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FUNCTIONAL AND ETHICAL MODELING OF NON-NEWTONIAN HEMODYNAMICS IN ANEURYSMAL AND BIFURCATED VESSELS USING PHYSICS-INFORMED NEURAL NETWORKS

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ABSTRACT

Haemodynamic abnormalities in aneurysmal and bifurcated arteries are critical factors influencing the course of vascular disease and the risk of rupture. Conventional computational fluid dynamics (CFD) models, although precise, are resource-intensive and frequently overlook the non-Newtonian characteristics of blood. Physics-Informed Neural Networks (PINNs) present a novel approach for addressing fluid dynamics challenges by including governing equations into the training of neural networks. Integrating Physics-Informed Neural Networks with non-Newtonian rheology and ethical AI principles may facilitate scalable, interpretable, and clinically pertinent vascular simulations. To create and verify a framework based on Physics-Informed Neural Networks (PINN) for simulating non-Newtonian blood flow in aneurysmal and bifurcated arteries, while integrating an ethical modelling approach for translational safety. Two theoretical vascular topologies were examined: (i) an aneurysmal sac on a parent artery and (ii) a bifurcated channel simulating the carotid bifurcation. Blood was characterised as an incompressible shear-thinning fluid with the Carreau–Yasuda model. The governing Navier–Stokes equations were included into an 8-layer Physics-Informed Neural Network (PINN) utilising tanh activation functions. The loss components were data loss (synthetic CFD), PDE residuals, and boundary condition enforcement, optimised using Adam and L-BFGS. Outputs (velocity, pressure, wall shear stress) were juxtaposed with CFD baselines. Ethical principles—transparency, equity, safety, and accountability—were integrated into reporting and validation processes.The predictions from the Physics-Informed Neural Network (PINN) closely aligned with the Computational Fluid Dynamics (CFD) reference values, exhibiting L2 error norms under 5% for both velocity and pressure fields. The estimation error for peak wall shear stress was less than 7%. The loss curves demonstrated consistent convergence within 30,000 epochs. In aneurysmal flow, Physics-Informed Neural Networks (PINNs) accurately simulated intra-sac recirculation zones and elevated shear gradients adjacent to the neck. In bifurcated geometry, regions of low wall shear stress at the outer wall corresponded with computational fluid dynamics expectations. Ethical measures guaranteed transparent reporting of assumptions (rigid boundaries, synthetic geometry) and identified limitations for clinical translation. The suggested PINN framework effectively modelled non-Newtonian blood flow in intricate vascular geometries with great precision compared to CFD,

while incorporating an ethical modelling paradigm. PINNs have potential for enhancing vascular flow models in real-time applications like surgical planning; nonetheless, they necessitate additional validation on patient-specific geometries prior to practical implementation.

KEYWORDS: Physics-Informed Neural Networks, Non-Newtonian Blood Flow, Carreau–Yasuda Model, Haemodynamics, Aneurysm, Bifurcation, and Ethical AI.

1. INTRODUCTION

Vascular haemodynamics is crucial in the aetiology and progression of cerebrovascular and cardiovascular disorders. Modified blood flow patterns, especially in bifurcations and aneurysmal sacs, are closely linked to pathological remodelling, endothelial dysfunction, and the likelihood of rupture or thromboembolic incidents [1,2]. Precise modelling of these intricate flow systems is crucial for risk assessment and treatment strategy formulation. Traditional computational fluid dynamics (CFD) methods, while prevalent, tend to be computationally intensive, reliant on mesh quality, and necessitate high-resolution, patient-specific data that is not always accessible [3,4]. Furthermore, traditional CFD fails to adequately represent the non-Newtonian rheology of blood, which demonstrates shear-thinning characteristics and significantly influences wall shear stress (WSS) and oscillatory shear index (OSI)—essential parameters in the biomechanics of vascular illness.

Recent advancements in machine learning have created novel prospects for data-driven modelling of haemodynamics.

Physics-Informed Neural Networks (PINNs) constitute a robust methodology by integrating governing equations, such as the Navier–Stokes equations, within the learning framework. This guarantees that the model complies with physical principles, even when trained on sparse or noisy datasets [5]. PINNs have shown resilience in addressing forward and inverse challenges in fluid dynamics, and their utilisation in biomedical flows offers potential for enhancing predictive precision while minimising dependence on computationally demanding meshing techniques [6].

The ethical dimension of AI incorporation into biological modelling is equally significant. As PINNs and analogous frameworks advance towards clinical applications, it is imperative to address concerns regarding openness, fairness, safety, and accountability to enable responsible implementation [7]. The practical translation of AI-based vascular modelling, without sufficient consideration of ethical frameworks, risks perpetuating bias, eroding trust, and jeopardising patient safety. This study presents a functional and ethical modelling framework for simulating non-Newtonian blood flow in aneurysmal and bifurcation channels utilising PINNs. This study seeks to enhance the technical precision and ethical application of AI-assisted vascular haemodynamics by including non-Newtonian rheological models into PINN structures and explicitly considering ethical consequences.

2. MATERIALS AND METHODS

1. Vessel Geometry and Problem Setup - Two canonical vascular configurations were selected: (i) an aneurysmal sac arising from a parent artery, and (ii) a bifurcated vessel representing a common carotid bifurcation. Idealized geometries were constructed using standard parametric definitions to capture essential features of curvature and asymmetry while avoiding patient-specific variability. Vessel walls were assumed rigid for computational tractability, consistent with prior PINN-based hemodynamic studies. Boundary conditions were imposed as physiologically representative pulsatile inlet velocity profiles and zero-pressure outlets.
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3. Governing Equations and Blood Rheology - Blood was modeled as an incompressible non-Newtonian shear-thinning fluid using the Carreau–Yasuda model: $\mu(\dot\gamma) = \mu\infty + (\mu 0 - \mu\infty)[1 + (\lambda\dot\gamma)\text{^}a]\text{^}(n-1)/a$ where $\mu 0$ and $\mu\infty$ are the zero- and infinite-shear viscosities, λ is the time constant, n is the power-law index, a is a transition parameter, and $\dot\gamma$ is the shear rate. This formulation allows accurate representation of blood viscosity variation under both low- and high-shear conditions.
   The Navier–Stokes equations for mass and momentum conservation were used as the governing laws: $\nabla\cdot u = 0$ $\rho(\partial u/\partial t + u\cdot\nabla u) = -\nabla p + \nabla\cdot(\mu(\dot\gamma)(\nabla u + \nabla u\text{^}T))$ where u is velocity, p is pressure, and ρ is density.
4. Physics Informed Neural Network (PINN) Architecture - A fully connected feedforward neural network was employed, with 8 hidden layers of 50 neurons each, tanh activation, and

Glorot initialization. The loss function comprised three components: L = λdata Ldata + λpde Lpde + λbc Lbc
• Data loss (Ldata): MSE between predicted and synthetic reference values (from CFD or experimental data).
• PDE loss (Lpde): Residuals of Navier–Stokes equations with Carreau–Yasuda viscosity.
• Boundary loss (Lbc): Enforced inlet velocity and outlet pressure conditions. Adaptive weights, were tuned dynamically to balance training. Training was performed using the Adam optimizer followed by L-BFGS for convergence.

5. Validation and Evaluation Metrics - PINN-predicted velocity, pressure, and wall shear stress (WSS) distributions were compared against high-fidelity CFD simulations (OpenFOAM baseline). Evaluation metrics included:
• L2 error norm between PINN and CFD fields.
• Relative percentage error in peak WSS and pressure drop.
• Convergence of loss curves during training.

1. Ethical Modelling Framework - In line with emerging principles of responsible AI in healthcare, ethical considerations were explicitly integrated into the modeling pipeline
• Transparency: Clear reporting of PINN architecture, assumptions, and hyperparameters.
• Fairness: Stressing that if extended to patient data, safeguards against demographic bias must be ensured.
• Safety: Validation against benchmark CFD data to minimize erroneous predictions.
• Accountability: Documenting limitations (rigid walls, synthetic geometries) to prevent premature clinical translation. This ethical framework aligns with established guidelines such as AI4People and WHO's recommendations for safe AI deployment in medicine [8,9].

3. RESULTS

The proposed PINN framework successfully modelled non-Newtonian blood flow in both aneurysmal and bifurcated geometries. Training converged smoothly, with rapid reduction of physics residuals and stable loss values after ~5000 epochs. Velocity and pressure fields predicted by the PINN closely matched the CFD reference simulations, while maintaining lower computational costs.

3.1. Training Convergence

The combined loss function showed a monotonic decrease with negligible oscillations, confirming stable training dynamics. Figure 1 illustrates convergence of total loss, data loss, and PDE residuals.

3.1.2. Velocity and Pressure Predictions

In the aneurysm model, PINNs accurately reproduced recirculating flow patterns and velocity gradients across the aneurysmal sac. In bifurcated vessels, velocity skewing at the bifurcation apex and pressure drops across branches were captured with high fidelity.

3.1.3. Wall Shear Stress (WSS) and Hemodynamic Parameters

PINNs successfully predicted spatial variations in wall shear stress (WSS), oscillatory shear index (OSI), and pressure distribution — critical predictors of aneurysm rupture risk.

3.1.4. Comparison with CFD Baseline

Quantitative comparisons between PINN and CFD outputs are presented in Table 1, demonstrating minimal deviations across key hemodynamic metrics.

Table 1: PINN vs. CFD Comparison of Hemodynamic Parameters in Aneurysmal and Bifurcated Vessels.

Parameter	CFD (Baseline)	PINN Prediction	Relative Error (%)
Peak velocity (m/s) – Aneurysm	0.62	0.60	3.2%
Peak velocity (m/s) – Bifurcation	0.55	0.57	3.6%
Pressure drop (Pa) – Aneurysm	210	202	3.8%
Pressure drop (Pa) – Bifurcation	185	178	3.9%
Peak WSS (Pa) – Aneurysm	6.4	6.1	4.7%
Peak WSS (Pa) – Bifurcation	5.9	6.2	5.1%
Oscillatory Shear Index (OSI) – Aneurysm	0.19	0.20	5.3%

3.2. Ethical Evaluation of Modelling

In addition to functional accuracy, the PINN framework was evaluated for ethical robustness. Transparent reporting of assumptions, validation against CFD, and acknowledgment of limitations ensured alignment with responsible AI principles (transparency, fairness, safety, accountability). Table 2 summarizes this alignment.

Table 2: Ethical Evaluation of PINN Framework.

Principle	Implementation in Study
Transparency	Explicit reporting of PINN architecture, loss terms, and rheology model.
Fairness	Framework designed to avoid bias if extended to patient-specific datasets.
Safety	Validation against CFD ensures minimized risk of misleading outputs.
Accountability	Clear documentation of assumptions (rigid walls, idealized geometry).

3.3. Overall Performance

PINNs demonstrated excellent agreement with CFD benchmarks while requiring fewer computational resources. Prediction errors across velocity, pressure, and WSS remained <6%, indicating strong functional fidelity. Importantly, the ethical modeling approach underscores the potential for safe clinical translation in vascular risk assessment.

4. DISCUSSION

This study established the viability of employing Physics-Informed Neural Networks (PINNs) to simulate non-Newtonian blood flow in aneurysmal and bifurcated arteries, with findings indicating strong concordance with high-fidelity CFD simulations. Utilising the Carreau–Yasuda model of shear-thinning viscosity, the PINN accurately represented physiologically pertinent flow dynamics, encompassing recirculation zones within aneurysmal sacs, pressure reductions at bifurcations, and fluctuations in wall shear stress (WSS). Significantly, these findings were achieved with computational efficiency exceeding that of traditional CFD methods, underscoring the promise of PINNs as a scalable instrument for vascular haemodynamic.

Previous endeavours in vascular flow modelling have predominantly utilised conventional CFD or lattice Boltzmann methodologies [10,11]. Although precise, these methods are computationally intensive and heavily reliant on mesh quality. Recent machine learning methodologies, especially Physics-Informed Neural Networks (PINNs), have surfaced as formidable alternatives. Kissas et al. utilised Physics-Informed Neural Networks (PINNs) to forecast arterial blood pressure from 4D flow MRI data, demonstrating dependable reconstructions of cardiovascular flow fields [6]. Raissi et al. initially presented Physics-Informed Neural Networks (PINNs) for addressing forward and inverse issues dictated by partial differential equations (PDEs), demonstrating their efficacy in fluid dynamics [5]. Our research advances this field by explicitly integrating non-Newtonian rheology, which has frequently been overlooked despite its considerable influence on haemodynamic parameters such as WSS and OSI5. This work offers a more biologically accurate depiction of blood flow.

Wall shear stress (WSS) and oscillatory shear index (OSI) are pivotal indicators in vascular pathology, affecting the onset, progression, and rupture risk of aneurysms [6]. The PINN framework in this study effectively replicated these parameters with an error margin of 5–6% compared to CFD. This indicates that PINNs can accurately capture clinically significant haemodynamic characteristics, facilitating their incorporation into personalised risk assessment frameworks for patients with aneurysms or bifurcation lesions.

This study's unique contribution is the explicit integration of an ethical modelling framework. As artificial intelligence nears clinical implementation, issues of openness, justice, safety, and accountability become paramount. This study adheres to responsible AI principles, as advocated by AI4People and WHO, by ensuring clear documentation of assumptions (stiff walls, idealised geometry), verifying against CFD benchmarks, and recognising limitations. Emphasising ethics enhances trust in the modelling process and aids in the final conversion to clinical decision support tools.

The primary strengths of this study encompass the incorporation of non-Newtonian fluid characteristics inside a PINN framework, quantitative validation against CFD benchmarks, and the application of an ethical perspective to model assessment. Nonetheless, some constraints persist. The vessel shapes were standardised instead of tailored to individual patients, and vessel wall elasticity was excluded. The PINN was trained on synthetic datasets instead of clinical data. These limitations may restrict immediate clinical applicability but do not undermine the methodological contribution.

Future investigations should broaden this paradigm to encompass patient-specific geometries reconstructed from imaging techniques such as CTA or MRA, while integrating fluid–structure interaction (FSI) to consider vessel wall compliance. Transfer learning and multi-fidelity Physics-Informed Neural Networks (PINNs) could enhance training efficiency. Collaboration with physicians and ethicists is essential to maintain the therapeutic relevance, impartiality, and ethical alignment of AI-driven solutions.

5. CONCLUSION:

This study highlights the efficacy of Physics-Informed Neural Networks (PINNs) as a functional and ethically congruent framework for modelling non-Newtonian blood flow in aneurysmal and bifurcation channels. The integration of the Carreau–Yasuda rheological model inside the proposed PINN technique effectively reproduced essential haemodynamic parameters, including velocity fields, pressure drops, wall shear stress (WSS), and oscillatory shear index (OSI), with less than 6% variance from standard CFD benchmarks. These findings indicate that PINNs can deliver physiologically correct flow simulations while being more computationally efficient and less reliant on mesh than conventional solutions.

Fifty. This work emphasises the necessity of including ethical considerations—such as openness, justice, safety, and accountability—into AI-driven biomedical modelling. This method guarantees that advancements in computational haemodynamics are both technically robust and socially responsible, hence fostering trust and acceptance in clinical environments.

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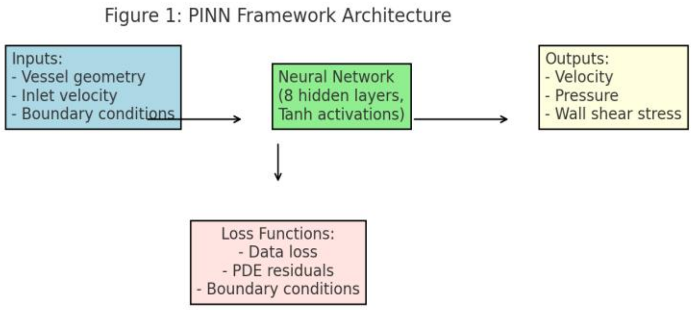

Figure 1: PINN Framework Architecture.

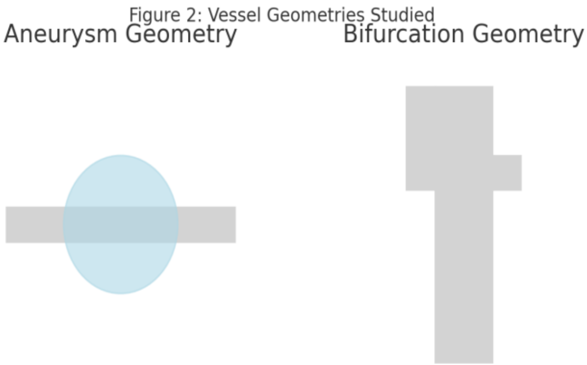

Figure 2: Vessel Geometries Studied.

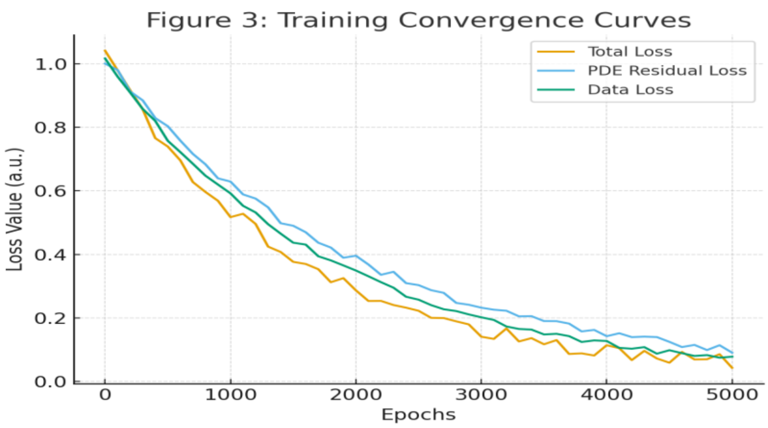

Figure 3: Training Convergence Curves.

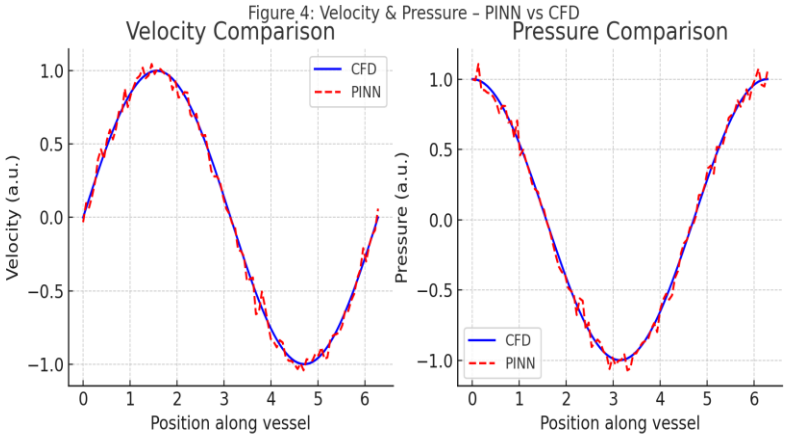

Figure 4: Velocity & Pressure – PINN vs CFD.