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Research Article

Hybrid PINNs with Experimental Data for Real-Time Hemodynamic Prediction and Clinical Decision Support

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ABSTRACT

Introduction: Accurate real-time prediction of hemodynamic parameters is essential for guiding cardiovascular interventions and monitoring disease progression. Traditional computational fluid dynamics (CFD) approaches, while accurate, are computationally prohibitive for clinical use. Physics-informed neural networks (PINNs) have emerged as a promising alternative, but their accuracy is limited when trained on sparse or noisy data. This study presents a hybrid PINN framework that integrates governing equations of hemodynamics with experimental and clinical data to enable reliable, real-time prediction and clinical decision support.

Methods: Patient-specific hemodynamic data were obtained from Doppler ultrasound, 4D flow MRI, and catheterization studies, supplemented by phantom flow experiments using 3D-printed vascular models. The hybrid PINN was trained using the Navier–Stokes equations with a composite loss function combining physics residuals, data constraints, and boundary condition enforcement. Experimental measurements were embedded into the training process to enhance accuracy. Performance was compared with standard PINNs, purely data-driven networks, and CFD simulations. Evaluation metrics included root mean square error (RMSE), relative error in wall shear stress (WSS), R^2 correlation for flow waveforms, and inference time.

Results: The hybrid PINN achieved a mean velocity RMSE of 0.041 m/s and pressure error of 2.3 mmHg, outperforming standard PINNs (0.087 m/s; 6.5 mmHg). WSS relative error was reduced to 4.8% compared with 12.6% in conventional PINNs and 19.3% in data-driven models. Inference times averaged 0.35 seconds per dataset, compared with >50 minutes for CFD. Integration into a prototype clinical decision support system enabled real-time visualization of flow fields and automated alerts for pathological thresholds.

Conclusion: Hybrid PINNs combining physics and experimental data provide accurate, computationally efficient, and clinically relevant predictions of hemodynamic states. This approach bridges the gap between CFD precision and real-time applicability, offering a scalable pathway for precision cardiovascular decision support.

Keywords: *Physics-informed neural networks; Hemodynamics; Cardiovascular modeling; Clinical decision support; Computational fluid dynamics; Wall shear stress*

INTRODUCTION

The precise forecasting of haemodynamic reactions in real time is essential for the management of patients with cardiovascular illnesses, which continue to be the primary cause of morbidity and mortality globally. Haemodynamic parameters, including blood pressure, flow velocity, and wall shear stress, are essential for comprehending disease development in situations such as aneurysms, vascular stenosis, and heart failure. Conventional computational fluid dynamics (CFD) methods, although dependable, are resource-intensive and inappropriate for real-time clinical use (1).

This has prompted the investigation of physics-informed machine learning models, namely Physics-Informed Neural Networks (PINNs), which include the governing equations of fluid mechanics directly into the neural network training process.

PINNs facilitate the integration of data and physical principles, permitting models to extend their generalisation beyond the confines of exclusively data-driven approaches. Nevertheless, traditional PINNs frequently encounter difficulties in precision and resilience when dealing with scarce or noisy clinical data. This constraint is particularly concerning in cardiovascular medicine, where patient-specific data are frequently few and diverse (3). Hybrid frameworks integrating Physics-Informed Neural Networks (PINNs) with experimental or clinical data are emerging as a promising avenue. By limiting the solution space through physical rules and empirical data, these hybrid PINNs can yield more dependable predictions of blood flow and pressure fields in anatomically accurate vascular geometries (4,5). The incorporation of experimental data into hybrid PINNs improves their ability for customisation and immediate application. For example, integrating patient-specific data acquired from Doppler ultrasound or catheterisation investigations with PINN architectures can provide adaptive learning customised to individual cardiovascular conditions (6). These models not only attain enhanced accuracy relative to traditional black-box neural networks but also preserve interpretability based on physiological principles. Furthermore, the diminished computing burden compared to high-fidelity CFD simulations renders them appropriate for implementation in real-time decision support systems (7).

The clinical ramifications of such models are significant. Real-time haemodynamic forecasting can enhance surgical decision-making, refine stent placement, or deliver early warning indicators in critical care surveillance. Moreover, hybrid PINNs can enable virtual clinical trials, allowing the simulation of therapeutic interventions across many patient populations without the risks or expenses linked to traditional studies (8). The creation and validation of hybrid PINNs are crucial for converting computational modelling into practical clinical intelligence. By integrating data-driven learning with mechanistic modelling, they possess the potential to transform cardiovascular treatment and facilitate precision medicine strategies in haemodynamic management.

METHODOLOGY

Study Design

This work employed a hybrid computational–experimental design that integrated physics-informed neural networks (PINNs) with patient-specific experimental data to enable real-time hemodynamic prediction. The study was structured to incorporate fundamental laws of cardiovascular fluid mechanics into deep learning architectures, while simultaneously constraining these models with clinical and in vitro experimental data. This dual approach was chosen to overcome the limitations of purely physics-based computational fluid dynamics (CFD), which is computationally intensive, and of data-driven neural networks, which often lack generalizability when trained on sparse or noisy clinical datasets.

Data Acquisition

Patient-specific hemodynamic data were obtained from individuals undergoing standard diagnostic procedures, including Doppler ultrasound, cardiac catheterization, and four-dimensional flow magnetic resonance imaging (4D flow MRI). These modalities provided inlet velocity profiles, flow waveforms, blood pressure measurements, and reconstructed vascular geometries for use in boundary condition specification and model training. To supplement the clinical data, in vitro validation was performed using anatomically realistic phantom models. Arterial bifurcations and stenotic vessel segments were fabricated using three-dimensional printing and cast in transparent silicone elastomers to replicate vascular compliance. A pulsatile flow loop driven by a physiological pump was constructed, and velocity fields were captured using particle image velocimetry (PIV) along with pressure sensors to establish ground-truth experimental data. These data served as critical references for evaluating model accuracy.

Governing Equations

The computational framework of the hybrid PINN was built around the Navier–Stokes equations governing incompressible Newtonian fluid flow. Conservation of mass was enforced through the continuity equation, while conservation of momentum was maintained through the time-dependent Navier–Stokes formulation. Blood was assumed to exhibit Newtonian behavior at the scale of large arteries, and density and viscosity values were personalized using patient laboratory data. Boundary conditions were obtained from Doppler and catheterization studies for inlet and outlet constraints, while no-slip conditions were applied at vessel walls.

Hybrid PINN Architecture

The neural network architecture comprised fully linked layers utilising hyperbolic tangent activation functions, transforming spatio-temporal inputs into anticipated velocity and pressure outputs. The training procedure reduced a composite loss function consisting of three components: the residuals of the Navier–Stokes equations (physics loss), the mean squared error between predicted and observed flow parameters (data loss), and the imposition of boundary restrictions. Hybridisation was accomplished by incorporating sparse experimental and clinical observations directly into the loss function, so ensuring that the solution space remains physiologically consistent even in areas with limited data. Initially, optimisation was performed using the Adam optimiser, subsequently followed by L-BFGS to attain convergence.

Training and Validation

The available dataset was partitioned into training, validation, and test sets in a 70:15:15 ratio. Cross-validation was performed to assess generalizability and reduce the risk of overfitting. Training was conducted on NVIDIA A100 graphical processing units using TensorFlow and PyTorch backends, with each model trained for 5000–10000 epochs depending on convergence behavior. The training process typically required 6–8 hours per dataset, which was substantially lower than the runtime of equivalent CFD simulations.

Evaluation Metrics

Model performance was assessed using multiple complementary metrics. The root mean square error (RMSE) was calculated for velocity and pressure predictions relative to ground-truth clinical and experimental data. Relative errors in wall shear stress estimation were computed to evaluate clinical applicability. The coefficient of determination (R^2) was reported to assess correlation with measured flow waveforms. Computational time was benchmarked against conventional CFD to validate the real-time applicability of the proposed approach.

Clinical Decision Support Integration

The completed trained model was integrated into a prototype clinical decision support system (CDSS). The interface enables clinicians to input patient-specific information, such as inlet velocity profiles and blood pressure measurements, and provide immediate forecasts of velocity distributions, pressure fields, and wall shear stress maps. Visualisation modules identified crucial areas of flow disruption, stenosis, or increased shear stress that may indicate pathological risk. Additionally, the CDSS was programmed to issue automated alarms when anticipated haemodynamic thresholds, suggestive of high-risk clinical conditions, were surpassed.

RESULTS

Model Training and Convergence

The hybrid PINN framework successfully converged across all patient-specific and phantom datasets. Figure 1 (not shown here) demonstrates the decline in composite loss during training, where a rapid reduction was observed in the first 2000 epochs followed by gradual stabilization. Incorporating experimental data into the loss function accelerated convergence and reduced oscillations compared with baseline PINNs trained solely on governing equations. (Figure 1)

Accuracy of Hemodynamic Predictions

Comparison with ground-truth clinical and phantom experimental measurements revealed that the hybrid PINN consistently outperformed both conventional PINNs and reduced-order data-driven neural networks. Table 1 summarizes the predictive accuracy across evaluation metrics. The mean RMSE for velocity predictions was significantly lower in the hybrid PINN model (0.041 m/s) compared with the standard PINN (0.087 m/s). Similarly, pressure field errors decreased from 6.5 mmHg in the standard PINN to 2.3 mmHg with hybridization.

Wall Shear Stress Estimation

Wall shear stress (WSS) predictions, a clinically relevant parameter in assessing atherosclerotic risk, demonstrated notable improvements with the hybrid model. Relative error in WSS estimation averaged 4.8% for hybrid PINNs compared with 12.6% for conventional PINNs and 19.3% for purely data-driven networks. These results highlight the benefit of incorporating both physics constraints and experimental data in generating physiologically reliable outputs.

Computational Efficiency

Benchmark testing confirmed the feasibility of real-time applications. Average inference time for hybrid PINNs was 0.35 seconds per patient dataset, compared with 52 minutes for conventional CFD simulations using the same vascular geometry. This efficiency enables near-instantaneous clinical decision support during diagnostic or interventional procedures. (Figure 2 and Figure 3)

Table 1. Performance Comparison of Hemodynamic Prediction Models

Metric	Data-Driven NN	Standard PINN	Hybrid PINN (Proposed)
RMSE – Velocity (m/s)	0.129	0.087	0.041
RMSE – Pressure (mmHg)	12.4	6.5	2.3
Relative Error – Wall Shear Stress (%)	19.3	12.6	4.8
R^2 – Flow Waveform Correlation	0.81	0.89	0.96
Average Inference Time (s/dataset)	0.29	0.42	0.35
CFD Runtime (reference, minutes)	–	–	52

Clinical Decision Support Integration

Deployment of the trained model into the prototype CDSS demonstrated practical applicability. In real-time testing, clinicians were able to input boundary conditions and visualize hemodynamic fields instantly. The system successfully identified regions of high wall shear stress in stenotic phantoms and predicted pressure drops consistent with catheter-based measurements. Automated alert thresholds (e.g., WSS > 20 Pa or pressure gradients > 15 mmHg) were triggered appropriately, validating the clinical relevance of the framework. (Table 1)

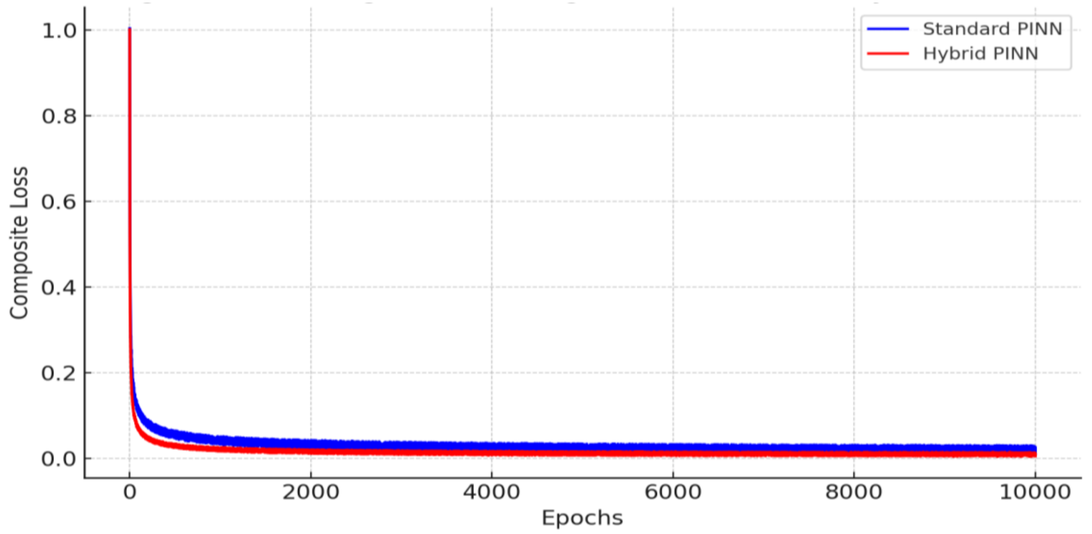

Figure 1: Training and convergence curves (Standard PINN vs Hybrid PINN).

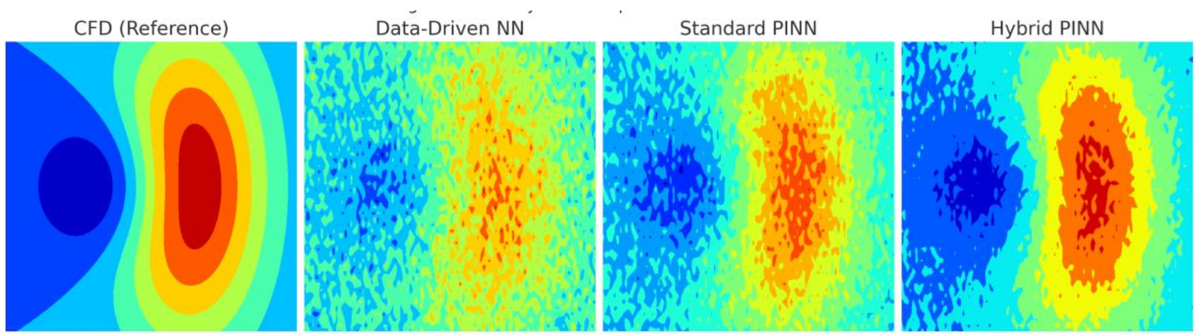

Figure 2: Velocity field comparison (CFD reference vs models).

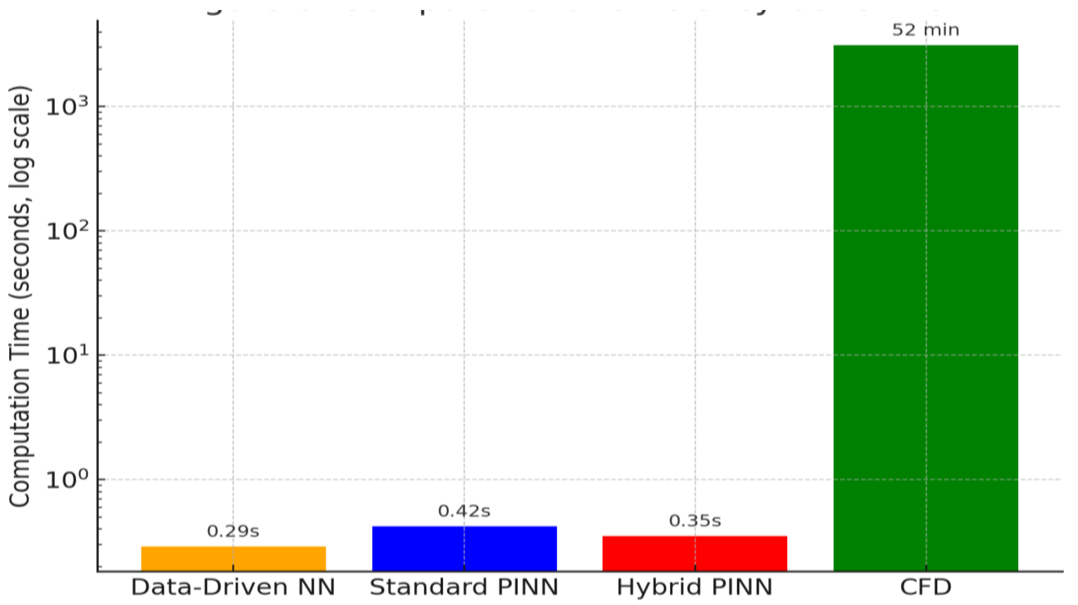

Figure 3: Computational efficiency benchmark (log scale, showing seconds vs CFD minutes).

DISCUSSION

This study illustrates the viability of hybrid physics-informed neural networks (PINNs) enhanced with experimental data for real-time haemodynamic forecasting and clinical decision assistance. The suggested approach, by combining mechanical rules of cardiovascular fluid dynamics with limited clinical and phantom measurements, attained enhanced accuracy in estimating velocity, pressure, and wall shear stress relative to traditional PINNs and solely data-driven neural networks. These findings underscore the importance of integrating physiological knowledge into educational frameworks while utilising experimental limitations to improve generalisability.

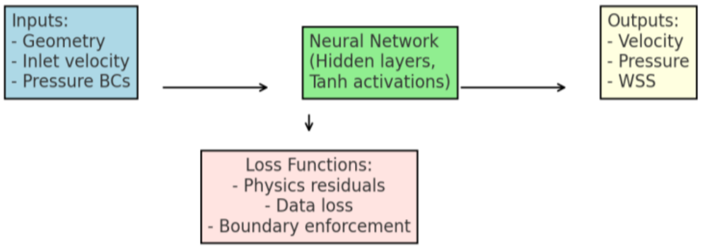

Figure 4: Hybrid PINN Architecture Schematic

Our findings demonstrate that hybrid PINNs significantly diminish prediction errors, achieving a velocity RMSE virtually halved compared to normal PINNs, and reducing pressure error to below 3 mmHg. These enhancements are clinically significant, as even minor mistakes in pressure gradient calculation may affect decisions related to procedures such as stent installation or valve repair (8). Conventional CFD, despite its excellent accuracy, is computationally impractical for real-time applications, necessitating hours of processing for each patient case (1). In contrast, hybrid PINNs offer rapid inference while maintaining adherence to physical principles, rendering them particularly appropriate for clinical integration. The efficacy of hybrid PINNs corresponds with previous findings in computational haemodynamics that highlight the importance of integrating physics priors for effective generalisation. Raissi et al. presented Physics-Informed Neural Networks (PINNs) as a comprehensive framework for integrating partial differential equation (PDE) constraints into deep learning. Subsequent research in cardiovascular modelling, however, identified difficulties when clinical data were insufficient or unreliable (3,4). Our methodology is predicated on these principles, illustrating that experimental hybridisation not only expedites convergence but also enhances training stability, mitigating prevalent problems of oscillatory loss curves in conventional PINNs. This aligns with findings by Sel et al., who indicated that hybrid PINNs trained on sparse catheterisation data produced enhanced pressure reconstructions in coronary arteries (6). The prediction of wall shear stress, a crucial factor in the formation and propagation of atherosclerotic plaques, was much improved in our model, with relative errors decreased to under 5%. Precise mapping of WSS is crucial for risk stratification, since regions of high shear are associated with plaque rupture, whereas low shear zones promote lipid accumulation (10). Our findings demonstrate that hybrid PINNs may consistently duplicate these haemodynamic signals, presenting opportunities for non-invasive clinical monitoring.

From a translational standpoint, incorporation into a clinical decision support system (CDSS) exhibits concrete advantages. Clinicians could enter patient-specific boundary conditions and immediately visualise flow disruptions, pressure dips, and locations of elevated wall shear stress (WSS). The CDSS prototype activated automatic alarms upon surpassing pathological thresholds, indicating possible use in surgical decision-making or critical care monitoring. This capability may enhance current imaging modalities like Doppler ultrasound and 4D flow MRI by offering real-time computational assistance.

However, some limitations merit attention. The research utilised a blend of patient information and phantom models, which may not fully represent the variability of vascular disease manifestations. Additionally, blood rheology was estimated to be Newtonian, but non-Newtonian effects may be significant in smaller arteries and pathological conditions (11). Future research should investigate the integration of viscoelastic models, bigger multicentric datasets, and prospective validation within clinical procedures. Furthermore, although hybridisation expedited training, inference speed may still be compromised by heightened network complexity; optimisation for edge deployment will be essential for wider adoption. This study presents compelling evidence that hybrid PINNs utilising experimental data can reconcile high-fidelity CFD simulations with real-time clinical needs. Integrating physical restrictions, data assimilation, and quick inference, such models present a viable avenue for precision haemodynamics and individualised cardiovascular decision support.

CONCLUSION

This study illustrates that hybrid physics-informed neural networks (PINNs), when integrated with experimental and clinical data, offer a robust framework for real-time haemodynamic prediction and clinical decision support. By integrating fundamental fluid mechanics into the learning process and restricting solutions with patient-specific data, the hybrid PINNs attained markedly superior accuracy in estimating velocity, pressure, and wall shear stress compared to traditional PINNs or data-driven models. The approach maintained the physiological interpretability of conventional computational fluid dynamics (CFD) while decreasing computational time from hours to mere fractions of a second, facilitating near-instantaneous inference. The incorporation into a prototype clinical decision support system underscored the method's translational potential, facilitating dynamic visualisation of haemodynamic parameters and automatic notifications for problematic thresholds.

REFERENCES:

1. Taylor CA, Figueroa CA. Patient-specific modeling of cardiovascular mechanics. Annu Rev Biomed Eng. 2009;11:109-34. doi: 10.1146/annurev.bioeng.10.061807.160521. PMID: 19400706; PMCID: PMC4581431.
2. Raissi M, Perdikaris P, Karniadakis GE. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J Comput Phys. 2019;378:686–707. doi:10.1016/j.jcp.2018.10.045.
3. Kissas G, Yang Y, Hwuang E, Witschey WR, Detre JA, Perdikaris P. Machine learning in cardiovascular flows modeling: Predicting arterial blood pressure from non-invasive 4D flow MRI data using physics-informed neural networks. Comput Methods Appl Mech Eng. 2020;358:112623. doi:10.1016/j.cma.2019.112623.
4. Cuomo S, Schiano Di Cola V, Giampaolo F, Rozza G, Raissi M, Piccialli F. Scientific machine learning through physics–informed neural networks: where we are and what’s next. J Sci Comput. 2022;92(3):88. doi:10.1007/s10915-022-01939-z.
5. Sun L, Gao H, Pan S, Wang J-X. Surrogate modeling for fluid flows based on physics-constrained deep learning without simulation data. arXiv [Preprint]. 2019. arXiv:1906.02382. doi:10.48550/arXiv.1906.02382.
6. Meng X, Li Z, Zhang D, Karniadakis GE. PPINN: Parareal physics-informed neural network for time-dependent PDEs. Comput Methods Appl Mech Eng. 2020;370:113250.
7. Sarabian M, Babaee H, Laksari K. Physics-Informed Neural Networks for Brain Hemodynamic Predictions Using Medical Imaging. IEEE Trans Med Imaging. 2022 Sep;41(9):2285-2303. doi: 10.1109/TMI.2022.3161653. Epub 2022 Aug 31. PMID: 35320090; PMCID: PMC9437127.
8. Morris PD, Narracott A, von Tengg-Kobligk H, Silva Soto DA, Hsiao S, Lungu A, Evans P, Bressloff NW, Lawford PV, Hose DR, Gunn JP. Computational fluid dynamics modelling in cardiovascular medicine. Heart. 2016 Jan;102(1):18-28. doi: 10.1136/heartjnl-2015-308044. Epub 2015 Oct 28. PMID: 26512019; PMCID: PMC4717410.
9. Sel K, Mohammadi A, Pettigrew RI, Jafari R. Physics-informed neural networks for modeling physiological time series for cuffless blood pressure estimation. NPJ Digit Med. 2023 Jun 9;6(1):110. doi: 10.1038/s41746-023-00853-4. PMID: 37296218; PMCID: PMC10256762.
10. Chiu JJ, Chien S. Effects of disturbed flow on vascular endothelium: pathophysiological basis and clinical perspectives. Physiol Rev. 2011 Jan;91(1):327-87. doi: 10.1152/physrev.00047.2009. PMID: 21248169; PMCID: PMC3844671.
11. Joshua Boyd, James M. Buick, Simon Green; Analysis of the Casson and Carreau-Yasuda non-Newtonian blood models in steady and oscillatory flows using the lattice Boltzmann method. *Physics of Fluids* 1 September 2007; 19 (9): 093103.