https://doi.org/10.1038/s41591-026-04621-1

A global digital navigator of human health for precision medicine

Kang Zhang, Jiahong Dong, Hang Wong, Sian Liu, Kai Wang, Wei Wu, Kaixin Zhou, Kanmin Xue, Edward Zhang, Jonathan Gootenberg, Omar O. Abudayyeh, Michelle Williams, Xian Shen, Alexandre Loupy, Trey Ideker, Patrick Tan, Joseph Wu, Akrit Sodhi, Eric Oermann, Tao Xu & Guang Ning

Check for updates

The International Consortium of Digital Twins in Healthcare and Medicine was established to advance medical digital twin technology as a new infrastructure for precision health.

Human health is a complex and dynamic process shaped by ancestry, development, aging, lifestyle, environmental exposure, disease progression and treatment response. Yet current clinical practice still captures much of this complexity through fragmented snapshots, including genomic profiles, laboratory tests, imaging studies, electronic health records and risk scores measured at particular time points. While multimodal health data are expanding rapidly, they remain poorly integrated into models that can represent how health states evolve, disease progresses and individuals respond to interventions.

Against a backdrop of population aging, chronic disease, multimorbidity and growing pressure on healthcare systems, medicine must move beyond static diagnosis toward dynamic prediction and prevention across the life course. Precision health seeks to tailor prevention and treatment by integrating multidimensional data over time. Achieving this goal requires systems that can continuously track physiological change, infer future health trajectories, and support earlier, more personalized intervention before disease becomes established.

A digital twin is a dynamic model that remains continuously synchronized with real-world data, allowing the simulation of future scenarios in a virtual environment before they occur in the physical world[1].

In healthcare, the entity being twinned may be a patient, organ system, disease process, hospital workflow or population health system. A medical digital twin integrates clinical, molecular, imaging, physiological, behavioral and environmental data to create a dynamic virtual representation that evolves over time, moving medicine beyond static records toward prediction, prevention and intervention planning. The resulting workflow, from identifying the current health state to forecasting trajectories, simulating alternative interventions and learning from subsequent outcomes, is summarized in Fig. 1.

Building a global digital navigator of human health

The International Consortium of Digital Twins in Healthcare and Medicine (ICDT-HM) was established in 2024 to advance this vision. By linking multimodal health data with continuously updated virtual counterparts, the consortium seeks to move medicine from static description to dynamic navigation. Its goal is to build a global digital navigator of human health, a shared framework that can represent how

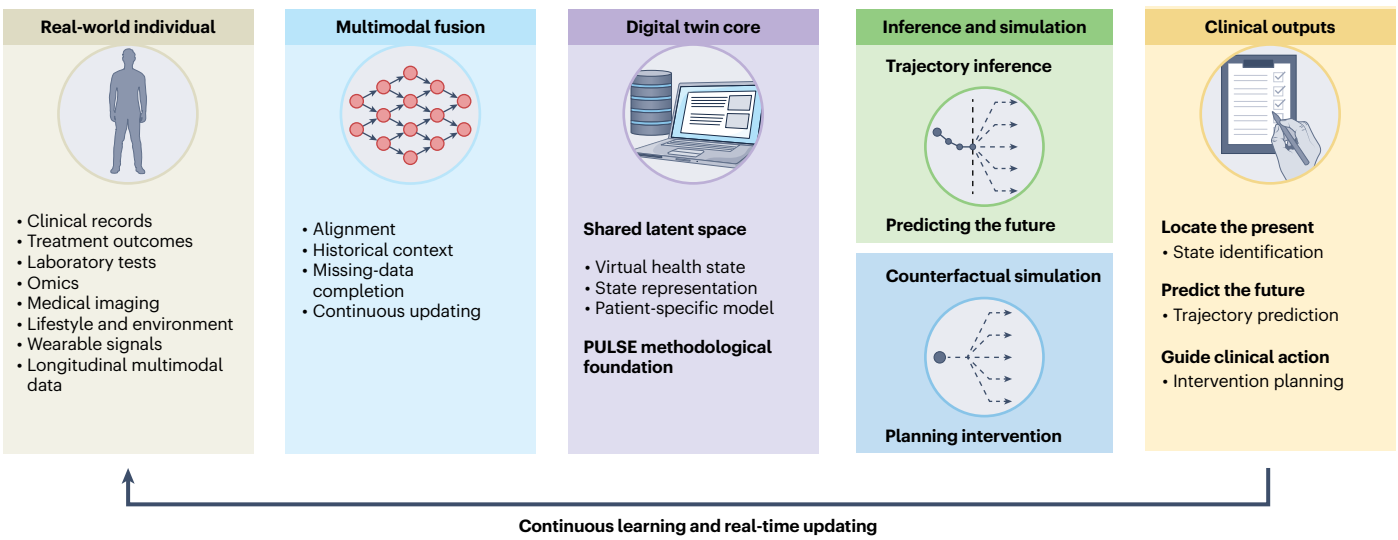

Fig. 1 | Trajectory inference framework for an individual digital twin. Multimodal health data are integrated to identify an individual's current health state and construct a personalized digital twin. Trajectory inference (green box, fourth column) estimates possible future paths. Counterfactual simulation (blue box, fourth column) evaluates how interventions may redirect these paths, while real-world outcomes are fed back into the model to support continuous updating and a closed-loop approach to precision in prevention.

human physiology changes across life stages, populations, environments, diseases and health systems.

The ICDT-HM is organized around the following three long-term goals:

(1) Decode health-state transitions. Current medical practice can often define when a person already has a disease, but it is less able to explain how a person moves from health to risk, from risk to disease, or from disease to recovery. These changes usually happen gradually, through shifts in molecular function, organ physiology, clinical signs, environment and treatment response. ICDT-HM aims to use longitudinal multimodal data to map these health-state transitions and identify the rules that drive them.
(2) Build life-course human health models. Health changes across the whole life course, but childhood development, adult disease risk and aging are often studied separately. This makes it difficult to understand how early-life biology, inherited risk, clinical events, lifestyle and environment shape health later in life[2]. Recent studies of inherited cancer susceptibility in pediatric populations further highlight the importance of incorporating early-life genetic risk into life-course digital twin models. ICDT-HM aims to build dynamic life-course models that connect development, adulthood and aging, so that human health can be represented as a continuous trajectory rather than as isolated disease labels or single time-point measurements.
(3) Enable digital navigation and virtual trials. Owing to the lack of personalized predictive tools, when faced with several viable treatment options, clinicians often struggle to determine which specific intervention aligns perfectly with that individual patient's unique biological makeup. Many prevention and treatment strategies also cannot be tested repeatedly, early enough or across every relevant population. ICDT-HM aims to use digital twins and virtual cohorts to predict possible health trajectories and compare interventions before they are applied in the real world.

Counterfactual simulation requires more than accurate prediction. In observational data, treatment assignment is systematically related to prognosis, so a model may reproduce observed outcomes without reliably estimating what would have happened under an alternative intervention. Credible digital-twin counterfactuals require an explicit causal question, target-trial emulation or other appropriate identification strategies, explicitly stated and investigated identifying assumptions — including exchangeability, positivity and consistency — and sensitivity analyses for unmeasured confounding. Twins intended to guide intervention should make their assumptions, uncertainty and predicted responses to plausible alternatives explicit. Previous work on virtual patient populations[3], in silico trials[4,5], synthetic control arms[6], hospital digital twins[7] and health-system simulations[8] has shown that computational models can support trial design, clinical decision-making and healthcare planning. However, many existing systems focus on a single disease, trial, hospital workflow or health-system problem, and they are often based on fixed datasets or limited data types.

ICDT-HM aims to connect these approaches across scales. Rather than modeling only a single trial population or hospital workflow, it seeks to link continuously updated individual digital twins with organ-level models, virtual cohorts, and population- or health-system-level simulation. This approach integrates heterogeneous and potentially discordant data, including longitudinal clinical records with imaging, '-omics', physiological, behavioral, environmental and treatment data, allowing health states and disease trajectories to be updated as new data become available. Through a federated international network, the consortium also aims to test and validate these models across different populations, environments and health systems. The goal is not simply to collect more data but to develop more robust, generalizable and equitable models of health and disease.

While individual digital twins focus on one patient, virtual cohorts extend this approach to groups of patients. A virtual cohort is a group of synthetic but non-identifiable patients generated from patterns in real-world data. These patients do not correspond to any real individual person but can retain important population-level features, such as age, biomarkers, disease stage, treatment history and outcomes[9,10].

Virtual cohorts can then be used to simulate disease progression, treatment responses and possible prevention or treatment strategies across different patient groups. They may support in silico trials, trial design, patient selection, rare-disease and pediatric studies, privacy-preserving analysis, and evaluation of interventions that would be difficult, costly or ethically challenging to test directly in real populations.

Four forms of medical digital twins

Spanning current-state assessment, trajectory prediction, intervention guidance, and continuous adaptation, digital twin capabilities can be organized into the following four increasingly mature forms of medical digital twins:

(1) Static twins project the present. Static twins integrate available clinical data to describe a person's current health state. This requires methods that can combine incomplete and heterogeneous data, such as clinical records, laboratory tests, imaging and '-omics' results. PULSE provides an example of this approach[11]: it uses patient history and data collected across multiple visits to build an updateable representation of an individual person's physiological state, even when some high-dimensional measurements are missing. This provides a practical basis for constructing a current-state digital twin from routine clinical data.
(2) Progressive twins trace the future. Progressive twins use longitudinal data to model how health changes over time[12]. LifeClock shows that routine clinical records can be used to model trajectories of development, aging and disease risk across the life course[13]. MoChiAgent extends this approach to maternal–infant health by modeling linked trajectories of mothers and children and predicting future transgenerational risks. Together, these studies show that digital twins can move beyond describing the present to estimating how health states may change over time.
(3) Operational twins guide intervention. Operational twins use predicted trajectories to compare possible clinical decisions. The Digital Prostate Model provides an organ-level example by integrating longitudinal clinical records, multi-omics data, magnetic resonance imaging and digital pathology to model the prostate disease spectrum. Oncoformer further extends progressive twins to cancer by learning longitudinal representations from routine clinical data that support future cancer prediction, stage inference, treatment-response prediction and prognosis within a unified framework[12]. At the population level, virtual cohorts extend this capability by allowing intervention strategies to be compared across groups of similar but non-identifiable patients.

(4) Autonomous twins provide continuous learning. Autonomous twins would go one step further by updating their predictions as new clinical data and treatment outcomes become available. The current models provide important components for this goal, including longitudinal state modeling, missing-data handling, trajectory prediction and treatment-response forecasting. However, fully autonomous twins will require prospective clinical validation, continuous feedback from real-world outcomes, monitoring for data drift and bias, and clinical and ethical oversight.

Six pillars for implementation

Realizing this vision requires more than individual algorithms or datasets; it demands an integrated ecosystem in which data, computation, infrastructure and governance evolve together. ICDT-HM is therefore building six interconnected pillars.

The first is global biospecimens and population cohorts that connect population-scale cohorts, disease-specific cohorts and biobank resources across ancestries, environments and health systems.

The second is multimodal measurement innovation, integrating clinical records, imaging, laboratory tests, and '-omics', microbiome, wearable, behavioral and environmental data to keep virtual counterparts synchronized with real-world biology.

The third is latent-space computational science. A medical digital twin should not simply stack multimodal data; it should align clinical records, laboratory tests, imaging, '-omics' data, wearable data, environmental exposures, treatments and outcomes into a shared latent space that represents underlying physiological states. This latent space serves as the computational map where health states are represented, trajectories are inferred and interventions are simulated.

The fourth is big-science infrastructure, including automated pipelines, secure computing environments, federated platforms, quality-control systems and continuous model-updating workflows for scalable digital twin generation.

The fifth is open resources and data protocols, including common data models, metadata standards, validation benchmarks, FAIR (findable, accessible, interoperable and reusable)-compliant resources and privacy-preserving federated learning portals.

The sixth is international governance and research teams (Table 1) coordinated through steering, scientific and executive committees, expert working groups and global nodes that bring together clinicians, data scientists, engineers, ethicists, public health experts, industry partners and policy stakeholders.

These pillars provide the data, technologies, computation, governance and global collaboration needed to build a digital navigator of human health.

A federated global operating model

To translate these six pillars into a durable international infrastructure, ICDT-HM will adopt a federated global operating model. The consortium will be coordinated through regional hubs across Asia-Pacific, Europe and North America, with additional national and institutional nodes contributing population cohorts, disease-specific resources, technical platforms and clinical validation networks. Rather than centralizing all data or decision-making, this structure will allow local institutions to retain data sovereignty while participating in shared model development, external validation and cross-population comparison.

Table 1 | Representative institutional network of ICDT-HM

Region	Institution (representative(s))
Asia-Pacific (Greater China)	Macau University of Science and Technology (Kang Zhang); Guangzhou National Laboratory (Tao Xu); Wenzhou Medical University (Xian Shen); Tsinghua University (Jiahong Dong); Peking University (Wei Wu); Shanghai Jiao Tong University School of Medicine (Guang Ning)
Asia-Pacific (Southeast Asia)	Duke-NUS Medical School (Patrick Tan)
North America	Harvard Medical School (Jonathan Gootenberg and Omar O. Abudayyeh); Stanford University (Michelle Williams and Joseph Wu); New York University (Eric Oermann); Johns Hopkins University School of Medicine (Akrit Sodhi)
Europe	Université Paris Cité INSERM PARCC (Alexandre Loupy); University of Oxford (Trey Ideker)

ICDT-HM will be guided by a steering committee responsible for strategic direction; a scientific committee that oversees research priorities and methodological standards; an executive committee that coordinates implementation; and expert working groups in data science, clinical validation, ethics, regulation and translation. This structure is designed to ensure that medical digital twins develop not as a loose collection of isolated models but as a coordinated global learning system with shared standards, distributed accountability and regional adaptability.

Ethics, governance and social responsibility

Medical digital twins raise distinct ethical and governance challenges because they may integrate longitudinal health data across the life course and inform clinical decisions. Privacy, data sovereignty, fairness, transparency and accountability must therefore be built into the system from the beginning.

ICDT-HM is committed to a federated governance model in which sensitive health data remain under local control. Federated learning, privacy-preserving analytics, secure multiparty computation, blockchain-enabled audit trails and role-based access can allow models to learn across institutions without requiring centralization of raw data[14].

Transparency and accountability are equally essential. Each step, from data collection and model training to state identification, trajectory prediction, counterfactual simulation and clinical deployment, should be auditable, explainable and clinically validated.

Global inclusion is a scientific requirement[15]. ICDT-HM will systematically map the demographic, geographic and clinical coverage of participating cohorts, including ancestry, age, sex, geographic setting and disease burden, where available. This mapping will identify coverage gaps and guide the inclusion of under-represented populations. The consortium will then use its international network to evaluate model performance across populations, healthcare settings and regions, identifying where models generalize well and where further validation is required. This approach will support more robust and equitable medical digital twins.

Where mapping identifies populations that are absent or thinly represented, ICDT-HM will prioritize partnership with institutions in those settings, and will not release models for clinical use in any population in which they have not been externally validated. The consortium will pre-specify minimum calibration and performance thresholds by subgroup, together with the actions triggered when a model fails to meet them, and will ensure that contributing sites in under-represented

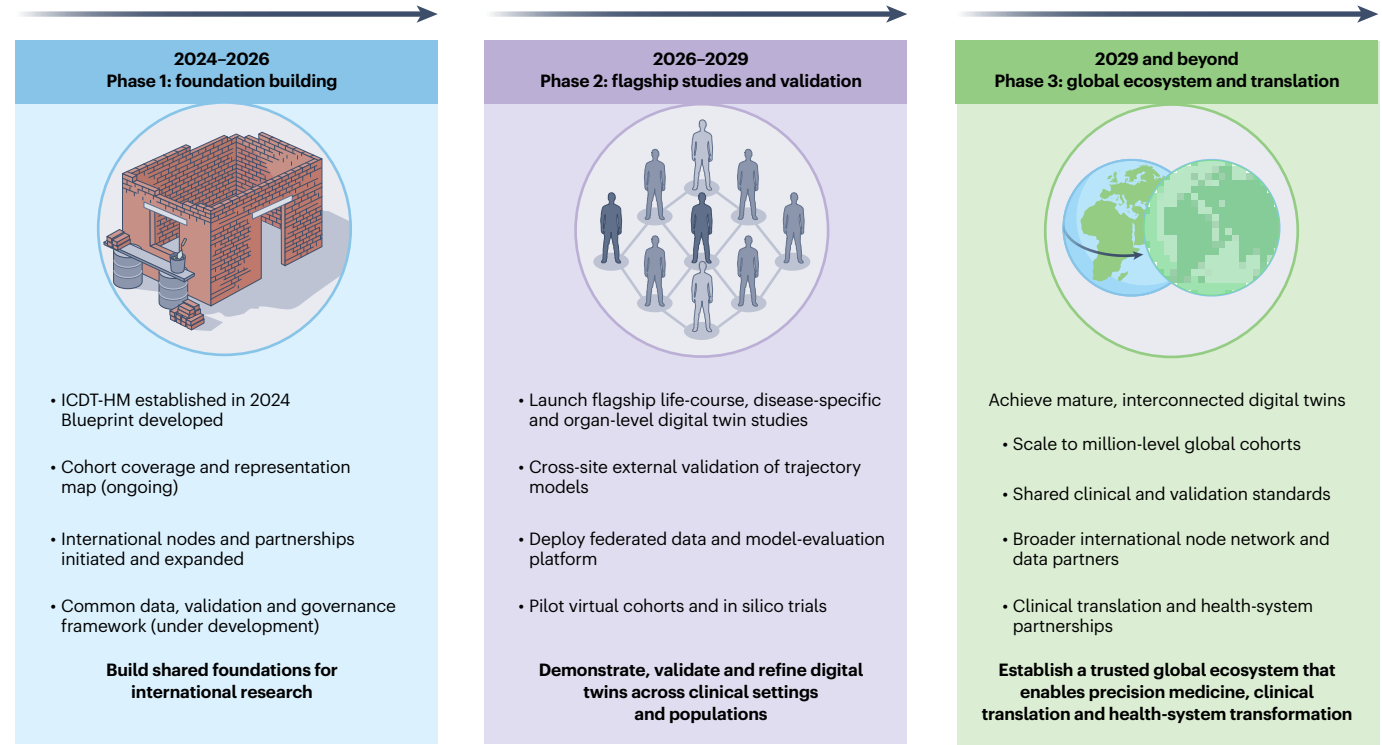

Fig. 2 | ICDT-HM roadmap from blueprint to a global digital twin ecosystem. The roadmap outlines three phases: foundation building and network development (2024–2026); flagship studies and cross-site validation (2026–2029); and expansion toward a global ecosystem for clinical translation and health-system impact (2029 and beyond).

settings share in the resulting scientific and clinical benefit, including authorship, capacity building and access to derived tools. The roadmap sets out the next steps for ICDT-HM over the coming years: consolidating shared standards, cohort mapping and international governance; expanding and connecting existing digital twin studies in maternal–infant health, cancer-risk stratification and aging; and validating digital twin models across international health systems before wider clinical translation. These steps will build on the consortium's existing computational and clinical foundations to develop a practical and responsible digital navigator of human health for prevention, diagnosis, treatment planning and population health research. The three proposed implementation phases and their indicative timelines are summarized in Fig. 2.

Kang Zhang[1,2,3,21] ✉, Jiahong Dong[4,21] ✉, Hang Wong[3,21], Sian Liu[3,21], Kai Wang[1], Wei Wu[5], Kaixin Zhou[2], Kanmin Xue[6], Edward Zhang[1], Jonathan Gootenberg[7,8], Omar O. Abudayyeh[7,8], Michelle Williams[9] ✉, Xian Shen[10,11] ✉, Alexandre Loupy[12,13] ✉, Trey Ideker[14,15] ✉, Patrick Tan[16] ✉, Joseph Wu[17] ✉, Akrit Sodhi[18] ✉, Eric Oermann[19] ✉, Tao Xu[2] ✉ & Guang Ning[20] ✉

[1]Artificial Intelligence Cross Disciplinary Research Institute and Faculty of Medicine, Macau University of Science and Technology, Macau, China. [2]Guangzhou National Laboratory, Guangzhou, China. [3]State Key Laboratory of Eye Health and Clinical Data Science Institute, Eye Hospital, Wenzhou Medical University, Wenzhou, China. [4]Hepatopancreatobiliary Center, Beijing Tsinghua Changgung Hospital, Key Laboratory of Digital Intelligence Hepatology, Ministry of Education, School of Clinical Medicine, Tsinghua University, Beijing, China. [5]Department of Big Data and Biomedical AI, College of Future Technology, Peking University and Peking-Tsinghua Center for Life Sciences, Beijing, China. [6]Nuffield Department of Clinical Neurosciences, University of Oxford, Oxford, UK. [7]Division of Engineering in Medicine, Department of Medicine, Brigham and Women's Hospital, Harvard Medical School, Boston, MA, USA. [8]Gene and Cell Therapy Institute, Mass General Brigham, Cambridge, MA, USA. [9]Department of Epidemiology and Population Health, Stanford University School of Medicine, Stanford, CA, USA. [10]Clinical Data Science Institute and the Zhejiang Key Laboratory of Intelligent Cancer Biomarker Discovery and Translation, the First Affiliated Hospital, Wenzhou Medical University, Wenzhou, China. [11]Department of General Surgery, Department of Hepatobiliary Surgery, Zhejiang-Germany Interdisciplinary Joint Laboratory of Hepatobiliary-Pancreatic Tumor and Bioengineering, The First Affiliated Hospital of Wenzhou Medical University, Wenzhou, China. [12]Université Paris Cité, INSERM U970 PARCC, Paris Institute for Transplantation and Organ Regeneration, Paris, France. [13]Department of Kidney Transplantation, Assistance Publique-Hôpitaux de Paris, Paris, France. [14]Departments of Medicine and Bioengineering, Moores Cancer Center, School of Medicine, University of California San Diego, San Diego, CA, USA. [15]Big Data Institute, Oxford University, Oxford, UK. [16]Duke-NUS Medical School, Singapore, Singapore. [17]Departments of Medicine (Cardiovascular Medicine) and Radiology, Stanford University School of Medicine, Stanford, CA, USA. [18]Wilmer Eye Institute, Johns Hopkins School of Medicine, Baltimore, MD, USA. [19]Departments of Neurosurgery, Radiology and Data Science,

Neuroscience Institute, NYU Langone Medical Center, New York University, New York, NY, USA. [20]National Clinical Research Center for Metabolic Diseases (Shanghai), Key Laboratory for Endocrine and Metabolic Diseases of the National Health Commission of the PR China, National Research Center for Translational Medicine, Shanghai Key Laboratory for Endocrine Tumor, State Key Laboratory of Medical Genomics, Ruijin Hospital, Shanghai Jiao Tong University School of Medicine, Shanghai, China. [21]These authors contributed equally: Kang Zhang, Jiahong Dong, Hang Wong, Sian Liu.
✉e-mail: kang.zhang@gmail.com; dongjiahong@mail.tsinghua.edu.cn; mawilliams91@stanford.edu; shenxian@wmu.edu.cn; alexandreloupy@gmail.com; trey.ideker@gmail.com; gmstanp@duke-nus.edu.sg; joewu@stanford.edu; asodhi1@jhmi.edu; eric.oermann@nyulangone.org; xutao@ibp.ac.cn; gning@sibs.ac.cn

Published online: 11 September 2026

References

1. Zhang, K. et al. *Patterns* **5**, 101028 (2024).
2. López-Otín, C., Blasco, M. A., Partridge, L., Serrano, M. & Kroemer, G. *Cell* **186**, 243–278 (2023).
3. Pammi, M. et al. *Lancet Digit. Health* **7**, 100851 (2025).
4. Viceconti, M., Henney, A. & Morley-Fletcher, E. *Int. J. Clin. Trials* **3**, 37–46 (2016).
5. Ruhrberg Estévez, S. et al. *npj Digit. Med.* **9**, 582 (2026).
6. Bertolini, D. T., Fuller, F., Smith, A. M., Walsh, J. R. & Zhuang, R. Preprint at https://doi.org/10.48550/arxiv.2605.12832 (2026).
7. Riahi, V., Diouf, I., Khanna, S., Boyle, J. & Hassanzadeh, H. *J. Med. Internet Res.* **27**, e55015 (2025).
8. Katsoulakis, E. et al. *npj Digit. Med.* **7**, 77 (2024).
9. Goncalves, A. et al. *BMC Med. Res. Methodol.* **20**, 108 (2020).
10. Valanarasu, J. M. J. et al. *Cell* **189**, 386–400.e19 (2026).
11. Wu, W. et al. *Nat. Comput. Sci.* https://doi.org/10.1038/s43588-026-01026-5 (2026).
12. Liu, F. et al. *Cell* https://doi.org/10.1016/j.cell.2026.07.009 (2026).
13. Wang, K. et al. *Nat. Med.* **31**, 4225–4235 (2025).
14. Rieke, N. et al. *npj Digit. Med.* **3**, 119 (2020).
15. Obermeyer, Z., Powers, B., Vogeli, C. & Mullainathan, S. *Science* **366**, 447–453 (2019).

Competing interests

T.I. is a member of the scientific advisory boards of Ideaya Biosciences and Eikon Therapeutics and holds equity in both companies. T.I. is also a co-founder and advisory board member of Data4Cure and Serinus Biosciences and holds equity in both companies. These arrangements have been reviewed and approved by the University of California San Diego in accordance with its conflict-of-interest policies. J.S.G. is a co-founder of Monet Therapeutics and Transit Therapeutics. O.O.A. is a co-founder of Monet Therapeutics, Transit Therapeutics and Helios Intelligence. P.T. reports stock ownership in Tempus AI and Auristone. J.C.W. is a co-founder and scientific advisory board member of Greenstone Biosciences. A.S. is a co-founder of and holds equity in HIF Therapeutics. Within the past 12 months, E.K.O. has received grant or research support from the US National Institutes of Health, the Keck Foundation, and the Ministry of Science and ICT and the Institute for Information & Communications Technology Planning & Evaluation, Republic of Korea; has served as a consultant to Google, Sofinnova and AlphaTec; and holds equity in Artisight and MarchAI. E.K.O.'s spouse is employed by Eikon Therapeutics. The remaining authors declare no competing interests.