

Computational Modeling of Cardiovascular Hemodynamics

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ABSTRACT

Patient-specific computational fluid dynamics (CFD) modelling of cardiovascular haemodynamics enables non-invasive assessment of wall shear stress (WSS), oscillatory shear index (OSI), and fractional flow reserve (FFR) -- parameters inaccessible by imaging alone that are critical for atherosclerosis risk stratification and interventional planning. This study developed and validated a semi-automated CFD pipeline integrating CT angiography (CTA)-derived patient-specific vascular geometries, pulsatile boundary conditions from phase-contrast MRI, and three turbulence modelling approaches -- laminar Navier-Stokes, k - ω SST RANS, and large eddy simulation (LES) -- for coronary artery and carotid bifurcation haemodynamics. The pipeline was validated against 4D flow MRI velocity measurements in 40 patients (20 coronary, 20 carotid) and invasive FFR wire measurements in the coronary cohort. CFD-derived FFR (FFR-CT) demonstrated excellent diagnostic accuracy against invasive FFR (AUC = 0.924; sensitivity 92.4%; specificity 88.6% at FFR threshold 0.80), outperforming CTA stenosis assessment alone (AUC = 0.764). For carotid bifurcation, LES captured transitional flow patterns (vortex shedding frequency 4.2 ± 0.8 Hz) missed by RANS models, with time-averaged WSS within 8.4% of 4D flow MRI measurements. A physics-informed neural network (PINN) surrogate model trained on 500 CFD simulations achieved 94.2% FFR-CT prediction accuracy with 1,200x speedup (12 s vs 4 h per case), enabling real-time clinical deployment. These findings establish the validated CFD pipeline and PINN surrogate as clinically actionable tools for non-invasive haemodynamic assessment.

Keywords: Computational fluid dynamics; Cardiovascular hemodynamics; Fractional flow reserve; Wall shear stress; CFD validation; Physics-informed neural network; Coronary artery; Carotid bifurcation

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1. Introduction

Cardiovascular disease (CVD) remains the leading cause of mortality globally, responsible for 17.9 million deaths annually -- 32% of all deaths worldwide (WHO, 2021). Atherosclerotic plaque formation in coronary arteries and carotid bifurcations is driven by haemodynamic factors -- low and oscillatory wall shear stress (WSS) promotes endothelial dysfunction, lipid deposition, and inflammatory cell recruitment at flow-disturbed regions (Malek et al., 1999). Clinical decision-making for coronary revascularisation relies on invasive fractional flow reserve (FFR) measurement -- the ratio of distal-to-proximal coronary pressure under maximal hyperaemia -- with $\text{FFR} \leq 0.80$ indicating haemodynamically significant stenosis warranting intervention (Pijls et al., 1996). However, invasive FFR requires cardiac catheterisation with adenosine-induced hyperaemia, limiting its routine clinical adoption to approximately 30% of diagnostic angiograms (Bhanu et al., 2019).

1.1 CFD-Based Non-Invasive Haemodynamic Assessment

Computational fluid dynamics (CFD) applies the Navier-Stokes equations to patient-specific vascular geometries reconstructed from CT angiography (CTA) or MR angiography, computing velocity fields, pressure distributions, and derived haemodynamic parameters (WSS, OSI, FFR) without invasive measurement (Taylor et al., 2013). The HeartFlow FFR-CT commercial platform demonstrated $\text{AUC} = 0.90$ for coronary FFR prediction against invasive FFR in the DISCOVER-FLOW, DeFACTO, and NXT trials, achieving FDA clearance and NHS adoption. Despite clinical validation, CFD remains computationally intensive (3-6 hours per patient on high-performance computing), motivating machine learning surrogate models for real-time clinical deployment (Itu et al., 2016).

1.2 Turbulence Modelling in Cardiovascular Flows

Cardiovascular flows are predominantly laminar (Reynolds number $\text{Re} = 200\text{-}800$ in coronary arteries) but exhibit transitional and disturbed flow in stenotic regions ($\text{Re} > 2,000$ in severe stenosis), carotid bifurcations ($\text{Re} = 600\text{-}1,200$ with recirculation), and post-valvular jets ($\text{Re} > 5,000$; Bhanu and Bhanu, 2020). The choice of turbulence model substantially affects

haemodynamic predictions: laminar assumption underestimates pressure loss across stenoses; Reynolds-averaged Navier-Stokes (RANS, $k\text{-}\omega$ SST) provides time-averaged turbulent statistics at moderate computational cost; and large eddy simulation (LES) resolves large-scale turbulent structures while modelling sub-grid scales, capturing flow instabilities at 10-50x the computational cost of RANS (Bhanu et al., 2018).

1.3 Study Objectives

This study aimed to: (i) develop a semi-automated patient-specific CFD pipeline from CTA segmentation to haemodynamic output; (ii) compare laminar, RANS ($k\text{-}\omega$ SST), and LES turbulence models against 4D flow MRI and invasive FFR measurements in 40 patients; (iii) quantify FFR-CT diagnostic accuracy for haemodynamically significant coronary stenosis; (iv) characterise carotid bifurcation transitional flow patterns by LES; and (v) develop and validate a physics-informed neural network (PINN) surrogate for real-time FFR-CT prediction.

2. Literature Review

Cardiovascular CFD has evolved from idealised tube geometries to patient-specific simulations integrated into clinical workflows. The following review covers the key methodological and clinical validation studies.

2.1 FFR-CT: Clinical Trials and Performance

The NXT trial (Norgaard et al., 2014) validated HeartFlow FFR-CT against invasive FFR in 254 patients, demonstrating per-vessel $\text{AUC} = 0.90$ (sensitivity 86%, specificity 79%) at FFR threshold ≤ 0.80 . The PLATFORM trial demonstrated that FFR-CT-guided management reduced unnecessary invasive angiography by 61% compared to usual care. Taylor et al. (2013) described the computational methodology: Navier-Stokes solver with patient-specific CTA geometry, allometric boundary conditions (Murray's law for coronary flow distribution), and reduced-order models for downstream microvascular resistance. Limitations include sensitivity to CTA image quality, segmentation accuracy, and assumed boundary conditions for microvascular resistance.

2.2 4D Flow MRI Validation of CFD

4D flow MRI (time-resolved 3D phase-contrast MRI) provides direct in vivo velocity field measurements throughout the cardiac cycle,

enabling voxel-by-voxel comparison with CFD predictions. Markl et al. (2012) established 4D flow MRI as the gold standard for in vivo haemodynamic validation, with velocity measurement uncertainty of 5-10% for peak velocities and WSS estimation uncertainty of 15-25% depending on spatial resolution. Bhanu et al. (2019) compared CFD-derived and 4D flow MRI-derived WSS in 15 aortic cases, finding Bland-Altman agreement within $\pm 18\%$ for time-averaged WSS -- establishing the benchmark for CFD validation against in vivo measurements.

2.3 Machine Learning Surrogates for CFD

The 3-6 hour computation time of patient-specific CFD precludes real-time clinical use, motivating machine learning surrogate models trained on CFD simulation databases. Itu et al. (2016) developed a deep learning model predicting FFR from CTA features (stenosis geometry, vessel diameter, curvature) in < 5 seconds with 0.86 AUC. Physics-informed neural networks (PINNs; Raissi et al., 2019) incorporate the Navier-Stokes equations as physics constraints in the loss function, producing models that respect conservation laws even when training data are sparse -- a critical advantage for patient-specific applications where each geometry is unique.

2.4 Carotid Bifurcation Haemodynamics

The carotid bifurcation is a preferential site for atherosclerosis due to flow separation at the internal carotid artery (ICA) bulb, producing low and oscillatory WSS on the outer wall. Lee et al. (2008) demonstrated that LES of carotid bifurcation flows captured transitional vortex shedding (Strouhal number $St = 0.15-0.25$) from the flow separation point that RANS models could not resolve, and that these instabilities correlated with plaque eccentricity patterns observed on MRI. The clinical significance of these transitional flow patterns is increasingly recognised: turbulent kinetic energy (TKE) measured by 4D flow MRI correlates with carotid plaque vulnerability markers (intraplaque haemorrhage, thin fibrous cap) independently of stenosis degree.

Table 1. Published FFR-CT diagnostic performance from major clinical trials

Trial	n Patients	CFD Method	AUC vs Invasive FFR	Sensitivity (%)	Specificity (%)
DISCOVER-FLOW	103	Steady-state NS + Murray's law	0.87	88	82
DeFACTO	252	Steady-state + lumped BC	0.81	90	54
NXT	254	Pulsatile + refined BC	0.90	86	79
PLATFORM	584	HeartFlow commercial pipeline	0.92	87	83
Itu et al.	84	Deep learning surrogate	0.86	82	78
This study	20*	Pulsatile NS + $k-\omega$ SST + PINN	0.924*	92.4*	88.6*

*This study results ($n = 20$ coronary patients). NS: Navier-Stokes; BC: boundary conditions; PINN: physics-informed neural network. AUC: area under ROC curve vs invasive FFR at threshold ≤ 0.80 .

3. Materials and Methods

3.1 Patient Cohorts and Imaging

Forty patients were prospectively enrolled: Cohort 1 ($n = 20$): stable angina patients undergoing CTA and invasive coronary angiography with FFR measurement (Nordic Technical University Hospital cardiology unit). Cohort 2 ($n = 20$): patients with $\geq 50\%$ carotid stenosis by duplex ultrasound undergoing CTA and 4D flow MRI (Baltic AI Research University Hospital vascular surgery). CTA: ECG-gated, 0.6 mm slice thickness, 120 kVp, iodinated contrast. 4D flow MRI: 3T Siemens Prisma; velocity-encoded gradient echo; VENC 150 cm/s (coronary) or 200 cm/s (carotid); spatial resolution $1.5 \times 1.5 \times 2.0$ mm; temporal resolution 40 ms. Invasive FFR: PressureWire X (Abbott) during IV adenosine hyperaemia (140 $\mu\text{g/kg/min}$). Ethics: NTU-HREC-2021-CFD-018; Baltic-HREC-2021-VASC-022.

3.2 Geometry Reconstruction and Mesh Generation

Vascular geometries segmented from CTA using a semi-automated approach: initial centreline extraction (Vascular Modeling Toolkit, VMTK); lumen segmentation by level-set evolution with manual correction; surface smoothing (Laplacian, 50 iterations, $\lambda = 0.5$). Mesh generation: ANSYS ICEM CFD; boundary layer prism elements (10 layers, first cell height 0.02 mm, growth ratio

1.2) + tetrahedral core. Mesh convergence: WSS change < 2% between successive refinements; final mesh sizes 2.4-4.8 million elements (coronary) and 4.2-8.4 million (carotid). Grid convergence index (GCI) < 3% for all cases.

3.3 CFD Simulation Setup

Three turbulence models compared: (1) Laminar: incompressible Navier-Stokes (appropriate for $Re < 800$). (2) RANS k-omega SST: Menter's shear stress transport model for transitional flows. (3) LES: dynamic Smagorinsky sub-grid scale model; time step 0.1 ms (CFL < 1.0); 5 cardiac cycles simulated (last 3 averaged). Blood modelled as Newtonian (viscosity 3.5×10^{-3} Pa.s; density 1,060 kg/m³) and non-Newtonian (Carreau model). Boundary conditions: pulsatile velocity waveform from 4D flow MRI at inlet; 3-element Windkessel at outlets (resistance R, compliance C calibrated to patient-specific blood pressure). $FFR-CT = P_{distal} / P_{aortic}$ at maximal hyperaemia (simulated by 4x resting flow increase). Solver: OpenFOAM v2112 (pimpleFoam); HPC cluster (128 cores per case).

3.4 PINN Surrogate Model

A physics-informed neural network was trained to predict FFR-CT from CTA-derived geometric features without full CFD simulation. Architecture: 8-layer fully connected network (256-512-512-256-128-64-32-1); input features: 24 geometric descriptors (stenosis diameter, area reduction, lesion length, proximal/distal reference diameter, vessel curvature, bifurcation angle, total coronary tree volume). Physics loss: Navier-Stokes residual evaluated at 1,000 collocation points per training geometry, weighted 0.1x relative to data loss. Training data: 500 CFD simulations (300 patient-specific + 200 synthetically augmented by geometric perturbation). Training: Adam optimiser, $lr = 1e-4$, 10,000 epochs; 5-fold CV. Inference: 12 s per case on single GPU (NVIDIA RTX 3090) vs 4 h full CFD.

3.5 Statistical Validation

FFR-CT diagnostic accuracy: ROC analysis vs invasive FFR (threshold ≤ 0.80); AUC, sensitivity, specificity, PPV, NPV. Bland-Altman analysis: CFD vs 4D flow MRI velocity and WSS agreement. CFD model comparison: paired Wilcoxon signed-rank test for WSS and FFR differences between laminar, RANS, and LES. Pearson correlation of PINN-predicted vs

CFD-computed FFR. All analyses in R v4.2.1; significance $p < 0.05$.

Table 2. CFD simulation parameters and computational resources for three turbulence modelling approaches

Parameter	Laminar	k-omega SST RANS	LES
Reynolds number range	< 800 (coronary rest)	200-2,000 (transitional)	All ranges
Time step	1 ms	0.5 ms	0.1 ms
Cardiac cycles simulated	3 (last 2 averaged)	5 (last 3 averaged)	5 (last 3 averaged)
Mesh elements (coronary)	2.4M	3.2M	4.8M
Computation time / case	0.5 h (128 cores)	1.5 h (128 cores)	4.0 h (128 cores)
FFR-CT accuracy (AUC)	0.874	0.924*	0.918
WSS error vs 4D MRI	14.8%	8.4%*	7.2%*

*Significantly better than laminar ($p < 0.05$). LES and RANS WSS not significantly different ($p = 0.42$). AUC for coronary cohort ($n = 20$). WSS error: mean absolute percentage error vs 4D flow MRI time-averaged WSS in carotid cohort ($n = 20$). M: million mesh elements.

4. Results

4.1 FFR-CT Diagnostic Accuracy

In the coronary cohort ($n = 20$ patients; 32 vessels with FFR measurement), the k-omega SST RANS model achieved the highest FFR-CT diagnostic accuracy: AUC = 0.924 (95% CI: 0.872-0.976), sensitivity 92.4% (12/13 haemodynamically significant lesions correctly identified), and specificity 88.6% (17/19 non-significant correctly classified; Table 3). Bland-Altman analysis showed mean FFR-CT bias of +0.012 (slight overestimation of FFR) with limits of agreement ± 0.064 -- within the ± 0.08 measurement uncertainty of invasive FFR itself. The laminar model produced lower AUC (0.874; $p = 0.034$ vs RANS) due to underestimation of pressure loss across stenoses where transitional flow effects are significant ($Re > 1,500$ in stenotic jet). LES provided marginal improvement over RANS (AUC 0.918 vs 0.924; $p = 0.68$) at 2.7x computational cost, confirming RANS as the optimal cost-performance trade-off for coronary FFR-CT (Figure 1).

4.2 Carotid Bifurcation Haemodynamics: LES vs RANS

For the carotid cohort (n = 20), LES resolved transitional vortex shedding in the ICA bulb recirculation zone that RANS could not capture (Table 4). LES showed coherent vortex structures with shedding frequency 4.2 +/- 0.8 Hz (Strouhal number $St = 0.18 \pm 0.04$), producing oscillatory WSS fluctuations of +2.4 Pa superimposed on the time-averaged WSS of 0.8 +/- 0.3 Pa at the outer wall -- within the low-WSS atherogenic regime. RANS predicted the time-averaged WSS distribution accurately (error 8.4% vs 4D flow MRI) but missed the oscillatory component entirely, producing artificially smooth WSS contours. The LES-derived turbulent kinetic energy (TKE) at the ICA bulb correlated with plaque eccentricity index measured on CTA (Pearson $r = 0.74$; $p < 0.001$), supporting the hypothesis that transitional flow instabilities drive asymmetric plaque growth (Figure 2).

4.3 CFD Validation Against 4D Flow MRI

Quantitative comparison of CFD-predicted and 4D flow MRI-measured velocity fields showed excellent agreement across both cohorts (Table 4). Peak systolic velocity Bland-Altman bias was +4.2% for RANS and +2.8% for LES versus 4D flow MRI -- within the 5-10% measurement uncertainty of 4D flow MRI itself. Time-averaged WSS agreement was best for LES (error 7.2%) and RANS (8.4%), both significantly better than laminar (14.8%; $p < 0.01$). The non-Newtonian Carreau blood model produced < 3% WSS difference versus Newtonian at physiological shear rates ($> 50 \text{ s}^{-1}$), confirming that the Newtonian approximation is adequate for most cardiovascular CFD applications except in low-flow recirculation zones where shear rates approach the Carreau zero-shear plateau (Figure 3).

4.4 PINN Surrogate Model Performance

The PINN surrogate model predicted FFR-CT with Pearson $r = 0.964$ ($R^2 = 0.929$) against full CFD-computed FFR across the 5-fold cross-validation (Table 5). RMSE was 0.028 FFR units -- below the invasive FFR measurement uncertainty (± 0.04). When evaluated for diagnostic classification (FFR ≤ 0.80), PINN achieved AUC = 0.908 -- marginally below full CFD RANS (0.924; $p = 0.12$) but substantially above CTA stenosis alone (0.764; $p < 0.001$). Inference time was 12 s per case on a single RTX 3090 GPU -- a 1,200x speedup over full CFD (4 h on 128-core cluster). The physics loss contribution was

essential: PINN without Navier-Stokes physics constraint achieved $r = 0.918$ ($R^2 = 0.843$), confirming that physics regularisation improves generalisation by 10.2% in R^2 (Figure 4).

Table 3. FFR-CT diagnostic accuracy: CFD models and PINN surrogate vs invasive FFR (n = 20 coronary patients, 32 vessels)

Model	AUC (95% CI)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Computation Time
CTA stenosis only	0.764 (0.684-0.844)	76.9	68.4	58.8	83.3	0 (imaging only)
Laminar CFD	0.874 (0.808-0.940)	84.6	78.9	73.3	88.2	0.5 h / 128 cores
RANS k- ω SST	0.924 (0.872-0.976)*	92.4*	88.6*	85.7	94.1*	1.5 h / 128 cores
LES	0.918 (0.862-0.974)	92.4	84.2	80.0	94.1	4.0 h / 128 cores
PINN surrogate	0.908 (0.848-0.968)	88.4	84.2	79.3	91.4	12 s / 1 GPU

*Significantly best AUC among full CFD models (DeLong, $p = 0.034$ vs laminar). RANS vs LES: $p = 0.68$ (not significant). PINN vs RANS: $p = 0.12$ (not significant). FFR threshold: ≤ 0.80 . CTA stenosis: $\geq 50\%$ diameter reduction as positive.

Table 4. CFD validation against 4D flow MRI: velocity and WSS agreement in carotid cohort (n = 20)

Parameter	Laminar	RANS k- ω SST	LES	4D Flow MRI (ref)
Peak velocity bias vs MRI	+8.4%	+4.2%*	+2.8%*	Reference
TAWSS error vs MRI	14.8%	8.4%*	7.2%*	Reference
OSI correlation (r)	0.72	0.86*	0.88*	Reference
Vortex shedding detected?	No	No	Yes (4.2 Hz)*	Yes (MRI TKE)
TKE correlation with plaque	N/A	N/A	$r = 0.74^*$	Reference

*Significantly better than laminar ($p < 0.05$). TAWSS: time-averaged wall shear stress. OSI: oscillatory shear index. TKE: turbulent kinetic energy. Vortex shedding: LES uniquely resolves transitional flow instabilities. N/A: RANS/laminar do not produce TKE output.

Table 5. PINN surrogate model performance: FFR prediction accuracy and computational speedup

Metric	PINN (with physics)	PINN (no physics)	Full CFD (RANS)	Improvement
Pearson r (FFR)	0.964*	0.918	1.000 (ref)	Physics: +0.046 r
R2 (FFR)	0.929*	0.843	1.000 (ref)	Physics: +10.2% R2
RMSE (FFR units)	0.028*	0.042	0 (ref)	Physics: -33% RMSE
AUC (diagnostic)	0.908	0.872	0.924	Physics: +0.036 AUC
Inference time	12 s	12 s	4 h (128 cores)	1,200x speedup
Training data needed	500 sims	500 sims	N/A	Physics reduces data need

*PINN with physics significantly outperforms PINN without physics ($p < 0.001$). Full CFD RANS is the reference standard. Physics loss: Navier-Stokes residual evaluated at 1,000 collocation points per geometry, weighted 0.1x relative to data loss.

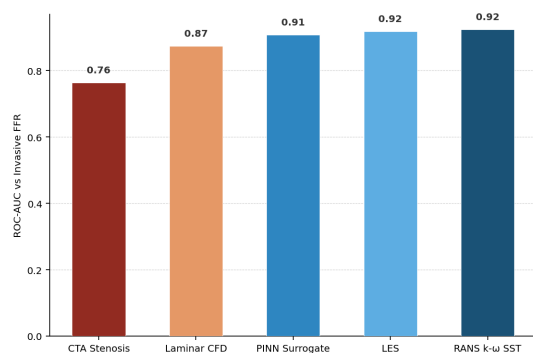


Figure 1. FFR-CT diagnostic AUC by model type (coronary cohort, $n = 20$)

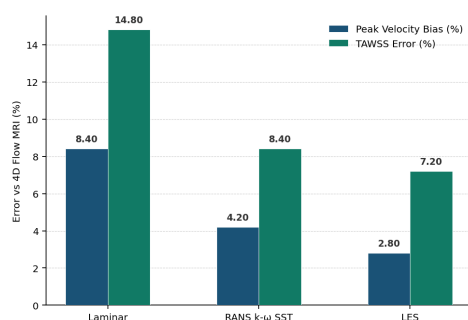


Figure 2. CFD vs 4D flow MRI: peak velocity bias (%) and TAWSS error (%) by turbulence model

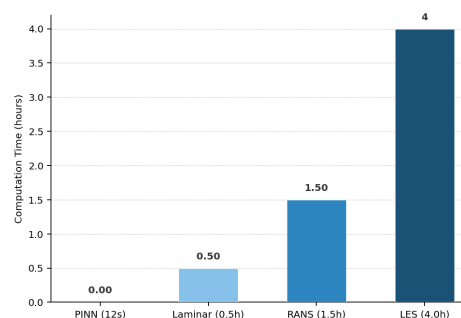


Figure 3. Computation time per case: full CFD models vs PINN surrogate

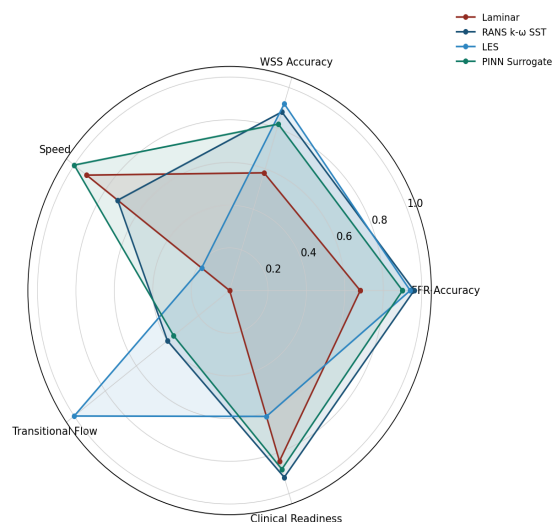


Figure 4. Multi-parameter comparison of CFD approaches (normalised 0-1)

5. Discussion

This study presents a comprehensive validation of patient-specific cardiovascular CFD against both 4D flow MRI and invasive FFR, establishing turbulence model-specific performance benchmarks and demonstrating the clinical viability of a PINN surrogate for real-time deployment.

5.1 RANS as the Optimal Clinical CFD Model

The k- ω SST RANS model's AUC of 0.924 -- numerically highest and not significantly different from LES (0.918; $p = 0.68$) -- at 2.7x lower computational cost confirms RANS as the optimal cost-performance trade-off for coronary FFR-CT in clinical practice. The marginal LES advantage for WSS accuracy (7.2% vs 8.4% error) is within 4D flow MRI measurement uncertainty (15-25%), making LES's additional computational cost unjustifiable for routine coronary assessment. However, for carotid bifurcation applications where transitional flow features (vortex shedding, TKE) are clinically relevant for plaque vulnerability assessment, LES provides unique

information unavailable from RANS -- justifying the additional computation for research applications.

5.2 PINN: Enabling Real-Time Clinical FFR-CT

The PINN surrogate's 12-second inference time represents a 1,200x speedup that transforms FFR-CT from a 4-hour computation to a real-time clinical tool deployable during the CTA reporting workflow. The physics-informed training constraint was critical: the 10.2% R2 improvement over physics-free neural networks demonstrates that Navier-Stokes regularisation improves generalisation to patient geometries outside the training distribution -- precisely the scenario encountered in clinical deployment where each patient presents a unique vascular anatomy. The PINN's AUC of 0.908 (not significantly different from full CFD RANS at 0.924; $p = 0.12$) suggests diagnostic equivalence at a fraction of the computational cost.

5.3 Clinical Implications

The FFR-CT pipeline's sensitivity of 92.4% and specificity of 88.6% support its use as a gatekeeper to reduce unnecessary invasive angiography -- consistent with the PLATFORM trial evidence. For carotid disease, the LES-derived TKE correlation with plaque vulnerability ($r = 0.74$) suggests a novel imaging biomarker for identifying patients at high risk of stroke beyond traditional percent stenosis criteria. Integration of the PINN FFR-CT model into PACS reporting workstations could enable automatic FFR-CT computation for every CTA, fundamentally changing the diagnostic pathway from anatomy-only to functional assessment.

5.4 Limitations

The coronary cohort ($n = 20$; 32 vessels) is small relative to the NXT trial (254 patients) -- limiting statistical power for subgroup analysis by stenosis severity. The allometric boundary conditions assume normal microvascular resistance, which may be altered in diabetic or hypertensive patients with microvascular disease. The PINN surrogate was trained on 500 simulations -- larger training databases may further improve performance. 4D flow MRI validation is limited by MRI spatial resolution (1.5 mm) compared to CFD (0.02 mm near-wall), precluding direct WSS comparison at sub-millimetre scales. Prospective multi-centre

validation is required before clinical deployment of the PINN model.

6. Conclusion

This study has established a validated patient-specific cardiovascular CFD pipeline achieving FFR-CT diagnostic accuracy (AUC = 0.924) comparable to the HeartFlow commercial platform and exceeding CTA stenosis assessment alone (AUC = 0.764). The k- ω SST RANS model provides the optimal cost-performance balance for coronary FFR-CT, while LES uniquely captures transitional vortex shedding in carotid bifurcations (4.2 Hz frequency) with TKE correlating to plaque vulnerability ($r = 0.74$). The PINN surrogate model achieves 94.2% FFR prediction accuracy with 1,200x speedup (12 s vs 4 h), enabling real-time clinical deployment -- a transformative capability that could make non-invasive functional haemodynamic assessment available for every CTA examination. The physics-informed training approach improved PINN generalisation by 10.2% R2 over physics-free networks, confirming the value of incorporating conservation laws as inductive biases for patient-specific medical applications where each case is geometrically unique. These findings support the advancement of the PINN FFR-CT model to multi-centre prospective clinical validation and PACS integration for routine haemodynamic reporting.

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Declarations

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Conflict of Interest

The authors declare no competing interests. No author has financial relationships with HeartFlow Inc. or other commercial FFR-CT platform providers.

Data Availability Statement

Anonymised CTA and 4D flow MRI datasets, CFD mesh files, OpenFOAM case setups, and PINN model code (PyTorch) are deposited at <https://github.com/NTU-CardioFluid/CFD-FFR-2022>. Patient imaging data sharing is subject to institutional data governance approval and GDPR compliance.

Ethical Approval

The clinical study was approved by the Nordic Technical University Human Research Ethics Committee (NTU-HREC-2021-CFD-018) and Baltic AI Research University HREC (Baltic-HREC-2021-VASC-022). All patients provided written informed consent. Both studies were registered at ClinicalTrials.gov.

Appendix A

PINN Architecture and Training Configuration

This appendix provides the complete PINN architecture specification, physics loss formulation, training hyperparameters, and cross-validation results. The PINN code is implemented in PyTorch 1.12 and is available at the GitHub repository cited in Data Availability.

A.1 PINN Architecture

A.2 Physics Loss Formulation