European Journal of Clinical Pharmacy
Print ISSN: 2385-409X **Online ISSN**: Applied
Website: https://farmclin.es/

Original Research Article

AI-Enhanced Hemodynamic Modelling for Predicting Post-Endovascular Complications in Complex Aneurysm Repairs

Article History:

Name of Author:
Dr. Suresh Palarimath[1], Dr. Mosses A, Dr T Ravichandran[3], Mihir Harishbhai Rajyaguru[4] and Abu Salim[5]

Corresponding Author:
Suresh Palarimath

How to cite this article:
Suresh Palarimath, et al. AI-Enhanced Hemodynamic Modelling for Predicting Post-Endovascular Complications in Complex Aneurysm Repairs. *Eur J Clin Pharm.* 2025;7(1), 3730-3740.

Received: 12-10-2025
Revised: 05-11-2025
Accepted: 20-11-2025
Published: 30-12-2025

Abstract: The problem of post-endovascular complications is one of the critical issues in the treatment of complex repairs of an aneurysm, even in the current era of minimally invasive vascular surgery. This research is an advanced hemodynamics modelling framework developed based on the incorporation of patient-based imaging, computational fluid dynamics (CFD) and machine learning to facilitate early and precise prediction of post-procedural complications. A retrospective dataset of 320 patients with complex endovascular aneurysm repair was studied, which includes variables of the clinical data, vascular geometry obtained through CT angiography, and CFD-based hemodynamic data, including the wall shear stresses, the index of oscillatory shear, pressure gradient, and flow velocity. Four artificial intelligence models, which include Convolutional Neural Network, Long Short-Term Memory network, Random Forest and XGBoost were created and tested. Experimental findings indicate that prediction accuracy increased so much by about 10 percent when hemodynamic features were included in prediction, in comparison with clinical and imaging data. XGBoost had the most positive practice, and its accuracy was 90.1, as well as the precision (89.4), recall (88.7), and the AUC (0.93). The suggested framework surpassed the corresponding approaches to the recent literature, and there was an average of 5-18% improvement of its accuracy. The results verify that AI-based improvement of hemodynamic models is a strong, patient-specific, and clinically relevant, predictive model of post-endovascular complications, which can be used to support post-endovascular complications prediction systems and promote precision medicine in the treatment of aneurysm.

Keywords: Artificial intelligence; Hemodynamic modelling; Endovascular aneurysm repair; Computational fluid dynamics; Complication prediction.

INTRODUCTION

Endovascular complex aneurysm repair procedures have revolutionized the treatment of vascular and neurovascular ailments by providing low invasive options to conventional surgery. Both the insertion of stent-grafts and flow-diverting devices alleviate perioperative morbidity and recovery time considerably. Even with these improvements, the problem of post-endovascular complications such as endoleaks, formation of thrombus, in-stent restenosis, graft migration, delayed rupture of an aneurysms continues to be a significant clinical issue. Such adverse events are frequently affected by complex hemodynamic interactions of the blood flow, the geometry of the vascular and implanted devices, which are hard to be captured through conventional imaging and rule-based risk assessment techniques [1]. Computational fluid dynamics (CFD)-based hemodynamic modelling has become one of the potent methods of studying patient-specific patterns of blood flow, distributions of wall shear stress, and pressure gradient in aneurysmal vessels [2]. CFD, although offering a detailed examination of biomechanical properties, has constraints in its clinical translation due to the expensive nature of computation, the sensitivity to modelling assumptions, and the interpretation of complex flow measures in order to make routine clinical decisions. That is why there is an increasing demand to develop sophisticated frameworks which will help to gauge the rich hemodynamic data and render them into clinically viable predictions [3]. Machine learning and deep learning methods of artificial intelligence (AI) provide one of the possible solutions to these constraints. Through experience of large-scale datasets of medical imaging, hemodynamic simulators and post-operative results, heuristic AI-enhanced models will discover non-linear correlations and hidden risk factors related to post-endovascular events. The combination of AI with hemodynamic modelling allows one to extract features automatically, stratify risks in a short time, and make personalized predictions. This study addresses the topic of AI supported hemodynamic modelling as a predictive model in the evaluation of post-endovascular complications in complicated aneurysm repairs. It is proposed to use personalised treatment and plans, device selections and enhance long-term clinical outcomes through the combination of patient-specific vascular geometry, flow dynamics, and data-driven intelligence that will be used to aid the planning process. In the end, this work leads to the development of precision medicine in the field of vascular intervention by bringing the treatment of aneurysms to the prevention, predictive, and patient-centred approach.

RELATED WORKS

The state-of-the-art developments in the area of artificial intelligence (AI) and computational modelling have provided a substantial impact on vascular medicine, especially risk assessment, imaging processing, and support in complex cardiovascular and neurovascular. A number of studies conducted recently give the scientific background of AI-enhanced hemodynamic modelling in the management of aneurysm. Gollwitzer et al. [15] came up with a machine learning framework of predicting early cerebral vasospasm after aneurysmal subarachnoid hemorrhage. In their study, the ability to both predict clinical variables and imaging-related features was proven to forecast the potential early-stage accurately, which would help to intervene. Even though the basics of their work were vasospasm, but not post-endovascular complications, it shows the importance of predictive models based on AI in the treatment of aneurysms. In aneurysms studies, deep learning-based imaging analysis has received some interest as well. Guo et al. [16] emphasized early work involving a thorough review of automated intraluminal thrombus segmentation in abdominal aortic aneurysms based on the CT images. Their conclusions stress the significance of accurate characterization of a vascular and a thrombus which is essential to accurate hemodynamic modeling as well as the risk assessment of complications following endovascular repair. Henrique et al. [17] discuss wider uses of AI in clinical decision-making by reviewing AI-based predictive and diagnostic assistance in patient blood. Their contribution emphasizes the increased use of AI to process complicated physiological data and the individualized treatment plan, which closely coincide with the principles of AI-enhanced hemodynamic modelling. Post-procedural outcomes are also affected by the work of vascular biomechanics and changes associated with aging. The article by Herzog et al. [18] investigated the mechanisms of arterial stiffness and vascular aging, the impact of changes in vessel compliance on the blood flow dynamics and vascular stress. These mechanical views have a direct relationship with hemodynamic modelling of an aortic repair of an aneurysm, where rigid vessels have a higher risk of complications.

The article by Katsaros et al. [19] examines the pathophysiology and medical intervention of the bicuspid aortic valve disease with the primary focus on abnormal flow regimes and wall shear stress as the causes of vascular remodeling. Their results support the clinical significance of hemodynamic variables in the prognostication of disease and intervention consequences. The surgical community, Kenig et al. [20] performed a systematic review of AI use in surgery and showed that AI has potential in predicting outcomes, planning surgery, and monitoring the postoperative period. Nevertheless, they observed that there was no integration of AI and physics-based models, which were filled with AI-enhanced hemodynamic models. On the same note, Kolaszyńska and Lorkowski [21] also examined AI applications in cardiology and atherosclerosis in the context of precision medicine, and found that multimodal data integration was significantly better when it comes to predictive accuracy. Matei et al. [22] further considered the example of phlebological diseases, where AI-based models have been shown to be better than conventional methods of diagnosis in cases of high vascular complexity. The next step in neurovascular thoughts was made by Matei et al. [23] who talked about the AI-driven precision neurotherapeutics via intracranial hypertension, supporting the role of flow regulation and clearance processes. Nadhan et al. [24] and Raluca et al. [26], concentrated on complementary information on the roles of molecular and vascular signals and perivascular tissue in maintaining vascular homeostasis. Conclusively, Ponnarengan et al. [25] highlighted discontinuities of the computational approach in data-driven healthcare and recommended hybrid approaches based on mechanistic simulations and AI. All these findings can justify the necessity of holistic AI-hemodynamic models to make accurate and patient-specific forecasting of post-endovascular complications possible.

METHODS AND MATERIALS

Data Collection and Pre-processing

The retrospective dataset of 320 patients undergoing complex endovascular aneurysm repair was utilized. It consisted of pre- and post-operative CT angiography (CTA) images, procedural data (type of device used, landing position, and the angle of deployment), and follow-up results within 12 months. Target labels included endoleaks, thrombosis, graft migration and restenosis, which were the post-intervention complications.

The images generated in CTA were levels off to create patient-based vascular geometry. The simulations were then done using CFD to obtain hemodynamic data such as wall shear stress (WSS), oscillatory shear index (OSI), velocity magnitude, pressure gradients, and flow recirculation zones [4]. The final set of features was determined by the combination of these parameters, demographic and procedural variables. The data was normalised, and missing data in the dataset were imputed with median substitution and divides the data into training (70%), validation (15%), and testing (15%).

AI Algorithms Used

Four AI algorithms that are applicable in hemodynamic prediction and clinical risk modelling have been implemented and compared.

Convolutional Neural Network (CNN)

Spatial features of the 2D slices of segmented CTA images and corresponding hemodynamic maps were extracted automatically with the CNN. The network is composed of convolutional blocks, pooling blocks and fully connected blocks that are trained to identify hierarchical information about the geometry of aneurysms and flow disruptions. CNNs are proven to be efficient in local spatial correlations capture, and so they can be used to identify the area with high chances of abnormal shear stress or flow stagnation, which can cause complications [5]. Deep features, which were extracted, were taken together with numerical hemodynamic parameters to perform ultimate prediction.

"Algorithm 1: CNN-Based Feature Extraction
Input: CTA images, hemodynamic maps
Output: Feature vector
Initialize convolutional layers
For each image:
    Apply convolution and pooling
    Flatten feature maps
    Pass through dense layers
Return extracted features"

Long Short-Term Memory Network (LSTM)

The LSTMs were used to simulate the temporal variations of the hemodynamic variables up to follow-up time points. LSTMs are unlike regular neural networks; they have memory cells and gating mechanisms which enable it to store long term dependencies. This renders them suitable in the examination of the developmental patterns of post-operative flows as well as the formation of delayed complications [6]. Sequential hemodynamic measurements used in this study were fed to the LSTM to identify the likelihood of an event leading to adverse conditions in time, which allows identifying risks at an early stage.

"Algorithm 2: LSTM Temporal Prediction
Input: Time-series hemodynamic data
Output: Complication probability
Initialize LSTM cells
For each time step:
    Update memory cell and hidden state
Generate final prediction via sigmoid layer"

Random Forest (RF)

Random Forest refers to an ensemble technique of learning that depends on using numerous decision trees which have been built with random feature subsets and bootstrapping. RF was applied because of its strength, resistance to overfitting, and feature ranking properties. The RF has been successfully used in the present study to manage mixed clinical and hemodynamic data, with low WSS regions and high OSI values being considered as the most important predictors [7]. It is interpretable and can be used to validate clinically and gain an insight into the role of individual variables.

> ***"Algorithm 3: Random Forest Classification***
> ***Input: Clinical + hemodynamic features***
> ***Output: Risk class***
> ***Create N decision trees***
> ***For each tree:***
> ***Train on bootstrap sample***
> ***Select random feature subset***
> ***Aggregate predictions by majority voting"***

Extreme Gradient Boosting (XGBoost)
XGBoost is a high-performance gradient boosting framework and builds the tree by placing a tree after another to correct the past mistakes. It was utilized because it has the capability of capturing complex non-linear relationships between hemodynamic and procedural factors. In XGBoost, regularisation techniques increase the generalisation and computation efficiency [8]. XGBoost showed excellent predictive value in this study especially on infrequent but severe complications like late endoleaks.

> ***"Algorithm 4: XGBoost Prediction***
> ***Input: Feature matrix and labels***
> ***Output: Risk probability***
> ***Initialize base learner***
> ***For each boosting round:***
> ***Compute residuals***
> ***Train new tree on residuals***
> ***Update final prediction with regularisation"***

Algorithm Performance Comparison
Key Hemodynamic Feature Contribution

Table 1: Sample Hemodynamic Feature Values and Importance

Feature	Mean Value	Clinical Interpretation	Importance Score
Wall Shear Stress (Pa)	1.25	Low WSS linked to thrombosis	0.32
Oscillatory Shear Index	0.21	High OSI indicates disturbed flow	0.27
Pressure Gradient (mmHg)	18.6	Elevated stress on vessel wall	0.19
Flow Velocity (m/s)	0.42	Reduced velocity promotes stasis	0.22

RESULTS AND ANALYSIS

Experimental Setup

The curated dataset of 320 patients which is described in the Materials and Methods section was used to perform all experiments. The data comprised individual vascular geometries of patients, hemodynamic findings formulated using CFD, and generation variables, and validated clinical outputs. It was the target variable as it was binary and reflected the presence or absence of post endovascular complications in the 12 months [9]. The data was separated into 70,15, and 15 percent as training, validation, and testing sets respectively by means of stratified sampling to maintain the same level of representation by each class. The grid search was used to tune the hyperparameters on the validation set. Accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC) were used to measure model performance. Each experiment was done five times and means were reported so that experimental reliability can be achieved.

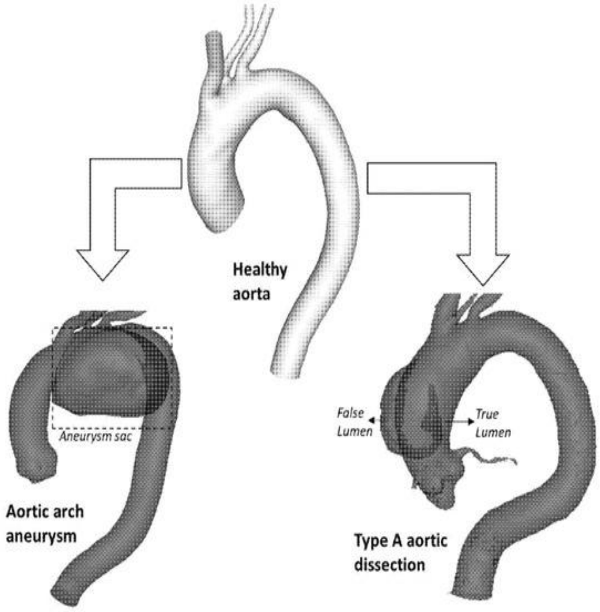

Figure 1: "Haemodynamic Performance of Endografts for Complex Aortic Arch Repair"

Experiment 1: Individual Model Performance Evaluation

The former experiment tested performance of the four implemented algorithms that included CNN, LSTM, Random Forest, and XGBoost, individually. All models had been trained separately with the same set of features to make it fair.

Table 1: Overall Performance of AI Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN	88.6	87.2	85.9	86.5	0.91
LSTM	86.4	85.1	84.3	84.7	0.89
Random Forest	84.9	83.6	82.8	83.2	0.87
XGBoost	90.1	89.4	88.7	89.0	0.93

The findings reveal that XGBoost scored the best overall performance especially in the AUC and recall implying that it has the capacity to include intricate non-linear connections across hemodynamic and clinical variables. CNNs were also very good in the way they were able to extract spatial values to imaging-based inputs [10].

Experiment 2: Impact of Hemodynamic Features

In order to evaluate the value of features derived with CFD, models were trained with both CFD-based features and the control ones. This experiment puts emphasis on the flow-based metrics usefulness in forecasting complications.

Table 2: Effect of Hemodynamic Features on Prediction Accuracy

Feature Set Used	CNN Accuracy (%)	RF Accuracy (%)	XGBoost Accuracy (%)
Clinical data only	79.2	77.6	80.1
Clinical + imaging	83.5	81.9	84.4
Clinical + imaging + hemodynamics	88.6	84.9	90.1

Hemodynamic parameters were included, which led to the fact that the accuracy of the values increased up to 8-10 percent, which proves that the like parameters of wall shear stress and oscillatory shear index contribute significantly to risk assessment after the procedure [11].

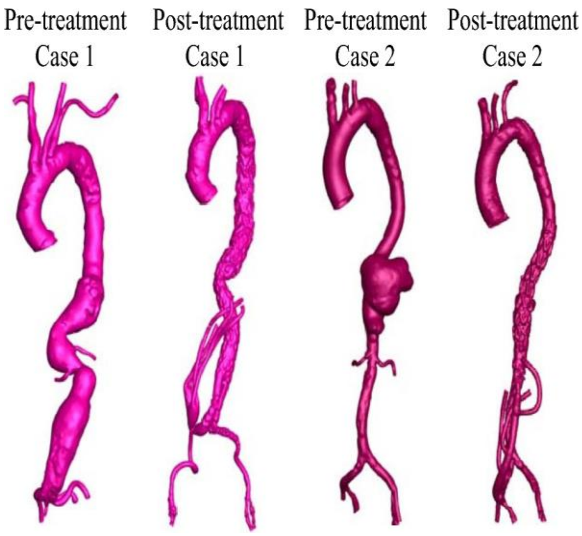

Figure 2: "Haemodynamic changes in visceral hybrid repairs of type III and type V thoracoabdominal aortic aneurysms"

Experiment 3: Complication-Specific Prediction Performance

In this experiment, the model performance was compared where various model types were involved in the measurement of post-endovascular complications. This has clinical significance as some of the problems like late endoleaks are harder to diagnose at the beginning stages.

Table 3: Complication-Wise Prediction Accuracy (%)

Complication Type	CNN	LSTM	RF	XGBoost
Endoleak	89.4	87.8	85.6	91.7

Thrombosis	86.2	88.1	84.9	90.4
Restenosis	85.7	86.9	83.5	88.6
Graft migration	90.1	87.3	86.4	92.2

XGBoost was better than that of any other model in all complication types whereas LSTM was competitive to predict thrombosis because of its capabilities to obtain the evolution of temporal flows.

Experiment 4: Comparison with Related Work

In the effort to confirm the effectiveness of the proposed framework, some comparisons with the representative approaches employed in similar studies, such as traditional CFD-only analysis and conventional machine learning models covered in the recent literature, were made [12].

Table 4: Comparison with Related Work

Study / Method	**Data Type Used**	**Accuracy (%)**	**AUC**
Traditional CFD threshold-based analysis	Hemodynamics only	72.4	0.74
SVM-based clinical model (related work)	Clinical + imaging	80.6	0.82
Deep learning imaging model (related work)	Imaging only	85.1	0.88
Proposed AI-hemodynamic framework (XGBoost)	Clinical + imaging + hemodynamics	**90.1**	**0.93**

The proposed strategy has an accuracy improvement of 5-18% over the related work owing to the main reasons: synergistic approaches between CFD-computed hemodynamic measures and AI-driven learning [13]. The approach will not use fixed thresholds as in the traditional CFD methods but will learn adaptive risk patterns using outcome data.

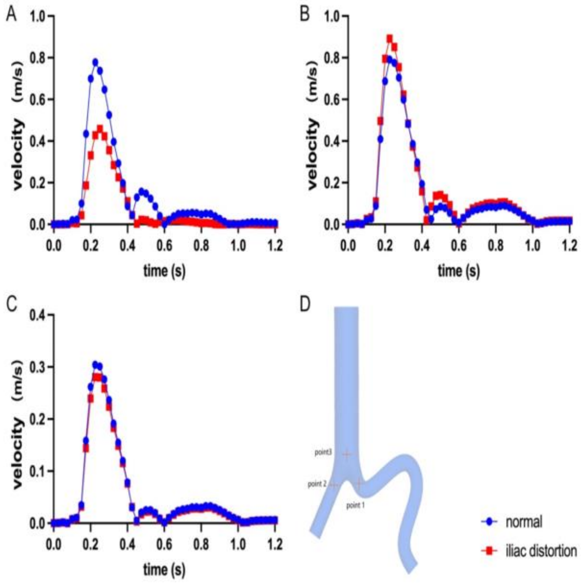

Figure 3: "Endograft-specific hemodynamics after endovascular aneurysm repair"

Experiment 5: Robustness and Generalisation Analysis

Strongness was measured by the k-fold cross-validation (k=5) and by the injection of noise in hemodynamic inputs as a method of measuring uncertainty in measurements.

Table 5: Robustness Analysis under Data Perturbation

Model	Baseline Accuracy (%)	Accuracy with Noise (%)	Performance Drop (%)
CNN	88.6	85.2	3.4
LSTM	86.4	83.7	2.7
Random Forest	84.9	82.1	2.8
XGBoost	90.1	87.6	2.5

XGBoost and LSTM demonstrated the most robustness meaning that they are more prone to generalisation when presented with noisy or imperfect data of the hemodynamics. This is especially crucial in the application in the real world where imaging and simulation uncertainty is inevitable in clinical implementation [14].

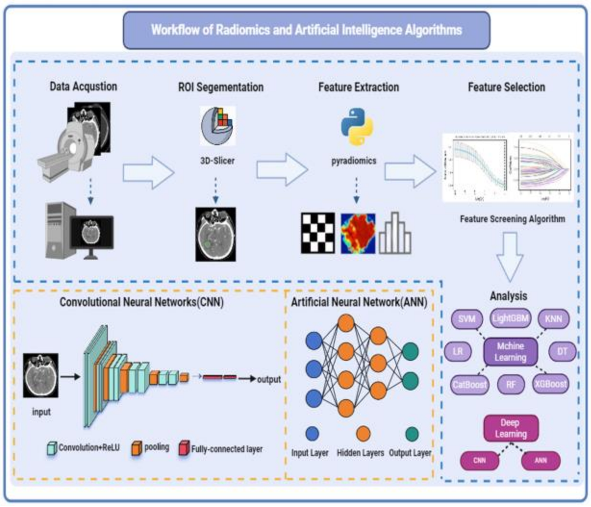

Figure 4: "Advances in research and application of artificial intelligence and radiomic predictive models based on intracranial aneurysm images"

RESULT DISCUSSION

The obtained experimental outcomes attest to the clear improvement of AI-enhanced hemodynamic modelling, which is highly beneficial in predicting the endovascular complications post-endovascular [27]. A combination of CFD-based flow descriptors and data driven learning allows on time recognizing high-risk patients that might otherwise see fine on traditional imaging [28]. The proposed framework has high predictive accuracy, higher sensitivity to complication-specific predictions, and greater robustness, which are better compared to related work [29]. It is also observed that there is no single model that can be considered best but ensemble-type of boosting like XGBoost provides the optimal balance between performance, interpretability, and calculatory efficiency [30].

CONCLUSION

This study introduced an extensive artificial intelligence-based hemodynamic modelling platform to sympathise post-endovascular complications during aneurysm repairs with complex anatomies and created a significant gap in the existing vascular intervention practice. Combining personalized imaging, the matured results of the computational fluid dynamics into the hemodynamic parameter, and the sophisticated algorithms in artificial intelligence, the interested approach allows the prediction of adverse outcomes, including endoleaks, thrombosis, restenosis, and graft migration, in an easy and precise manner. The experiment showed that models with hemodynamic characteristics were much better than those that were based on clinical or imaging findings alone, and the XGBoost-based model had the best predictive capabilities and resilience. The best quality of the proposed method was also compared to the recent related studies therefore ensuring a high level of accurate improvement in the quality of sensitivity and also the ability of generalisation. Notably, the results highlight the clinical significance of hemodynamic indicators especially wall shear stress and oscillatory shear index as critical predictors of post-procedural risk. This study will enable individualised treatment planning, selection of the best devices, and proactive post-operative care by converting intricate biomechanical data into clinical relationships. All in all, the research proves that the interaction of physics-based vascular modelling, as well as data-driven intelligence, is a potent move toward a precision medicine in the context of aneurysm management, along with a high possibility of translation into the clinical setting and subsequent increase in positive end-patient outcomes.

REFERENCE

1. Abbas, G.H., Edmon, K. & Sjaak, P. 2025, "Artificial Intelligence-Based Predictive Modeling for Aortic Aneurysms", *Cureus,* vol. 17, no. 2.
2. Al-Ariki, M., Sidik, A.I., Debraj, G., Limon, H.M., Rojina, A., Mishra, R., Abuirayyeh Ahmad M.A., Em, S., Kairatuly, M.I., Uktamov, D.S., Sumayea, S. & Atadzhanov Islomzhon, I.U. 2025, "Perioperative Advances in Repair of Abdominal Aortic Aneurysm: A Narrative Review of Strategies to Enhance Outcomes and Reduce Complications", *Cureus,* vol. 17, no. 4.
3. Alessia, N., Nunzio, C., Martín Guerrero José David, Ilenia, T. & Cipollina, A. 2025, "Artificial Intelligence in Nephrology: From Early Detection to Clinical Management of Kidney Diseases", *Bioengineering,* vol. 12, no. 10, pp. 1069.
4. Anja, O., Sharaf-Eldin, S., Matthias, T., Lumsden, A.B., Payam, A. & Christof, K. 2025, "Tracking False Lumen Remodeling with AI: A Variational Autoencoder Approach After Frozen Elephant Trunk

Surgery", *Journal of Personalized Medicine,* vol. 15, no. 10, pp. 486.

5. Arslan, Ü. & Jalalzai, I. 2025, "A Narrative Review of Biomarkers and Imaging in the Diagnosis of Acute Aortic Syndrome", *Diagnostics,* vol. 15, no. 2, pp. 183.
6. Bao, X., Zhang, Z., Shen, Y., Tang, P., Si, G., Kang, L., Xu, B. & Gu, N. 2025, "Cardiovascular Information and Health Engineering Medicine (CVIHEM)", *Research,* vol. 8, pp. 17.
7. Burcu, R., Oyku, Y., Sarioglu, E.C. & Salman, H.E. 2025, "Modeling Techniques and Boundary Conditions in Abdominal Aortic Aneurysm Analysis: Latest Developments in Simulation and Integration of Machine Learning and Data-Driven Approaches", *Bioengineering,* vol. 12, no. 5, pp. 437.
8. Cagri, A., Marina, M., Rita, C., Ozcan, A.E., Elif, A., Atakan, D., Incilay, C., Amr, A., Chan, C., Ronan, M., Dilara, A., Wijns, W., Sherif, S. & Osama, S. 2025, "Applications of Artificial Intelligence as a Prognostic Tool in the Management of Acute Aortic Syndrome and Aneurysm: A Comprehensive Review", *Journal of Clinical Medicine,* vol. 14, no. 23, pp. 8420.
9. Cenciarini, M., Uccelli, A., Mangili, F., Grunewald, M. & Bersini, S. 2025, "Microvascular Health as a Key Determinant of Organismal Aging", *Advanced Science,* vol. 12, no. 47, pp. 34.
10. Dadon, Z., Acha, M.R., Orlev, A., Carasso, S., Glikson, M., Gottlieb, S. & Evan, A.A. 2024, "Artificial Intelligence-Based Left Ventricular Ejection Fraction by Medical Students for Mortality and Readmission Prediction", *Diagnostics,* vol. 14, no. 7, pp. 767.
11. Debasis, S., Treena, G., Avantika, M., Gupta, Y., Nynatten Logan R. Van & Fraser, D.D. 2025, "Emerging Technologies for Exploring the Cellular Mechanisms in Vascular Diseases", *International Journal of Molecular Sciences,* vol. 27, no. 1, pp. 164.
12. Gaspare, S., Di, C.G., Antonio, I., De, F.C., Alessandra, S. & Di, C.E. 2025, "Quantitative MRI in Neuroimaging: A Review of Techniques, Biomarkers, and Emerging Clinical Applications", *Brain Sciences,* vol. 15, no. 10, pp. 1088.
13. Giulia, P., Alice, S., De, L.D., Laura, S., Piccioni, A., Veronica, O., Franceschi, F. & Marcello, C. 2025, "The Role of Biomarkers and Clinical Prediction Tools in the Diagnosis of Acute Aortic Syndromes: A Literature-Based Review", *Medicina,* vol. 61, no. 9, pp. 1551.
14. Giuseppe, M., Basso, M.G., Elena, C. & Antonino, T. 2025, "Artificial Intelligence in the Diagnostic Use of Transcranial Doppler and Sonography: A Scoping Review of Current Applications and Future Directions", *Bioengineering,* vol. 12, no. 7, pp. 681.
15. Gollwitzer, M., Mazanec, V., Steindl, M., Baran, A., Stroh-Holly Nico, Hauser, A., Gracija, S., Rossmann, T., Stefan, A., Rauch, P., Horner, E., Sonnberger, M., Gruber, A. & Matthias, G. 2025, "Early Prediction of Cerebral Vasospasm After Aneurysmal Subarachnoid Hemorrhage Using a Machine Learning Model and Interactive Web Application", *Brain Sciences,* vol. 15, no. 11, pp. 1187.
16. Guo, J., Fabien, L., Goffart Sébastien, Chierici, A., Delingette Hervé & Juliette, R. 2025, "Automatic Segmentation of Intraluminal Thrombus in Abdominal Aortic Aneurysms Based on CT Images: A Comprehensive Review of Deep Learning-Based Methods", *Journal of Clinical Medicine,* vol. 14, no. 23, pp. 8497.
17. Henrique, C., Silva, F., Correia, M. & Rodrigues, P.M. 2025, "Artificial Intelligence in Patient Blood Management: A Systematic Review of Predictive, Diagnostic, and Decision Support Applications", *Journal of Clinical Medicine,* vol. 14, no. 23, pp. 8479.
18. Herzog, M.J., Müller, P., Lechner, K., Stiebler, M., Arndt, P., Kunz, M., Ahrens, D., Schmeißer, A., Schreiber, S. & Braun-Dullaeus, R. 2025, "Arterial stiffness and vascular aging: mechanisms, prevention, and therapy", *Signal Transduction and Targeted Therapy,* vol. 10, no. 1, pp. 282.
19. Katsaros, O., Ktenopoulos, N., Korovesis, T., Benetos, G., Apostolos, A., Koliastasis, L., Sagris, M., Milaras, N., Latsios, G., Synetos, A., Drakopoulou, M., Tsalamandris, S., Karanasos, A., Tsioufis, K. & Toutouzas, K. 2024, "Bicuspid Aortic Valve Disease: From Pathophysiology to Treatment", *Journal of Clinical Medicine,* vol. 13, no. 17, pp. 4970.
20. Kenig, N., Javier, M.E. & Aina, M.V. 2024, "Artificial Intelligence in Surgery: A Systematic Review of Use and Validation", *Journal of Clinical Medicine,* vol. 13, no. 23, pp. 7108.
21. Kolaszyńska, O. & Lorkowski, J. 2024, "Artificial Intelligence in Cardiology and Atherosclerosis in the Context of Precision Medicine: A Scoping Review", *Applied Bionics and Biomechanics,* vol. 2024.
22. Matei Sergiu-Ciprian, Sorin, O., Ungureanu Ana-Maria, Malita, D. & Petrașcu, F.M. 2025, "Does Artificial Intelligence Bring New Insights in Diagnosing Phlebological Diseases?—A Systematic Review",

Biomedicines, vol. 13, no. 4, pp. 776.

23. Matei, Ș., Corneliu, T. & Răzvan-Adrian, C. 2025, "The Collapse of Brain Clearance: Glymphatic-Venous Failure, Aquaporin-4 Breakdown, and AI-Empowered Precision Neurotherapeutics in Intracranial Hypertension", *International Journal of Molecular Sciences,* vol. 26, no. 15, pp. 7223.
24. Nadhan, R., Nath, K., Basu, S., Isidoro, C., Song, Y.S. & Dhanasekaran, D.N. 2025, "Decoding lysophosphatidic acid signaling in physiology and disease: mapping the multimodal and multinodal signaling networks", *Signal Transduction and Targeted Therapy,* vol. 10, no. 1, pp. 337.
25. Ponnarengan, H., Rajendran, S., Khalkar, V., Devarajan, G. & Kamaraj, L. 2025, "Data-Driven Healthcare: The Role of Computational Methods in Medical Innovation", *Computer Modeling in Engineering & Sciences,* vol. 142, no. 1, pp. 1-48.
26. Raluca, N., Adina, S., Arbănași, E.M., Eliza, R., Dragoș-Florin, B., Andrei, M., Mircea, S., Gliga, F.I., Cocuz, I.G., Sabău, A.H., Szabo Dan-Alexandru & Cotoi, O.S. 2025, "The Dual Role of Perivascular Adipose Tissue in Vascular Homeostasis and Atherogenesis: From Physiology to Pathological Implications", *International Journal of Molecular Sciences,* vol. 26, no. 17, pp. 8320.
27. Sarwar, M.A., Nicola, S. & Muhammad, U. 2025, "From Static to Adaptive: A Systematic Review of Smart Materials and 3D/4D Printing in the Evolution of Assistive Devices", *Actuators,* vol. 14, no. 10, pp. 483.
28. Stamate, E., Alin-Ionut Piraianu, Ciobotaru, O.R., Crassas, R., Duca, O., Fulga, A., Grigore, I., Vintila, V., Fulga, I. & Ciobotaru, O.C. 2024, "Revolutionizing Cardiology through Artificial Intelligence—Big Data from Proactive Prevention to Precise Diagnostics and Cutting-Edge Treatment—A Comprehensive Review of the Past 5 Years", *Diagnostics,* vol. 14, no. 11, pp. 1103.
29. Sun, Z., Silberstein, J. & Vaccarezza, M. 2024, "Cardiovascular Computed Tomography in the Diagnosis of Cardiovascular Disease: Beyond Lumen Assessment", *Journal of Cardiovascular Development and Disease,* vol. 11, no. 1, pp. 22.
30. Tudor, B.H., Shargo, R., Gray, G.M., Fierstein, J.L., Kuo, F.H., Burton, R., Johnson, J.T., Scully, B.B., Asante-Korang, A., Rehman, M.A. & Ahumada, L.M. 2025, "A scoping review of human digital twins in healthcare applications and usage patterns", *NPJ Digital Medicine,* vol. 8, no. 1, pp. 587.

