Exploration of Digital Health Technologies

Open Exploration

Open Access Perspective

# Towards the future of personalized medicine: digital twin technology

Keren Mazuz[1]*, Seema Biswas[2]

[1]School of Management, Jerusalem Multidisciplinary College (former Hadassah Academic College), Jerusalem 9101001, Israel
[2]Department of Health Studies, Royal Holloway University of London, Egham TW20 0EX, United Kingdom of Great Britain and Northern Ireland

***Correspondence:** Keren Mazuz, School of Management, Jerusalem Multidisciplinary College (former Hadassah Academic College), Jerusalem 9101001, Israel. kerenma@jmc.ac.il

**Academic Editor:** Mohammad Reza Saeb, Medical University of Gdańsk, Poland
**Received:** September 9, 2025 **Accepted:** November 17, 2025 **Published:** January 14, 2026

**Cite this article:** Mazuz K, Biswas S. Towards the future of personalized medicine: digital twin technology. Explor Digit Health Technol. 2026;4:101181. https://doi.org/10.37349/edht.2026.101181

## Abstract

Digital twin technology is emerging as a transformative paradigm in healthcare, shifting practice from provider-centered models toward more personalized forms of medicine. As dynamic virtual representations of the human body, digital twins integrate biometric data, lifestyle patterns, and clinical records to simulate, monitor, and predict health trajectories in real time. Their growing use raises not only technical possibilities but also important questions about how patients relate to these data-driven counterparts, particularly when twins inform everyday health decisions in chronic care, such as diabetes or oncology. This perspective examines these relational dynamics and their ethical, cultural, and experiential implications for autonomy, decision-making, and the lived experience of being represented in data. To guide this analysis, we introduce a scale framework with three intersecting lenses: time, distinguishing asynchronous from synchronous updating; twining, ranging from close mirroring to more augmentative forms of representation; and control, spanning human-led to twin-driven decision authority. Using this framework, we position four common types of digital twins: mirror, shadow, intelligent, and simulacra as an evolution from basic representation to transformative modeling. We argue that future healthcare and public health policy must go beyond technical innovation to address patients' lived experiences, ensuring that digital twins enhance rather than diminish autonomy, trust, and equity. This perspective thus calls for a patient-centered approach in designing and implementing digital twin technologies.

## Keywords

digital twin, artificial intelligence, personalized medicine

## Introduction

Digital twin (DT) technology has gained increasing attention as healthcare systems transition toward models of care that emphasize personalization, prevention, and active patient participation. Originally developed in engineering and industrial contexts, DTs are now conceptualized as dynamic, virtual representations of the human body, continuously updated by real-time data streams from multiple sources, including wearable sensors, mobile health applications, and clinical records [1, 2].

These models do more than simply replicate physiology; they allow simulation, prediction, and adaptation, offering a framework in which health decisions can be informed by continuously evolving data. For example, experience with DT technology has shown its efficacy in dietary intervention. Drawing upon metabolomic profiles, clinical records, phenotypic indicators, and behavioral information, it becomes possible to construct a comprehensive patient DT [3]. Such model integrates behavioral dimensions (i.e., sleep, nutrition, and activity patterns) within computational simulations, which in turn support evidence-based design of dietary management and lifestyle interventions and the promotion of healthy aging. Similarly, oncology research has begun to integrate DT simulations into individualized treatment planning, adapting interventions to tumor progression dynamics [4].

The promise of DTs in healthcare extends beyond their technical capabilities. They mark a profound shift in how the relationship between the patient and the digital model is understood. Rather than functioning solely as tools for providers, DTs may serve as co-actors in the patient's health journey by providing feedback, shaping decision-making, and even influencing behavior. This relational dimension is especially relevant as health policy increasingly adopts a patient-centered orientation, where individual agency, lived experience, and cultural context must be integrated alongside biomedical data. Thus, DT technology is envisioned as enabling more precise monitoring, simulation, and prediction, thereby creating new possibilities for both individuals and healthcare systems.

DT brings together self-monitoring biometric data collected by patients from wearable devices, mobile health, and lifestyle applications on personal devices with clinical data, such as laboratory results and electronic medical records stored by healthcare service providers, to build a digital model of an individual, an avatar of the patient. This is a deliberate move toward personalizing healthcare and toward bridging the interface between healthcare provision and consumption, as people take on more responsibility for their own health and as healthcare providers look for innovative ways to address the rising costs of healthcare provision and demands on health resources.

The purpose of this perspective is to focus on the relational patterns between the human (real world) and the virtual model (digital world) because they deserve close attention, as they carry ethical and cultural implications for autonomy, decision making, and the lived experience of being represented in data.

## Current state of DT applications in healthcare

Recent advances show that human DTs rely on several enabling technologies, including network and edge-computing systems for real-time synchronization [5], mobile AIGC (AI-Generated Content) techniques that create personalized digital models and outputs [6], and generative-AI frameworks that integrate IoT data into healthcare environments [7]. Together, these developments situate our framework within a fast-evolving technical landscape and illustrate that autonomy and user experience are deeply shaped by underlying system architectures.

## The three digital-twin variants and their interrelation model

DTs are described in terms of three core mechanisms: physical, virtual, and the dynamic connection between them, enabling continuous information exchange through real-time data connection [1]. Over time, as technology and interactions advanced, the field has expanded beyond the early 'static twin' to introduce variants, such as the mirror, shadow, and, more recently, the intelligent twin.

The mirror twin remains a static representation, whereas functional twins incorporate dynamic behaviors and have been applied in contexts such as surgical simulation, digital clinical trial modeling, and adaptive research designs. The so-called shadow twin is a self-adaptive model that continually synchronizes with real-world inputs, allowing iterative updates. These twins have been explored in areas like medical device development and biomarker discovery.

At the frontier is the intelligent twin, an adaptive model underpinned by artificial intelligence. This form of twin incorporates reasoning, learning, and decision-making functions, and can also interact with other digital representations (this model is also known as cognitive or extended DTs or physical avatars). For such systems to operate, they require continuous bidirectional data exchange between the physical counterpart and its virtual representation.

Ongoing data exchange between real-world and digital models allows refinement of simulations and the use of machine learning to generate predictions, optimize processes, and accelerate decision-making. Applications have emerged in clinical workflow planning, hospital operations, personalized care, and wellness programs. Importantly, such twins can guide treatment pathways, with each new dataset enabling further adaptation of the model before interventions reach the patient.

Based on the Simulacra theory, Rubeis (2023) [8] defines the twin, especially the intelligent twin, as a simulacra twin, a hyperreal, that leads to a situation where patients are reduced to their data: "There is no room for doubt or misinterpretation, since the DT as simulacrum does not represent a physical entity, but in a way is this entity ... a representation of a physical entity that relies solely on quantifiable data. This leaves little room for a more holistic view of the patient that contextualizes physiological data with the patient's personal situation, his or her sociodemographic background, and other individual characteristics" (pg. 203). From this perspective, intelligent twins act as hyperreal simulacra: they go beyond simple mirroring, not just reflecting reality but actively reshaping, reinterpreting, and transforming it. Their functioning relies on both patient-generated data and algorithm-driven recognition methods, such as pattern analysis, data mining, and machine-learning approaches.

To enhance technical clarity, the four DT types can also be defined using measurable criteria such as data latency, update frequency, bidirectional data exchange, level of decision automation, and the balance between physiological and contextual data inputs, as seen in Table 1. In this spectrum, mirror twins operate with low-frequency updates and no predictive capacity; shadow twins enable near-real-time adaptation; intelligent twins provide autonomous decision support; and simulacra twins combine high-dimensional data with autonomous control.

**Table 1. Technical indicators for digital-twin types.**

| Digital-twin type | Data latency | Update frequency | Predictive capability | Decision autonomy | Data scope |
|---|---|---|---|---|---|
| **Mirror twin** | High latency | Intermittent updates | None | Human-only control | Physiological data only |
| **Shadow twin** | Medium–low latency | Continuous iterative updates | Limited prediction | Shared human-guided control | Physiological + medical device data |
| **Intelligent twin** | Low latency | Continuous + adaptive updates | Predictive analytics | Semi-autonomous support | Physiological + behavioral data |
| **Simulacra twin** | Near-zero latency | Continuous + generative updates | Predictive + simulation modeling | Autonomous control with human override safeguards | Physiological + behavioral + contextual data |

We can summarize the relational patterns between the human (real world) and the DT (virtual world) in the scale framework shown in Table 2. The framework consists of three key aspects: (1) time; (2) twining; (3) control in decision-making. Each aspect represented a continuum ranging from one end to the other.

**Table 2. The scale framework.**

| Three aspects | Scale range | | |
|---|---|---|---|
| 1. Time | Asynchronized | to | Synchronized |
| 2. Twinning | Integrated | to | Complementary |
| 3. Control in decision-making | Human control | to | Twin control |
| The digital twin types: | Mirror twin | | Intelligent twin |
| | Shadow twin | | Simulacra twin |

1. Time: It ranges from asynchronous systems, where twin updates occur intermittently, to synchronous systems that reflect an individual's state in real time.
2. Twinning: It ranges from integrated models that closely mirror physiological and behavioral states to complementary models that operate more independently and provide additional insights.
3. Control in decision-making: It ranges from human-led decisions, where the twin serves as a support tool, to twin-led decisions, where AI models autonomously guide or initiate actions.

Within this spectrum, mirror and shadow twins tend to be asynchronous, integrated, and human-controlled, whereas intelligent and simulacra twins are typically synchronous, complementary, and capable of autonomous decision-making.

## Operational parameters and disease-adaptive scenarios

To illustrate how the time–twinning–control framework can inform practical design, we apply it to three representative disease scenarios. As shown in Table 3, digital-twin configuration, autonomy, and patient acceptance differ by clinical need, risk profile, and emotional burden. Future work can further test and validate this approach in real healthcare settings.

**Table 3. Disease-specific digital-twin applications and acceptance considerations.**

| Condition | Digital-twin configuration | Control mode | Patient acceptance factors |
|---|---|---|---|
| Diabetes (chronic metabolic disorder) | Real-time glucose–insulin modeling with continuous sensor input | Human-led decisions with automated alerts and suggested actions | High acceptance when autonomy is preserved; usefulness tied to reducing burden and uncertainty |
| Cardiac rehabilitation (post-acute recovery) | Predictive modeling of exercise tolerance, cardiovascular load, and risk events | Shared control between clinicians, patients, and twins | Acceptance depends on explainability, safety monitoring, and clinician endorsement |
| Oncology (complex high-stakes treatment) | Multimodal simulation for treatment effects and toxicity prediction | Clinician-governed control with a twin providing decision support | Patients prefer physician authority; emotional reassurance and transparency are essential |

These cases show that digital-twin design must adapt to disease context, with differences in real-time data needs, acceptable autonomy levels, emotional burden, and clinical safety requirements. In other words, a single model cannot fit all conditions; effective DT systems should scale and adjust to clinical complexity and patient sensitivity. Future work may further validate and refine this framework through real-world clinical use.

## Discussion

The purpose of this perspective is to draw attention to the relational patterns between human beings and their DTs, since these interactions carry important ethical, cultural, and experiential implications for autonomy, decision making, and the lived experience of being represented in data. Using the scale framework of time, twining, and control, DT models can be positioned along a continuum that reflects not only their technical sophistication but also their impact on patients' sense of agency and responsibility within healthcare systems.

From a temporal perspective, synchronization intensifies the immediacy of feedback and support. For example, shadow and intelligent twins enable patients to see the near-real-time effects of medication or lifestyle choices, reinforcing adherence and reducing uncertainty. While such immediacy can empower patients, it also risks producing digital stress if the constant flow of information becomes overwhelming [9]. Thus, balancing temporal precision with emotional reassurance remains a critical design consideration.

The second lens, twinning, concerns how closely the human and digital models are connected. Mirror and shadow twins emphasize integration, helping patients see the consequences of their actions in a controlled way, whereas intelligent and simulacra twins shift toward complementarity by offering predictions and guidance beyond direct mirroring. Integration can risk reducing patients to data points, while complementarity raises questions of trust, whether patients accept guidance from a system that interprets and transforms their data [8]. This aligns with qualitative findings [10], where individuals oscillate between trust and skepticism when engaging with algorithmic interpretations of their health information.

The third dimension, control in decision-making, is ethically critical. Human-controlled systems, such as the mirror twin, protect autonomy but may offer limited support for complex treatment decisions, whereas twin-controlled systems, such as the simulacra twin, improve prediction and coordination yet heighten concerns about accountability and transparency [9]. As authority shifts from person to twin, risks to patient agency grow, particularly for vulnerable groups, underscoring the need to ensure patients remain co-authors of their care. Simplifying individuals into pseudo-image models also introduces data-representation risks. Dimensionality-reduction methods must preserve clinically meaningful variance, and loss-estimation techniques can model how missing psychosocial or contextual information may influence decisions through error-propagation formulas. To safeguard autonomy, a structured risk-assessment matrix can determine when a twin informs, recommends, or acts. A human-veto mechanism should override twin decisions when predicted harm exceeds defined thresholds, allowing twin autonomy only under low-risk, high-certainty conditions.

Beyond these three lenses, broader social and ethical implications must be considered. Inequities in digital literacy, access, and cost may limit who benefits from DT technologies and risk widening existing health disparities if not addressed [11, 12]. As Rubeis [8] notes, the simulacra twin, in particular, risks reducing humans to a hyperreal construct where personal and cultural context may be lost. This reduction could undermine not only clinical autonomy but also the social and emotional meaning of health, care, and cure for patients.

Privacy and security are equally critical. DTs rely on continuous, multi-source health data streams, creating heightened risks of re-identification, long-term surveillance, and cross-platform data leakage. Severe privacy breaches could result if safeguards are inadequate. Robust protections, such as differential privacy, federated learning, secure multiparty computation, and strong consent and governance frameworks, are therefore essential to ensure safe and equitable deployment.

To conclude, positioning DTs along the axes of time, twining, and control illuminates the complex relational shifts they bring to healthcare. These shifts are not simply technical but deeply cultural, shaping how patients understand themselves, their health, and their place within healthcare systems.

Future research must therefore move beyond technical design to explore patient experiences: how individuals emotionally respond to being mirrored, guided, or represented by a twin; how trust and consent can be dynamically negotiated in twin-controlled systems; and how different cultural and demographic groups perceive the legitimacy of these digital counterparts. By keeping patients at the center of this evolving technology, healthcare can ensure that DTs enhance rather than diminish autonomy, trust, and equity.

## Abbreviations

DT: digital twin

## Declarations

### Author contributions

KM: Conceptualization, Investigation, Writing—original draft, Writing—review & editing. SB: Conceptualization, Investigation, Writing—original draft, Writing—review & editing. Both authors read and approved the submitted version.

### Conflicts of interest

The authors declare that they have no conflicts of interest.

### Ethical approval

Not applicable.

### Consent to participate

Not applicable.

### Consent to publication

Not applicable.

### Availability of data and materials

Not applicable.


### Funding

Not applicable.




## Publisher's note

Open Exploration maintains a neutral stance on jurisdictional claims in published institutional affiliations and maps. All opinions expressed in this article are the personal views of the author(s) and do not represent the stance of the editorial team or the publisher.

## References


1. Katsoulakis E, Wang Q, Wu H, Shahriyari L, Fletcher R, Liu J, et al. Digital twins for health: a scoping review. NPJ Digit Med. 2024;7:77. [DOI] [PubMed] [PMC]
2. Sun T, He X, Li Z. Digital twin in healthcare: Recent updates and challenges. Digit Health. 2023;9: 20552076221149651. [DOI] [PubMed] [PMC]
3. Gkouskou K, Vlastos I, Karkalousos P, Chaniotis D, Sanoudou D, Eliopoulos AG. The "Virtual Digital Twins" Concept in Precision Nutrition. Adv Nutr. 2020;11:1405–13. [DOI] [PubMed] [PMC]
4. Stahlberg EA, Abdel-Rahman M, Aguilar B, Asadpoure A, Beckman RA, Borkon LL, et al. Exploring approaches for predictive cancer patient digital twins: Opportunities for collaboration and innovation. Front Digit Health. 2022;4:1007784. [DOI] [PubMed] [PMC]
5. Chen J, Yi C, Okegbile SD, Cai J, Shen X. Networking Architecture and Key Supporting Technologies for Human Digital Twin in Personalized Healthcare: A Comprehensive Survey. IEEE Commun Surv Tutor. 2024;26:706–46. [DOI]
6. Chen J, Yi C, Du H, Niyato D, Kang J, Cai J, et al. A Revolution of Personalized Healthcare: Enabling Human Digital Twin with Mobile AIGC. IEEE Netw. 2024;38:234–42. [DOI]
7. Yang Y, Shi Y, Yi C, Cai J, Kang J, Niyato D, et al. Dynamic Human Digital Twin Deployment at the Edge for Task Execution: A Two-Timescale Accuracy-Aware Online Optimization. IEEE Trans Mob Comput. 2024;23:12262–79. [DOI]
8. Rubeis G. Hyperreal Patients: Digital Twins as Simulacra and their impact on clinical heuristics. In: Loh J, Grote T, editors. Medizin – Technik – Ethik. Techno: Phil – Aktuelle Herausforderungen der Technikphilosophie. Berlin: Springer Berlin Heidelberg; 2023. pp. 193–207. [DOI]
9. Nyholm S. Should a medical digital twin be viewed as an extension of the patient's body? J Med Ethics. 2021;47:401–2. [DOI] [PubMed]
10. Tretter M. Perspectives on digital twins and the (im)possibilities of control. J Med Ethics. 2021;47: 410–1. [DOI] [PubMed]

11. Vaportzis E, Clausen MG, Gow AJ. Older Adults Perceptions of Technology and Barriers to Interacting with Tablet Computers: A Focus Group Study. Front Psychol. 2017;8:1687. [DOI] [PubMed] [PMC]
12. Coorey G, Figtree GA, Fletcher DF, Redfern J. The health digital twin: advancing precision cardiovascular medicine. Nat Rev Cardiol. 2021;18:803–4. [DOI] [PubMed]