



WHITE PAPER | PRECISION ONCOLOGY

Precision oncology doesn't have a data problem only. It has a context and learning problem.

Why the next leap in cancer care comes from unifying each patient's biology into one living context, and closing the loop between every decision and its outcome.

EXECUTIVE SUMMARY

Precision oncology doesn't have a data problem only. It has a context and learning problem.

We sequence more tumors, run more panels and store more imaging than ever. Yet care is still shaped by whichever fragment a clinician finds before the consult, and the system rarely learns whether a decision was the right one. This paper sets out the two gaps and how GeneSilico's **gSage™** platform closes them.

Context

Unify every data input into one living, longitudinal patient record.

Simulation

Compute the patient's current Biological Tumor State and model response.

Learning

Feed every outcome back so the next decision is better than the last.

01 THE REFRAME

More data has not made cancer care more precise

We sequence more tumors than ever. We run more panels, capture more imaging, store more pathology slides and log more treatment decisions. Yet a patient's care is still too often shaped by whichever fragment a clinician can find in the ten minutes before the consult.

And once a decision is made, the system rarely learns whether it was the right one. The outcome sits in a different record, months later, disconnected from the reasoning that led to it.

That is the problem we have been working on at GeneSilico.

02 THE CONTEXT PROBLEM

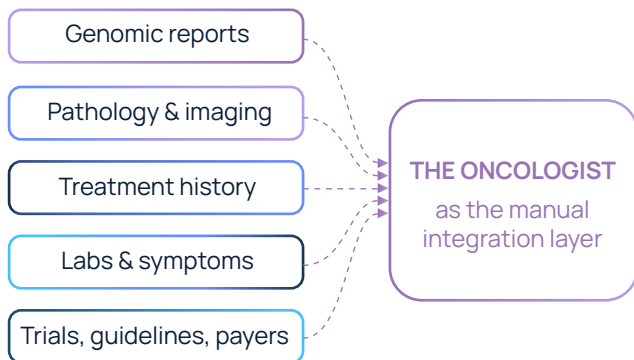
A patient's story, scattered across systems

A cancer patient's story is scattered across systems that were never designed to talk to each other.

- Genomic reports arrive as PDFs, read once and filed away.
- Pathology, radiology and staging live in separate systems.
- Lines of therapy, toxicities and dose changes are buried in progress notes.
- Comorbidities, labs and patient-reported symptoms sit somewhere else again.
- Trial eligibility, guidelines and payer criteria are checked by hand, against all of the above.

Today

Context rebuilt in someone's head, every visit



With gSage™

Context assembled once, kept current, reused everywhere

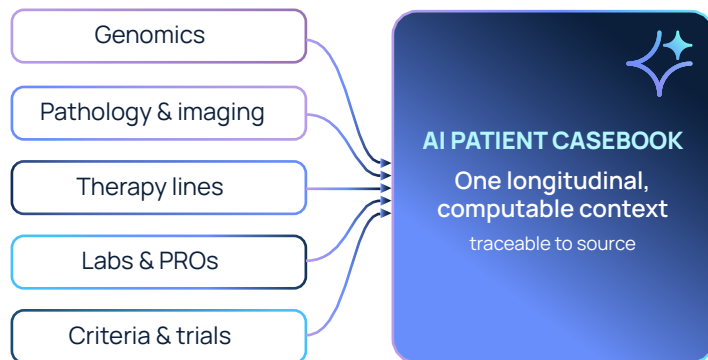


FIGURE 1. From fragments reconciled by hand to a single patient context that every downstream decision can read.

Each fragment is accurate. None of them, on its own, tells you what is happening in the tumor today. The oncologist becomes the integration layer, assembling context in their head, patient after patient.

More data does not fix this. More data, without context, just makes the haystack bigger.

03 THE LEARNING PROBLEM

Care that forgets what it just learned

Even when context is assembled, it is used once and thrown away.

A treatment decision is made. The patient responds, or progresses, or develops a resistance mutation. But that outcome rarely flows back to the reasoning that produced the decision. The next patient with a similar tumor starts from zero.

Cancer is not static. Tumors evolve under the pressure of every therapy we give. A system that cannot learn from what happened to the last patient, or from how this patient's tumor has changed, will always be a step behind the disease.

**Precision oncology needs more than records.
It needs memory, and it needs a feedback loop.**

gSage: one context, one learning loop, across the treatment lifecycle

We started by building intelligence around oncology data. Over time, the bigger opportunity became clear: the intelligence should not live in separate features. It should run across the entire treatment lifecycle, and it should get smarter with every patient.

That is **gSage**, our AI-first precision oncology platform, built on three pillars:

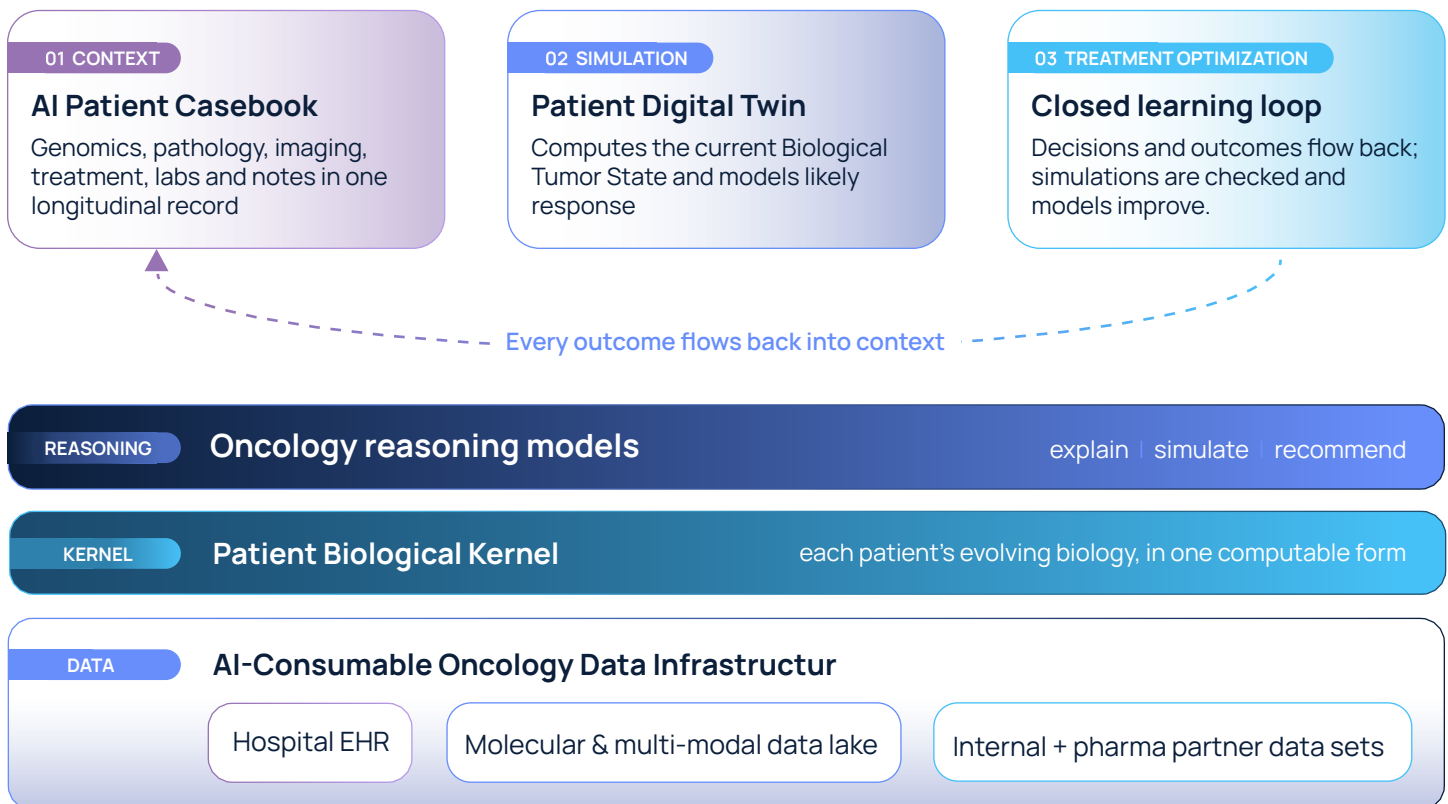


FIGURE 2. The gSage platform: three pillars running on oncology reasoning models, the Patient Biological Kernel and an AI-consumable oncology data infrastructure, joined by a closed learning loop.

Underneath sits the **Patient Biological Kernel**, the core that holds each patient's evolving biology in one computable form, and our **oncology reasoning models**, which read that kernel to explain, simulate and recommend.

Beneath both is an **AI-consumable oncology data infrastructure** that brings together the hospital EHR, a data lake of molecular and multi-modal data, and internal and pharma partner data sets.

Every step stays traceable back to the evidence.

01 The AI Patient Casebook

CONTEXT

A living, structured record that unifies genomics, pathology, imaging, treatment history, labs and notes into one longitudinal view. It is the context layer everything else is built on.

02 The Patient Digital Twin

SIMULATION

From that context, gSage computes the patient's current Biological Tumor State and models how it is likely to respond to the options on the table.

03 The Closed Learning Loop

TREATMENT OPTIMIZATION FOR EVERY PATIENT

Every decision and every outcome flows back into the system. Simulations are checked against what actually happened, and the models improve.

05 WHAT IT MAKES POSSIBLE

What context and learning make possible

● Tumor boards that start prepared

A case summary assembled before the meeting, not during it.

● Response tracked against the twin

Assays and monitoring show whether the tumor behaves as the twin expected, and when to change course.

● Genomic reports that explain themselves

Variants linked to therapies, trials and the patient's own history.

● Pre-authorization with evidence attached

Clinical rationale packaged once, from the same context, for payers.

● Options weighed against the patient

The Digital Twin shows how this tumor, in this patient, is likely to respond, not the average patient.

● Research cohorts that build themselves

Real-world precision cohorts for trials and drug development, drawn from structured AI case records.

The goal is not another dashboard in an already crowded workflow. It is to make the systems cancer centers already use, the EHR, the tumor board and the lab, more intelligent.

From model output to treatment decision

Much of the effort in medical AI goes into the model. What happens after it produces an output is just as hard.

A recommendation is only worth something if it reaches the right person, in time, with the patient context needed to act on it.

That last mile is a safety-critical system in its own right. Across the sector it stays under-resourced because it falls between the AI vendor, hospital IT and the clinical teams, and no single party owns it. In oncology the Casebook already sits across all three, so we treat the last mile as part of the platform, not an integration afterthought.



FIGURE 3. Every recommendation carries a chain of evidence from output to outcome. That chain is what the learning loop learns from.

This is also what makes the learning loop work. If you cannot show that a recommendation was seen and acted on, its outcome cannot be attributed to it, and nothing is learned.

We hold the last mile to five standards:

STANDARD	WHAT IT MEANS IN ONCOLOGY
Bounded time to the decision point	Results arrive before the tumor board, the consult, the next cycle or the pre-auth deadline. Critical findings, such as severe toxicity or critical labs, escalate immediately.
Native to hospital systems	Works through the hospital's own standards (HL7, FHIR, DICOM) and the EHR, not another portal to log into..
Proof, not assumption	Each output is tracked from delivery to acknowledgment to action, including overrides and the reasons for them.
Audit logs that are watched	Logs are continuously analyzed for missed deliveries, override patterns and drift, not just stored.
Validated where it runs	Tested in shadow mode against live hospital interfaces before it influences care.

We measure it the way we measure the model: time to acknowledgment, share of outputs acted on, override rate, delivery failures and time to treatment decision. The next wave of value in hospitals will come from engineering this last mile as rigorously as the model itself.

The question guiding us

There is a lot more to build. We are doing it alongside hospitals in India and through our participation in leading health innovation programs in the US. But the question guiding us is becoming clearer.

What could cancer care look like if every patient's context was complete, and every outcome made the next decision better?

If you lead a cancer center, a molecular lab, an oncology practice or a life-sciences team, I would like to hear where fragmented context or the missing learning loop is holding you back. That is where we are focused.

Mohammed Farooq

Founder & Chairman, GeneSilico

genesilico.ai

About GeneSilico. GeneSilico builds **gSage™**, an AI-first precision oncology platform that unifies each patient's biology into a living AI Patient Casebook, simulates likely response with the Patient Digital Twin, and improves with every outcome through a closed learning loop. Learn more at genesilico.ai.