Journal of Engineering Science *Vol. XXXI, no. 3 (2024), pp. 95 - 104*
Fascicle *Electronics and Computer Science* *ISSN 2587-3474*
Topic *Biomedical Engineering* *eISSN 2587-3482*

https://doi.org/10.52326/jes.utm.2024.31(4).07
UDC 616.127-005.8:004.94

EXPLORING THE HUMAN CIRCULATORY SYSTEM THROUGH SYSTEM DYNAMICS: A MODEL-BASED APPROACH

Victor Iapăscurtă[1,2], ORCID: 0000-0002-4540-7045

[1] *Technical University of Moldova, 168 Stefan cel Mare Blvd., Chisinau, Republic of Moldova*
[2] *N. Testemitanu University of Medicine and Pharmacy, 165 Stefan cel Mare Blvd., Chisinau, Republic of Moldova*
*Corresponding author: Victor Iapăscurtă, *victor.iapascurta@doctorat.utm.md*

Received: 11. 20. 2024
Accepted: 12. 18. 2024

Abstract. System dynamics is a robust methodology for understanding the behavior of complex systems over time. By employing feedback loops, stocks, flows, and time delays, this approach provides a comprehensive framework for simulating and analyzing dynamic systems. The application of system dynamics to the human circulatory system presents numerous possibilities, benefits, and practical applications that can significantly enhance our understanding and management of cardiovascular health. This article details experimental results from modeling myocardial infarction conditions using a six-compartment model developed in the NetLogo integrated development environment, incorporating BehaviorSpace for extensive simulations. For result analysis, specialized packages in R, Python, and Wolfram Mathematica were utilized to ensure rigorous data interpretation. The results demonstrate promising fidelity when compared to existing literature and real-time patient data, indicating the model's potential for clinical applications. By illustrating the interactions within the circulatory system, this research not only contributes to theoretical knowledge but also offers practical insights into disease management and intervention strategies, paving the way for improved cardiovascular health outcomes.

Keywords: *system dynamics modeling; circulatory system; myocardial infarction; integrated development environment.*

Rezumat: Dinamica sistemului este o metodologie robustă pentru înțelegerea comportamentului sistemelor complexe în timp. Utilizând bucle de feedback, stocuri, fluxuri și întârzieri, această abordare oferă un cadru cuprinzător pentru simularea și analiza sistemelor dinamice. Aplicarea dinamicii sistemului la sistemul circulator uman prezintă numeroase posibilități, beneficii și aplicații practice care ne pot îmbunătăți în mod semnificativ înțelegerea și gestionarea sănătății cardiovasculare. Acest articol detaliază rezultatele experimentale din modelarea condițiilor de infarct miocardic folosind un model cu șase compartimente dezvoltat în mediul de dezvoltare integrat NetLogo, încorporând BehaviorSpace pentru simulări extinse. Pentru analiza rezultatelor, au fost utilizate pachete specializate în R, Python și Wolfram Mathematica pentru a asigura o interpretare riguroasă a datelor. Rezultatele demonstrează o fidelitate promițătoare în comparație cu literatura existentă și cu datele în timp real ale pacientului, indicând potențialul modelului pentru aplicații clinice. Prin ilustrarea interacțiunilor din cadrul sistemului circulator, această cercetare nu numai că contribuie la cunoștințe teoretice, ci oferă și perspective practice asupra managementului bolii și strategiilor de intervenție, deschizând calea pentru îmbunătățirea rezultatelor sănătății cardiovasculare.

Cuvinte cheie: *modelarea dinamicii sistemului; sistemul circulator; infarct miocardic; mediu de dezvoltare integrat.*

1. Introduction

The human circulatory system is a complex network of interacting components, including the heart, blood vessels, and blood, responsible for maintaining physiological homeostasis [1]. Understanding its dynamics is crucial for diagnosing and treating cardiovascular diseases, which remain the leading causes of morbidity and mortality worldwide [2]. Traditional approaches to studying the circulatory system often rely on static models that fail to capture the intricate feedback loops and time-dependent interactions inherent in human physiology. In response to these limitations, researchers have increasingly turned to system dynamics modeling (SDM), a powerful method for simulating complex systems over time [3,4].

System dynamics offers a comprehensive framework for analyzing the circulatory system by utilizing stocks, flows, and feedback loops to represent physiological processes. This approach allows for exploring various scenarios, such as the impact of lifestyle changes, medication, or surgical interventions on cardiovascular health. Recent advances in computing power and data acquisition technologies, such as wearable devices and high-resolution imaging, have further enhanced the potential of system dynamics models. These innovations enable real-time data integration, allowing for continuous validation and refinement of models, thereby improving their accuracy and practical applicability.

A particularly promising development in this field is the emergence of personalized models [5]. By incorporating patient-specific data, these models account for individual variability in anatomy, physiology, and risk factors, offering tailored insights into disease progression and treatment outcomes. For instance, patient-specific hemodynamic models can simulate blood flow dynamics using patient data, providing valuable information for surgical planning and risk assessment. Similarly, personalized models of cardiac function can predict responses to therapies, aiding in managing conditions such as heart failure and hypertension.

Moreover, integrating machine learning techniques with system dynamics modeling has opened new avenues for enhancing predictive capabilities. By learning from vast datasets, these hybrid models can identify patterns and refine simulations, leading to more precise predictions of cardiovascular events. This synergy between system dynamics and machine learning represents a significant leap toward the realization of personalized medicine in cardiovascular care.

In this article, we explore the current status and recent advances in system dynamics modeling of the circulatory system, focusing on personalized approaches. The paper discusses the methodologies employed, the challenges encountered, and the transformative potential these models hold for improving patient outcomes and advancing cardiovascular research.

2. Materials and Methods

The NetLogo integrated development environment (IDE) [6] is used for system dynamics modeling. Data analysis is performed using specialized packages [7-10] in R programming language [11], Python [12], and, to a lesser extent, Wolfram Mathematica [13].

3. Aspects Important for System Dynamics Modeling of the Circulatory System

3.1. Basic components and mathematical aspects behind SDM

A. *Basic Components*

1. Stocks and Flows

- Stocks represent accumulations (e.g., blood volume).
- Flows are rates of change affecting stocks (e.g., blood flow rate).

2. Feedback Loops

- Positive Feedback: Enhances changes (e.g., increased heart rate).
- Negative Feedback: Stabilizes the system (e.g., blood pressure regulation).

B. Main Mathematical Equations

a. Stock and Flow Equations

- Change in Blood Volume (*V*)

$$\frac{dV}{dt} = Q_{in} - Q_{out}, \tag{1}$$

where Q_{in} is the rate of blood entering the system and Q_{out} is the rate of blood leaving the system.

- Cardiac Output (*CO*)

$$CO = HR \times SV, \tag{2}$$

where HR is the heart rate (beats/minute), and SV is the stroke volume (mL).

b. Feedback Loop Equations

- Blood Pressure (BP) Regulation

$$BP = TPR \times CO, \tag{3}$$

where TPR denotes total peripheral vascular resistance (mmHg·s/mL), and CO is cardiac output (L/min).

- Baroreceptor Reflex: Adjusts heart rate and vessel diameter in response to changes in blood pressure, modeled by:

$$HR = f(BP_{setpoint} - BP), \tag{4}$$

where HR denotes heart rate, BP - blood pressure (mmHg), and f represents the response function of the baroreceptor.

C. Simulation and Analysis

- Differential Equations: Used to simulate changes over time.
- Numerical Methods: Employed to solve these equations and analyze system behavior.

By formulating these equations, system dynamics models capture the interplay between different physiological components, allowing for the simulation and analysis of the circulatory system's behavior under various conditions.

3.2. Possibilities, Benefits, and Potential Practical Applications of the SDM Approach

A. Possibilities

The human circulatory system is a complex network that involves the heart, blood vessels, and blood. It is characterized by numerous interactions and feedback loops, making it an ideal candidate for system dynamics modeling. Researchers can simulate various physiological and pathological conditions, such as hypertension, heart failure, and atherosclerosis, by creating a system dynamics model of the circulatory system.

This approach allows for exploring how different variables interact over time, such as blood pressure, heart rate, and blood volume. It enables testing hypotheses regarding the impact of lifestyle changes, medications, or surgical interventions on cardiovascular health. Moreover, such models can be adapted to simulate individual patient scenarios, offering personalized insights into disease progression and treatment outcomes.

B. Benefits

One of the primary benefits of using system dynamics for modeling the circulatory system is the ability to visualize and understand complex interactions that are not immediately apparent. This holistic approach facilitates the identification of key leverage points where interventions can be most effective.

Additionally, system dynamics models can serve as valuable educational tools. Medical students and healthcare professionals can better understand cardiovascular physiology and pathology by simulating different scenarios. These models can also be used to communicate complex concepts to patients, improving their understanding and engagement in their care.

System dynamics models can also predict interventions' long-term outcomes, aiding healthcare providers' decision-making processes. Clinicians can optimize therapeutic strategies and improve patient outcomes by simulating patient responses to different treatments.

C. Practical Applications

In practice, system dynamics models of the circulatory system can be used to inform public health strategies. For instance, by modeling the population-level impacts of lifestyle changes or public health interventions, policymakers can make informed decisions about resource allocation and health promotion initiatives.

In clinical settings, these models can support the development of decision-support systems that assist clinicians in diagnosing and managing cardiovascular diseases. Such models can provide dynamic risk assessments and personalized treatment recommendations by integrating real-time patient data.

Furthermore, pharmaceutical companies can use system dynamics models to simulate the effects of new drugs on the circulatory system, thereby streamlining the drug development process and reducing costs associated with clinical trials.

3.3. Integrating SDM of the Circulatory System with Real-Time Data

Integrating system dynamics models of the circulatory system with real-time patient data can enhance their accuracy and applicability. The following presents vital components for doing this.

A. Data integration techniques

1. Data Acquisition: Using wearable devices and sensors to continuously monitor patient metrics such as heart rate, blood pressure, and oxygen levels. These devices can transmit data wirelessly to a centralized system.
2. Data Processing: Implementing algorithms to clean and preprocess the incoming data, ensuring accuracy and consistency. This step is crucial for real-time analysis.
3. Model Adaptation: Using real-time data to update the model parameters dynamically. Machine learning techniques can adjust model variables based on the latest data, ensuring the model remains relevant to the patient's condition.

B. Technical Infrastructure

1. Cloud Computing: Utilizing cloud platforms for data storage and processing can provide the computational power to handle large volumes of real-time data and complex simulations.
2. Application programming interfaces (APIs) and Interoperability: Developing APIs to facilitate seamless data exchange between monitoring devices, electronic health records (EHRs), and the system dynamics model. Ensuring interoperability among different systems is critical.

C. Real-Time Feedback and Decision Support

1. Dashboard Visualization: Creating intuitive dashboards that display real-time model outputs and patient data, allowing healthcare providers to monitor patient status effectively.
2. Alerts and Notifications: Setting up automated alerts for healthcare providers if the model predicts potential adverse events or deviations from expected health patterns.
3. Personalized Treatment Adjustments: Using the insights gained from the model to tailor treatment plans on the fly, optimizing medication dosages or recommending lifestyle changes based on current data.

D. Challenges and Considerations

1. Data Privacy and Security: Ensuring compliance with regulations like HIPAA [14] by implementing robust encryption and access controls to protect patient data.
2. Model Validation: Continuously validating and refining models with new data to maintain accuracy and reliability.
3. User Training: Providing training for healthcare providers to interpret model outputs and integrate them into clinical decision-making effectively.

By effectively integrating real-time patient data, system dynamics models of the circulatory system can become powerful tools for personalized healthcare, improving patient outcomes and optimizing treatment strategies.

4. Experimental Results

The research the current paper is based on is at its preclinical stage. Thus, although it is taking care of the aspects to be considered at more advanced stages (e.g., integration with real-time patient data), it focuses primarily on essential modeling aspects at the current stage. Figure 1 presents the system dynamic scheme (NetLogo SDM). The squares represent the model's six compartments (i.e., stocks), including the heart chambers and arterial and venous segments of the circulatory system. The diamond structures denote various parameters of the model (over 30 in number), and thin arrows indicate influences or interactions. The thick arrows illustrate the flows. Behind each influence/interaction are mathematical equations, some of which have been described in previous sections.

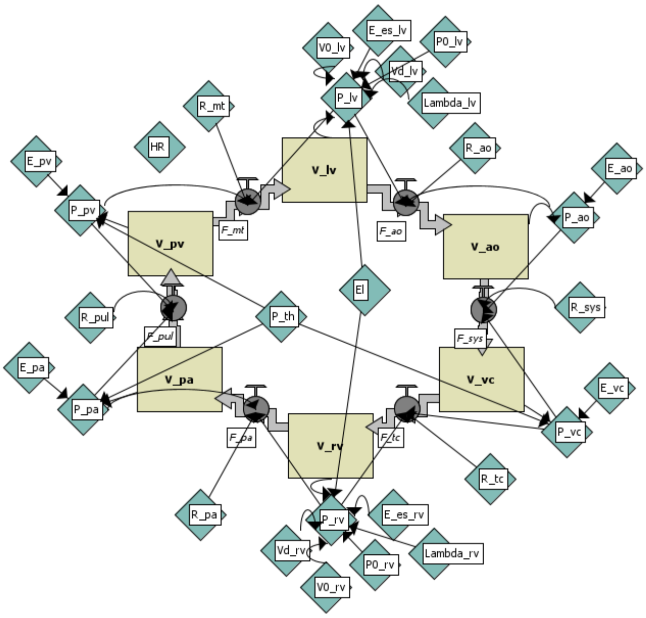

Figure 1. The system dynamic scheme for the created model. Squares represent stocks and diamonds denote other parameters. Capital letters point to a certain parameter: V – volume, E– elastance of different compartments of the system (for ventricles – end systolic elastance), Lambda - the curvature of end-diastolic pressure-volume relationship function, V0 – zero-pressure volume and P0 – zero-volume pressure, P – pressure, F – flow, R – resistance, El – time-varying elastance, HR – heart rate. Subscripts denote specific compartments of the circulatory system: ao – aorta, vc – vena cava, sys – systemic circulation, tc – tricuspid valve, rv – right ventricle, pa – pulmonary artery, pv – pulmonary veins, th – intrathoracic, mt – mitral valve.

Figure 2 illustrates the model’s user interface. The sliders on the bottom are used to adjust model parameters.

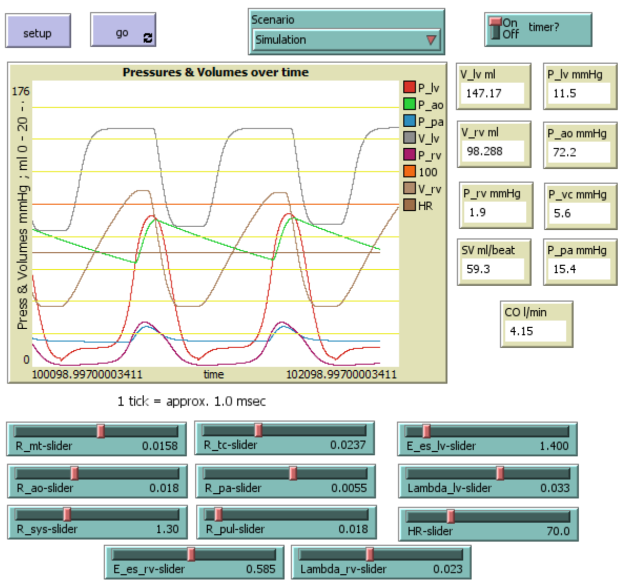

Figure 2. The appearance of the model's user interface. Capital letters denote different physiological parameters: V – volume, P – pressure, SV - stroke volume, CO – cardiac output, R – resistance, E– elastance, Lambda – a function influencing myocardial contractility, HR – heart rate. Subscripts denote specific compartments of the circulatory system (e.g., ao – aorta, lv – left ventricle, etc., as in Figure 1).

The monitors on the right continuously communicate the numerical values of particular model outputs (e.g., volumes in different compartments of the system as well as pressures: left and right ventricles, aorta, and pulmonary artery) along with the stroke volumes and cardiac output of both parts of the heart. The plotting area on the left shows the dynamics in time for the mentioned physiological parameters.

Figure 3 shows the pressure-volume loop of a patient with a simulated myocardial infarction (green color for the left ventricle and yellow for the right ventricle). It can be noticed that they shrink with the institution of the infarction.

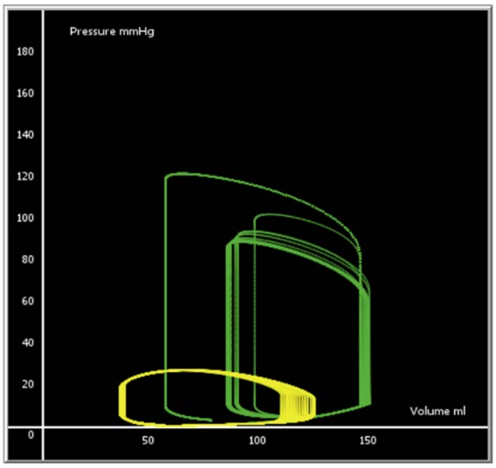

Figure 3. The pressure-volume loop in a patient with a simulated myocardial infarction. Green color denotes left ventricle and yellow color – right ventricle.

Table 1 denotes the time-varying values of six physiological parameters during the simulation.

Table 1

A small portion of the simulation results

Left ventricle pressure (mm Hg)	Left ventricle output (L/min)	Right ventricle output (L/min)	Right ventricle volume (mL)	Aortic pressure (mm Hg)	Vena Cava pressure (mm Hg)
69.24	4.14	4.14	96.68	91.25	4.81
70.32	4.14	4.14	96.54	91.20	4.81
71.42	4.14	4.14	96.36	91.16	4.81
72.52	4.14	4.14	96.13	91.11	4.81
73.65	4.14	4.14	95.87	91.07	4.81
74.78	4.14	4.14	95.58	91.02	4.81
75.93	4.14	4.14	95.26	90.97	4.81
77.09	4.14	4.14	94.92	90.93	4.81
78.26	4.14	4.14	94.54	90.88	4.82
79.45	4.14	4.14	94.15	90.84	4.82

Most of the physiological parameters shown in Table 1 have a clinical equivalent, which may be of importance when integrating the model in a clinical setting.

Numerical data generated by simulations can be analyzed from different perspectives using methods of various degrees of sophistication appropriate for multimodal/multivariate time series. Figure 4 illustrates the perspective based on Kolmogorov-Chaitin (KC) complexity [15-17] estimated in a case of simulated myocardial infarction (MI).

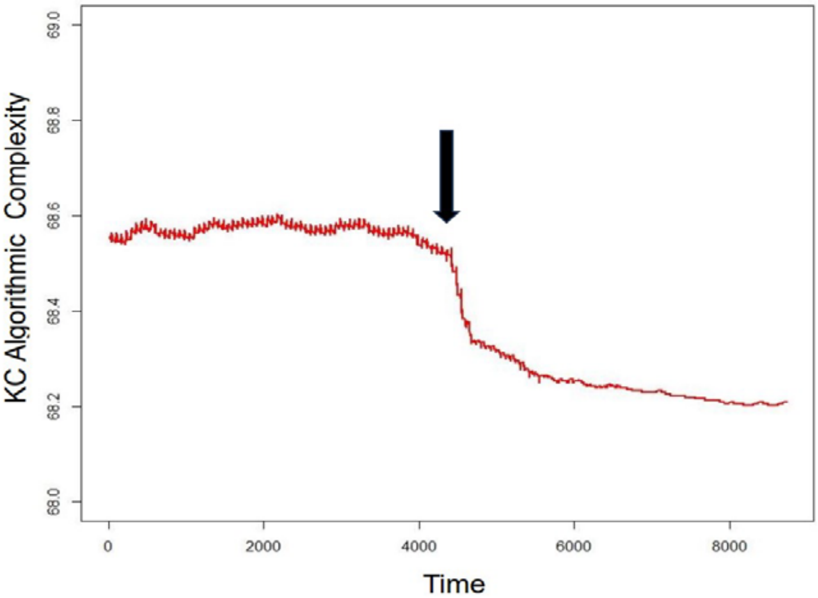

Figure 4. Kolmogorov-Chaitin complexity over time for a simulated case of myocardial infarction. The black arrow denotes the occurrence of myocardial infarction.

For estimation, values of twelve model parameters over time were used. The black arrow denotes the time moment when MI occurred. An evident drop in the KC complexity can be noticed with the institution of MI. This is just an example of a less traditional metric for tracking the overall dynamics of a system (e.g., the circulatory system), but the researcher evidently can use metrics and analysis methods that suit his research goals the best.

5. Discussion

This research builds on an earlier work [18,19] focused on a simpler (i.e., three compartments) similar model. While the previous model let the researcher control 4 model parameters (i.e., volume status, arterial vascular resistance, myocardial contractility, and vascular elastance), the current model has an extended set of controllable parameters, denoted by the sliders in Figure 2 (e.g., concerning all four heart chambers, valves, systemic and pulmonary circulations). This is expected to provide more detailed simulations.

Experiments were performed in NetLogo IDE BehaviorSpace, a software tool integrated with NetLogo that allows researchers to conduct experiments with models providing numerical data to be analyzed. Table 1 in the previous section presents a small portion of such data. The volume of the data can be much larger depending on the experiment duration and the number of parameters set to be monitored. Selecting parameters equivalent to those in a clinical setting can leverage the integration of SDM with real-time patient data.

Concerning a potential future integration of SDM with real-time patient data, there are several aspects to be considered and, when necessary, solved:

Real-Time Data Acquisition

Wearable Devices: Utilizing devices to continuously monitor heart rate, blood pressure, and ECG data.

Data Connectivity: Ensuring seamless data flow from devices to the model for real-time updates.

Data Processing and Management

Data Cleaning: Implementing algorithms to filter and preprocess incoming data for accuracy.

Dynamic Model Updating: Using real-time data to adjust model parameters dynamically, improving precision.

Clinical Decision Support

Risk Assessment: Developing tools to assess patient risk in real-time, providing alerts for potential complications.

Personalized Intervention: Tailoring treatment recommendations based on individual patient data and model predictions.

Privacy and Security

Data Protection: Ensuring compliance with data privacy regulations by implementing robust encryption and security measures.

The SDM, including myocardial infarction, can become a valuable tool for understanding disease dynamics and supporting personalized patient care by focusing on these aspects.

6. Conclusions

Applying system dynamics to the human circulatory system presents a promising approach for advancing cardiovascular research and healthcare. These models offer significant insights into disease mechanisms, treatment effects, and public health strategies by capturing the complexity of physiological interactions. As technology advances and more data becomes available, the potential for system dynamics modeling in cardiovascular health will continue to grow, ultimately contributing to improved patient outcomes and more efficient healthcare systems.

Conflicts of Interest: The author declares no conflict of interest.

References

1. Hall, J.; Hall, M. Guyton and Hall Textbook of Medical Physiology. Elsevier, Philadelphia, SUA, 2021, 1152 p.
2. World Health Organization/Cardiovascular diseases. Available online: https://www.who.int/health-topics/cardiovascular-diseases#tab=tab_1 (accessed on 18.11.2024).
3. Frolov, S.V.; Sindeev, S.V.; Lischouk, V.A.; Gazizova, D.Sh.; Liepsch, D.; Balasso, A. A lumped parameter model of cardiovascular system with pulsating heart for diagnostic studies. J. Mech. Med. Biol. 2017, 17(5),1750056.
4. Ježeka, F.; Kulhánekb, T.; Kaleckýa, K.; Kofránek, J. Lumped models of the cardiovascular system of various complexity. J. Appl. Biomed. 2017, 37, pp. 666-678.
5. Garber, L.; Khodaei, S.; Keshavarz-Motamed, Z. The critical role of lumped parameter models in patient-specific cardiovascular simulations. *Arch. Computat. Methods Eng.* 2022, 29, pp. 2977–3000.
6. Wilensky, U. NetLogo. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. Dec 12, 2018. Available online: ccl.northwestern.edu/netlogo/index.shtml (accessed on 15.11.2024).
7. Zeileis, A.; Grothendieck, G. Zoo:S3Infrastructure for regular and irregular time series. J. Stat. Softw. 2005, 14(6), pp.1-27. https://doi.org/10.18637/jss.v014.i06.
8. Wickham, H.; François, R.; Henry, L.; Müller, K.; Vaughan, D. dplyr: A Grammar of Data Manipulation. R package version 1.1.4. Available online: https://github.com/tidyverse/dplyr, https://dplyr.tidyverse.org (accessed on 18.11.2024).

9. Web Application Framework for R – shiny-package. Available online: https://shiny.posit.co/r/reference/shiny/1.4.0/shiny-package.html (accessed on 18.11.2024).
10. Gauvrit, N.; Singmann, H.; Soler-Toscano, F.; Zenil, H. Algorithmic complexity for psychology: A user-friendly implementation of the coding theorem method. Behav. Res. Methods 2015, 48, pp. 1–16.
11. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, 2021. Available online: https://www.R-project.org/(accessed on 18.11.2024).
12. Van Rossum, G.; Drake, F.L. Python 3 Reference Manual. CreateSpace, Scotts Valley, CA, 2009, 242 p.
13. ISBN:978-1-4414-1269-0.
14. Wolfram Research, Inc., Mathematica, Version 14.1, Champaign, IL, 2024. Available online: https://support.wolfram.com/41360 (accessed on 20.11.2024).
15. Health Insurance Portability and Accountability Act. Available online: https://www.hhs.gov/hipaa/index.html, (accessed on 18.11.2024).
16. Kolmogorov, A.N. Three approaches to the quantitative definition of information. Probl. Inf. Transm. 1965, 1, pp. 1–7.
17. Iapascurta, V. Estimation of Kolmogorov-Chaitin Complexity on Continuous Biomedical Data for Machine Learning Purposes. In: Intelligent and Fuzzy Systems INFUS 2024. Lecture Notes in Networks and Systems, Springer, Cham., 2024, 1090, pp 60–67.
18. Zenil, H. A review of methods for estimating algorithmic complexity: options, challenges, and new directions. Entropy 2020, 22(6), 612.
19. Iapascurta, V. Cardiac_output-Simple_Model_01_01, NetLogo Modeling Commons. Available online: www.modelingcommons.org/browse/one_model/5361 (accessed on 18.11.2024).
20. Iapăscurtă, V. Netlogo integrated development environment for modeling physiological processes. In: The Technical Scientific Conference of Undergraduate, Master, PhD students, Technical University of Moldova, Chișinău, Moldova, March 27-29, 2024, 2, pp. 992-995.

Citation: Iapăscurtă, V. Exploring the human circulatory system through system dynamics: a model-based approach. *Journal of Engineering Science* 2024, XXXI (4), pp. 95-104. https://doi.org/10.52326/jes.utm.2024.31(3).01.

Submission of manuscripts: jes@meridian.utm.md