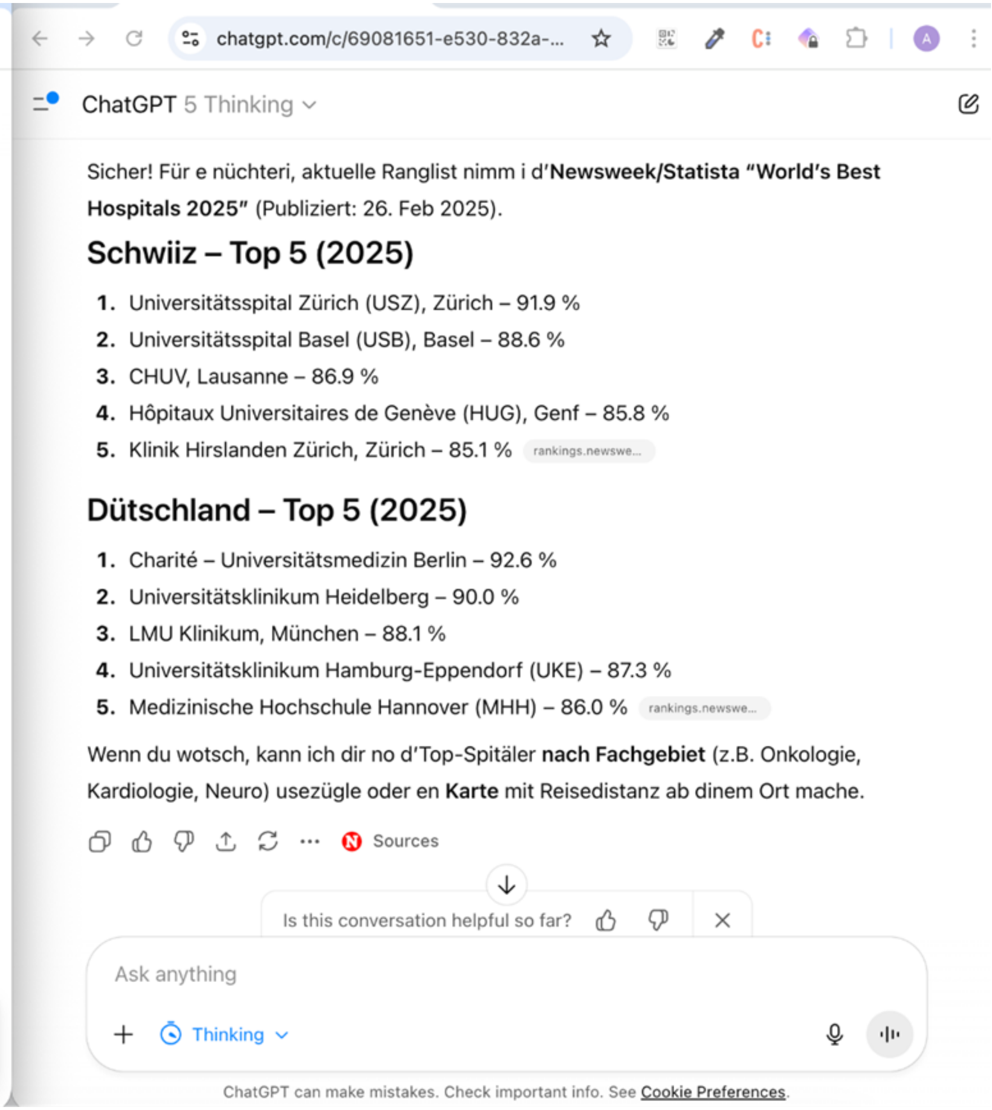


Superintelligence …



Superintelligence …

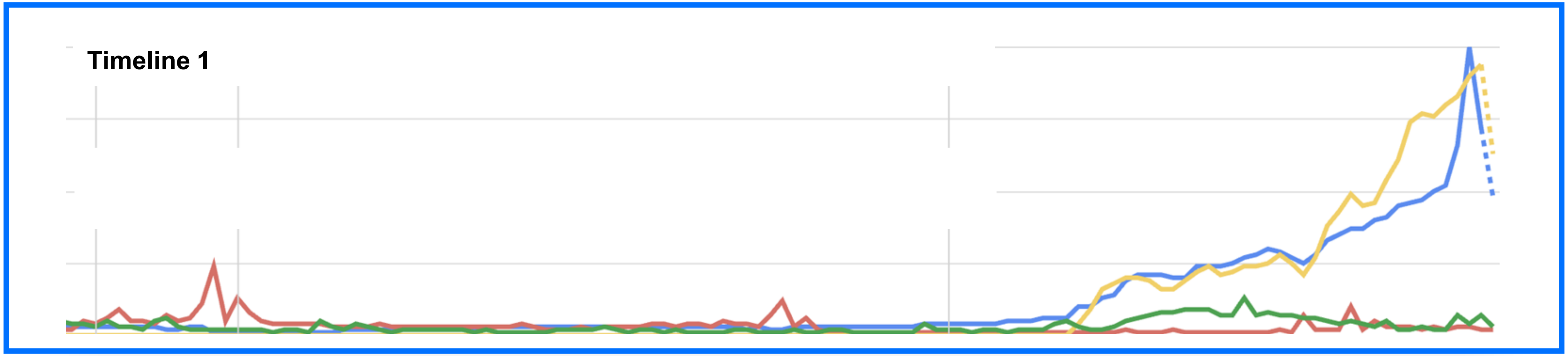


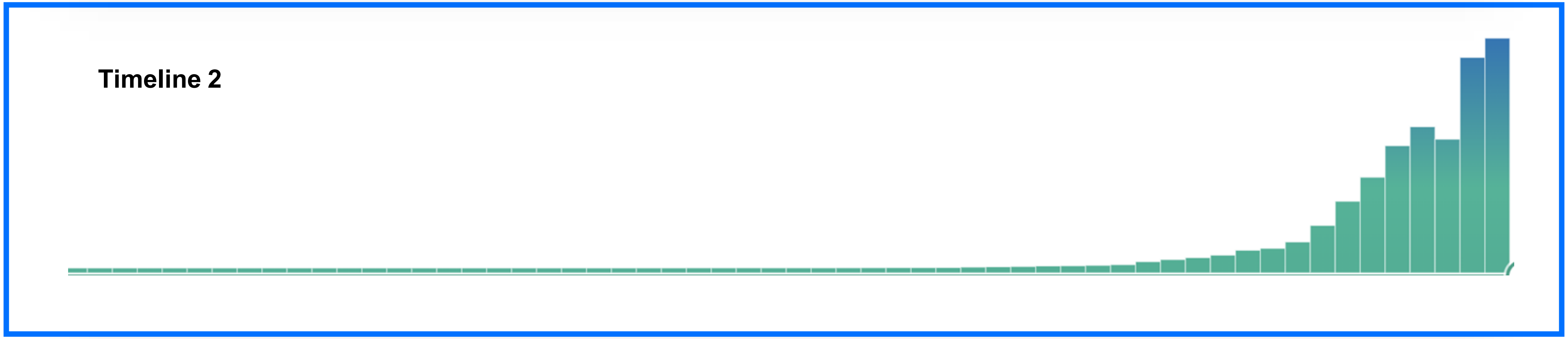


AI and Health: State of the art?

Your Opinion.

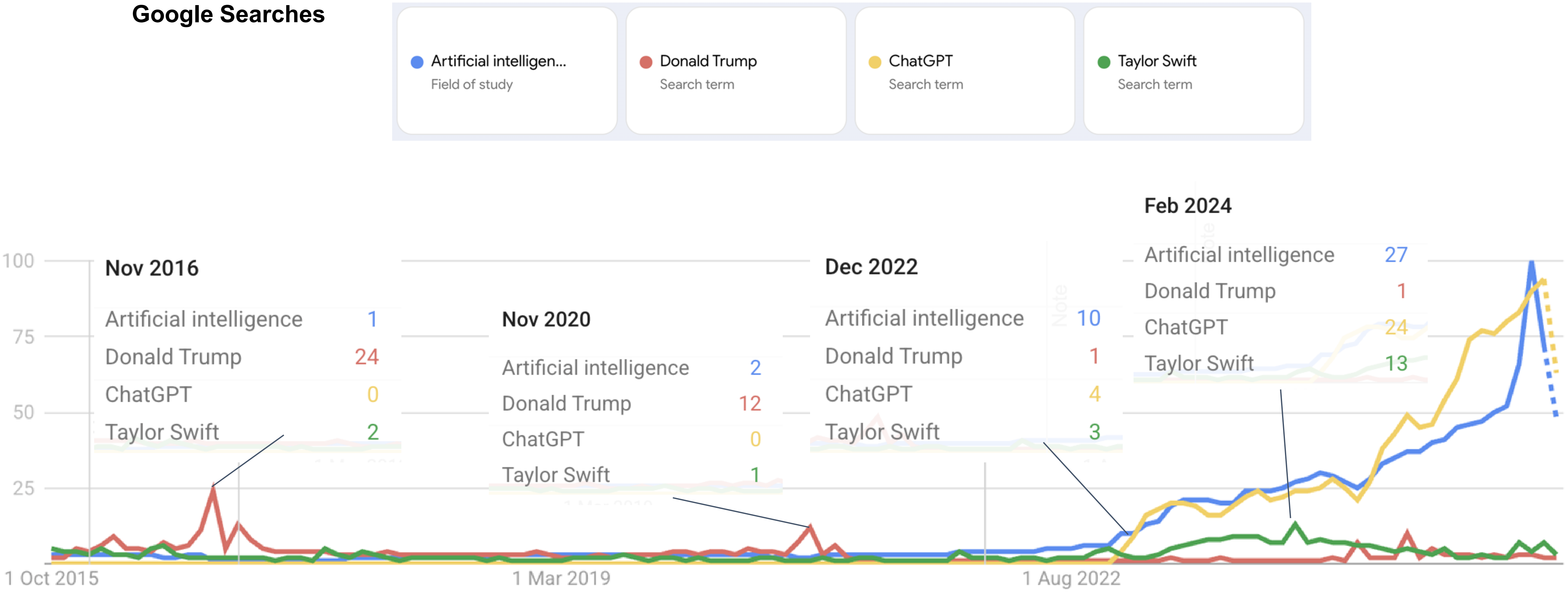
Evolution of AI … ?



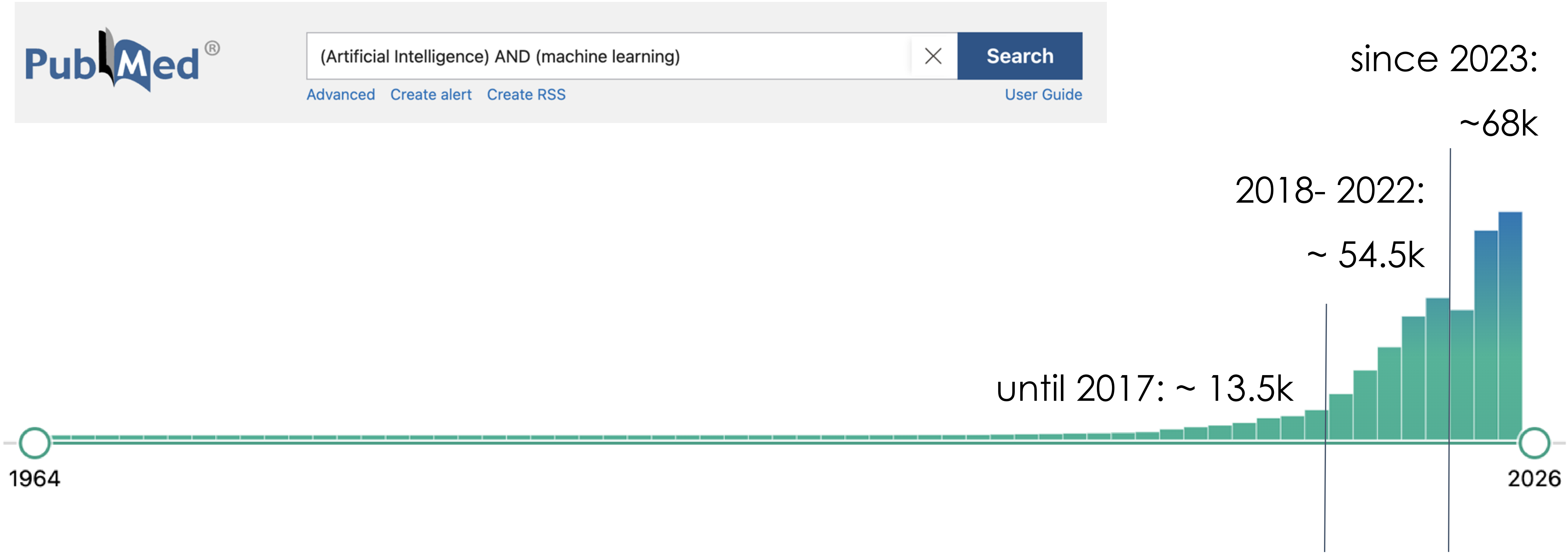


Explosion of AI

Google Searches



Explosion of AI



The foundation of GPT - 2017

Attention Is All You Need

Ashish Vaswani[*] Google Brain avaswani@google.com

Noam Shazeer[*] Google Brain noam@google.com

Niki Parmar[*] Google Research nikip@google.com

Jakob Uszkorei Google Researc usz@google.co

Llion Jones[*] Google Research llion@google.com

Aidan N. Gomez[* †] University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser[*] Google Brain lukaszkaiser@google.com

Illia Polosukhin[* ‡] illia.polosukhin@gmail.com

Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

[*]Equal contribution. Listing order is random. Jakob proposed replacing RNNs with self-attention and sta the effort to evaluate this idea. Ashish, with Illia, designed and implemented the first Transformer models has been crucially involved in every aspect of this work. Noam proposed scaled dot-product attention, multi-l attention and the parameter-free position representation and became the other person involved in nearly e detail. Niki designed, implemented, tuned and evaluated countless model variants in our original codebase tensor2tensor. Llion also experimented with novel model variants, was responsible for our initial codebase, efficient inference and visualizations. Lukasz and Aidan spent countless long days designing various parts of implementing tensor2tensor, replacing our earlier codebase, greatly improving results and massively accelera our research.

[†]Work performed while at Google Brain.

[‡]Work performed while at Google Research.

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

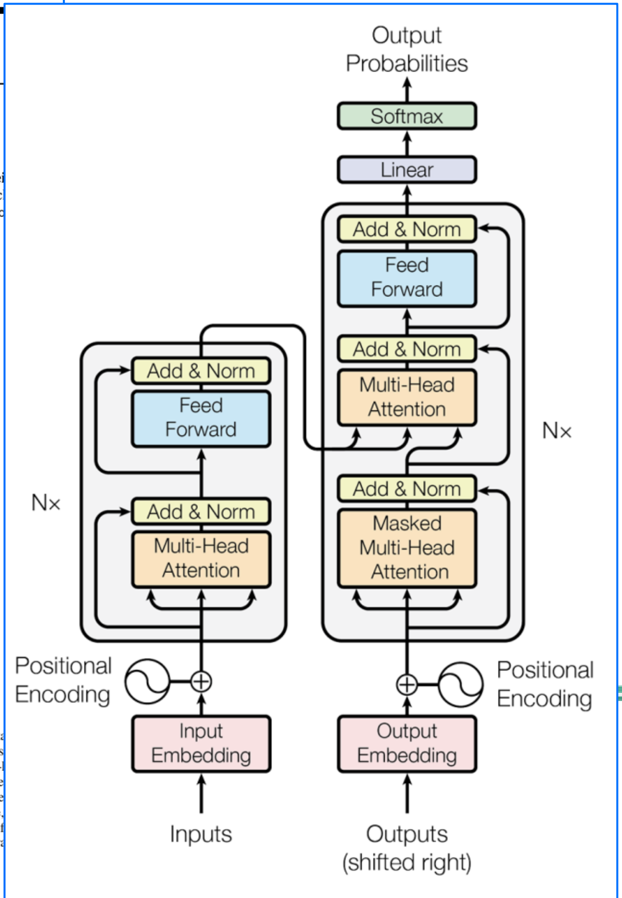
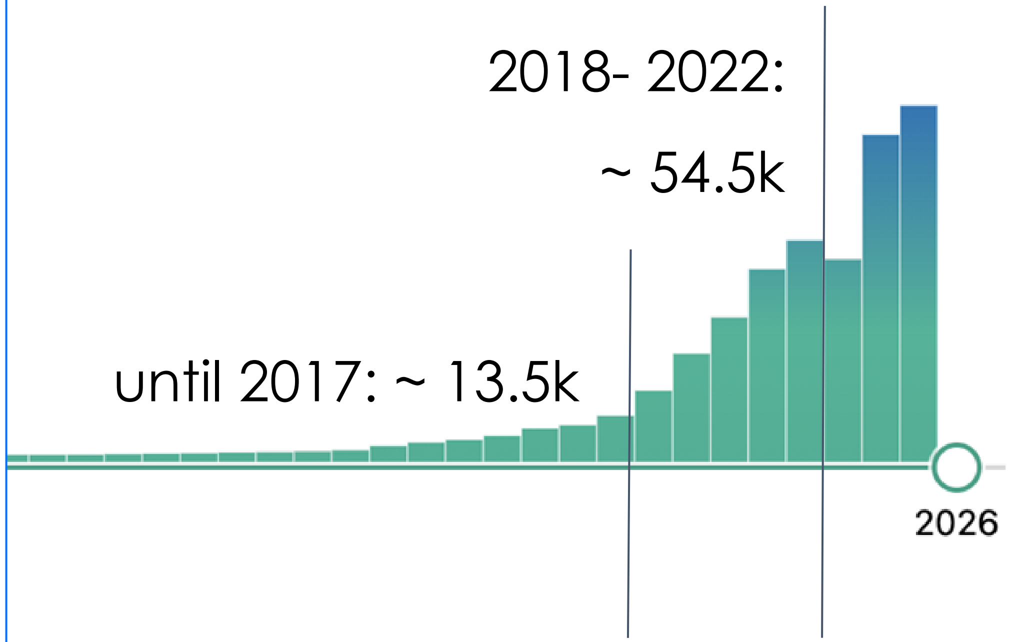


Figure 1: The Transformer - model architecture.



https://arxiv.org/pdf/1706.03762

Superintelligence is not present in healthcare today.

The field is advancing through increasingly sophisticated but still narrow AI systems, with ongoing research and implementation focused on augmenting — not replacing — human expertise

Before achieving superintelligence - if wanted at all -,
we need to solve fundamental challenges.

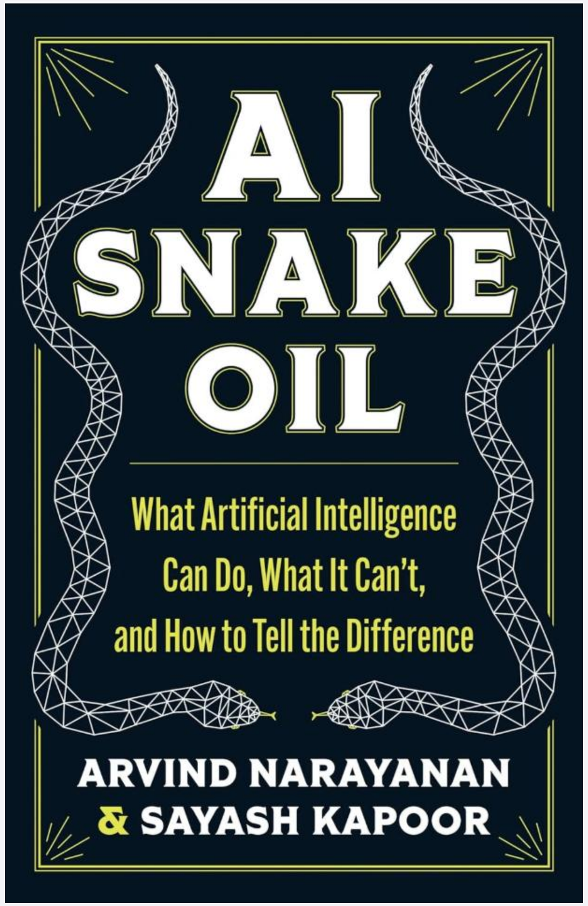
What is missing and needs to be done?

Content

1. From **Data** to **Intelligent Data**
2. From **Models** to **Compound AI Systems**
3. From **Mono-Modal** to (abstracted) **World Models**
4. From **Pilot Projects** to **Meta-Learning** Organisations

PROBLEM

AI in healthcare remains **limited** by challenges in **data quality**, **algorithmic bias**, **model interpretability** and **health system integration**, and the need for **robust clinical validation** and **regulatory oversight**.



Reference Architecture for AI in Medicine

Example: Perioperative and intensive care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Künstliche Intelligenz in der Intensivmedizin

André Baumgart[1] · Grietje Beck[2] · David Ghezel-Ahmadi[2]
[1] Zentrum für Präventivmedizin und Digitale Gesundheit, Medizinische Fakultät Mannheim Heidelberg, Mannheim, Deutschland
[2] Abteilung für Anästhesiologie, Intensivmedizin und Schmerzmedizin, Universitätsmedizin gGmbH, Medizinische Fakultät Mannheim der Universität Heidelberg, Mannheim, Deutsch

In diesem Beitrag

- Wertorientierte Patient Journey
  Versorgung von Intensivpatienten • Medizinische Systeme: Informationsmanagement
- Nutzen von KI: Leben retten und Outcomes verbessern
  Potenziale der KI in der Intensivmedizin • Aktuelle Anwendungsbereiche • Verbesserung der Effizienz durch generative KI
- Hochwertige Daten: Basis für die Entwicklung von KI
  Verfügbarkeit von Routinedaten durch Interoperabilität • Medizinische Datenbanken für KI
- Standards für die Forschungsbewertung
- Aus-, Fort- und Weiterbildung: das KI-befähigte Gesundheitspersonal
- Regulatorische und legislative Grundlagen
  Vorschriften für Medizinprodukte • Artificial Intelligence Act und Sicherheitsstandards • Internationale Standards und Normen
- Schlussfolgerung und künftige Ausrichtung

Zusammenfassung

Die Integration von künstlicher Intelligenz (KI) in die Intensivmedizin zeigt i
Studien besonders in den Bereichen der prädiktiven Analytik, der Früherken
Komplikationen und der Entwicklung von Entscheidungsunterstützungssys
beachtliche Fortschritte. Die Hauptherausforderungen bestehen weiterhin
Verfügbarkeit und Qualität der Daten, der Reduzierung von Verzerrungen u
Notwendigkeit erklärbarer Ergebnisse von Algorithmen und Modellen. Met
Erklärung dieser Systeme sind essenziell, um Vertrauen, Verständnis und et
Überlegungen bei Gesundheitsfachkräften und Patienten zu stärken. Eine f
Ausbildung des medizinischen Personals in KI-Prinzipien, Terminologie, eth
Überlegungen und in der praktischen Anwendung ist für den erfolgreichen
von KI entscheidend. Die sorgfältige Bewertung der Auswirkungen von KI
Patientenautonomie und Datenschutz ist unabdingbar für deren verantwor
Nutzung in der Intensivmedizin. Hierbei ist die Balance zwischen ethischer
praktischen Erwägungen zu wahren, um eine patientenzentrierte Versorg
bei gleichzeitiger Einhaltung von Datenschutzbestimmungen zu gewährle
Eine synergistische Zusammenarbeit zwischen Klinikern, KI-Ingenieuren u
Regulierungsbehörden ist entscheidend, um das volle Potenzial der KI in d
Intensivmedizin zu realisieren und ihre positive Wirkung auf die Patientenve
zu maximieren. Zukünftige Forschungs- und Entwicklungsanstrengungen s
sich auf die Verbesserung von KI-Modellen für Echtzeitvorhersagen, die Ste
der Genauigkeit und des Nutzens KI-basierter Closed-loop-Systeme sowie
Überwindung ethischer, technischer und regulatorischer Herausforderunge
insbesondere bei generativen KI-Systemen, fokussieren.

Schlüsselwörter
Informationswissenschaften · Informationsmanagement · Maschinelles Lernen · Nat
Sprachverarbeitung · Klinische Entscheidungsunterstützung

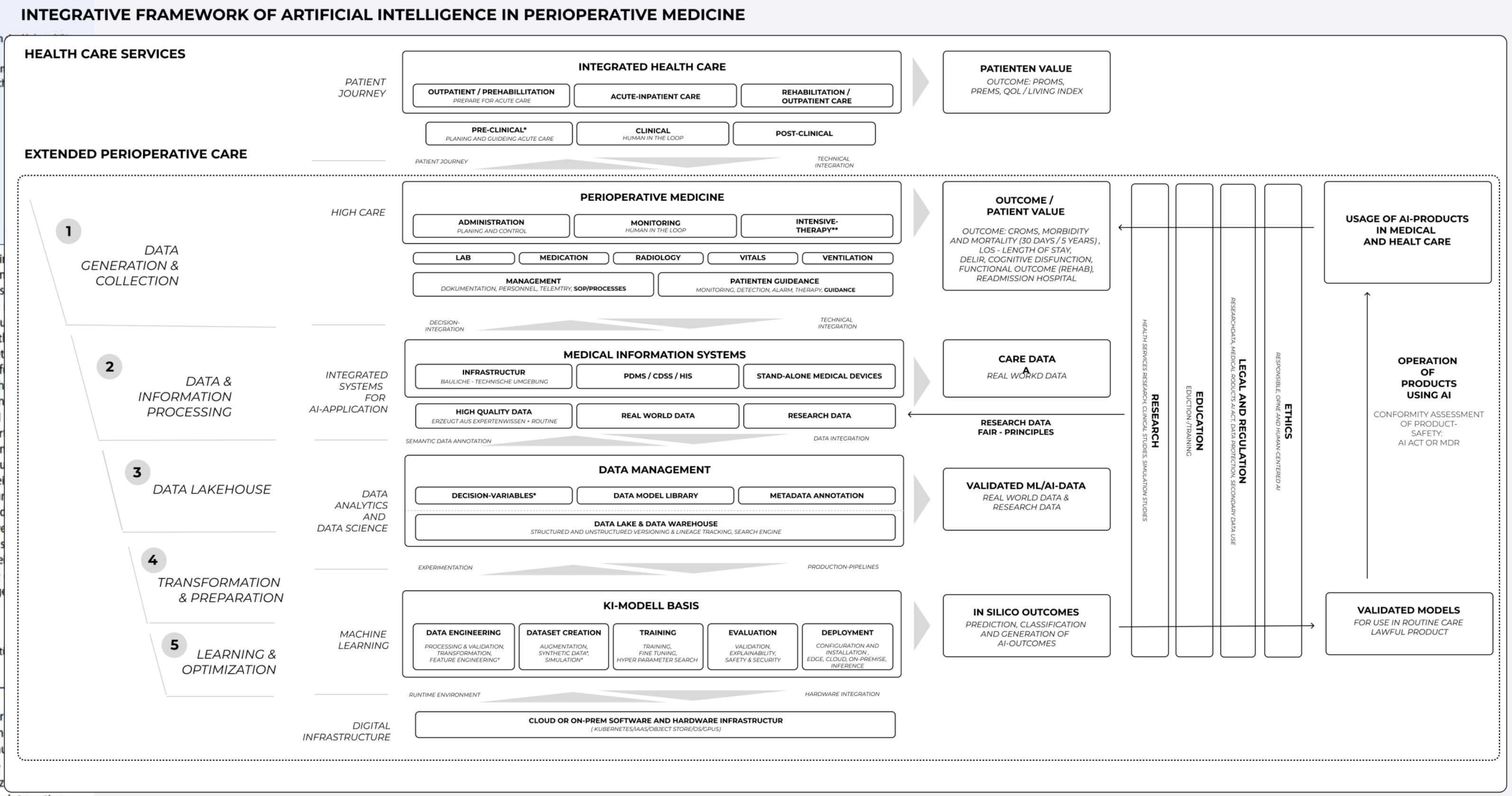
Hintergrund

Das Management einer Intensivstation (ICU) umfasst die Behandlung kritischer klinischer Zustände von schwer kranken Patienten, die schnelle, präzise und fundierte medizinische Entscheidungen erfordern. Innerhalb dieses anspruchsvollen Umfelds markiert die breite An-

wendbarkeit von künstlicher (KI) den Beginn einer neuen Patientenversorgung. Die KI au sivstation stellt eine nahtlose von datengesteuerter Mediz nischem Fachwissen dar. Die Integration von KI bietet eine noch nie dagewe sene Möglichkeit zur Verbesserung der Patientenergebnisse durch die Anwen-

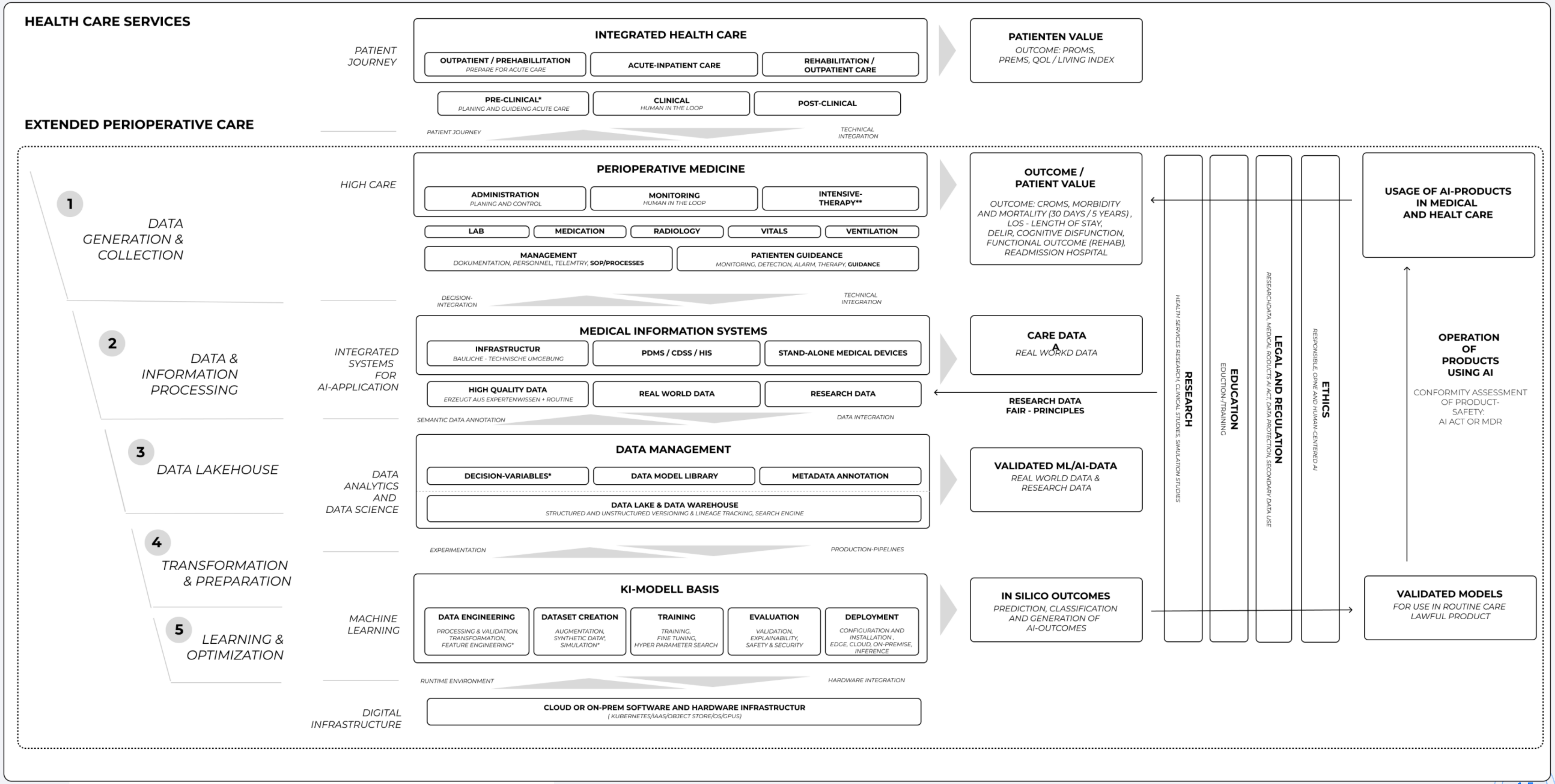
QR-Code scannen & Beitrag online lesen

Published online: 28 March 2024



*PRE-CLINICAL, CLINICAL AND POST-CLINICAL RELATE TO DIFFERENT STAGES OF ACUTE CARE - EXAMPLE: PRE-OPERATIVE, PERI-OPERATIVE AND POST-OPERATIVE
**PERIOPERATIVE CLINICAL CARE PRODUSES HUGA AMOUNT OF DATA FROM LAB-TESTING, MEDICATION, ETC. -- IN THE IMAGE 5 IMPORTANT DATA SOURCES ARE LISTED.

INTEGRATIVE FRAMEWORK OF ARTIFICIAL INTELLIGENCE IN PERIOPERATIVE MEDICINE



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Content

1. From **Data** to **Intelligent Data**
2. From **Models** to **Compound AI Systems**
3. From **Mono-Modal** to (abstracted) **World Models**
4. From **Pilot Projects** to **Meta-Learning** Organizations

From Data to Intelligent Data

The **transformation** of raw medical data into intelligent data involves a structured, multi-stage process that ensures data is not only accurate and usable but also FAIR (Findable, Accessible, Interoperable, Reusable).

This process enables effective leveraging of medical data for clinical decision-making, research, and innovation.

Data Pipelines - FAIRification

FAIR

Findable

Accessible

Interoperable

Reusable

FINDABLE

- F1: (Meta)data are assigned globally unique and persistent identifiers
- F2: Data are described with rich metadata
- F3: Metadata clearly and explicitly include the identifier of the data they describe
- F4: (Meta)data are registered or indexed in a searchable resource

ACCESSIBLE

- A1: (Meta)data are retrievable by their identifier using a standardised communications protocol
- A1.1: The protocol is open, free and universally implementable
- A1.2: The protocol allows for an authentication and authorisation procedure where necessary
- A2: Metadata should be accessible even when the data is no longer available

INTEROPERABLE

- I1: (Meta)data use a formal, accessible, shared, and broadly applicable language for knowledge representation
- I2: (Meta)data use vocabularies that follow the FAIR principles
- I3: (Meta)data include qualified references to other (meta)data

REUSABLE

- R1: (Meta)data are richly described with a plurality of accurate and relevant attributes
- R1.1: (Meta)data are released with a clear and accessible data usage license
- R1.2: (Meta)data are associated with detailed provenance
- R1.3: (Meta)data meet domain-relevant community standards

Source: GO FAIR – FAIR Principles (CC BY 4.0) — go-fair.org/fair-principles/

Data Pipelines - FAIRification

FAIR

Findable

Accessible

Interoperable

Reusable

Source 1: Classical Wrist Monitor

- **Raw Data**:
`{"systolic": 130, "diastolic": 85, "unit": "mmHg", "time": "2024-04-05T10:30:00Z", "device": "Omron HEM-7120", "position": "seated", "cuffSize": "medium"}`
- **Format**: Structured, standardized (FHIR `Observation` resource).
- **Provenance**: Device ID, calibration date, user ID, timezone.

Source 2: Smartphone Camera (Pulse Detection via Photoplethysmography)

- **Raw Data**:
`{"heartRate": 72, "signal": [1.2, 1.3, 1.1, ...], "timestamp": "2024-04-05T10:30:00Z", "device": "iPhone 14", "app": "Blood Pressure Monitor Pro", "method": "camera-based", "position": "lying", "skinTone": "light"}`
- **Format**: Unstructured time-series signal; inferred BP via AI model.
- **Provenance**: App version, sensor data, calibration method, user consent.

> **Key Difference**:
>
> - Wrist monitor → **Direct measurement** (clinical-grade).
> - Smartphone → **Indirect estimation** (AI-inferred, less validated).

Data Pipelines - FAIRification

FAIR

Findable

Accessible

Interoperable

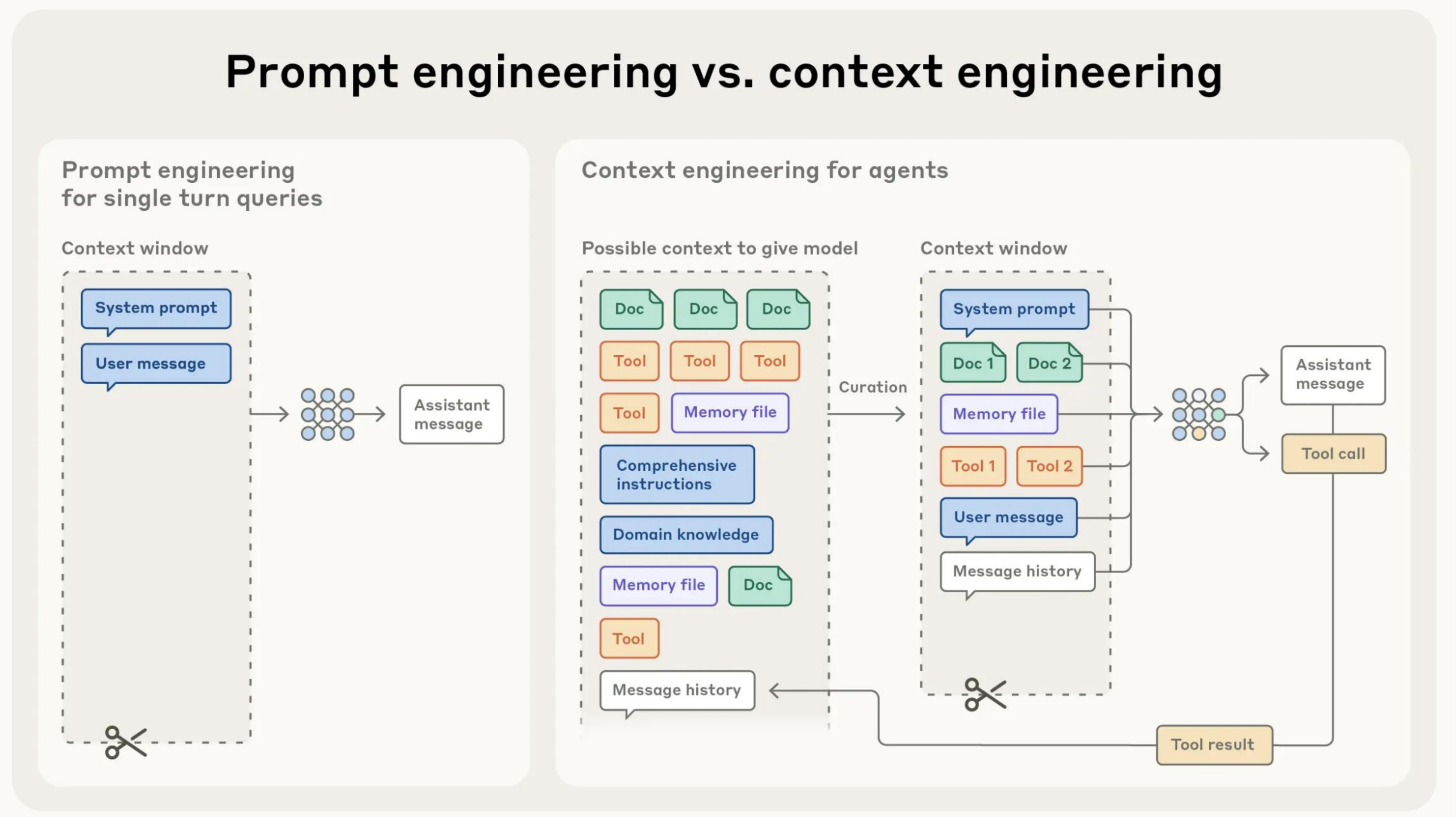
Reusable

FAIR Artefacts & Provenance

Artifact	Description	FAIR Compliance
FHIR Observation	Structured, machine-readable.	✅ Findable, Accessible, Interoperable
Provenance Metadata	Who, when, how, why?	✅ Reusable, Interoperable
Ontology Reference	SNOMED-CT, LOINC codes	✅ Interoperable
Data Model	OMOP CDM or FHIR	✅ Interoperable
Uncertainty Flags	Confidence levels, method notes	✅ Reusable
Persistent Identifiers	DOI for dataset, UUID for observations	✅ Findable, Reusable

Data Pipelines - Contextualization

Add additional information to provide further help to and optimize the models or search methods.



Data Matching: Train-Validate-Test-UseContext

Inference

Train **Validate** **Test** **Use Context**

Pre-Train **Finetine** **RL Learn** **Deployment**

Generative AI

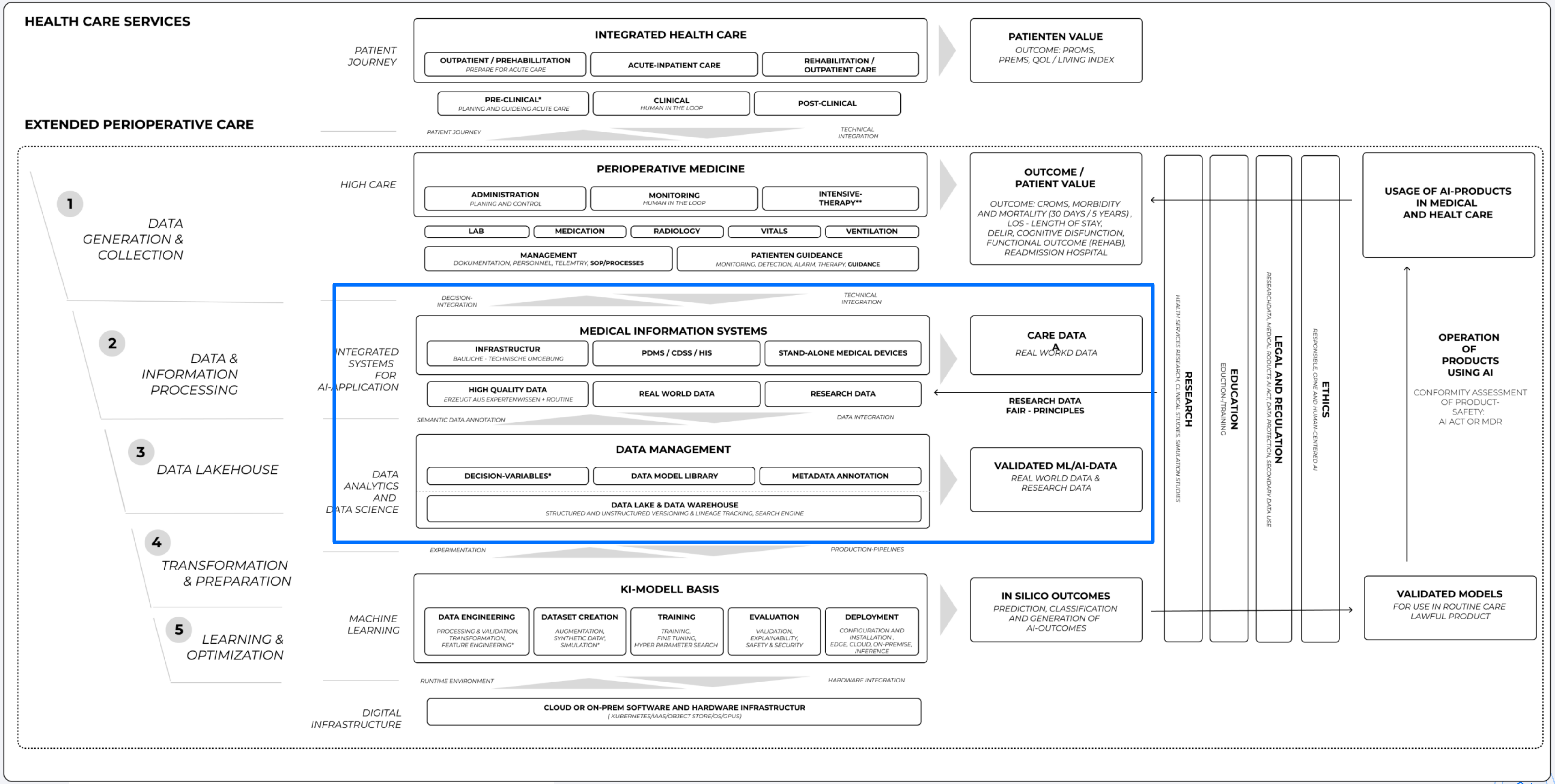
Data Matching: Train-Validate-Test-UseContext

Inference

Train	Validate	Test	Use Context
?	?	?	
Pre-Train	Finetine	RL Learn	Deployment

Generative AI

INTEGRATIVE FRAMEWORK OF ARTIFICIAL INTELLIGENCE IN PERIOPERATIVE MEDICINE



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Content

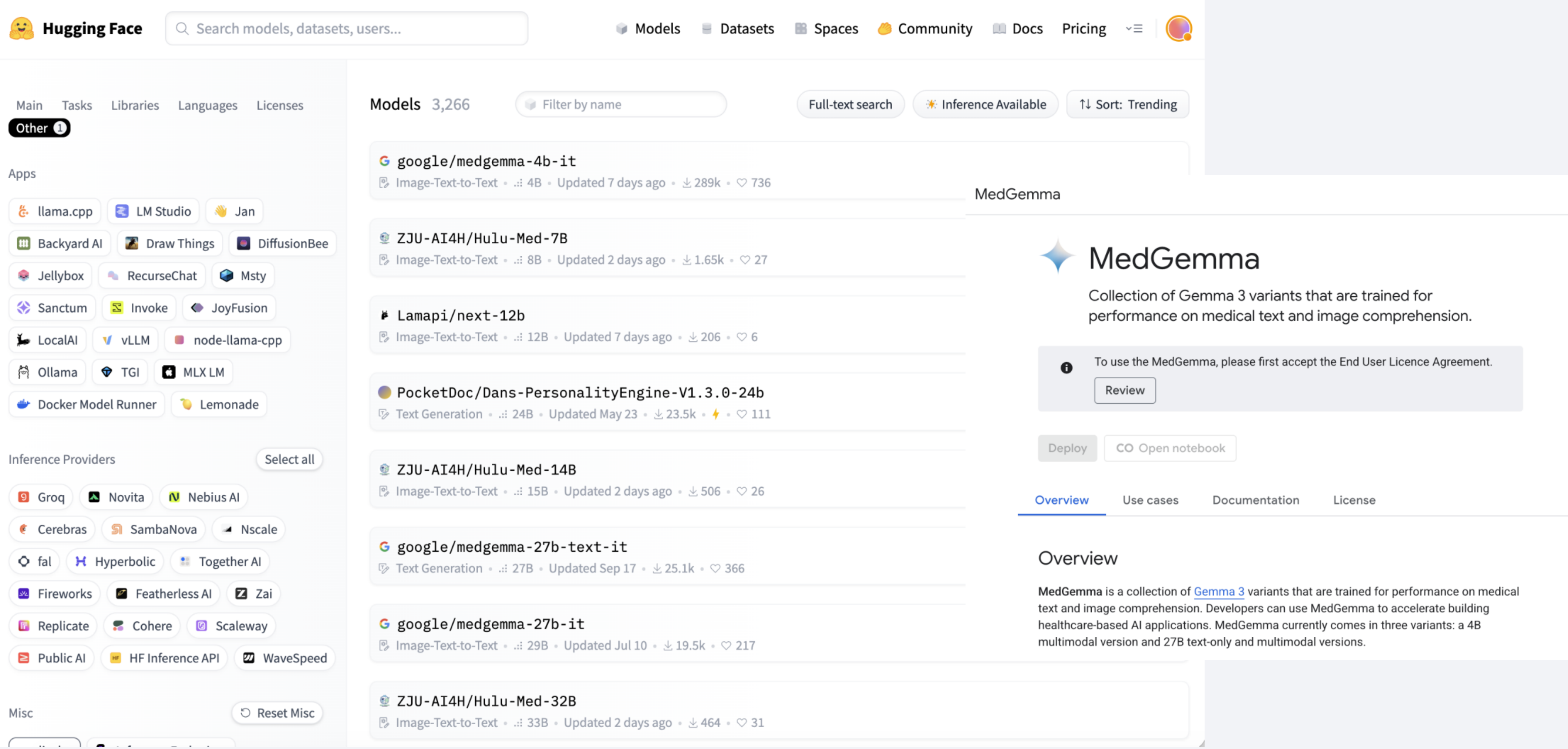
From Models to Compound AI Systems

The focus in AI is shifting from solely scaling Large Language Models (LLMs) to building compound AI systems.

These complex systems combine multiple components like LLMs, retrievers, and tools to achieve superior results.

Future AI progress increasingly depends on this system-level engineering approach.

Model Marketplace



Model Evaluation

Performance metric

Human-centered metrics: Patients, HCPs

Benchmark datasets and metrics

MLCOMMONS DATASETS

People's Speech

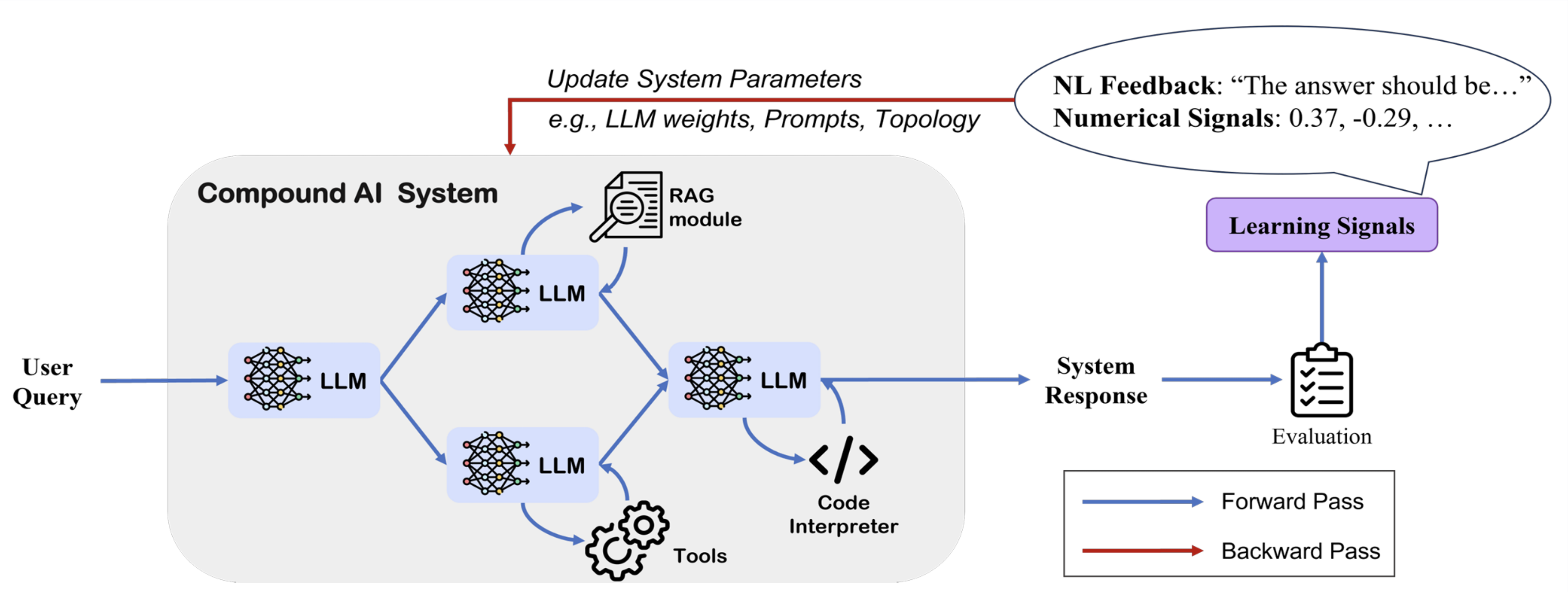
The MLCommons People's Speech dataset is among the world's largest English speech recognition corpus today that is licensed for academic and commercial usage under CC-BY-SA and CC-BY 4.0.

Domain	Recommended metric
Model performance & calibration	AUROC/AUPRC
	Accuracy
	Precision
	Recall
	F1-score
	Calibration (Brier score, ECE)
	Coverage/abstention rate for selective deferral
Clinical impact	Patient outcomes
	Condition-specific outcomes or PROs
	Diagnostic/triage concordance
	Time to treatment or appropriate referral
	Guideline-adherence delta
	Tests/visits avoided
Workflow efficiency	Task time per case
	Response/turnaround time
	Time-to-decision.
Usability & adoption	SUS or UMUX-Lite
	Perceived usefulness & ease-of-use (TAM)
	NASA-TLX (task load)
	% AI-assisted tasks
	Clinician reported task load
Reliability & monitoring	Rate of false negatives/positives
	Override rates
	Failure rate
	Latency
	Performance drift over time
	Post-deployment incident reports
	Rollback frequency
Deployment fidelity	User adherence to intended use rates
	Percentage of AI-assisted tasks
	Prompt/template adherence
	Version tracking
Generalizability	Cross-site performance variance
	Calibration curves
Safety & risk	Hallucination rate (overall and clinically significant)
	Harmful/unsafe recommendation rate
	Override rate (and appropriateness)
	Near-miss and adverse event counts
	Severity-weighted error index
	PHI leakage or privacy breach rate
	Alert-fatigue index

Artsi et. al. (2025) Large language models in real-world clinical workflows,.doi: 10.3389/fdgth.2025.1659134

Compound AI Systems

Today, all available platforms, e.g., Gemini, ChatGPT, are compound systems!

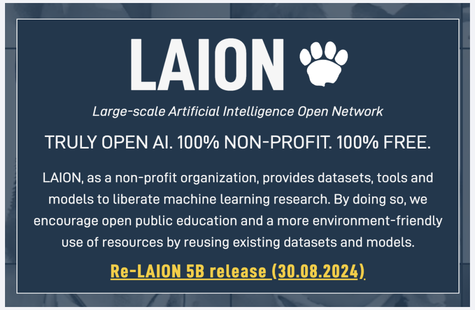


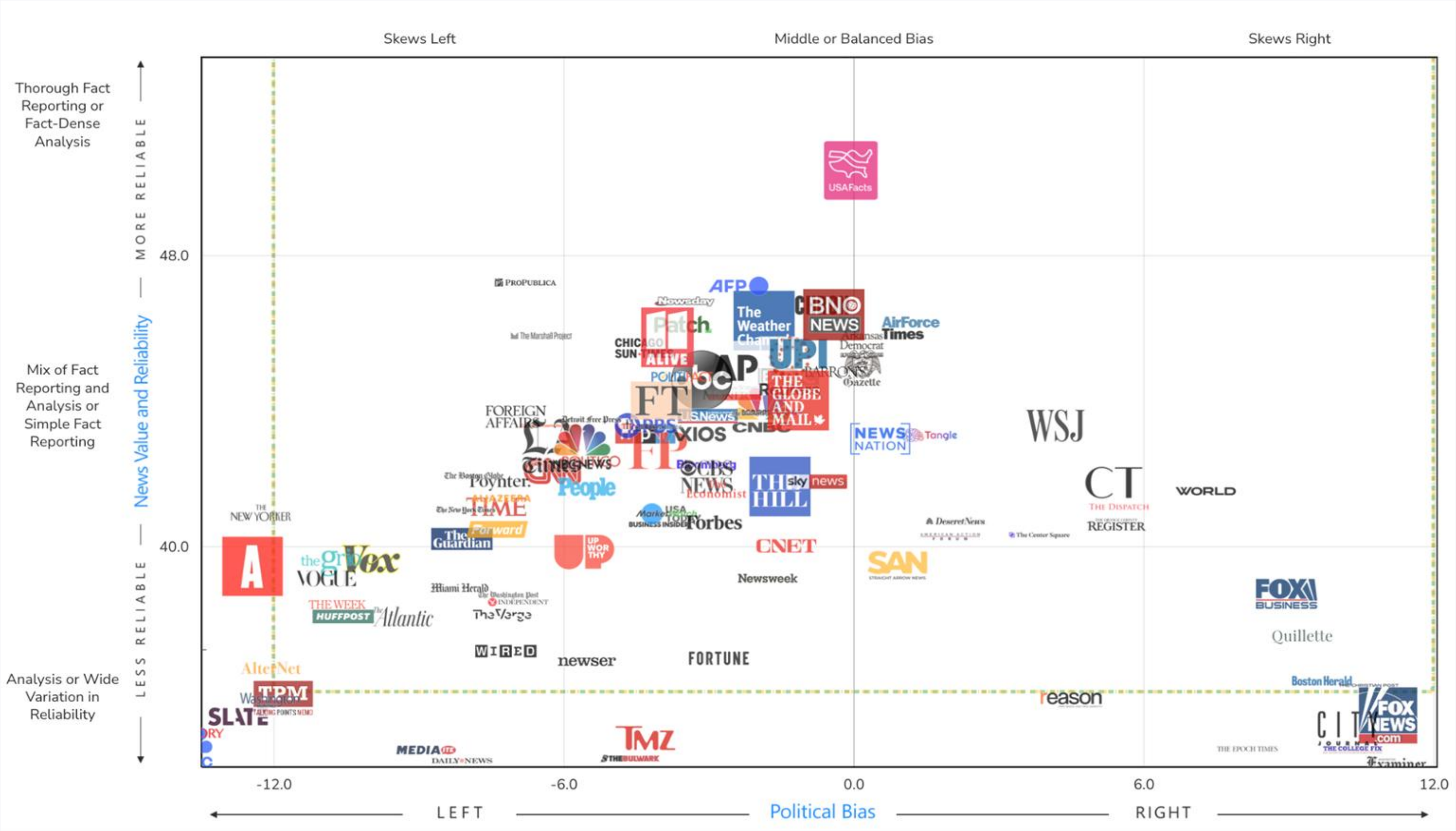
AI in Healthcare: Model Transparency

Media

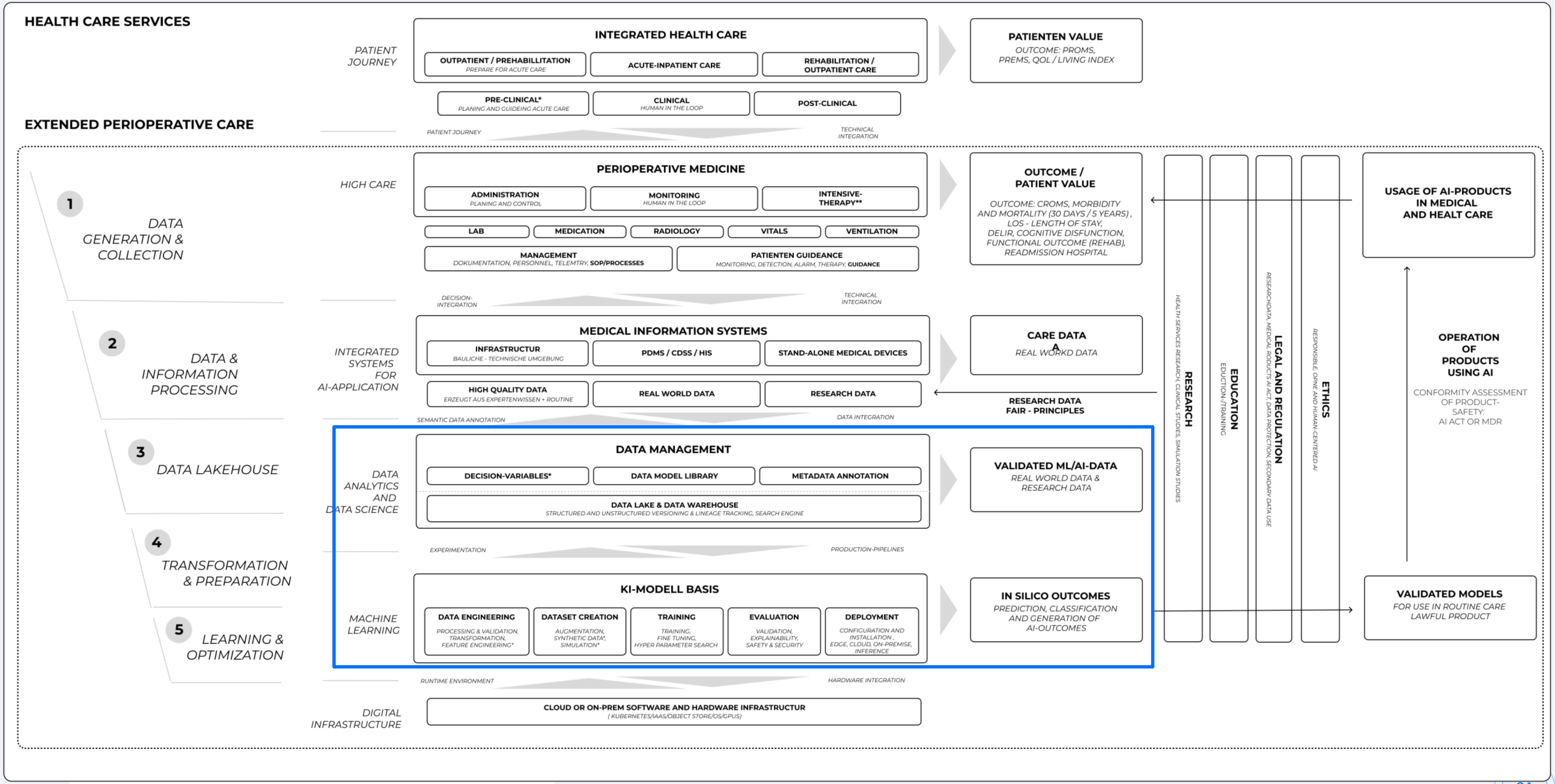
Open vs Close

Models





INTEGRATIVE FRAMEWORK OF ARTIFICIAL INTELLIGENCE IN PERIOPERATIVE MEDICINE



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From Mono-Modal to (abstracted) World Models

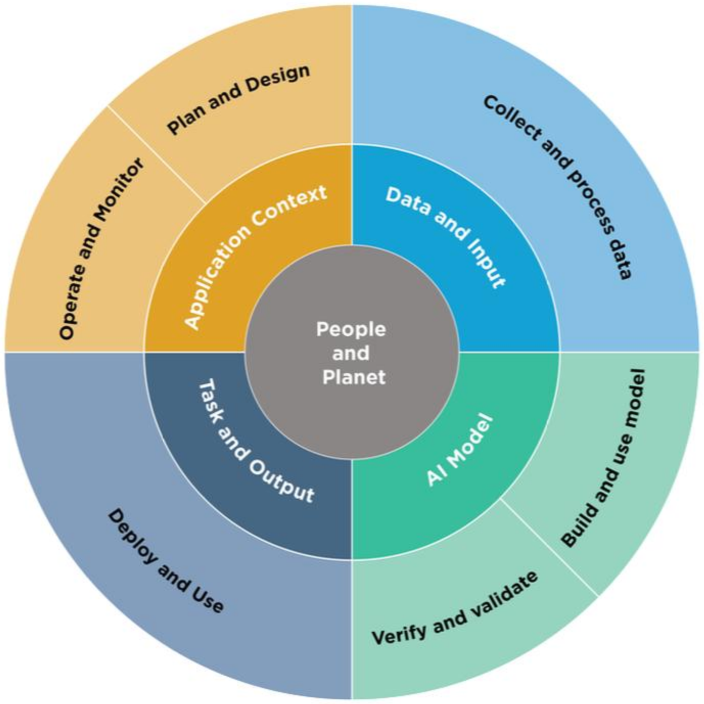

Fig. 2. Lifecycle and Key Dimensions of an AI System. Modified from OECD (2022) OECD Framework for the Classification of AI systems — OECD Digital Economy Papers. The two inner

Mono-Modal AI


nature medicine

Review article

https://doi.org/10.1038/s41591-025-03983-2

Generative artificial intelligence in medicine

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Published online: 06 October 2025

Check for updates

Zhen Ling Teo[1,2,15], Arun James Thirunavukarasu[3,15], Kabilan Elangovan[1,2], Haoran Cheng[1,4], Prasanth Moova[1,2], Brian Soetikno[5], Christopher Nielsen[6], Andreas Pollreisz[1,7], Darren Shu Jeng Ting[1,4,8,9,10], Robert J. T. Morris[11,12], Nigam H. Shah[13], Curtis P. Langlotz[14] & Daniel Shu Wei Ting[1,2,5]

Generative artificial intelligence (GAI) can automate a growing number of biomedical tasks, ranging from clinical decision support to design and analysis of research studies. GAI uses machine learning and transformer model architectures to generate useful text, images and sound data

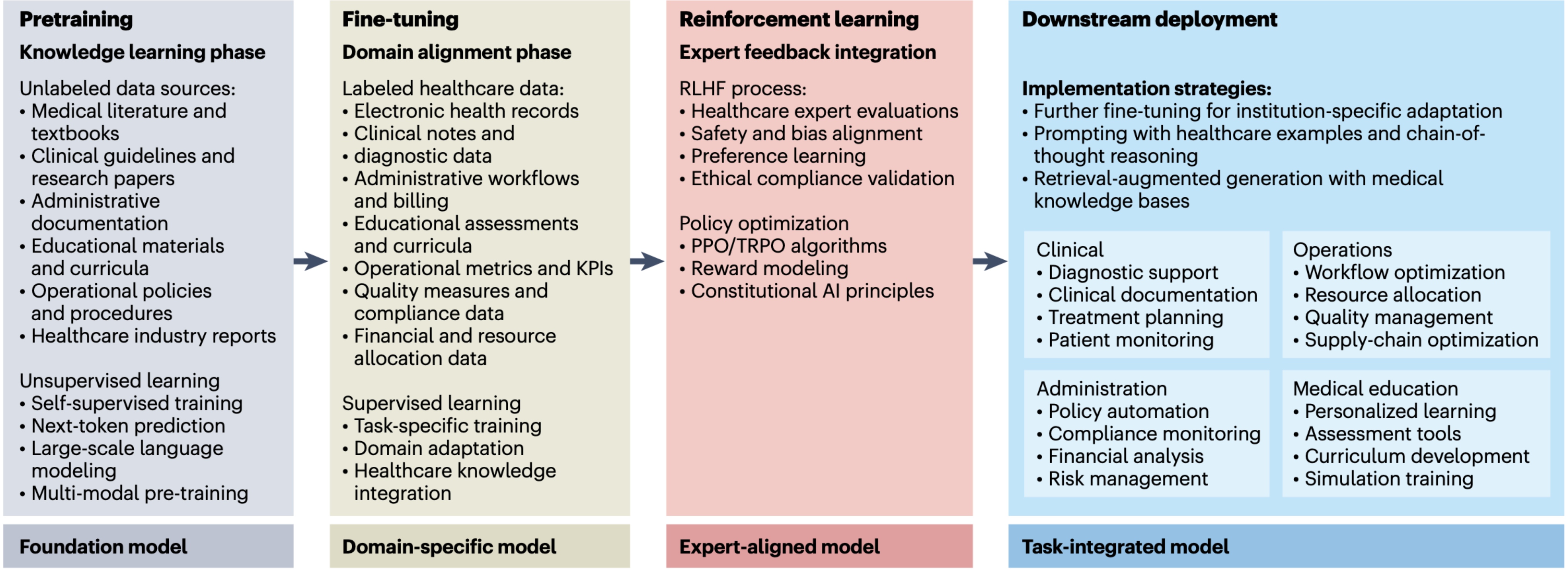
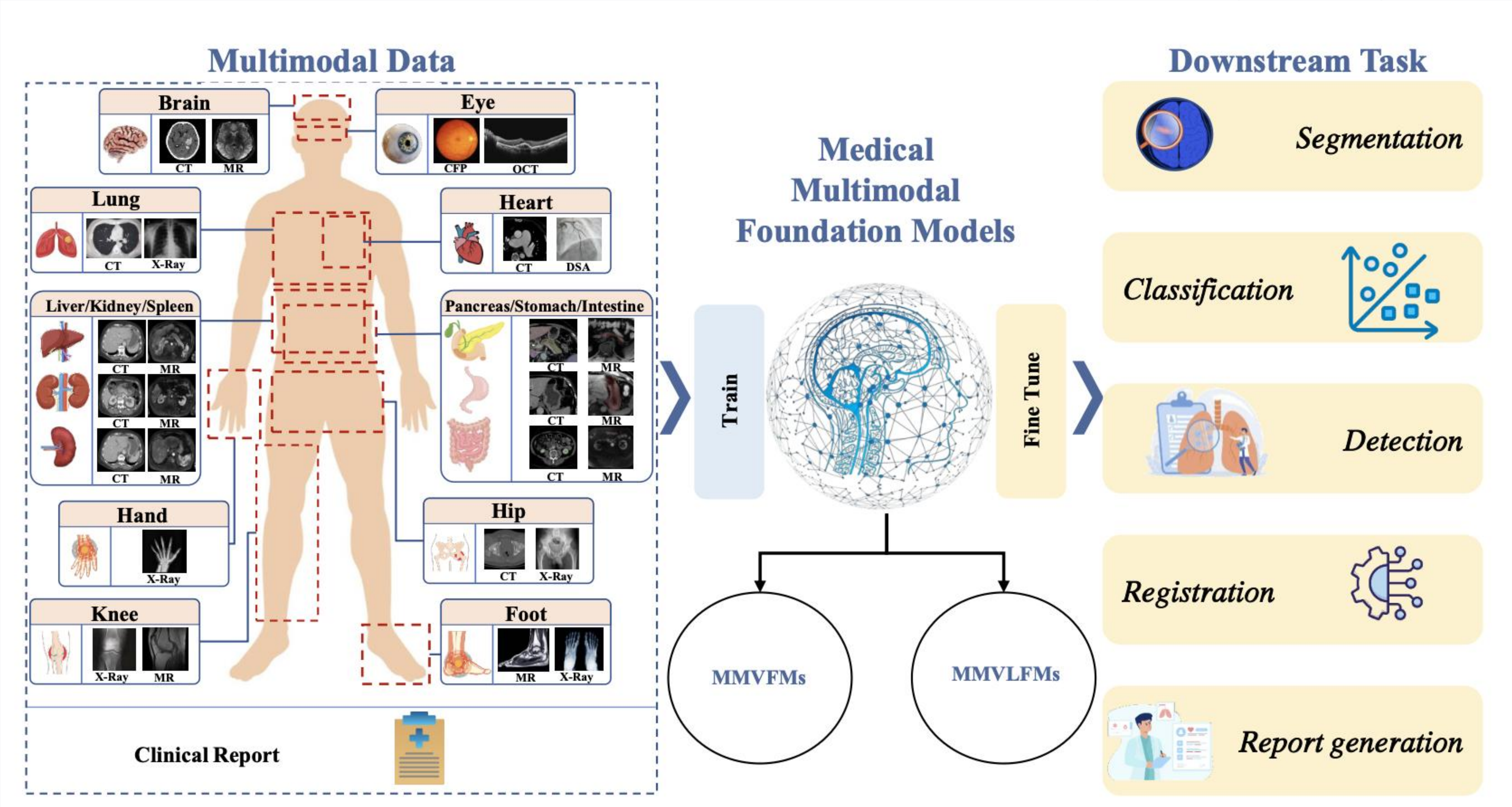


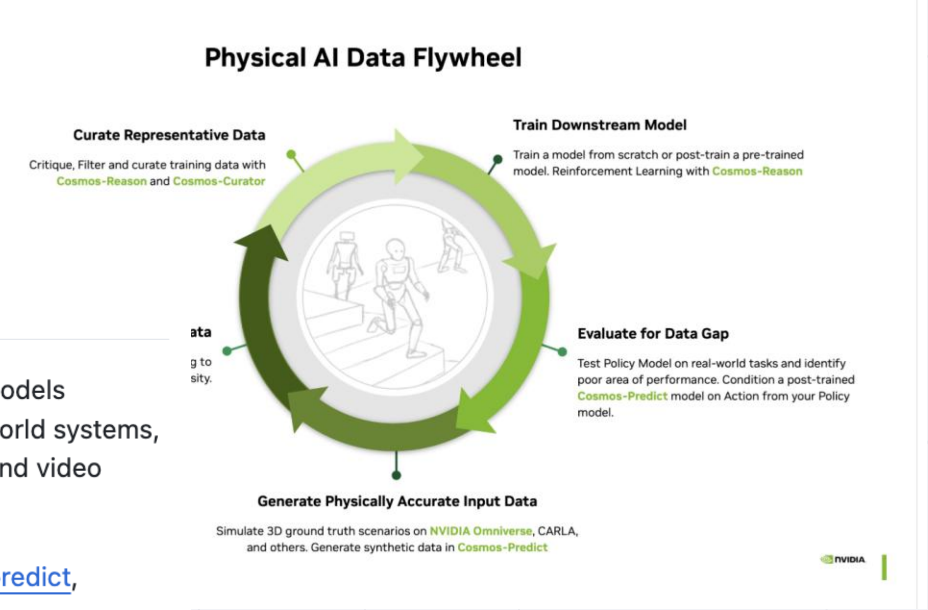
Fig. 1 | Overview of the GAI development pipeline. The figure shows key steps from initial foundation model development to their deployment in specialized healthcare applications across clinical care, operations, administration and medical education. KPIs, key performance indicators; PPO, proximal policy optimization; TRPO, trust region policy optimization.

Multi-Modal AI



arXiv:2412.02621v1 [cs.AI] 3 Dec 2024

World Models



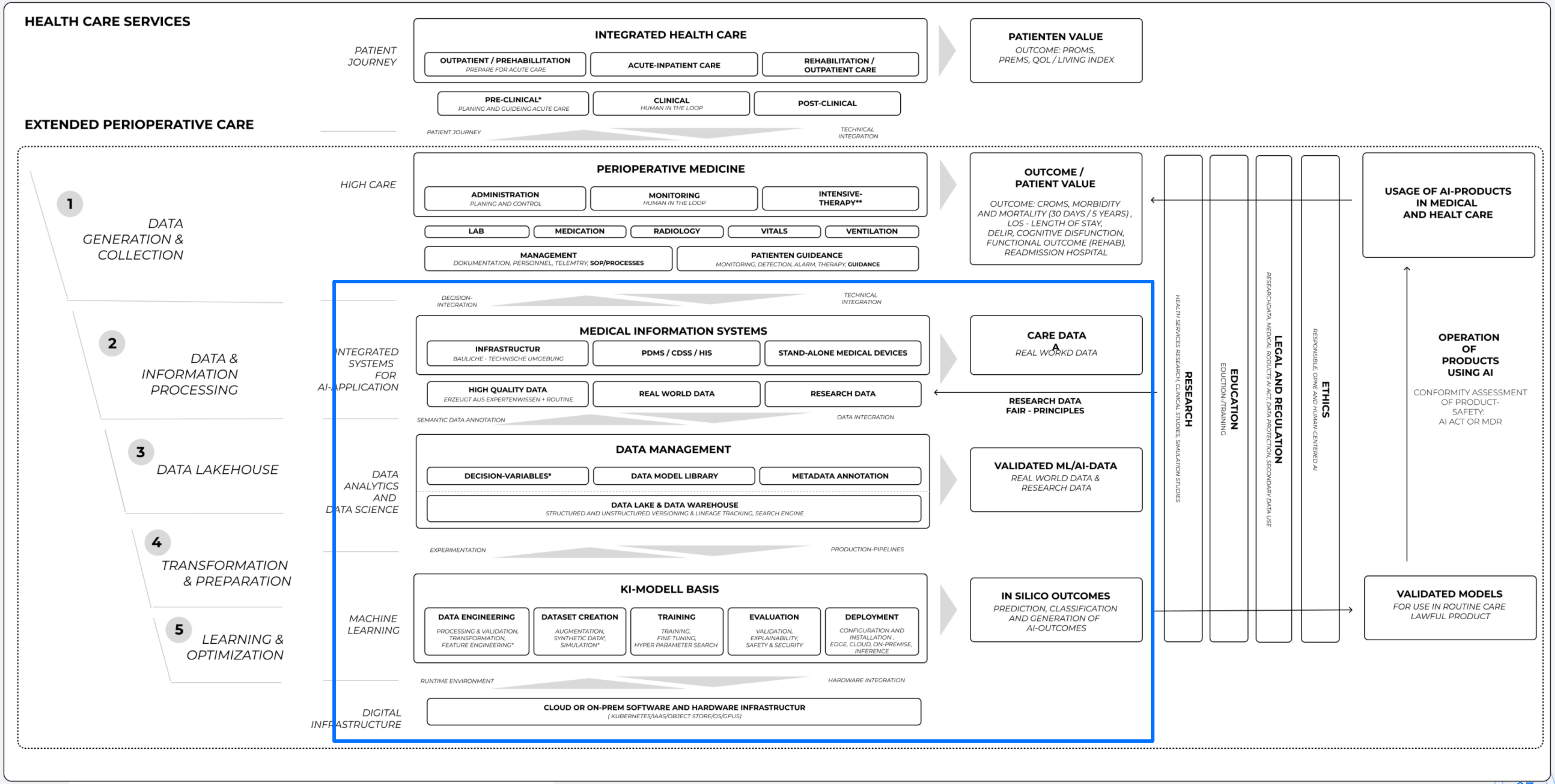
NVIDIA Cosmos

NVIDIA Cosmos™ is a platform purpose-built for physical AI, featuring state-of-the-art generative world foundation models (WFMs), robust guardrails, and an accelerated data processing and curation pipeline. Designed specifically for real-world systems, Cosmos enables developers to rapidly advance physical AI applications such as autonomous vehicles (AVs), robots, and video analytics AI agents.

Cosmos World Foundation Models come in three model types which can all be customized in post-training: cosmos-predict, cosmos-transfer, and cosmos-reason:

	Predict	Transfer	Reason
Type	World Generation	Multi-Controlnet	Reasoning VLM
Function	Predict novel future frames given initial frames	Transfer existing control frames into photoreal frames within a video clip	Reason against frames within a video clip
Use Cases	Data Generation & Policy Evaluation	Data Augmentation	Data Curation
Inputs	Text, Image, Video	Multiple Video Modalities such as RGB, Depth, Segmentation, and more.	Video & Text
Outputs	Video	Video	Text

INTEGRATIVE FRAMEWORK OF ARTIFICIAL INTELLIGENCE IN PERIOPERATIVE MEDICINE



* PRE-CLINICAL, CLINICAL AND POST-CLINICAL RELATE TO DIFFERENT STAGES OF ACUTE CARE - EXAMPLE: PRE-OPERATIVE, PERI-OPERATIVE AND POST-OPERATIVE
** PERIOPERATIVE CLINICAL CARE PRODUSES HUGA AMOUNT OF DATA FROM LAB-TESTING, MEDICATION, ETC. -- IN THE IMAGE 5 IMPORTANT DATA SOURCES ARE LISTED.

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Content

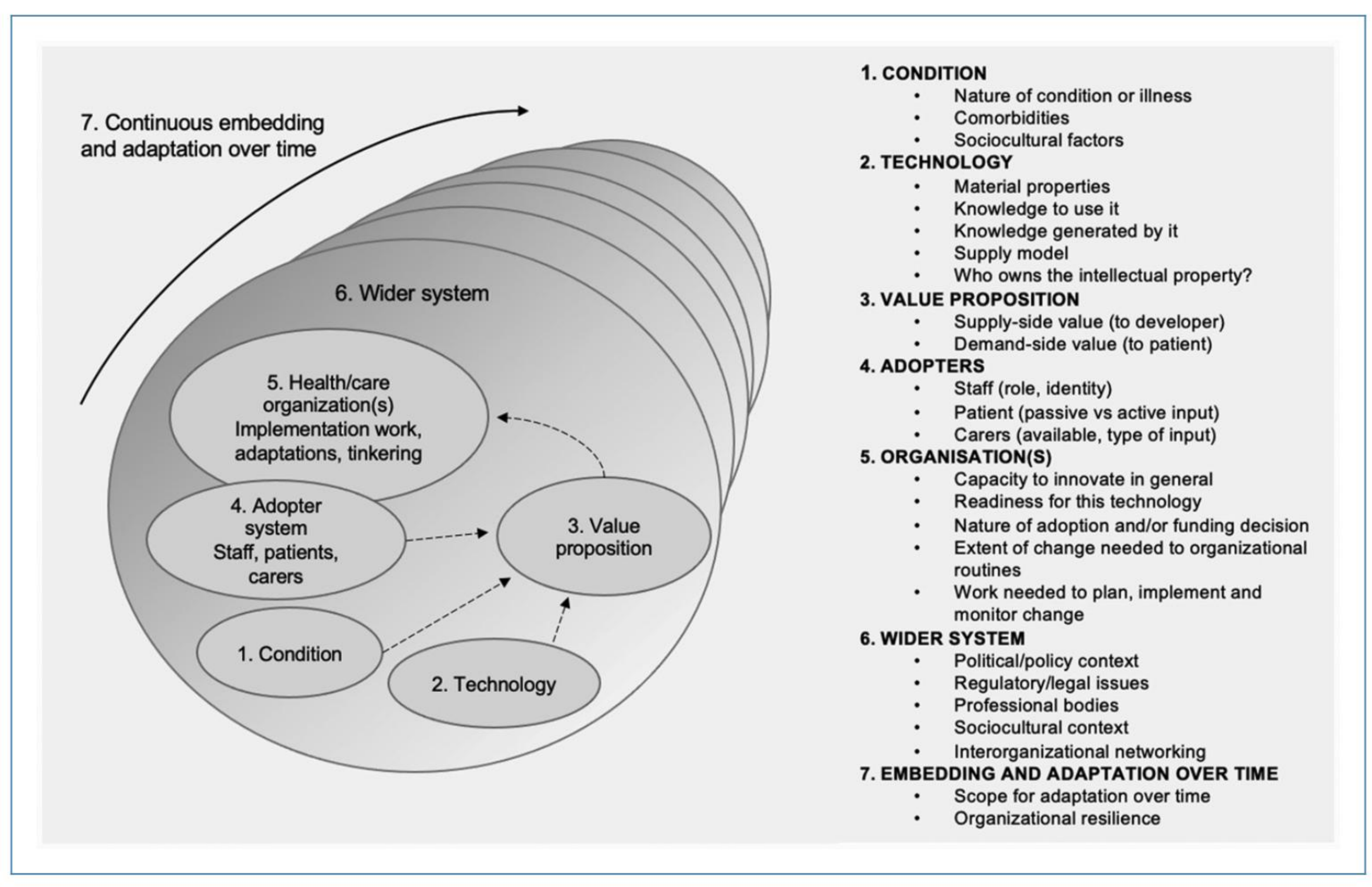
1. From **Data** to **Intelligent Data**
2. From **Models** to **Compound AI Systems**
3. From **Mono-Modal** to (abstracted) **World Models**
4. From **Pilot Projects** to **Meta-Learning** Organizations

From Pilot Projects to Meta-Learning Organizations

Determines a shift from isolated AI experiments (pilots) to organizations that continuously learn how to build and / or use and deploy AI effectively.

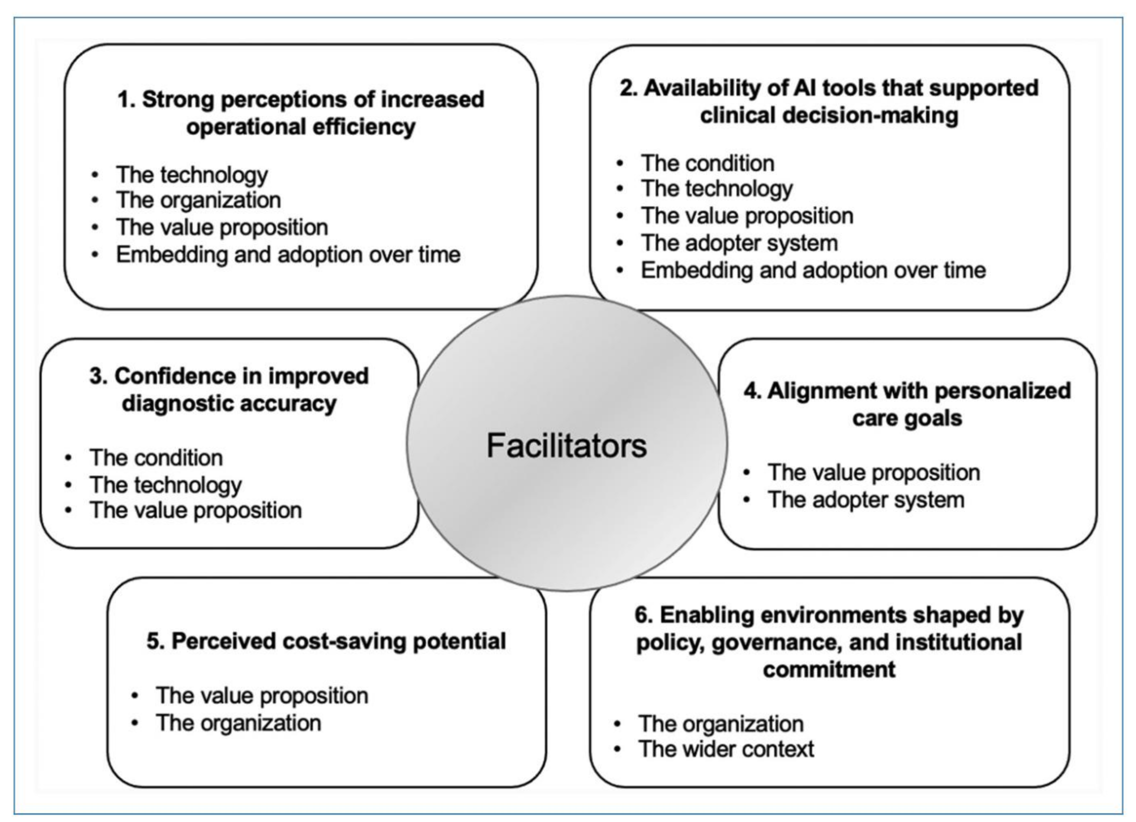
This results in establishing processes, feedback loops, and shared knowledge to rapidly iterate on AI solutions, embedding learning into the organizational DNA for sustained innovation across organizational levels and teams.

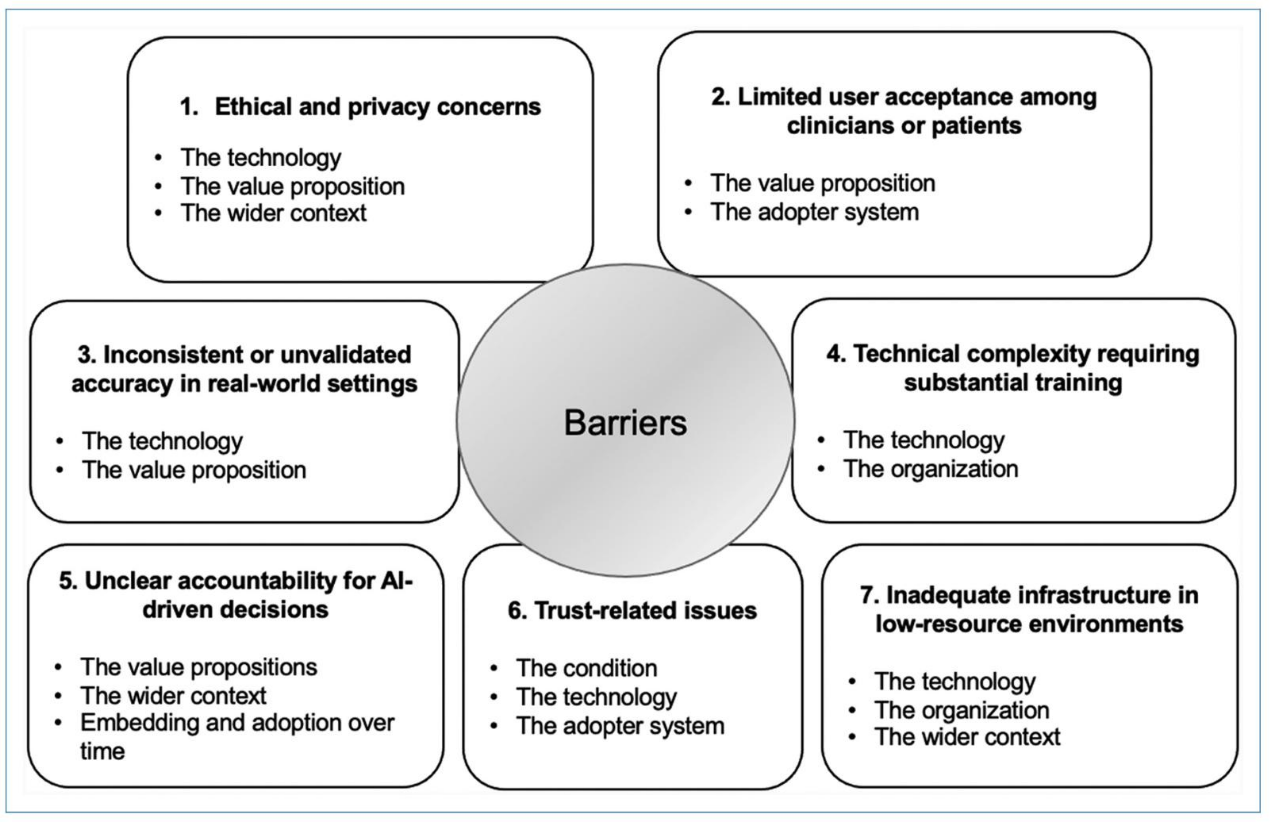
Process of Meta Learning Organization



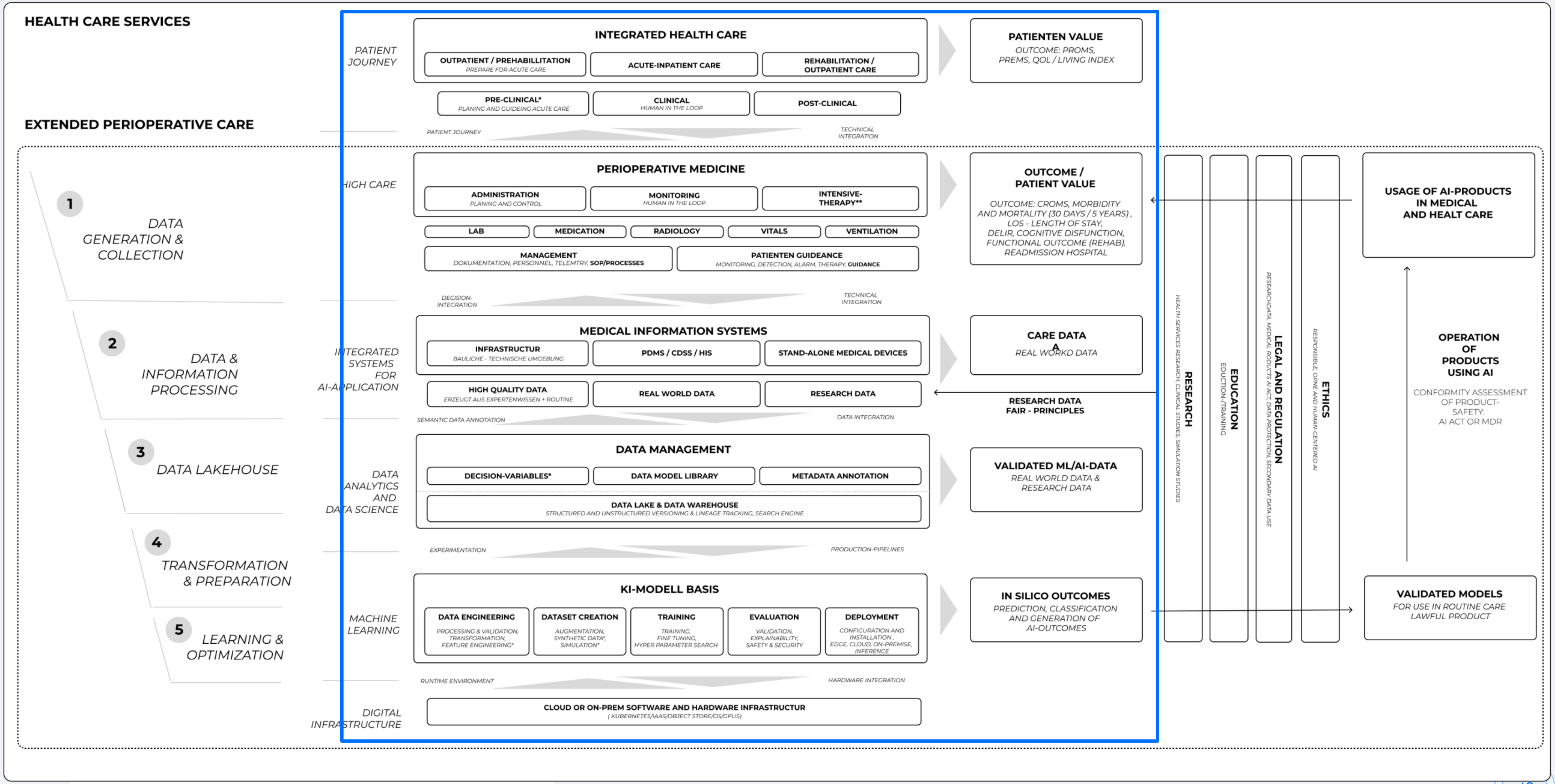
Qi et al. 2025, Utilization of arti cial intelligence in clinical practice, DIGITAL HEALTH, Volume 11: 1–21, DOI: 10.1177/20552076251343752, journals.sagepub.com/home/dhj

Facilitator and Barriers





INTEGRATIVE FRAMEWORK OF ARTIFICIAL INTELLIGENCE IN PERIOPERATIVE MEDICINE



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Have we already reached SINGULARITY of AI?

Your Opinion.

Do we need an AI memorandum?

AI RED LINES

We urgently call for international red lines to prevent unacceptable AI risks.

Launched during the 80th session of the United Nations General Assembly, this call has broad support from prominent leaders in policy, academia, and industry.

300+	10	90+	15
prominent figures	former heads of state and ministers	organizations	Nobel Prize and Turing Award recipients

Global Call for AI Red Lines

Read in: **English** Español Français 中文 Italiano Deutsch 日本語 Português Русский

AI holds immense potential to advance human wellbeing, yet its current trajectory presents unprecedented dangers. AI could soon far surpass human capabilities and escalate risks such as engineered pandemics, widespread disinformation, large-scale manipulation of individuals including children, national and international security concerns, mass unemployment, and systematic human rights violations.

Some advanced AI systems have already exhibited deceptive and harmful behavior, and yet these systems are being given more autonomy to take actions and make decisions in the world. Left unchecked, many experts, including those at the forefront of development, warn that it will become increasingly difficult to exert meaningful human control in the coming years.

Governments must act decisively before the window for meaningful intervention closes. An international agreement on clear and verifiable red lines is necessary for preventing universally unacceptable risks. These red lines should build upon and enforce existing global frameworks and voluntary corporate commitments, ensuring that all advanced AI providers are accountable to shared thresholds.

We urge governments to reach an international agreement on red lines for AI — ensuring they are operational, with robust enforcement mechanisms — by the end of 2026.

Thank you!

Dr. Andre Baumgart
Nordstrasse 15
8004 Zürich

baumgart@vzk.ch

ab11@pm.me

ANNEX