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HUMAN DIGITAL TWIN MODELING FOR ADVANCING ARRHYTHMIA TREATMENT

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Abstract

Heart disease in all its forms remains a significant health threat. Arrhythmia is a type of heart disease whose diagnosis and treatment still primarily rely on conventional electrocardiogram-based diagnosis. However, this approach is limited, as it is reactive and captures cardiac conditions only at the time of electrocardiogram measurement, making it unable to continuously and individually monitor arrhythmia progression for each patient. This study explores digital twin technology and develops human digital twin models for the treatment of arrhythmia patients. The modeling framework integrates three core components: geometrical modeling, physical modeling, and data-driven modeling to represent the human heart and cardiovascular system in a digital environment. The output of this integrative process has been implemented in the initial prototype of the Human Digital Twin Cockpit, which is designed to treat arrhythmia. This prototype enhances the existing diagnosis and treatment, and also incorporates a proactive simulation system. Evaluation and system testing have successfully demonstrated their ability to integrate geometric data from medical imaging and physical data from electrophysiological sensors to predict arrhythmia in various scenarios.

Keywords: *Human Digital Twin, Electrocardiogram, Arrhythmia, Cardiac Electrophysiology*

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1 INTRODUCTION

Coronary artery disease remains the leading cause of death worldwide, including in Indonesia, with a steadily increasing annual prevalence [1,2]. This high mortality rate underscores the urgent need for more effective methods for early detection and prevention [3]. Although the electrocardiogram (ECG) has long been the gold standard for diagnosing cardiac rhythm disorders (arrhythmias), its utility is often limited to that of a reactive diagnostic tool, as it can only record cardiac activity at the time of measurement [4]. This presents a significant challenge because many arrhythmic events are sporadic and may be missed during brief recording sessions [5].

To address these limitations, the concept of a Digital Twin (DT) offers a transformative approach. Initially, DT was defined by three key dimensions: the physical entity, representing real-world objects; the virtual entity, which serves as their digital representation; and the connections that link these two dimensions together [6,7,8]. However, this model has evolved into a more comprehensive five-dimensional (5D) framework, incorporating two crucial additional components: digital twin data and services. Data can be aggregated and integrated from multiple sources, encompassing both historical and real-time information. Services comprise various intelligent functions—including simulations, predictions, and optimizations—executable on the virtual model [7] (see Figure 1).

The Human Digital Twin (HDT) is a virtual replica of a patient's heart that integrates medical imaging, physiological data, and real-time biosignals to model its structure and function. By enabling continuous monitoring, simulation, and risk prediction, HDT overcomes the limitations of conventional arrhythmia diagnosis and treatment, shifting healthcare from a reactive intervention model to a paradigm of personalized prevention. Through the creation of a continuously updated virtual heart replica that incorporates an individual's physiological data, we can not only monitor current conditions but also simulate specific scenarios to predict future arrhythmia risks and even virtually test the effectiveness of medical interventions prior to their clinical application [9,10]. This capability represents a concrete manifestation of the services dimension within the DT framework.

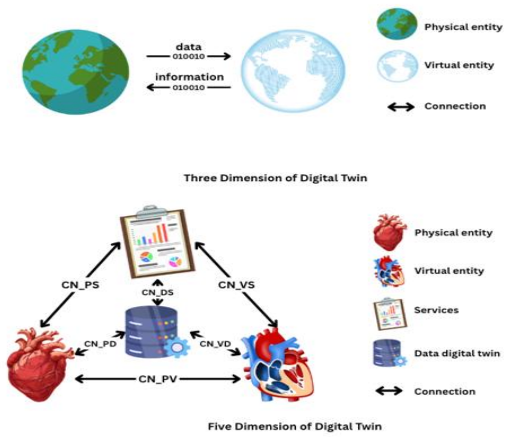

Figure 1. Digital Twin Evolution

The successful development of an accurate and functional Digital Twin critically depends on the ability to comprehensively model the physical object's various characteristics through multiple approaches. This process must incorporate diverse perspectives to adequately capture the complexity of biological systems like the human heart. A robust framework requires the integration of, at a minimum, three fundamental modeling types [11]. First, geometric modeling encompasses the spatial data needed to reconstruct an individual's unique cardiac anatomy, typically derived from medical imaging modalities like MRI or CT scans. Second, physical modeling involves directly measurable physiological parameters obtained through clinical instruments or wearable sensors. Finally, data-driven modeling incorporates computationally derived parameters that cannot be directly measured but are inferred through biophysical simulations and model calibration against empirical data.

To ensure that each modeling domain captures the necessary level of detail, the study commenced with an extensive literature review to identify the critical data and parameters required for accurate arrhythmia modeling. This systematic examination aimed to compile the essential electrophysiological information needed to replicate both normal and arrhythmic cardiac conditions within the Human Digital Twin (HDT) framework [12,13]. Through this comprehensive review, three primary categories of essential data were identified: (1) detailed anatomical data encompassing the dimensions and morphology of all four cardiac chambers, along with the precise locations of key conduction system components, including the sinoatrial node and atrioventricular node; (2) measurable physiological data, particularly multi-lead ECG signals that capture the heart's electrical activity from body surface recordings; and (3) derived biophysical parameters that cannot be directly measured, including intrinsic tissue properties such as electrical conductivity, refractory periods (cellular recovery time), and ion channel characteristics that govern cellular action potentials [14].

2 RESEARCH METHOD

This section details the methodological approach for designing a Human Digital Twin (HDT) for arrhythmia analysis. The process focuses on modeling the various characteristics of the physical entity—the patient's heart—to develop an HDT service capable of performing simulations and analytical functions. Our modeling strategy decomposes the heart's complex characteristics into three distinct domains: (1) geometric, (2) physical, and (3) data-driven/computational, which are subsequently integrated into a unified system.

2. 1 Geometrical Data Modeling

Following the identification of data requirements, the subsequent phase involves modeling the spatial characteristics of the physical entity—the patient's heart. The objective of this stage is to construct an accurate, personalized three-dimensional (3D) digital representation of the cardiac anatomy. This model not only replicates the heart's general morphology and dimensions but also incorporates structural details relevant to arrhythmia mechanisms [15], thereby establishing the foundational framework for all subsequent biophysical simulations [16].

The modeling process begins with the acquisition of patient medical images, such as computed tomography (CT) or magnetic resonance imaging (MRI) scans. These images are subsequently processed through segmentation, a procedure in which the contours of cardiac structures (e.g., atria and ventricles) are digitally identified and extracted [17]. The segmentation output is then converted into a computational mesh, forming both a 3D surface and a volumetric representation of the heart [18]. During this stage, key spatial characteristics—including chamber volumes, wall thickness, and other topological features—are quantified and encoded as numerical parameters for downstream analyses.

2. 2 Physical Data Modeling

The subsequent phase involves modeling measurable physical characteristics, focusing on directly acquired patient data. This stage aims to collect, process, and systematize cardiac dynamic measurements to establish a reference ground truth for validating the digital twin. By ensuring the precise replication of these datasets within the virtual model, this approach guarantees that the digital twin faithfully represents the patient's actual physiological state [19,20].

The implementation focuses on processing electrocardiogram (ECG) signals. Raw ECG data, acquired from real-time Holter monitoring or standard 12-lead recordings, serve as the primary inputs. These signals undergo preprocessing to eliminate artifacts—

such as noise and baseline wander—followed by feature extraction to quantify key parameters, including R-R intervals, QRS complex duration, and P-QRS-T wave morphology [21]. This physical modeling stage yields both cleaned ECG signals and their derived numerical features, which collectively form the validation benchmarks for assessing simulation model accuracy.

2. 3 Data-Driven Modeling

This phase represents the computational foundation of the digital twin framework, where non-measurable electrophysiological characteristics are modeled using advanced numerical methods. The primary objective is to simulate the subcellular processes that underlie ECG manifestations, including action potential propagation and ionic current dynamics.

As a data-driven model, it requires calibration against physical reference data specifically, measured ECGs to ensure simulation accuracy. This approach effectively bridges observed body-surface electrical patterns with their underlying biological mechanisms within the heart, establishing a closed-loop validation system comprising two key computational phases. First, the biophysical model implementation applies mathematical formulations governing electrical propagation (e.g., monodomain or bidomain equations) to the pre-constructed geometric mesh.

Each mesh element incorporates cellular-level models, such as the Luo-Rudy ionic formulation, to characterize action potential dynamics. The second phase involves personalized calibration the core computational process in which initially generic biophysical models are iteratively refined using optimization algorithms. In this phase, unmeasurable equation parameters including tissue conductivity distributions and ion channel gating functions are systematically adjusted until the discrepancy between simulated and clinically recorded ECG outputs is minimized [21]. This inverse problem-solving approach ultimately yields patient-specific numerical estimates for these otherwise unobservable electrophysiological parameters.

2. 4 HDTM Integration for Arrhythmia Twinning

In the final stage of the modeling process, the three developed model components geometric, physical, and data-based are integrated into a single, cohesive Human Digital Twin (HDT) system. The objective of this integration is to combine the anatomical framework, measured physiological data, and calibrated biophysical simulations into a functional digital replica of the patient's heart [14]. By unifying these elements, the HDT system becomes not merely a static representation but a dynamic model capable of mimicking the individual's specific electrophysiological behavior [21].

The conceptual workflow of this integrated system commences with an initialization phase, wherein the Geometrical Model (a 3D framework) is constructed from patient-specific MRI or CT data. Subsequently, the system enters the calibration stage, during which ECG data from the physical model serve as input for the Data-Driven Model. This model then executes an optimization process to adjust its biophysical parameters until the simulated ECG aligns with the patient's actual ECG. Once calibrated, the digital twin can continuously synchronize with new ECG data to maintain its accuracy. Finally, the finalized digital twin is prepared to deliver a range of analytical services, such as the visualization of electrical wave propagation, simulations to test for arrhythmia triggers, and predictive analysis to identify vulnerable cardiac regions.

3 RESULT

This section presents the results of the systematic development process for the Human Digital Twin (HDT) concept. The exposition begins with the outcomes from the geometric and physical modeling phases, followed by those from the data-driven modeling. We then provide a comprehensive justification for all models based on the existing literature, establishing their roles as essential components for arrhythmia twinning. Finally, the study demonstrates the integrated implementation of these models into an ECG-based arrhythmia analysis service, illustrating how this synthesized framework offers a viable solution for the prevention and management of arrhythmic disorders.

3. 1 Geometrical Data Model

This subsection presents the results of the geometric modeling phase, which established the foundational anatomical framework for the Human Digital Twin. The process began with the acquisition of patient-specific cardiovascular data using high-resolution medical imaging technologies, including magnetic resonance imaging (MRI), computed tomography (CT), and echocardiography [22]. These modalities captured detailed morphological information of the cardiac chambers, major vessels, and surrounding structures in both static and dynamic states.

The acquired imaging datasets were subsequently processed using advanced medical imaging software, such as 3D Slicer, Mimics, or comparable segmentation and reconstruction tools [23]. The software executed a sequential workflow consisting of three primary stages: (1) image segmentation to delineate cardiac structures from surrounding tissues; (2) surface reconstruction to generate a polygonal mesh; and (3) mesh refinement and smoothing to produce an anatomically accurate and optimized 3D representation. This process yielded a patient-specific, three-dimensional (3D) heart model that faithfully replicates the subject's unique cardiac morphology.

As illustrated in Figure 2, the reconstructed 3D model delineates both the heart's anatomical condition and the spatial relationships between its structures such as the proportional dimensions of the left ventricle relative to the aorta, and the positional orientation of the pulmonary veins in relation to the atrial walls. This detailed visualization facilitates clinical assessment of spatial alignment, detection of morphological abnormalities, and quantitative comparison of dimensional ratios between anatomical components.

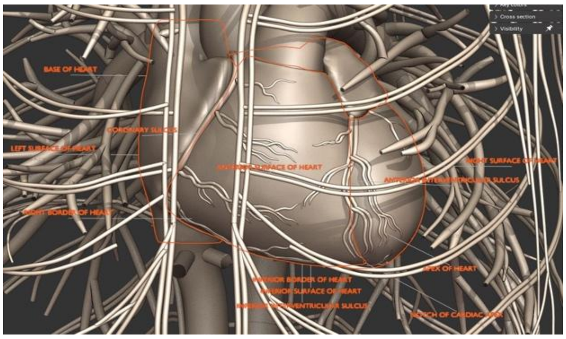

Figure 2. 3D Model of Heart

The reconstructed 3D model functions as the foundational visualization layer within the digital cockpit. For instance, regions of a patient's vasculature exhibiting abnormally high pressure can be highlighted in red directly onto the model, providing an intuitive, color-coded indicator. This integration transforms the anatomical reconstruction from a static representation into a dynamic clinical tool capable of real-time data overlay, thereby establishing a critical link between anatomical geometry and ongoing physiological monitoring.

Table 1. Geometrical Data Model

Characteristic	Unit	Measurement Sources
Left Atrial Volume	mL	Echocardiography, MRI
Ventricular Wall	mm	MRI
Myocardial Fiber Orientation	vector	DRI-MRI
Cardiac Chamber Geometry	3D mesh	MRI, CT
Aortic Geometry	mm	CT, MRI
Epicardial Surface	cm^2	3D reconstruction from CR/MRI
Conduction Pathway Length	mm	Electrophysiological simulation

The quantitative outputs of the geometrical modeling process are summarized in Table 1, which details parameters such as Left Atrial Volume (LAV), Ventricular Wall Thickness, Myocardial Fiber Orientation, and Conduction Pathway Length. For example, the measured LAV of 45.8 mL, as reported by Qian et al. [13], is closely associated with elevated atrial fibrillation risk. These numerical characteristics serve as critical inputs for subsequent physical modeling and data-driven simulations, ensuring that all predictive analyses are grounded in accurate, patient-specific anatomical data.

3. 2 Physical Data Model

Following the establishment of spatial characteristics through geometric modeling, the next critical step involves obtaining a representation of the physical characteristics that describe the real-time physiological state of the cardiovascular system. At this stage, physical entities—particularly the patient's circulatory and cardiac functions—are measured using clinically approved medical technologies. Electrocardiography, acquired via multi-lead clinical ECG machines, Holter monitors, or similar wearable devices, is used to capture the heart's electrical activity with high temporal resolution. Blood pressure is measured non-invasively using an automatic sphygmomanometer, while respiratory rate is recorded using capnography or a breathing belt. Core body temperature is obtained with a calibrated digital thermometer. These direct measurements provide highly specific physiological characteristics of the patient, which serve as ground truth for validating the computational twin.

The physical modeling process begins with the continuous or episodic acquisition of these parameters. This is followed by signal preprocessing including noise filtering and baseline correction and temporal alignment with the patient's anatomical reference frame, as established during geometric modeling. The resulting dataset comprises key electrophysiological metrics such as heart rate (HR), QT interval (representing ventricular repolarization), PR interval (indicating atrioventricular conduction delay), and QRS complex duration (reflecting ventricular depolarization velocity). Additional parameters, such as heart rate variability (HRV), are derived from the ECG signal to assess autonomic nervous system modulation; reduced HRV is a known biomarker associated with increased arrhythmic risk.

Table 2 summarizes the complete set of measured physiological parameters in the Physical Data Model.

Table 2. Physical Data Model

Characteristic	Unit	Measurement Sources
Heart Rate	bpm	ECG, wearable devices
QT Interval	ms	ECG
PR Interval	ms	ECG
QRS Duration	ms	ECG
Blood Pressure	mmHg	Blood Pressure Monitor
Respiration Rate	bpm	Capnography, wearables
Body Temperature	°C	Thermometer

The physical model provides a direct representation of the patient's functional state, translating raw measurements into clinically relevant parameters that can be visualized, tracked, and analyzed over time. When integrated into the HDT cockpit, these parameters can be overlaid onto the 3D heart model to provide an intuitive depiction of both anatomical and physiological conditions. For instance, elevated blood pressure can be visualized within the 3D vascular structures using a red color gradient. This allows clinicians to observe the spatial context of the abnormality—such as its relationship to the size and position of the heart and aorta—thereby enhancing diagnostic interpretation and clinical decision-making.

3. 3 Data-Driven Model

Building upon the foundation of geometrical and physical data, the research advances to the computational phase: data-driven modeling. This phase aims to derive characteristics of the cardiac system that cannot be directly measured using conventional clinical instruments [24]. These latent parameters are inferred by processing and integrating both geometrical and physical datasets through advanced computational techniques, including numerical simulations, statistical modeling, and machine learning algorithms. This approach enables the high-precision estimation of key electrophysiological properties such as tissue conductivity, cellular refractory periods, and region-specific electrical anisotropy which are critical for arrhythmia modeling despite being unmeasurable in vivo [25].

The computational workflow initiates by inputting the 3D anatomical mesh (derived from geometric modeling) and time-series physiological signals (obtained from physical modeling) into a multi-stage computational pipeline. This pipeline applies signal preprocessing, spatiotemporal alignment, and feature extraction, followed by inference using machine learning models trained on large-scale cardiac datasets. The models subsequently generate derived outputs such as spatial conduction velocity maps, distributions of electrophysiological properties, and patient-specific risk indices [26]. These results facilitate a deeper and more individualized representation of the patient's cardiovascular state, capturing aspects that are neither directly visible nor measurable through standard clinical practice.

Table 3 summarizes the principal characteristics generated through data-driven modeling.

Table 3. Data-Driven Model

Characteristic	Unit	Measurement Sources
Conduction velocity map	mm/ms	Machine Learning
Arrhythmia Risk Score	0-1 scale	Machine Learning
Myocardial Scar Probability	%/3D segmentation	Deep Learning
Electrophysiological Tissue Map	3D property grid	Machine Learning
Latent Patient Embedding	Vector	Machine Learning
Drug Response Simulation	Time series	Machine Learning
Pacing Optimization Output	ms/3D coordinate	Machine Learning

Among the most clinically impactful outputs is the conduction velocity (CV) map, which visualizes the spatial distribution of electrical propagation speeds across the myocardium. This map reveals regions of abnormally slow conduction, which are well established substrates for re-entrant arrhythmias. Another key output, the arrhythmia risk score, provides a probabilistic estimate of the likelihood of future arrhythmic events, enabling stratified patient monitoring and personalized intervention strategies. Furthermore, the myocardial scar probability map derived through AI-driven segmentation of medical images generates a spatial probability distribution of fibrotic or scarred tissue. This output is particularly crucial for planning targeted ablation therapy procedures.

Data-driven modeling enables a richer representation of patient-specific cardiac function by transforming abstract computational inferences into actionable visualizations and predictive indicators. When integrated into the HDT cockpit, these derived parameters are overlaid onto the 3D heart model. This integration allows clinicians to visualize critical information—such as highlighting regions of high scar probability in contrasting colors or annotating predicted arrhythmogenic zones—thereby providing a holistic, personalized, and predictive perspective on the patient's cardiovascular health.

3. 4 Digital Twin Model on Cockpit

The integration of the three modeling domains—geometric, physical, and data-driven—is realized within a unified user interface termed the HDT Cockpit (Figure 3). This cockpit consolidates multifaceted cardiovascular information into a single, clinically actionable platform. It enables clinicians to simultaneously visualize cardiac anatomy, monitor real-time physiological data, and review predictive computational outputs, thereby providing a comprehensive overview of the patient's cardiovascular status.

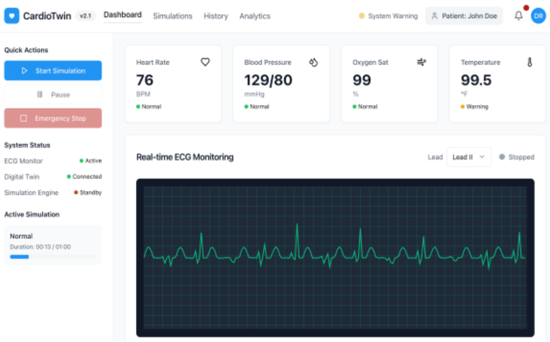

Figure 3. Cardio Twin as DT Cockpit

At the core of the cockpit interface is the personalized 3D heart model, generated through geometric modeling. Derived from patient-specific imaging data, this model accurately represents the patient's cardiac anatomy in high spatial detail, including atrial and ventricular geometry, wall thickness, and conduction system pathways. Its integration into the cockpit enables intuitive spatial analysis of structural abnormalities that may contribute to arrhythmogenesis.

Surrounding the anatomical model are real-time monitoring panels that display parameters acquired through physical modeling. These panels present direct physiological measurements—including ECG waveforms, heart rate, blood pressure, and heart rate variability (HRV). The integration of these live data streams into the cockpit provides clinicians with immediate access to the patient's current functional state, which is continuously updated during monitoring.

In addition to structural and measured physiological data, the cockpit displays predictive and inferred parameters obtained through Data-Driven Modeling. These computational outputs include the Conduction Velocity Map, Arrhythmia Risk Score, estimated myocardial wall stress, and predicted timelines for arrhythmia occurrence. Such information is derived by processing both geometrical and physical datasets using AI-driven algorithms, providing insights that are otherwise unattainable through direct measurement alone.

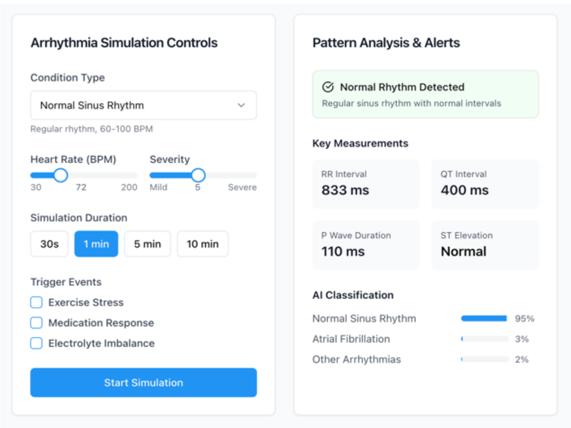

Figure 1. DT Cockpit for Simulation

Figure 4 highlights the Arrhythmia Simulation Control Panel, an interactive feature within the cockpit. Through this panel, clinicians can simulate electrophysiological conditions by applying virtual stimuli such as an ectopic beat at specific atrial or ventricular locations. The simulation then calculates electrical signal propagation based on the patient's calibrated HDT model, displaying the resulting conduction patterns on the 3D heart. This process supports the analysis of re-entry circuits and the evaluation of potential interventions, including ablation or pharmacological treatments, prior to real-world implementation.

In summary, the HDT Cockpit serves as the culmination of the proposed modeling concept. It integrates Geometrical Modeling for anatomical visualization, Physical Modeling for real-time physiological monitoring, and Data-Driven Modeling for predictive and scenario-based analysis. This unified platform not only consolidates diverse data types but also transforms arrhythmia management from a reactive approach to one that is predictive, preventive, and personalized.

4 DISCUSSION

This research introduces an integrated HDT framework designed to transform arrhythmia analysis from reactive diagnosis toward a proactive, personalized, and predictive approach. Its strength lies in the seamless integration of three modeling domains geometrical, physics-based, and data-driven culminating in the HDT on Cockpit Model.

In this framework, geometrical modeling establishes a patient-specific anatomical foundation, essential for realistic simulations. Physics-based modeling anchors the digital twin to real-time physiological measurements, ensuring synchronization with the patient's actual condition. Data-driven modeling delivers the most significant leap, using measurable data such as ECG to infer critical but unmeasurable biophysical parameters, including conduction velocity maps and scar probability. Together, these three layers convert a static anatomical model into a dynamic, functional, and clinically relevant replica.

The Cockpit concept enables clinicians to not only visualize the patient's heart in 3D but also simulate arrhythmia triggers, test interventions, and forecast outcomes, directly supporting precision medicine. While the current work remains at the conceptual stage, its integration of multiple modeling approaches into a unified workflow marks a significant advancement in digital cardiology and lays the groundwork for future functional prototypes and clinical validation.

5 CONCLUSION

This research has successfully formulated a conceptual framework for a Human Digital Twin (HDT) designed for ECG-based arrhythmia analysis, employing a tripartite modeling approach: geometric, physics-based, and data-driven. The geometric modeling component successfully reconstructed the anatomical foundation of the heart into a personalized three-dimensional model. Concurrently, the physics-based modeling quantified measurable physiological parameters from the patient, which served as the ground truth for validation. Subsequently, the data-driven modeling yielded predictive insights and latent characteristics, such as conduction velocity maps and risk scores, which are not obtainable through conventional measurement techniques.

The result of this research is the integration of these three models into an initial prototype of Human Digital Twin Cockpit. The cockpit serves as the primary interface between users and the Human Digital Twin system. It effectively merges anatomical representation, real-time functional data, and predictive analytics into a single, unified interface. Thus, this study successfully demonstrates that the Human Digital Twin concept can overcome the limitations of conventional ECG diagnostics, which are frequently reactive, by providing a proactive platform for simulation, personalized risk analysis, and the evaluation of virtual interventions.

The implication of this concept is that it paves the way for precision medicine in arrhythmia management, wherein therapeutic strategies can be optimized for each individual. Although the present study focuses on developing the conceptual framework, the recommended subsequent steps are the implementation of a more functional prototype of the "HDT cockpit" and the execution of clinical validation using patient data to assess its effectiveness in real-world applications.

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