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Challenges of Moving Beyond Digital Twins to Digital Patients

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ABSTRACT

The past decade has seen a rapidly expanding body of literature on the development and use of digital twins in medicine. Since 2020 around 3000 articles have been published that broadly address various topics related to digital twins, including their use in medicine. This paper focuses on the major challenges that come into play when considering the development of digital twins that seek to replicate an individual human and changes in health over time. Integrating the numerous medical digital twins that are currently being developed into a functional Digital Patient involves creating a detailed digital representation of a person that can simulate their behavior, health status and ranking on a variety of social determinants of health. The major challenges in the development of a multi-scale, interoperable, verifiable Digital Patient are highlighted in this paper. The overall challenge is to integrate the thousands of digital twins developed in the past few years into a usable Digital Patient. Issues that must be addressed include data collection, data integration and analysis, modeling and simulation, artificial intelligence (AI), visualization, clinical applications, security, and tools that facilitate development of usable simulated digital twins.

Keywords: Digital twins, Medical modeling, Simulation, Interoperability

INTRODUCTION

The past decade has seen a rapidly expanding body of literature on the development and use of digital twins in medicine. Since 2020 around 3000 articles have been published that broadly address various topics related to digital twins, including their use in medicine. This paper focuses on the major challenges that come into play when considering the development of digital twins that seek to replicate an individual human and changes in health over time.

Simulation is "providing experience under controlled conditions." The specific goals in medicine are the acquisition of improved motor skills, decision-making and communication skills, and operational skills (Oren et al., 2023). Simulation has been used in medicine for millennia and the simulators have become ever more sophisticated. The evolution from clay and wax models to augmented and virtual realities is amazing (Rosen et al., 2008). Today, the major types of simulation are task trainers, mannequins, standardized patients, virtual and augmented reality (AR) applications and hybrid combinations. The major sites used for simulations are skills labs, mock clinical spaces (including individual exam room, operating room and

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emergency room replicas), and hospitals and clinics. The move toward digital twins that are used in medical practice involves the development and use of more complicated simulations than the educational simulations currently being used.

CHALLENGES

Integrating the numerous medical digital twins that are currently being developed into a functional Digital Patient involves creating a detailed digital representation of a person that can simulate their behavior, health status and ranking on a variety of social determinants of health. The major challenges in the development of a multi-scale, interoperable, verifiable Digital Patient are highlighted in this paper.

The overall challenge is to integrate the thousands of digital twins developed in the past few years into a usable Digital Patient. Issues that must be addressed include data collection, data integration and analysis, modeling and simulation, artificial intelligence (AI), visualization, clinical applications, security, and tools that facilitate development of usable simulated digital twins.

Data Collection

The first step in building a Digital Patient is collecting the necessary data to replicate a person's status. This involves a wide range of data sources, including:

- Biometric Data: height, weight, age, DNA information, and other physical traits
- Health Metrics: Vital signs such as heart rate, blood pressure, glucose levels
- Behavioral Data: Daily routines, activities, preferences, and habits
- Psychological Data: Cognitive behaviors, emotional responses, and mental state monitoring
- Environmental Data: Interaction with environmental factors (e.g., sleep patterns, exercise, diet)
- Social Data: Interactions with people, location tracking, and social behavior

The enormity of building a digital twin that incorporates all this data is a major challenge. Some estimates of the data required in a functional Digital Patient range between 1 and 2 Zetabytes for a single Digital Patient.

Data Integration and Processing

When the data is obtained it must be integrated, processed, and cleaned. This process involves:

- Data Integration: Combining data from various sensors, devices (like wearables), and applications into a unified platform.
- Data Standardization: Ensuring the data is in a consistent format.

- Real-time Data Collection: Using IoT devices, sensors, and other wearables to continuously collect real-time data.
- Data Analytics: Using machine-learning models and AI to analyze and make sense of the data for predictive insights.

Modeling and Simulation

The Digital Patient is a multi-level simulation that integrates simulations ranging from the molecular to the community. This poses challenges in the time scales and types of data that must be integrated.

- Physics-based Models: Based on fluid dynamics that represent the physical characteristics of the person.
- Health Simulations: This involves using data to simulate a person's health status and response to treatments, medications, and different environments.
- Behavioral Modeling: The use of AI and machine-learning algorithms to simulate how a patient might respond in various situations based on their past behaviors.

AI AND MACHINE-LEARNING INTEGRATION

The use of AI and machine-learning will need to supplement the provider generated expectations about the outcome of treatments, including non-compliance.

- Predictive Models: These must incorporate AI to predict future behaviors and health outcomes. For example, a model might predict how likely a person is to develop a certain condition based on lifestyle habits.
- Personalization: The Digital Patient should adapt over time based on changes in a patient's behavior, health, or environment. Machine-learning algorithms will need to continuously refine the model with new data.

Visualization and Interaction

A Digital Patient, to be maximally useful, will need to demonstrate that it incorporates:

- Graphical Interface: A user-friendly interface to interact with the Digital Patient, whether for healthcare monitoring, virtual assistance, or improvements to the models within the simulations.
- AR/VR Integration: Augmented or virtual reality will need to create an immersive experience that visualizes the Digital Patient in real-time.

Clinical Applications

Digital patients will need to demonstrate that they address the following:

- Health Monitoring and Prediction: The Digital Patient must track and predict health issues, disease progression, and responses to treatments.

- Personalized Medicine: The Digital Patient must simulate the effectiveness of various medications and treatments for a specific individual.
- Behavioral Insights: The Digital Patient must incorporate potential variability in behavior as a result of medications, changes in social circumstances, and workplace behavior.

Privacy and Security Considerations

Since Digital Patients involve sensitive human data, it is important to ensure:

- Data Privacy: Secure storage and access to personal data.
- Informed Consent: Individuals should have control over what data is used and how it's shared.
- Data Anonymization: To prevent unauthorized access or misuse, data should be anonymized or encrypted.

Tools and Technologies

A variety of emerging technologies must be incorporated in the design of the Digital Patient:

- IoT devices (e.g., wearables, sensors, trackers) for data collection.
- Cloud Computing Platforms for processing large amounts of data.
- AI/Machine Learning (e.g., TensorFlow, PyTorch) for predictive analytics and personalized models.
- 3D Modeling Software (e.g., Blender, Unity) for visualizing the physical representation.
- Big Data Tools (e.g., Hadoop, Spark) for storing and processing the collected data.

Continuous Updates

- Digital Patients must evolve. As the person ages, changes their behavior, or interacts with different technologies, the Digital Patients should be regularly updated to reflect these changes.

Verification, Validation, and Uncertainty Quantification (VVU)

Verification, Validation, and Uncertainty Quantification is the fundamental framework used to ensure that a Digital Patient is actually accurate enough to use in clinical and research settings without putting real patients at increased risk. VVU is the "quality control" factor in the development and use of Digital Patients. The components of VVU are:

Verification ("Did we build the model right?")

Verification is a purely technical check. It looks at the math and the code. It ensures that the software equations describing blood flow, lung expansion, or drug metabolism are being solved correctly by the computer.

- **The Goal:** To prove there are no bugs in the logic and that the physics engine isn't "hallucinating" or crashing.

Validation ("Did we build the right model?")

Validation is where medicine meets engineering. It compares the simulator's output against real-world clinical data.

- **The Process:** If a simulator predicts that a patient's heart rate will climb to 120 BPM after receiving a specific dose of adrenaline, researchers compare that to actual patient records.
- **The Goal:** To ensure the simulator behaves like a real human being, not just a believable cartoon.

Uncertainty Quantification (UQ)

This is arguably the most important part of modern medical simulation. No two humans are identical; we vary by age, weight, genetics, pre-existing conditions and a myriad of other factors.

- **The Role of UQ:** It measures how much the "unknowns" (like a patient's unknown allergy or a slight sensor error in the mannequin) affect the outcome.
- **The Goal:** To define the "margin of error." Uncertainty Quantification answers the question: "How confident are we in this simulation's result?"

Why VVU Matters in the Digital Patient

Without a rigorous VVU process, medical simulation of patients is just a video game. In high-stakes environments, VVU provides:

- **Patient Safety:** Ensures surgeons aren't practicing on "glitchy" physics that don't translate to real flesh and bone.
- **Regulatory Approval:** The FDA and other bodies increasingly require VVU data before a new simulation-based device or software can be used for official medical certification.
- **Standardization:** It allows different hospitals to know that their "standard" training scenario is providing the same physiological challenge to every learner.

Verification is about the code, and Validation is about the biology, Uncertainty is about the reality that every patient is a little bit different.

Moving from a general medical simulator to a Digital Patient twin of a specific individual, the stakes for **VVU** skyrocket. No longer is the goal modeling a "generic 70kg male"; rather a Digital Patient involves modeling a specific person's unique anatomy, lifestyle, and pathology to predict their future health or surgical outcome.

In this context, VVU is the "trust bridge" that allows a healthcare provider to make a clinical decision based on a digital replica.

The VVU Framework for Digital Twins

Verification: The Digital Integrity

For a digital twin, verification ensures that the personalized data (from MRIs, wearables, or blood work) is being integrated into the model without distortion.

- **Code Verification:** Ensuring the algorithms simulating that specific patient's blood flow (Computational Fluid Dynamics) are mathematically sound.
- **Data Integrity:** Checking that the "sensor-to-twin" pipeline isn't introducing artifacts. If a wearable heart monitor glitches, the twin shouldn't interpret it as a cardiac arrest.

Validation: The "Bio-Identity" Match

This is the most challenging part of the twin process. The twin must actually mimic the **real-time behavior** of that specific human.

- **Retrospective Validation:** Feeding the twin the patient's data from last month and seeing if the twin "predicts" the health status the patient has today.
- **Physiological Consistency:** If the patient climbs stairs and their heart rate hits 130, the digital twin—under the same simulated load—should show the same response.

Uncertainty Quantification (UQ): Managing the "Known Unknowns"

Digital twins rely on "noisy" data (noisy sensors, subjective patient reporting, or missing lab results). UQ is the "Confidence Interval" of the twin.

- **Parameter Sensitivity:** If we aren't 100% sure of the patient's exact arterial wall thickness, UQ tells us how much that "guess" changes the surgical prediction.
- **Reliability:** Instead of a twin saying, "The patient will have a stroke in 2 years," a VVU-rigorous twin says, "There is an **85% probability** of a stroke based on current data variance."

CONCLUSION

The potential to develop Digital Patients is increasing, although substantial challenges remain. The overall challenge is to integrate the thousands of digital twins developed in the past few years into a usable Digital Patient.

Issues that must be addressed include data collection, data integration and analysis, modeling and simulation, artificial intelligence (AI), visualization, clinical applications, security, and tools that facilitate development of usable simulated digital twins.

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