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Digital Twins in Oncology

Seizing Opportunities Across Clinical Care, Drug Development, and Health Systems

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Executive summary

Digital twins — high-fidelity, dynamically updated computational replicas of individual patients — are moving from academic research into early clinical deployment. They promise to turn high-stakes decisions in cancer care into rapid and cost-effective ***in-silico*** experiments, rather than long and expensive real-world guesswork, helping spare patients' exposure to less effective or more toxic options during clinical trials.

By integrating multimodal data (clinical, molecular, imaging, longitudinal outcomes) and simulating alternative treatment paths, digital twins can support more effective treatment strategies over time, improve the design and interpretation of oncology trials, and generate new forms of evidence for payers and regulators. The economic opportunity is substantial. While market estimates vary widely depending on how broadly digital twins are defined, they consistently point to rapid growth from a small base, with oncology emerging as the leading edge. Similar approaches are emerging across cardiovascular medicine, chronic disease, and surgical planning.

For investors, the opportunity clusters into three distinct segments: R&D-focused modeling platforms serving pharma and biotech, clinical decision-support systems deployed in cancer centers, and system-level twins optimizing hospital operations and care pathways. The teams most likely to succeed will combine rigorous validation, productization discipline, and a clear focus on decision points where better prediction translates directly into better outcomes and measurable economics.

1. Why oncology first and what lies beyond

Digital twins are being explored in cardiology, neurology, intensive care, chronic-disease management and surgical planning. Oncology is not the only use case, but it is currently the most developed.

Cancer care is unusually data-rich: tumor sequencing, longitudinal imaging, digital pathology, structured treatment histories and follow-up outcomes are increasingly standard. This creates exactly the multimodal and longitudinal datasets digital twins rely on. Therapeutic choices are also expensive and consequential. The wrong line of therapy can carry large costs, significant toxicity and irreversible impact on quality of life. Any systematic improvement in predicting ***who*** benefits from ***what***, and ***when***, has outsized clinical and economic value.

Oncology is also relatively mature as a proving ground. Publications have grown significantly over the last decade, and oncology is frequently cited as the exemplar domain for digital twin methods, from tumor modeling to therapy response, prediction and trial design.

Many of the themes discussed in this paper such as data quality, clinical integration, validation and productization, generalize beyond oncology. Similar approaches are emerging in cardiovascular medicine, critical care, neurology and chronic disease management. Oncology can therefore be seen less as a niche and more as the leading edge of a broader move towards model-based, data-driven medicine.

2. What "digital twins" mean in oncology

"Digital twin" has quickly become a buzzword. In this paper, we follow the definition proposed by the US National Academies of Sciences, Engineering, and Medicine (NASEM) and adopted in recent work on human digital twins:

In healthcare, a digital twin must be personalized, dynamically updated, and have predictive capabilities that can be used to inform clinical decision-making.

A note on avatars vs digital twins

Some groups use the term avatar to describe a patient-specific representation. In oncology, avatar has also historically referred to physical surrogates (for example, patient-derived xenografts). In this paper we use digital twin consistently to refer to a computational, dynamically updated, predictive model of an individual patient. The distinction matters because not all "avatars" meet the NASEM criteria.

This definition excludes static risk models and one-time patient stratification tools. It emphasizes continuous learning and iterative clinical application. Building on that conceptual definition, we find it useful to **distinguish three practical dimensions that determine how meaningful a given twin is in oncology:**

2.1 Data breadth

Twins typically combine several layers:

Clinical Data

Diagnosis, stage, performance status, comorbidities, medications, laboratory values, toxicities

Molecular Data

Tumor sequencing (panels, WES/WGS), circulating tumor DNA (ctDNA), transcriptomics, proteomics

Imaging and Pathology

Radiology and digital pathology

Longitudinal Structure

Repeated measurements across lines of therapy and disease evolution

Real-World Data

Wearable sensors, patient-reported outcomes, adherence patterns

2.2 Modeling approach

Twins typically combine several layers:

Statistical and Machine-Learning Models

Learn patterns from large numbers of past patients to estimate risk, outcomes, and treatment effects

Mechanistic Models

Encode known biology and physiology, such as tumor growth, drug behavior, and immune response, to simulate how disease evolves under different conditions

Hybrid Approaches

Combine both approaches, using biological knowledge to guide data-driven learning and improve robustness and interpretability

A brief note on AI

In practice, many recent digital twins use machine-learning (ML) or other AI techniques for parts of the stack – for example, to extract structure from unstructured data, to learn low-dimensional representations of tumors, or to generate synthetic control trajectories. But AI is neither necessary nor sufficient for a system to qualify as a digital twin. Mechanistic models and more classical statistical approaches can underpin clinically useful twins just as well. What matters is personalization, dynamic updating and decision relevance, not the specific algorithmic label.

2.3 Level of "twinning"

- **Individual twins** simulate likely trajectories for a single patient under multiple regimens or strategies. For example: should this specific patient receive drug A or drug B as the next line of therapy?
- **Cohort or trial twins** generate virtual controls or synthetic trajectories for trial arms. For example: what would the control arm of this clinical trial have looked like under standard of care?
- **System twins** represent care pathways across cancer centers or networks, including capacity constraints and access patterns. For example: How should a cancer center allocate treatment capacity across different patient populations?

Biological scale also matters. Digital twins can operate at different levels of biological organization. Some models focus on cells or pathways (for example intracellular signaling or drug-target interactions), others on organoids, tissues or tumors (such as tumor-immune dynamics), and others on the whole patient, integrating biology with clinical trajectories over time. These layers are complementary: lower-scale twins often inform higher-level models, rather than replacing them.

Concretely, a digital twin in oncology might look like the following: A patient presents with metastatic lung cancer. The system ingests their imaging, tumor genomics, prior treatments, laboratory values and clinical history. It then simulates what is likely to happen over the next six to twelve months under therapy A versus therapy B versus a combination strategy. This approach allows estimating differences in tumor response, progression timing and expected toxicity. These simulations do not replace clinical judgment, but they make explicit the trade-offs clinicians are already considering, grounded in data from similar patients and known biology.

What is a Digital Twin in Oncology?

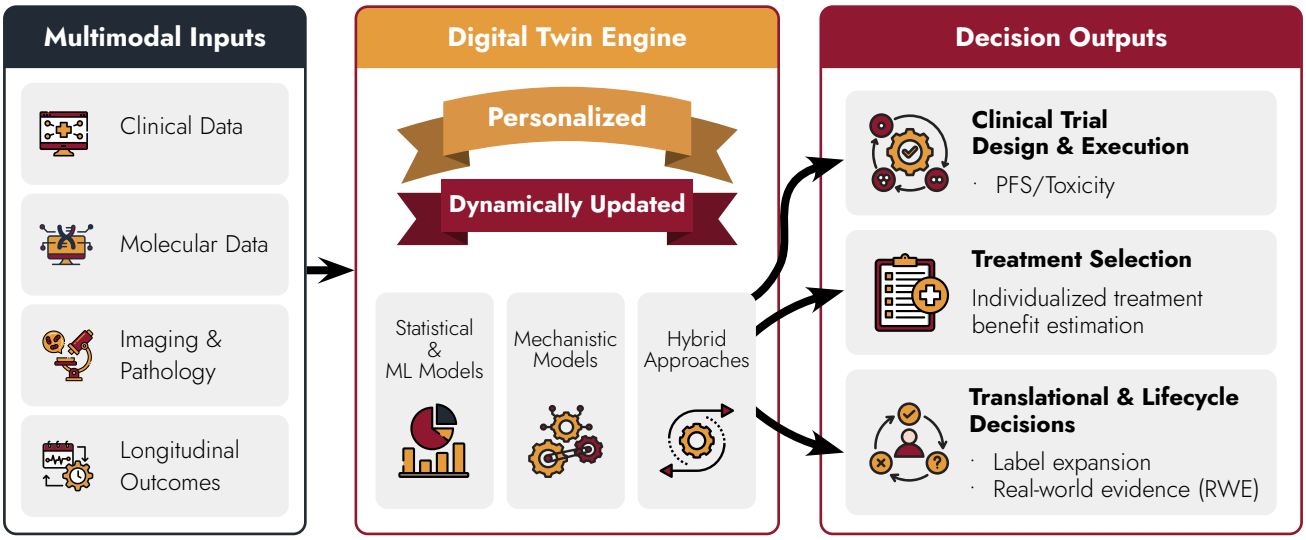

Figure 1 | Digital twin data and modeling framework in oncology.

Digital twins integrate multimodal and longitudinal patient data into a computational modeling engine that is personalized and dynamically updated over time. Different modeling approaches can underpin the twin creation engine. Digital twins can then generate patient – and cohort-level predictions that inform concrete decisions across clinical trial design, treatment selection, and translational and lifecycle management.

3. Why digital twins matter now

Several converging developments have made digital twins in oncology both feasible and relevant today.

Economics

Oncology concentrates features that favor digital twins: very expensive therapies, significant and sometimes irreversible toxicity, and persistent evidence gaps – especially around the order and combination in which therapies are used. In that environment, each marginal improvement in predicting benefit, toxicity or timing can materially change outcomes and costs.

Data and compute

Broad adoption of electronic health records, routine tumor sequencing and liquid biopsy, digital pathology and increasingly data-rich imaging, combined with scalable cloud compute and modern ML tooling, make it feasible to deploy multi-scale, patient-specific models that would have been impractical only a few years ago.

Adoption of digital tools

Health systems, payers and life-science companies are now deploying analytics and AI well beyond pilots. Much of the early value has been in documentation, revenue-cycle and operational tools, where ROI is immediate and risk is low. Digital twins sit closer to the core of clinical and development decisions. They demand more from data, validation and governance, but if they work, they speak directly to how we discover, develop and use cancer therapies.

A growing market

Although still small today (estimated around USD 1-2 billion), industry market analyses project rapid growth in healthcare digital twins, with compound annual growth rates around 25-30% and forecasts extending into the tens of billions of dollars by the mid-2030s (MarketsandMarkets, 2025; Precedence Research, 2025). Early adoption is expected in oncology, cardiovascular disease, metabolic disorders and clinical development, where the operational and clinical impact is clearest.

Emerging segments

Within this growing market, several distinct segments are emerging: (I) R&D-focused platforms selling modeling infrastructure to pharma and biotech, (II) clinical decision-support platforms providing patient-level models to cancer centers, and (III) system-level twins optimizing hospital pathways, capacity and resource allocation. These differ not only in use cases but also in buyers, pricing models and regulatory pathways.

Investment momentum

Several modeling-focused companies have raised significant rounds to scale digital twin approaches in development. For example, **Unlearn.AI** has secured over USD 130 million to advance its virtual control methodologies.

4. Where digital twins are most likely to create value

From an investment standpoint, technical elegance is insufficient: digital twins must change specific decisions for identifiable buyers. Across oncology, three clusters of use cases stand out. The examples below are illustrative rather than exhaustive, chosen to represent how different modeling approaches are beginning to influence real decisions.

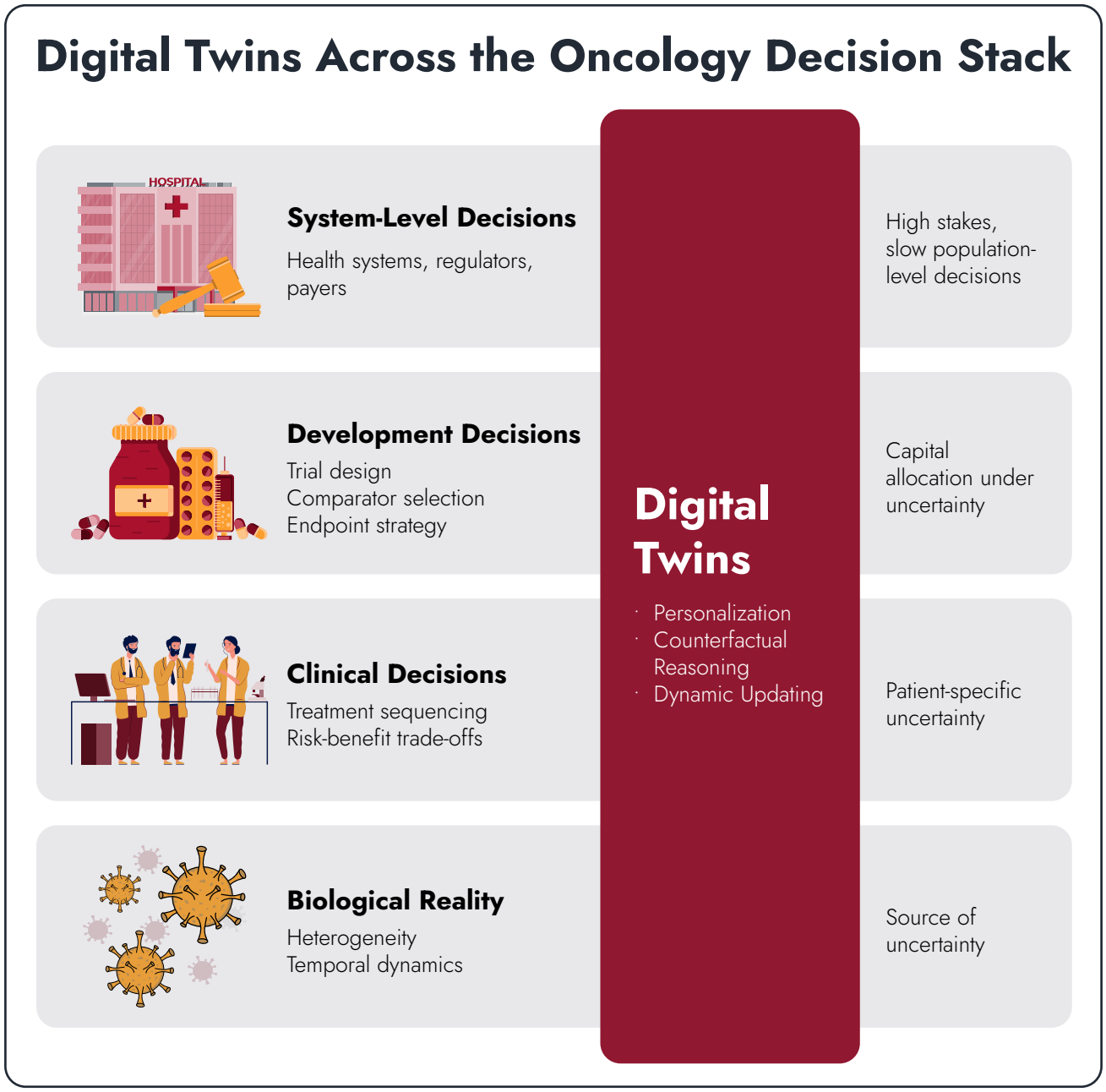

Figure 2 | Digital twins across the oncology decision stack.

Digital twins act as a cross-layer decision technology in oncology, connecting biological complexity to clinical, development, and system-level decisions. By enabling personalization, counterfactual reasoning, and dynamic updating, digital twins help reduce uncertainty across the oncology decision stack. Their impact spans from tumor biology and patient-level treatment decisions to clinical development, reimbursement, and guideline setting.

4.1 Clinical trial design and execution

Digital twins can help build **synthetic or virtual control arms,** using historical trials, registries and real-world data to match the outcomes patients would have experienced under standard of care. Properly constructed, these virtual controls can reduce or partially replace conventional control groups, particularly where randomizing to placebo or legacy regimens is slow, costly, or ethically constrained.

They can also support **eligibility and enrichment optimization** by simulating how different inclusion and exclusion criteria, biomarker thresholds and stratification schemes affect event rates, power and subgroup effects. More broadly, digital twins enable *in-silico* **scenario testing:** exploring alternative dosing, strategies or combinations before committing to expensive late-stage studies.

The economic buyer is clear (sponsors and CROs), and the value proposition — fewer patients, faster read-outs, lower costs, higher probability of technical and regulatory success — is both tangible and quantifiable.

Practical progress is already visible. For example, **Tempus** has introduced "molecular twin" models — patient-specific computational representations that integrate clinical, genomic and pathology data to characterize tumor biology and treatment response in oncology. While focused primarily on the molecular and phenotypic state of the patient rather than full longitudinal simulation, these models reflect core digital twin principles such as personalization, data integration and decision relevance. Their use illustrates how twin-based concepts are already being applied in oncology to inform trial design, cohort selection and translational research.

4.2 Treatment selection

In many cancers, clinicians now choose between multiple targeted agents, immunotherapies and combinations across several lines of therapy, with only partial evidence for the "right" option in each situation.

Digital twins can estimate **individualized treatment effects,** conditioned on tumor profile, comorbidities, prior therapies and observed disease course. They generate explicit scenario comparisons such as expected progression-free survival, overall survival, toxicity and cost under each strategy. When embedded into tumor boards or decision-support tools, these outputs make trade-offs more interpretable for clinicians and patients.

Value is highest where decisions are genuinely ambiguous, stakes are high and data density is adequate. For example, later-line metastatic disease or complex comorbidity profiles.

Early commercial efforts in this direction exist. **SOPHiA GENETICS** (NASDAQ: SOPH), for instance, has recently introduced a digital twin module that integrates clinical, imaging and genomic data to simulate alternative treatment paths for individual oncology patients. While still in its early deployment phase, it illustrates how multimodal, dynamically updated models can be embedded into real oncology decision-support workflows.

Illustrative example. A patient with metastatic colorectal cancer has progressed after first-line therapy. Today, clinicians choose the next line based largely on population averages and prior experience. A digital twin could simulate several treatment options, showing that although option B has slightly lower average response rates in the population, for this patient's specific tumor profile it has the highest predicted benefit and lowest expected toxicity. The output does not dictate care but helps structure discussion around individualized trade-offs.

4.3 Translational and lifecycle decisions

Between early research and routine care, digital twins can:

identify responder subgroups and biomarkers in early-stage studies

guide label expansion and therapy positioning across lines and combinations

support lifecycle management and market access by generating richer evidence on which patients benefit most, and under what conditions

These applications often begin as bespoke collaborations around specific assets, but they can become product modules if built on a shared modeling and data backbone.

In parallel, broader ecosystem efforts are shaping the translational landscape.

The European Virtual Human Twins (VHT) Initiative, launched by the European Commission in 2023, aims to build a continent-wide framework for multi-scale human digital twins spanning cellular, organ and physiological models. While not commercial, it reflects growing structural support for digital twin research and illustrates how shared modeling resources, validation frameworks and data-interoperability standards may accelerate translational development across oncology and beyond.

5. Clinical data: yes or no?

A central design choice in oncology digital twins is how much to depend on clinical data from routine care such as EHR, claims and real-world outcomes, versus more controlled sources such as multi-omic datasets.

5.1 Why clinical data matters

Clinical data captures the context around the tumor and the patient: demographics, comorbidities, concomitant drugs, dose reductions, off-label use, adherence, toxicity and supportive care. These factors often influence outcomes as much as biology itself.

Grounding models in this reality improves external validity and is particularly important for use cases such as external or synthetic controls, where virtual trajectories must closely reflect routine clinical practice. For regulators, payers and clinicians, this alignment with real-world care is often a prerequisite for trust.

5.2 Why clinical data is hard

Clinical data is noisy and incomplete: missing values, inconsistent coding, changing documentation practices and heterogeneous data models undermine reliability. Turning raw EHR extracts into analysis-ready inputs requires substantial engineering and clinical curation, and multi-site data sharing triggers non-trivial governance and privacy burdens, especially under European data-protection and emerging AI regulations.

5.3 A spectrum, not a verdict

In practice, oncology digital twin teams take different positions along a spectrum. Some double down on biology-rich, tightly controlled data, others work to integrate real-world clinical data as early as possible, many will gradually move from one end to the other as their use cases mature.

Rather than arguing for a single "right" answer, what matters is that the data strategy is explicit, aligned with the intended decisions, and backed by a plan for validation, monitoring and transparency about limitations.

6. Productization: when digital twins become investable

Scientifically impressive digital twins are not automatically good businesses. A pattern appears repeatedly: a team delivers a great one-off twin for a specific study or project, but what remains is a collection of scripts, analyses and slides – not a product.

From an investment perspective, the key question is how quickly one can move from a **project** to a **product.**

Platforms stuck in project-mode typically rely on bespoke studies, heavily customized models and service-like margins. Scalable platforms share a few traits:

- **a reusable core,** capable of supporting multiple indications and customers
- **a small number of repeatable workflows** with clear inputs, outputs and service levels
- **interfaces that fit existing workflows,** whether APIs for trial-design teams or embedded modules for tumor boards
- **evidence that customers care,** including case studies showing measurable impact and unit economics that improve as the platform scales

A simple way to assess this is to ask: if development stopped for a year, what could the company still sell tomorrow? If each new deployment strengthens the underlying data and models, the platform is compounding. If it merely produces another tailored analysis, it remains a services business.

7. How we see the opportunity

Digital twins in oncology remain early, but emerging evidence shows that, when well designed and validated, they can improve trial design and interpretation, support more personalized and transparent treatment strategies, and enable richer evidence for payers and regulators.
The biggest challenges are not purely algorithmic. They concern data quality, clinical integration, validation, governance and productization. The teams most likely to endure will:

- focus on decision points where better prediction clearly translates into better outcomes and economics
- treat validation and data limitations as seriously as model architecture
- build products that plug naturally into how trials are run and how care is delivered

If those points are met, digital twins can move from promising concept to a durable part of how we discover and use cancer therapies and, over time, how we deliver medicine more broadly.

Oncology is the best initial use case, but not the only one. In metabolic disease, for example, personalized computational models, such as those developed by **Twin Health**, have shown that patient-level simulation can materially improve real-world outcomes in Type 2 diabetes. Similar efforts in cardiovascular medicine, neurology and surgical planning indicate that the foundational ideas of digital twinning such as individual-level modeling, longitudinal updating and scenario simulation, extend well beyond oncology.

Switzerland is also emerging as a meaningful contributor. Switzerland has unique structural advantages for digital twin development. ETH Zurich, EPFL, and Swiss university hospitals maintain deep expertise in computational and systems medicine, particularly in oncology and cardiovascular modeling. Meanwhile, multinational life-science leaders—Roche, Novartis—are integrating multimodal clinical and molecular data with advanced modeling across research and development workflows.

National initiatives like the Swiss Personalized Health Network provide governance and data-interoperability frameworks. Together, these assets create favorable conditions for developing clinically credible, regulatory-aligned digital twin platforms with European reach.

Digital twin approaches reflect the aspects of health-tech we find most compelling: they leverage large-scale data and AI to deliver personalized care at scale. By enabling patient-specific simulations, they can improve outcomes, reduce waste and bend the healthcare cost curve. Those features **align closely with our mission to back solutions that enhance both patient lives and healthcare system efficiency.**

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About the Author

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She holds a PhD in bioinformatics and genetic epidemiology and has an academic and business background spanning computational oncology, precision medicine, and digital health. Prior to joining Vi Partners, she worked across the healthtech and consulting sectors, supporting the development, evaluation, and adoption of data-enabled healthcare technologies at the interface of science, clinical practice, and innovation.

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