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Correspondence author
@ A. I. Petrenko
tolja.petrenko@gmail.com

A. I. Petrenko, R. S. Tsymbaliuk, K. V. Kandel, V. V. Kazakov

National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine

APPLICATION OF DIGITAL TWIN TECHNOLOGY IN MEDICINE

In modern medicine, novel technologies play a key role in improving the diagnosis, treatment, and management of patient health. One of the most promising innovations is Digital Twin technology, which enables the creation of virtual models of real-world objects, including human organs. This technology opens new possibilities for personalised medicine, disease prediction, and the optimisation of medical processes. Digital Twins are already actively used in various industries, such as manufacturing, aviation, and urban planning, but their potential in medicine is only beginning to unfold. They allow for creating detailed models of an individual patient's body, contributing to more accurate diagnostics, simulation of treatment responses, and enhanced efficiency of medical interventions.

This article explores the key aspects of Digital Twin medical applications, their advantages, challenges, and development prospects. Special attention is given to the technical foundations of this technology, its use in personalised medicine, health monitoring, disease prediction, and the optimisation of healthcare facilities.

For the practical part, the study shows how to create a Digital Twin of a heart based on real patient data. Additionally, the study investigates a model of the heart's Digital Twin, demonstrates its use, and illustrates how to replicate heart functionality using the Digital Twin. The study describes how a part of a Digital Twin was created using the suggested architecture and outlines how to use and extend this functionality. More than that, the study shows how to integrate artificial intelligence into the Digital Twin architecture and how artificial intelligence algorithms help create Digital Twins. The research shows how to build the Digital Twin using machine learning and artificial intelligence technologies, and how to choose the mathematical model for the Digital Twin. To conclude, the study defines further work, problems, and difficulties in creating the Digital Twin of the heart. The study shows the perspectives on using Digital Twins, their practicality, and real-life cases where Digital Twins can save lives. Also, the study defines the next steps for the Digital Twin creation, testing, implementation, and usage in the real-life healthcare industry.

Keywords: mathematical modelling, Digital Twins (DTs), Internet of Things (IoT), AI application in DTs, personalised medicine.

Introduction

A Digital Twin (DT) is a virtual replica of a physical object continuously updated with real-world data. This technology is based on integrating the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning, and Big Data analytics. In medicine, a DT can represent a model of the human body, an organ, or even a cell, enabling detailed research and predicting treatment responses [1]. Personalised DT involves the combination of multidisciplinary patient data and various modelling mechanisms to reproduce the processes occurring in the body accurately and further predict responses to different treatment options.

Object of the study – DTs technology in medicine.

Subject of the study – influence and usage of heart DTs in medicine.

In the context of personalised medicine, the ability to create interactive DTs of patients can significantly improve clinical outcomes in both treatment and research. In particular, DTs offer physicians and researchers the ability to:

- Plan surgeries considering the specifics of the patient's condition, virtually "test" different surgical options to choose the most optimal approach, and train new specialists [1–4].
- Monitor chronic diseases and determine whether each patient belongs to different risk groups, taking into account current and historical medical data, to prevent and respond to deterioration of health status on time [4, 5].
- Conduct in silico studies to accelerate research in fields such as oncology, cardiology, neurology,

orthopaedics, and many others, particularly to substantiate the efficacy of experimental therapies and determine their risks [1–4].

The development of personalized medicine through the introduction and widespread use of DTs has the potential to respond to the urgent challenges facing modern healthcare systems: the increasing proportion of chronic diseases [5, 6], the growing importance of the most accurate diagnosis and individualized therapy, the need to optimize surgical interventions, and the rising costs of medical services, drugs, and new clinical trials [2–4, 7].

The main benefit of personalised medicine is the creation of new ways to predict a patient's response to a specific treatment, which helps physicians minimise risks and patients receive better and more targeted care. The prospects of using DTs in medicine are also confirmed by financial analysis – it is estimated that the global market for DTs in medicine will reach USD 3.81 billion in 2025, compared to USD 0.29 billion in 2020, which also indicates the fastest growth (over 1200 %) compared to other areas of DTs application, such as manufacturing, aviation, energy, etc. [8].

However, the success and widespread use of DTs in medicine, including personalised medicine, depends on solving several technical and methodological problems: from the collection of large amounts of medical data (structured and mostly unstructured [9]) and their reliable storage to the development of algorithms that can correctly reproduce complex biological and physiological processes.

Purpose of the study is to create a heart DT, examine its precision, effectiveness, and practicality, and suggest the most suitable mathematical model for the heart DT.

To achieve the stated purpose, the following *main research tasks* were identified:

- to review existing DT models;
- to collect a dataset of patients with heart problems;
- to build the architecture of the heart DT;
- to create a mathematical model that represents a heart;
- to collect patients' and doctors' feedback about the technology.

The term "Digital Twin" is usually interpreted as a virtual representation of a physical object or process kept up-to-date by data flows from the real object. The classic definition emphasises continuous bi-directional communication between the real and virtual environments, which allows monitoring, analysis, prediction, and adjustment of the object's behaviour and state based on simulations of virtual models [10]. An essential feature of the data centre is its ability not only to display the current state of the modelled objects, but also to predict changes in the future by providing different scenarios for interacting with and optimising the models, and performing analytics. This means that a data centre can help continuously improve and optimise the system in which it is used, using data from the history of the real object's operation and data coming in in real time. This way, the data centre becomes a tool for dynamic risk assessment, virtual experimentation, and complex decision-making based on personalised and contextualised information.

The concept of DTs originated in the industrial production environment, particularly in the aerospace sector and large manufacturing companies (General Electric, Siemens, etc.). In these industries, DTs monitor and diagnose complex technical systems, optimise production processes, detect defects, and improve equipment efficiency [11]. A key factor in the development of data centres has been the proliferation of the Internet of Things (IoT), which has made it possible to integrate real-time information about the state of equipment and automatically update virtual models.

With the spread of Industry 4.0 ideas and the development of high-performance computing, digitisation has expanded beyond manufacturing and transportation to include agriculture, urban planning, energy, and healthcare. Adapting digital health technology to healthcare is a logical step: the human body, like technical systems, is a complex, multilevel object whose state can be monitored, measured, and modelled. At the same time, advances in medical research are increasing the volume and complexity of patient data (medical images, biomarker information, genetic profiles) every year, while the development of available computing power opens up opportunities to create complex digital representations.

When considering DTs as one of the key technologies in projects related to real-time monitoring and digital modelling, it is crucial to understand the difference between a DT and other standard related terms, which usually lies in the level of interactivity and communication between the real and virtual environments:

- Digital model – a digital representation of a real object, usually created manually, which does not receive new data from the real object during its work, working "offline" [12]. The difference between a digital model and a digital data model is the absence of a constant connection from the real object to its digital representation and vice versa.
- The digital shadow is an evolution of the digital model technology, adding a permanent connection from a real object to its digital representation, which allows the latter to be updated in real time according to changes in the real world [12]. Unlike the DT, the digital shadow does not provide feedback from the digital representation to the real object. Therefore, changes in the digital shadow do not automatically cause changes in the real object.
- A virtual object, sometimes called a virtual twin [13], exists only in the digital environment, without a prototype in the real world, and therefore has no connections to the real environment.
- Thus, a DT has a mandatory prediction component, the ability to model scenarios of changes in a real object, and perform optimisation tasks. In addition, feedback from the real object is mandatory – the results obtained with the help of the digital data centre (real object settings) can be automatically displayed in the real world in real time.

Because of these features, using DTs opens up opportunities to change current medical practices that determine each patient's normal (or healthy) state based on general statistics from extensive cohort studies. The use of DTs will allow, based on a large amount of data collected separately for each patient, to determine the normal state of each patient individually, which is often different from the average normal state [14], thus improving the quality and reducing the risks of future treatment.

Materials and methods. There are several techniques for creating a digital heart twin, including mechanical models, electrical models, and so on. Mechanical models represent the heart as a pump sending blood around the body [15]. Electrical models represent the heart like an electric circuit with all its electrical signals and their interaction. All the mathematical representations use the Navier – Stokes equations to represent blood flow over the heart, which makes sense and shows good precision compared to a real heart.

The architecture of the DT includes two parts: a neural network that gets heart data from the echocardiography video and the mathematical model, which simulates retrieved echocardiography data on a mathematical abstraction. The process of creating the DT is shown in Fig. 1. Firstly, a patient enters a hospital and gets an echocardiography video of the cardiac cycle. It shows the cardiac cycle with heart chamber pressures, volumes, radii, etc. Then that video is passed to a neural network, which measures all the needed data for the mathematical DT model. Then, further mathematical model analysis helps to determine and diagnose heart failure preconditions.

To conclude, the DT has two main parts: a neural network, which analyses the echocardiographic video, and the mathematical model, which takes retrieved heart parameters and simulates the specific patient's heart. It helps the doctor simulate a wide range of heart conditions and specify some specific parameters that will show the patient's cardiac cycle. It will help to diagnose heart failure.

For the case study, a mathematical model was used to represent the cardiac cycle of a heart, which shows the systolic and diastolic cycles [16]. The model has good precision compared to a real heart and makes it possible to research Dilated Cardiomyopathy conditions in adults and children based on the mathematical model of the heart. It uses an electromagnetic analogy (Fig. 2) representing the blood flow from the right ventricle to the pulmonary arteries, then through the pulmonary veins and left atrium, right to the left ventricle.

The mathematical model should be revised to obtain the necessary data for the DT. The model was reworked using a MATLAB script that loads the described model, performs tests, and displays graphs of pressure and chamber volume for different parameters (such as aorta capacity and pulmonary veins resistance, etc.). As part of the DT, a neural network should be trained on an echocardiography video dataset, which will enable the detection of key heart features, such as chamber volume and ventricular thickness. It should be a CNN (Convolutional Neural Network), because this type of neural network is most suitable for echo pattern recognition.

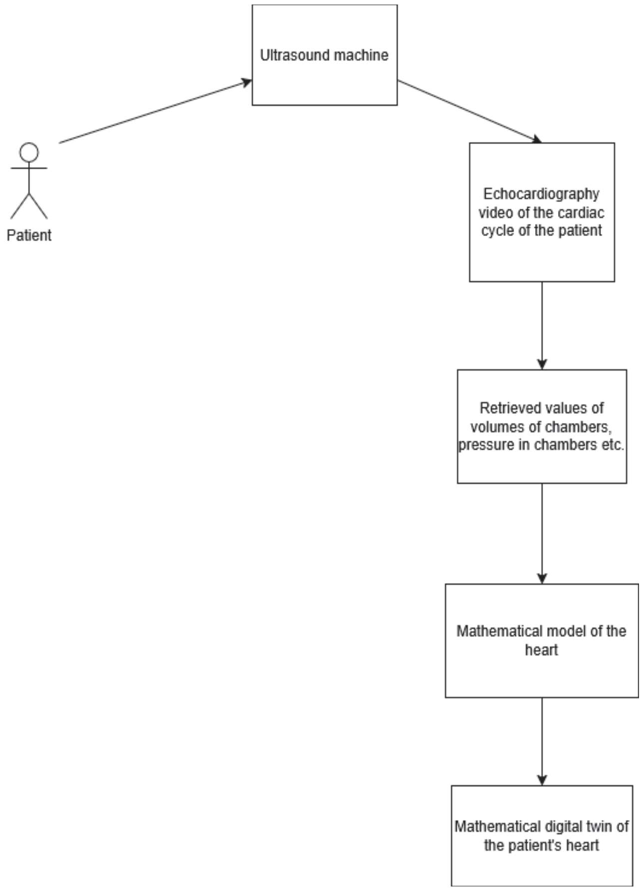

Fig. 1. Process of creation of the DT

Then, with the CNN and retrieved values of heart parameters from the echocardiography video, it is passed to the mathematical model. With the equation solver, parameters such as aorta resistance and pulmonary veins capacitance are obtained. With these parameters, heart behavior can be predicted and calculated with very high precision, as DT technology requires.

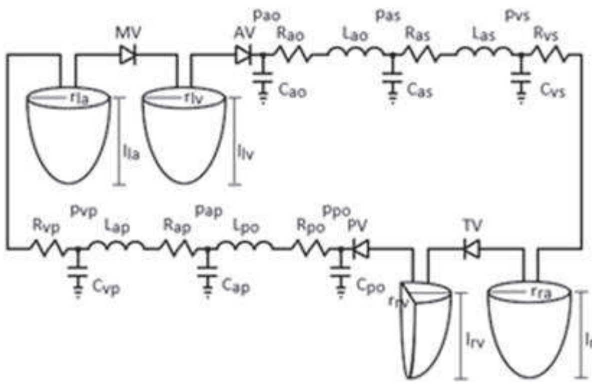

Fig. 2. Representation of the heart [16]

For the practical part, a dataset of patients was obtained. It holds more than 100 patients with heart diseases who have agreed to participate in the research. All the patients took part in echocardiography; crucial data of their hearts were measured, such as ejection fraction, heart chamber volumes, heart pressure, etc. The main goal of the experiments in the volume below was to use those data to fit with the mathematical model and show that it is possible to use the model to represent a real patient's heart.

Analysis of recent research and publications. The creation and use of a data centre in general and medicine involves data collection, data analysis, model building, and simulations that require a lot of computing and a specialised infrastructure. All of this relies on many technologies and involves several sequential stages (Fig. 3).

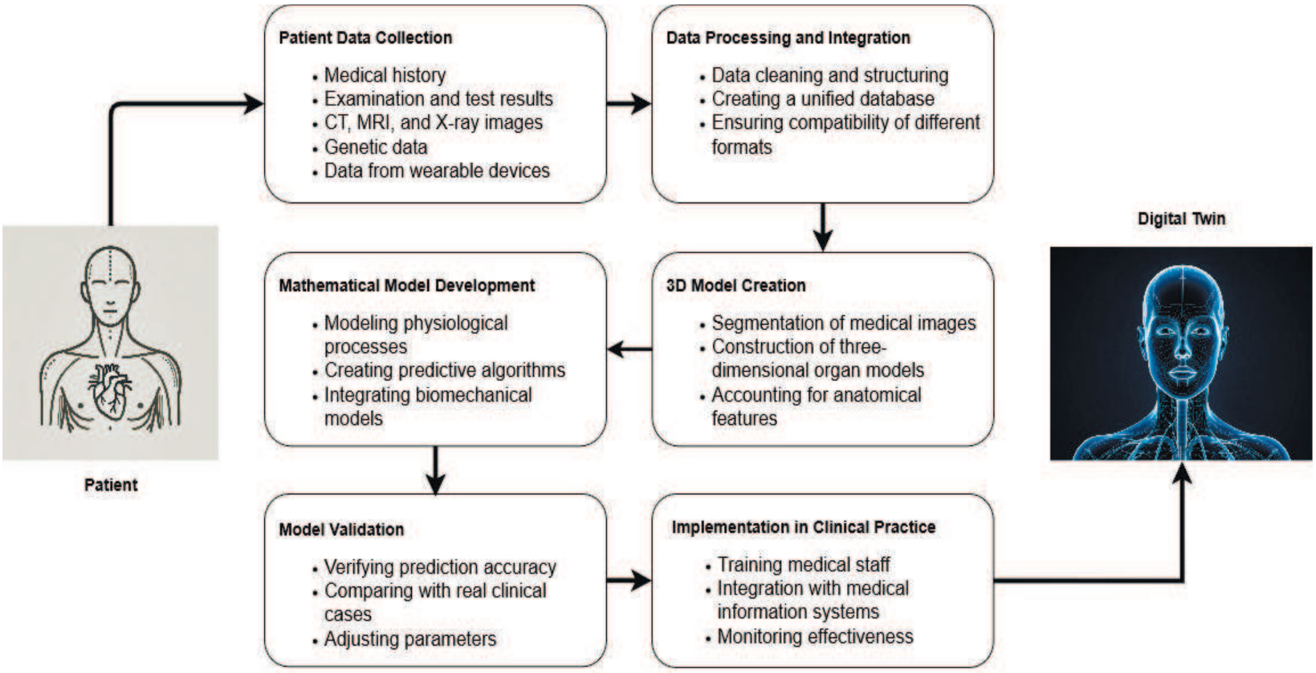

Fig. 3. Stages of creating patient DT

- Data Collection: medical images (computed tomography, magnetic resonance imaging, etc.), electronic medical records, wearable sensors and accompanying mobile applications, – Omics data (genomics, transcriptomics, proteomics, etc.) – all of which provide a comprehensive picture of the patient's condition [2, 17, 18].
- Data Processing and Integration. At this stage, the collected information is systematised and structured. All data is cleaned to remove errors and noise, standardised, and brought to a uniform format. A centralised database is created, where information is organised to ensure quick access and efficient analysis. Special attention is paid to ensuring compatibility between different data formats and creating reliable connections between various types of information. Data quality control systems and mechanisms for their regular updates are implemented.
- Data modelling and analysis: Various machine learning frameworks and algorithms (linear and logistic regression, decision trees, random forests, etc.) help to analyse large medical data sets, classify, and detect patterns. Certain types of neural networks, such as convolutional neural networks, are key tools for analysing and segmenting medical images and detecting pathologies [3, 18]. Methods for processing large and unstructured data allow for the preparation and integration of disparate data for further use in DT [9, 19]. At this stage, complex mathematical models are created that describe physiological processes in the body. Algorithms are developed that allow the body to predict its responses to various influences and interventions. Biomechanical models are integrated to describe the mechanical properties of tissues and their interaction. Systems of differential equations are created that describe metabolic processes, blood circulation, breathing mechanics, and other physiological functions.

Research results and their discussion

The functionality of the model was investigated using the MATLAB software. For example, left ventricular pressure has the following graphic (Fig. 4), which is very close to a real heart function. Left ventricle volume over the cardiac cycle is presented in Fig. 5, which is also accurate enough. Also, the same graphics for the right ventricle, left aorta, and right aorta can be built using the model. More than that, crucial heart parameters such as ejection fraction can be calculated. That gives us a powerful opportunity to model the heart and compare that data to a healthy heart, which will show us any irregularities that should cause heart disease. The main task is getting patient-dependent parameters representing the patient's heart.

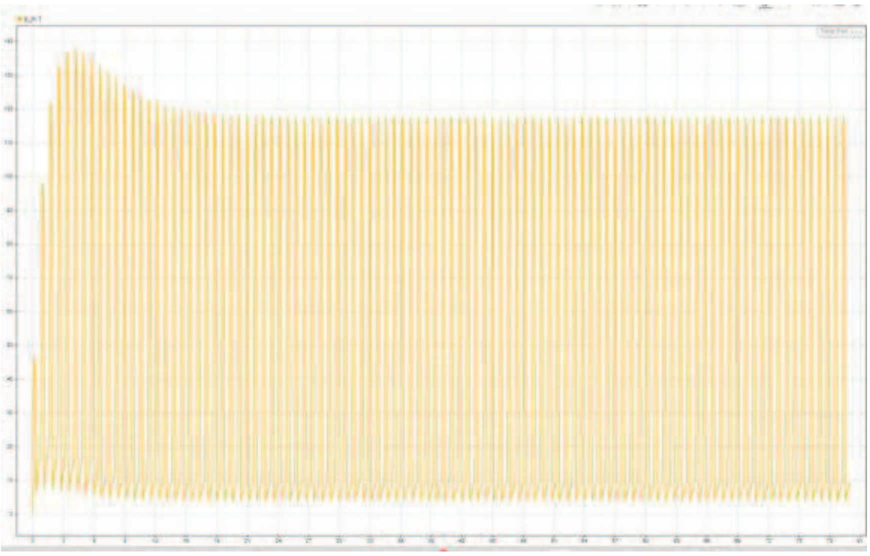

Fig. 4. Pressure in the left ventricle during the cardiac cycle

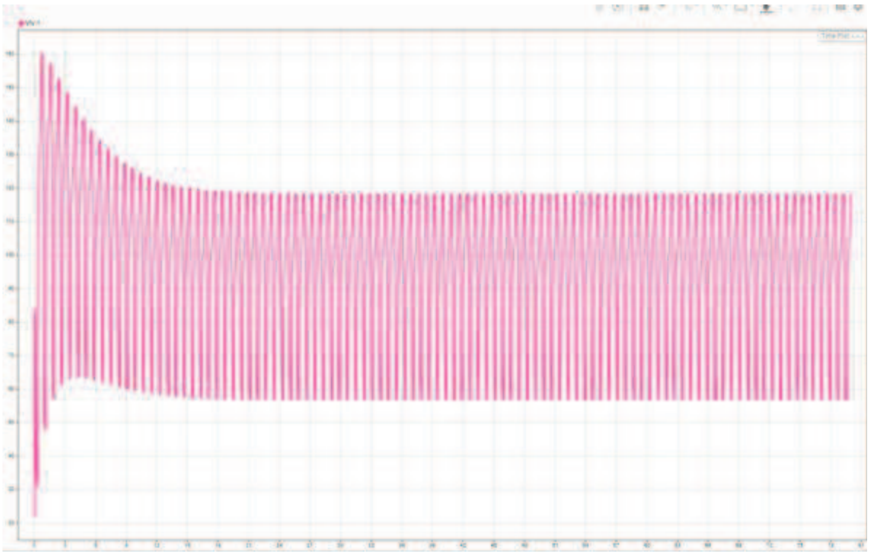

Fig. 5. Volume of the left ventricle during the cardiac cycle

The paragraph above describes the mathematical model of the heart. The main parameters used to simulate the heart are resistance parameters of the heart model (which show the blood flow through the heart), geometric parameters of the heart (such as chambers' and aorta's coefficients that represent the shape of the heart components). Altogether, the set of parameters describes the heart, and the task of the model is to define the mathematical model from the echocardiography video of the heart. With the model, it becomes possible to calculate additional parameters such as the velocity of blood flowing through the heart, the geometric chambers changing over time, etc. The figure below (Fig. 6) shows, for example, different pressures in the left chamber (mmHg) depending on the capacity parameter of systemic arterioles (mL/mmHg). As we see, increasing capacity decreases the maximum pressure in the left chamber.

The following experiment (Fig. 7) shows changing the parameter of changing pressure (mmHg) in the left chamber depending on aorta capacity (mL/mmHg). As we see, the pressure also decreases with the growth of the aorta capacity.

The figure below (Fig. 8) represents the growth of mitral valve resistance (mmHg s/mL) and changes in left chamber pressure (mmHg). As we see, the development of resistance leads to the growth of the pressure value.

The last experiment (Fig. 9) is to study the influence of the resistance of pulmonary veins (mmHg s/mL) on the pressure (mmHg) in the left chamber. As we can see, with the pulmonary veins' resistance increasing, the pressure decreases.

From those experiments, we can conclude that the parameters (aorta resistance, capacity, systemic arterioles resistance, inductance, etc.) represent the heart functionality during the cardiac cycle. That is why when general parameters are obtained from the echocardiography video (pressure, ejection fraction, heart chambers volume), it is possible to get a set of parameters (inductance, capacity, resistance) representing an electric analogue DT of the heart. When that DT is created, a great variety of simulations can be done and analysed, and different heart conditions can be predicted.

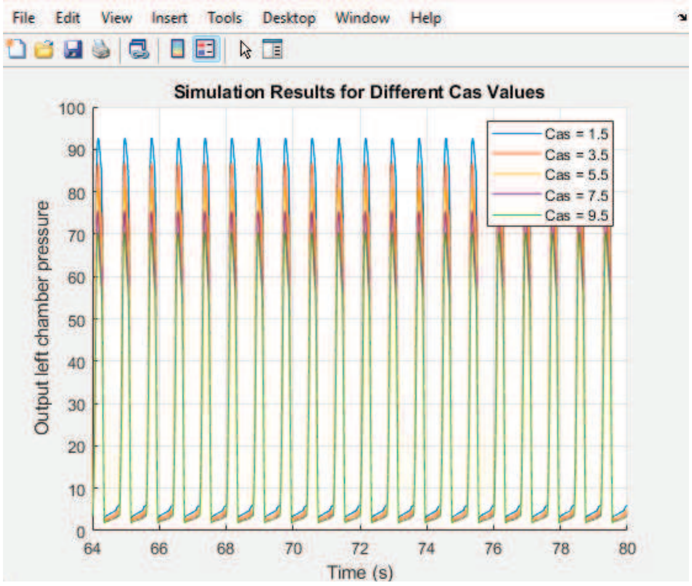

Fig. 6. Changing capacity of systemic arterioles

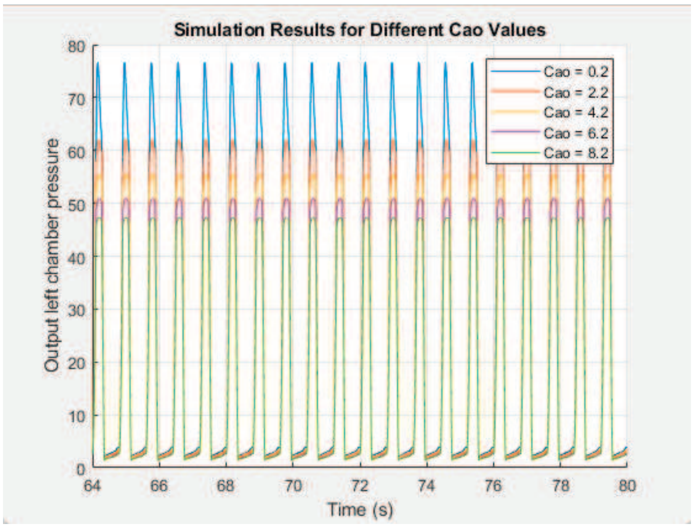

Fig. 7. Changing capacity of the aorta

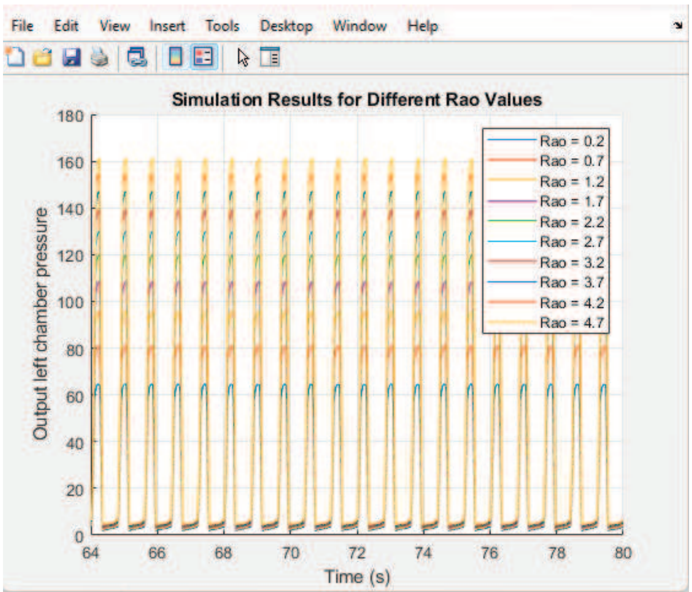

Fig. 8. Changing the resistance of the aorta

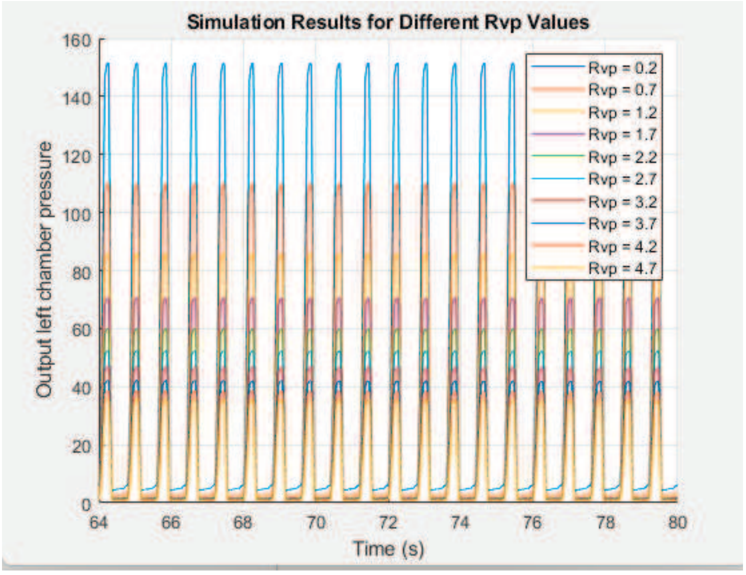

Fig. 9. Changing the pulmonary veins' resistance over left chamber pressure

As a result, a part of a DT was created. Changing electric parts (resistors, capacitors, inductors) changes the DT heart behaviour. As a result, adjusting the mathematical model can represent a real heart with its own behaviour.

The main goal of the research is to create a DT to diagnose heart failure. The DT will be built based on echocardiography results, representing the heart functionality with high precision. Heart failure diagnosis is a difficult task, and only blood analysis helps a doctor diagnose the disease. However, some echocardiography parameters can tell the doctor that the patient has a high risk of heart failure or already has heart failure [20]. One of those parameters is ejection fraction, which shows the percentage of the total amount of blood pumped out with each heartbeat. In addition, pressures of the left and right sides of the heart are crucial for diagnosing heart diseases [21]. Moreover, left atrial pressure also plays a role in diagnostic heart irregularities [22]. That is why mathematical modelling will highlight all that functioning and all the irregularities with non-invasive techniques, which will help doctors and patients. Also, heart failure parameters (such as ejection fraction) were analysed in real patients' cases.

The application of DTs opens new horizons for diagnosis, treatment, and human body research. This technology allows creating accurate virtual copies of both individual organs and entire body systems, including physical and behavioural aspects of a person (Fig. 10) [7].

- Organs Modelling: oncological research is the main area of organ modelling application. Unlike traditional methods limited to tumour cultivation, digital organ twins allow reproduction of the real situation of a specific patient. Modelling of the cardiovascular system and liver is developing particularly actively. For example, the Cardio Twin system provides comprehensive heart modelling using virtual and augmented reality technologies and robotics, enabling continuous monitoring and processing of collected information through edge computing [9].

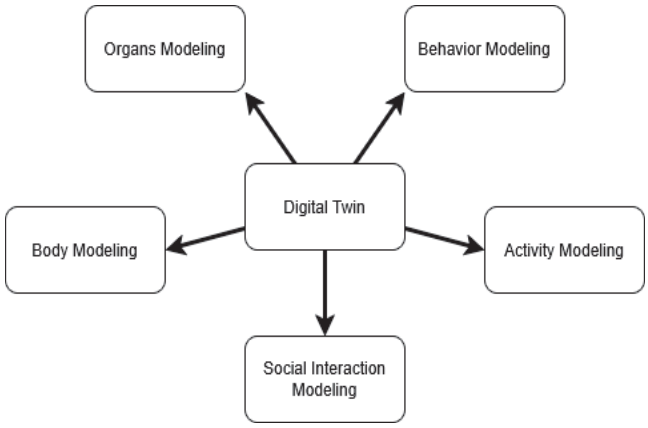

Fig. 10. Usage of DT

- Body Modelling: a digital body twin represents a comprehensive digital copy of a person's physical body. The modelling process includes reproducing the main body parameters: height, weight, and proportions. The most common approach is parametric modelling, which uses computer vision technologies to create 3D models based on frontal and lateral body projections. Additionally, RGB-D sequences and a combination of 3D scanning with 2D images achieve maximum accuracy in reproducing body shape.
- Behaviour Modelling: this direction aims to create a digital model that reproduces human behaviour in all its aspects. The process includes collecting data about human behaviour in the physical world and transferring these patterns to a virtual environment. The model considers individual behavioural characteristics and interaction with the environment, allowing for the creation of maximally realistic digital copies of human behavioural patterns.

- Activity Modelling: this type of modelling focuses on reproducing human physical activity, including facial expressions, walking, running, and other movements. Various technologies are used, including neural networks for facial expression recognition and motion analysis. This has proven especially useful in telemedicine, where DTs help doctors remotely assess patients' conditions by analysing their motor activity and facial expressions.
- Social Interaction Modelling: This direction focuses on reproducing ways of interaction between people in the digital environment. It includes both traditional forms of communication (personal communication, telephone conversations) and online interaction. In the medical context, this helps create models of interaction between doctor and patient and between medical staff. Special data exchange protocols and machine learning algorithms are used to analyse and predict patterns of social interaction.
- To date, DTs are being actively researched, developed, and implemented in some initiatives for various medical applications [23–25]. These include:
- Digital platforms for modelling individual human organs, including the heart (Dassault Systèmes' "SIMULIA Living Heart"), lungs (BreathEasy project), and brain (Living Brain project) [2, 3]. For example, the SIMULIA Living Heart cardiology platform models cardiac electrophysiology and haemodynamics, plans cardiac surgery, optimises pacemakers, etc. Other platforms perform similar tasks, allowing the simulation of normal and pathological behaviour of organs and their response to different treatment scenarios.
- Personalised oncology projects such as PRIMAGE and Predictive In-Silico Multiscale Analytics [3] use agent-based and systemic biological models to predict the response of different tumour types to cancer-targeted drugs or immunotherapy.
- Various virtual platforms for surgical planning and training, where 3D models of organs are created based on CT and MRI, and the surgeon can "rehearse" the operation in a simulated environment, gaining experience as close to reality as possible, which is difficult to achieve with traditional methods [25, 26].
- The maturity of most technologies varies from research and pilot projects to limited clinical implementation, particularly for planning complex surgical interventions. Significant challenges to the widespread adoption of digital health in medicine include the lack of standardised protocols for data exchange and storage, limited compatibility between different digital platforms, as well as issues of ethics, safety, and impartiality in the use of such technologies in medicine and the confidentiality of medical information [2, 3, 25].

Discussion of the research results. A comprehensive review shows that RNNs (Recurrent Neural Networks) and CNNs (Convolutional Neural Networks) are already used for building DTs[27]. For example, CNNs were used to analyse graphical data, as MRI scans and echocardiographic procedures. That even went further, and CNN was trained to detect a coronary artery atherosclerosis in CCTA scans [27]. RNNs, genetic algorithms, and Artificial Neural Networks were used to obtain analytics data based on patients' data. In addition, the study shows that it is possible to create a digital heart twin based on blood analysis, which contains crucial data, such as cholesterol level, chest pain in a patient, etc. [27]. That DT diagnoses if the patient has a heart attack and diagnoses that condition based on previous patients' disease history.

It's important to note that developing DTs in oncology is an ongoing process. Tumours are highly complex, and accurately modelling their behaviour requires sophisticated computational models. The goal is to use DTs to enable personalised medicine, tailoring treatments to the unique characteristics of each patient's tumour. A crucial aspect of these DTs is integrating diverse data sources, including genomics, imaging, and clinical records. Here's Table 1 summarizing key information based on current trends [28–31].

Table 1. DTs facilities in oncology

Developers	Functions
arrSight®-Twin (Concr)	Predicting patient response to chemotherapy. Simulating clinical trials across various tumor types. Optimizing treatment choice for individual patients. Integrating clinical data with molecular data (gene panel, whole-exome, transcriptome sequencing)
Various Research Initiatives (Academic)	Modeling tumor growth dynamics. Simulating the effects of different treatment strategies (chemotherapy, radiation, immunotherapy). Personalized treatment planning based on individual patient data. Virtual clinical trials to test new drug efficacy. Integrating multiscale data, from molecular to tissue level
Twin frameworks (Commercial and Research)	Enabling virtual patient simulations. Allowing clinicians to test clinical hypotheses. Refining therapeutic strategies in a personalized manner. Incorporating mechanistic models at the cellular and tissue levels, continuously updated with real-time clinical and multiomics data
MRI-informed DTs	Optimizing patient-specific radiotherapy regimens. Generating in silico cohorts of patients to test treatment strategies. Providing risk-based optimization under uncertainty. Personalizing treatment through calibration using MRI data
Agent-based modelling DTs	Grading cancer systems models that encode signaling at the cellular scale. Predicting tissue-level responses in a tumor microenvironment customized to patient cohorts. Facilitating personalized therapeutic strategies
Computational oncology platforms	Providing environments for building and testing computational models of tumor growth. Enabling the simulation of drug interactions with tumor cells. Aiding in the discovery of novel therapeutic targets
In silico tumour simulators	Able to capture tumor complexity. Updating with changes in the patient's condition

Scientific novelty of the obtained research results – a part of a heart DT was developed; the architecture of the DT was determined and proved for the usage.

Practical significance of the research results is crucial for personalized medicine and heart diseases prediction with the usage of the heart DT.

Conclusions

The technology of DTs demonstrates significant potential for transforming healthcare systems by offering innovative solutions for diagnosis, treatment, and disease prevention. Research shows this technology is particularly effective in four key areas: personalized medicine, surgical planning, patient monitoring, and medical research. In this study the part of a heart DT was developed; the architecture of the DT was determined and proved for use. Practical significance of the obtained results is crucial for personalized medicine and heart disease prediction using the heart DT.

The implementation of DTs enables the creation of precise virtual models of organs, the body, and patient behaviour, significantly increasing the effectiveness of medical care. The contribution of this technology to the development of personalized medicine is significant, where an individual approach to each patient is based on a comprehensive analysis of their digital model.

Analysis of development prospects shows that further integration of DTs with artificial intelligence and Internet of Things technologies opens new opportunities for improving healthcare quality. The DT market in medicine is expected to grow rapidly, reaching $33.4 billion by 2035.

Thus, DT technology is becoming an integral part of modern medicine, contributing to improved quality of medical care and the development of a personalized approach to patient treatment. Further research and development in this field should focus on enhancing AI Agent-based technologies, ensuring data security, and expanding the applications of DTs in medical practice.

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А. І. Петренко, Р. С. Цимбалюк, К. В. Кандель, В. В. Казаков

Національний технічний університет України "Київський політехнічний інститут імені Ігоря Сікорського", м. Київ, Україна

ВИКОРИСТАННЯ ЦИФРОВИХ ДВІЙНИКІВ У МЕДИЦИНІ

У сучасній медицині новітні технології відіграють ключову роль у покращенні діагностики та лікуванні пацієнтів. Однією із найперспективніших інновацій є технологія цифрових двійників, яка дає змогу створювати віртуальні моделі об'єктів реального світу, зокрема людських органів. Ця технологія відкриває нові можливості для персоналізованої медицини, прогнозування захворювань та оптимізації медичних процесів. Цифрові двійники (ЦД) вже активно використовуються в різних галузях, таких як виробництво, авіація, містобудування, але їхній потенціал у медицині тільки починає розкриватися. Вони дають змогу створювати детальні моделі тіла та деяких органів окремого пацієнта, що сприяє точнішій діагностиці, симуляції реакції на лікування та підвищенню ефективності медичного втручання.

У статті розглянуто ключові аспекти застосування цифрових двійників у медицині, їхні переваги, проблеми та перспективи розвитку. Особливу увагу звернено на технічні основи цієї технології, її використання у персоналізованій медицині, моніторингу здоров'я, прогнозуванні захворювань та оптимізації роботи медичних закладів. Насамкінець викладено результати досліджень прототипу створеного цифрового двійника серця.

У практичній частині дослідження описано створення цифрового двійника серця на основі реальних даних пацієнта. Також досліджено модель цифрового двійника серця, описано способи використання цієї моделі та методи імітації функціонування серця за допомогою цифрового двійника. У роботі висвітлено, як створено частину цифрового двійника відповідно до запропонованої архітектури, як користуватись цією функціональністю та розширювати її. Крім того, дослідження демонструє, як інтегрувати штучний інтелект у архітектуру цифрового двійника і як алгоритми штучного інтелекту сприяють його створенню. Також визначено подальші напрями роботи, проблеми та труднощі, що виникають під час створення цифрового двійника серця.

Ключові слова: математичне моделювання, цифрові двійники (ЦД), Інтернет речей (IoT), застосування штучного інтелекту в ЦД, персоналізована медицина.

Інформація про авторів:

Петренко Анатолій Іванович, д-р техн. наук, професор, професор кафедри системного проєктування.
Email: tolja.petrenko@gmail.com; https://orcid.org/0000-0001-6712-7792

Цимбалюк Роман Сергійович, аспірант кафедри системного проєктування.
Email: tsymbaljuk2001@gmail.com; https://orcid.org/0009-0008-3525-8892

Кандель Кирило Володимирович, аспірант кафедри системного проєктування.
Email: kirill.kandel@gmail.com; https://orcid.org/0000-0001-7152-5945

Казаков Владислав Володимирович, магістр кафедри системного проєктування.
Email: kazakov.vladyslav@lll.kpi.ua; https://orcid.org/0009-0000-2221-2053

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