Credibility Assessment of CFD Models for Gas Transfer in a Hollow-Fiber Oxygenator Bundle Using NASA-STD-7009A Factors

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Abstract

Computational predictions of oxygen and carbon dioxide exchange in hollow-fiber membrane oxygenators are increasingly used to guide device design and clinical integration. This article assesses the credibility of two computational fluid dynamics models against the factor framework of NASA-STD-7009A, applied to four mechanisms that dominate performance and risk: diffusion-limited oxygen uptake at clinical flow and hematocrit, carbon dioxide removal with bicarbonate chemistry and Haldane interaction, bundle-scale flow maldistribution, and the early fouling layer that forms on fiber surfaces. The first model is a bundle-scale Reynolds-averaged Navier–Stokes implementation with anisotropic porous resistance and volumetric interfacial transfer (RANS–Porous-Media Bundle Model; RANS-PM). The second model resolves fiber-scale transport with conjugate diffusion through the membrane and finite-rate blood chemistry on both sides (Micro-Resolved Unit-Cell Conjugate Model; UC-CP). Both models are exercised over clinically relevant flows (3–6 L/min), sweep gas ratios (2–10 L/min), hematocrits (0.35–0.45), and physiologic temperature (37 C), and compared to bench experiments and coupon-scale measurements. A private 0–10 Credibility Index is used with factor-specific decision rules, and scores are assigned separately for every factor in each model-by-mechanism pairing. We present two results tables, one per model, totaling 64 scored rows.

The assessment finds the bundle-scale method better aligned with predicting maldistribution and oxygenation under diffusion control, while the micro-resolved method more faithfully represents conjugate transfer physics and finite-rate chemistry for oxygen and carbon dioxide at the fiber scale. Both models show strong solver behavior and code-level verification with near second-order convergence in manufactured-solution tests. Remaining limitations concentrate in carbonate chemistry for the bundle model, macroscopic flow representation for the unit-cell model, and short-duration evidence for fouling resistance growth in both cases. The decision framework and its numeric rules are documented, and the dataset lineage, mesh convergence records, solver settings, and full score matrices are provided in the supplemental material.

Keywords: oxygenator, credibility assessment, CFD

1. Introduction

Membrane oxygenators are life-support components used in extracorporeal membrane oxygenation and cardiopulmonary bypass. Their task is to move oxygen into blood and carbon dioxide out of blood with minimal hemolysis and thrombotic risk while maintaining acceptable hydraulic losses. Computational models promise faster iteration and less expensive development by projecting performance across geometries and operating points. Yet the consequences of model error in this domain can be profound: under-predicted decarboxylation may lead to acid–base imbalance, while over-predicted oxygenation may erode safety margins. Credibility assessment frameworks help align the trust a decision-maker places in model outputs with the strength of evidence available for those outputs. NASA-STD-7009A has emerged as a comprehensive reference for such assessments, and here we adapt its factors to the oxygenator modeling context.

We evaluate two complementary models. The first represents the bundle as a porous medium with directional hydraulic resistance and an interfacial volumetric transfer term; it can run across the full device at realistic Reynolds numbers and deliver bundle-scale flow distributions and gas transfer. The second resolves an idealized unit cell that captures fiber surfaces, membrane thickness, gas-phase channels, and blood-side flow, with conjugate diffusion and finite-rate chemistry. It computes Sherwood numbers and local fluxes that can be upscaled. These approaches are common in the literature and in industrial practice: one is built for device-level trade studies, the other for physics closure and parameter estimation.

We focus the assessment on four mechanisms that drive design and use. First, oxygen uptake is often throttled by blood-side diffusion and reaction in the clinical flow and hematocrit range; understanding this bottleneck determines achievable arterialization and sets device size. Second, carbon dioxide removal interacts with bicarbonate buffering and the Haldane effect; kinetics can become limiting even if convection is strong. Third, bundle-scale maldistribution undermines performance by starving some regions while overfeeding others, a problem exacerbated by header geometry. Fourth, material

surfaces acquire a protein-rich layer within the first hours of use; this additional barrier can reduce transfer rates under steady operating knobs.

The outputs emphasized in the comparison—VO2, VCO2, outlet blood gases, and segmental utilization—map directly to clinical oxygenation targets and ventilatory management, supporting decision-making at the bedside. To convert these predictions into useful credibility statements, we define a private 0–10 index with factor-specific rules. We then apply the rules independently to each mechanism for each model because the physics at stake and the available evidence differ by mechanism.

By design, the assessment separates mathematical and physical correctness, numerical behavior, and the tie to clinical decisions. We summarize results in two compact tables, each limited to a single model, to align with how engineering teams actually read assessments during design reviews. The synthesis that follows the tables interprets mechanisms across models and points to priorities for future evidence-gathering.

Relevance of the quantities of interest — gradation.

a.
Outputs are generic fields without a clear mapping to stakeholder decisions.

b.
Outputs are post-processed into engineering measures, but clinical or operational thresholds are not explicitly defined.

c.
Outputs include directly actionable metrics tied to stakeholder thresholds, with traceable definitions.

d.
Outputs are calibrated to decision points and are expressed in the same units and formats used at the point of decision.

2. Device Description and Operating Scenarios

The device under study is a commercial-scale hollow-fiber membrane bundle with a total fiber surface area of 1.8–2.2 m2. Individual fibers have an outer diameter of 240–260 micrometers and an inner diameter of 200–220 micrometers. The membrane is microporous with a skinless, highly permeable structure and a nominal wall thickness of 25 ± 2 micrometers. Silicone or polypropylene support structures confine the bundle within a cylindrical shell. Headers distribute blood axially along the shell side, while gas flows through the fiber lumens. The principal hydraulic path for blood is outside the fibers, through tortuous, sub-millimeter interstices with high tortuosity and anisotropy; gas navigates smooth, laminar ducts inside the fibers.

Clinically, blood flow rates through adult bundles are 3–6 L/min. Gas sweep rates of 2–10 L/min are used to adjust carbon dioxide clearance and, with oxygen fraction, modulate oxygen delivery. The bundle is operated at 37 C and a hematocrit of 0.35–0.45, with pH management to maintain 7.40 ± 0.05. Arterialization targets include an outlet partial pressure of oxygen above 150 mmHg in post-oxygenator blood, saturation above 95%, and a carbon dioxide partial pressure reduction to 35–45 mmHg depending on ventilatory strategy. Device pressure losses are constrained to minimize hemolysis and reduce pump workload.

Four operating scenarios align with the mechanisms in this study. In the first, blood velocities place the system in a regime where oxygen uptake is throttled by transport through the boundary layer adjacent to the fiber, compounded by the time needed for hemoglobin to bind. In the second, the stoichiometry of carbon dioxide removal is paced not just by diffusion but by the interconversion of dissolved CO2, bicarbonate, and carbamino species; the Haldane effect ties oxygenation to carbon dioxide carriage. In the third, geometric features of the bundle and headers cause uneven blood flow, so large parts of the membrane area work below their kinetic limits. In the fourth, an adsorbed protein layer grows on the fibers, adding thickness and reducing effective diffusivity at the interface, lowering both oxygen supply and carbon dioxide removal at steady settings.

3. Mechanisms of Gas Transfer Considered

Diffusion-limited oxygen transfer is frequently encountered in adult oxygenators at blood flows above 3 L/min and moderate hematocrit. In this regime, even with 100% oxygen on the gas side, the rate at which oxygen molecules cross the blood-side film and bind to hemoglobin controls the outlet state. Convective changes on the blood side have limited effect once velocities are sufficient to keep the boundary layers thin but not negligible; residence time and local saturation gradients still shape final outcomes. For design, this mechanism sets minimum surface area and bundle length to reach target arterialization at acceptable pump speeds.

Carbon dioxide removal with bicarbonate chemistry and the Haldane interaction presents a different challenge. The efflux of CO2 depends on dissociation of bicarbonate in the plasma and carbamino groups on hemoglobin, processes that are influenced by oxygenation state. When oxygen binds, hemoglobin releases protons and CO2 more readily; this coupling enhances decarboxylation as blood becomes more oxygen-rich. In a device, the carbon dioxide side may be transport-limited at low sweep rates, but at typical sweeps, kinetics in the plasma and the red cell can constrain removal. The chemistry also controls acid–base status, making its quantitative capture a clinical priority.

Bundle-scale blood-flow maldistribution is perennially important and a function of both macro-geometry and microscopic anisotropy. Headers may introduce axial bias; fiber packing may impose directional resistance so that flow short-circuits accessible regions and bypasses denser areas. Because mass transfer is area-dependent, underused portions of the membrane lead to a lower overall performance even if local kinetics are strong where blood does flow. Characterizing and reducing maldistribution is a device-design objective.

Finally, a layer of proteins and other adsorbates forms on fiber surfaces shortly after initiation. Within the first 90–120 minutes, a relatively thin film can increase gas-side and blood-side resistances measurably. While this layer may continue to evolve over day-scale durations, the largest relative change

Figure 1: Schematic of the hollow-fiber bundle showing shell-side blood flow, fiber lumens with sweep gas, headers, and the anisotropic porous architecture that guides axial and radial blood transport; the fiber diameter, wall thickness, and representative flow paths are illustrated without scale.

in transfer can occur during the early period when the film is fresh and the membrane is otherwise clean. Modeling this phenomenon requires additional terms for interfacial resistance, and predicting clinical impact also depends on run duration and anticoagulation strategy.

4. Computational Models

Two computational approaches were implemented in the same codebase with shared linear algebra, mesh infrastructure, and post-processing routines. The RANS–Porous-Media Bundle Model (RANS-PM) solves steady Reynolds-averaged Navier–Stokes equations in the blood domain using an anisotropic Darcy–Forchheimer term to represent the packed fiber array and a pressure-based segregated scheme with Rhie–Chow stabilization for pressure–velocity coupling. Axial and radial permeabilities and the inertial coefficient are inputs, as are porosity and dispersion coefficients. Gas-side flow is modeled implicitly through a volumetric interfacial transfer term that drives exchange proportional to the interfacial area density, a mass transfer coefficient, and the local difference in driving potential. Constitutive choices include an effective blood viscosity model that depends weakly on hematocrit and shear rate; hemoglobin–oxygen binding uses a standard Hill-type saturation law for predictions and a finite-rate variant in sensitivity analysis. Carbon dioxide chemistry in RANS-PM is represented with an effective equilibrium approach augmented by a relaxation time to capture finite-rate effects at higher flows.

The Micro-Resolved Unit-Cell Conjugate Model (UC-CP) resolves a representative fiber, a shell-side gap, and a gas-side lumen in a periodic domain. Blood-side equations are incompressible Navier–Stokes at modest Reynolds numbers (fiber Reynolds 20–80) coupled to advection–diffusion–reaction of oxygen, carbon dioxide, bicarbonate, and protons in plasma and an aggregate red blood cell phase that exchanges with plasma via standard transfer resistances. Gas-side equations are laminar, low-Mach flow with advection–diffusion of oxygen and carbon dioxide. The membrane is a solid domain with multi-component diffusion; oxygen and carbon dioxide permeabilities are applied directly, and their solubilities are set by Henry's law at 37 C. Finite-rate hemoglobin chemistry is included with a widely used kinetic model for oxygen binding and release, while carbon dioxide chemistry follows a reduced but explicit set for bicarbonate formation and dissociation and the Haldane-mediated coupling to oxygen saturation. The UC-CP model computes local Nusselt-like and Sherwood-like coefficients along the fiber, area-averaged fluxes, and membrane-limited vs blood-film-limited contributions; it exports effective transfer coefficients to serve as closures in the bundle model.

Both models output quantities used in design and evaluation. RANS-PM yields bundle-scale oxygen uptake (VO2), carbon dioxide efflux (VCO2), outlet oxygen partial pressure and saturation, outlet carbon dioxide partial pressure, segmental utilization metrics that quantify underused area, and hydraulic pressure loss. UC-CP produces local and averaged Sherwood numbers for both species, interfacial flux distributions around the fiber circumference, and conjugate fluxes across the membrane, which can be multiplied by area to estimate bundle-scale transfer under assumed area utilization.

5. Quantities of Interest and Their Relevance

For both models, the primary quantities of interest are the oxygen uptake rate (VO2, mL/min at standard temperature and pressure), the carbon dioxide removal rate (VCO2, mL/min at standard temperature and pressure), the outlet partial pressures and saturations of oxygen and carbon dioxide in the blood, and the pressure drop across the oxygenator. Segmental utilization, defined as the fraction of fiber surface area exposed to actively perfused blood, is included in the bundle-scale outputs to detect maldistribution. In the UC-CP model, local and averaged Sherwood numbers for oxygen and carbon dioxide and membrane-side vs blood-side resistances are the core outputs; these map to an effective mass transfer coefficient (kLa) after applying area and utilization assumptions. The choice of these outputs ensures that model predictions can be compared one-to-one with bench measurements and that they can be turned into the same indicators used in clinical protocols, such as achieving VO2 above 200 mL/min at given flows and lowering outlet carbon dioxide to target ranges.

The alignment of these outputs with decision-making is reviewed again in the synthesis section to avoid confounding the technical definition of outputs with the assessment's single-sentence finding. Here we emphasize definitional clarity and traceability: how VO2 and VCO2 are computed from model fluxes, how partial pressures and saturations are derived from

equations of state and binding functions, and how segmental utilization is computed from resolved velocities and interfacial area density. These definitions follow documented conventions in extracorporeal support and measurement standards used in the test program.

Relevance of the quantities of interest — gradation.

a.
Model outputs are not traceable to clinical or engineering decisions.

b.
Model outputs can be post-processed into decision metrics with additional assumptions.

c.
Model outputs directly yield decision metrics with documented calculation steps.

d.
Model outputs are natively expressed as decision metrics with explicit thresholds and acceptance bands.

6. Data Pedigree and Test Conditions for Gas Transfer

Two experimental programs inform this assessment: a bundle-scale bench program with fresh bovine blood and a coupon-scale program with isolated fiber segments and membrane coupons. The bundle program includes 42 distinct operating points across blood flows of 3–6 L/min, sweep gas flows of 2–10 L/min, and hematocrits of 0.35–0.45 at 37.0 ± 0.2 C. The inlet oxygen saturation is 60–80%, and the inlet carbon dioxide partial pressure spans 45–80 mmHg. VO2 and VCO2 are computed from sweep-side gas analysis with paramagnetic and infrared sensors calibrated daily; repeatability of the computed rates is within ±3.1% for VO2 and ±4.5% for VCO2 at fixed operating points. Outlet blood gases are measured with blood gas analyzers with two-point calibration; the observed combined uncertainty is ±5 mmHg for oxygen and ±3 mmHg for carbon dioxide. Pressure loss is logged with differential transducers calibrated to ±1% full scale.

The coupon-scale program comprises six fiber–membrane coupons tested in a microfluidic channel for oxygen and four coupons tested for carbon dioxide transfer, with micro-PIV and microelectrode profiling to determine local boundary layers and interfacial fluxes. The Reynolds number based on fiber diameter ranges from 20 to 60, representing diffusion-dominated regimes. The buffer composition for carbon dioxide tests includes 25 mM bicarbonate to emulate plasma; the oxygen tests use serum or plasma substitutes of matched viscosity. Measured Sherwood numbers carry an uncertainty of ±7% from probe placement and velocity profile estimation. The thickness of early protein layers is measured optically with confocal z-stacks in four 90-minute fouling runs using 4% bovine serum albumin in saline at 37 C; the observed films range from barely detectable to approximately 3 micrometers on select fibers.

To interrogate maldistribution, nine bundle tests use dye injection and planar imaging at three axial planes combined with differential pressure mapping. These tests quantify a perfusion uniformity index defined as one minus the coefficient of variation of planar velocities in the shell; the index ranges from 0.64 to 0.82 across header settings, with higher values indicating more uniform flow. While three-dimensionality is acknowledged, the planar data capture relative differences across header design variants. A subset of the bundle tests uses 95% oxygen and 5% carbon dioxide in the sweep gas to explore carbon dioxide removal at elevated driving forces; these conditions inform chemistry modeling but depart from typical clinical air–oxygen mixes.

Run durations differ between programs. The bundle program focuses on steady operation with runs of 20–40 minutes per operating point, and a specific subset uses two-hour hold periods to study early fouling at constant settings. The coupon program uses shorter durations for oxygen and longer for carbon dioxide to allow concentration profiles to develop while capturing the initial adsorption period. These timelines have a practical basis in laboratory scheduling and blood availability. The limits are discussed later with respect to the early fouling mechanism and clinical use cases that can extend to days.

Raw data are archived with device serial numbers, lot numbers for consumables, and timestamped configurations. Environmental controls (room temperature and humidity) are logged, and calibrations of gas analyzers and blood gas analyzers are recorded. Data reduction scripts are versioned and checked against hand calculations on a subset of points. This structure enables reprocessing if model predictions suggest revisiting calculation steps.

Data pedigree — gradation.

a.
Data origins are undocumented and cannot be independently traced.

b.
Data are partially documented, with incomplete records for instruments or calibration.

c.
Data are fully documented, with calibration records and traceability to raw files.

d.
Data are fully documented and independently audited, with uncertainty quantification and version-controlled reductions.

7. Model Form: Governing Equations and Constitutive Assumptions

In the bundle-scale model, the blood-phase momentum equation includes a Darcy–Forchheimer drag term with a second-order tensor permeability K and an inertial coefficient C, such that the volume-averaged momentum budget reads as the classical RANS equations with an added mu K1 u rho C |u| u term. Axial permeability exceeds radial permeability to represent the pack’s orientation; the inertial term accounts for quadratic pressure losses at higher superficial velocities. Turbulence is negligible in the shell-side microchannels at the examined flows, and so the closure is laminar with added dispersion for species. Gas transfer is modeled via a volumetric

sink–source term S = a_s k_L (phi_b phi_eq), where a_s is the interfacial area density, k_L is the liquid-film mass transfer coefficient, phi_b is the blood-side driving potential (partial pressure or concentration), and phi_eq is determined from membrane-side and gas-side conditions. The oxygen binding curve uses a Hill function with parameters chosen to match adult hemoglobin at 37 C and pH 7.4; sensitivity runs introduce finite-rate corrections with a characteristic binding time of 0.1–0.2 s based on literature. Carbon dioxide chemistry is represented with an effective reaction timescale that blends bicarbonate dissociation and carbamino release; the time constant is calibrated at the device scale from carbon dioxide efflux at high sweep flows.

In the unit-cell model, conjugate heat and mass transfer analogues are solved in a three-domain system: gas lumen, solid membrane, and blood-side gap. The interface conditions enforce continuity of species chemical potential and flux. The membrane's multi-component diffusion uses Fickian transport with constant permeability at 37 C: 1.8 × 1010 mol m/(m2 s Pa) for oxygen and 6.0 × 1010 mol m/(m2 s Pa) for carbon dioxide, derived from coupon tests described later. Blood-side transport couples advection–diffusion with reaction terms for oxygen binding and carbon dioxide speciation. Oxygen kinetics follow a Monod-like rate law fitted to reproduce a Hill saturation curve under equilibrium but able to deviate when residence time is short; typical on-rates are 30–60 s1 with off-rates tuned to match partial pressure dynamics. Carbon dioxide chemistry includes hydration and hydroxylation, bicarbonate formation/dissociation, and carbamino formation, with rate constants from a reduced kinetic set; the Haldane interaction is represented by hemoglobin occupancy terms that change carbon dioxide binding affinity. The equations are stiff and solved with an implicit scheme in time for chemistry and a segregated approach for flow and species, with iterations to balance the coupling.

These model forms capture the dominant physics in their respective regimes: ease of running a full device with uncertain local fields for the bundle, and high-fidelity closure at the fiber for the unit cell. Notably, the bundle model sacrifices geometric detail and explicit chemistry for speed and scale, while the unit-cell model sacrifices coverage of flow nonuniformity.
Model form — gradation.

a.
Governing equations omit physics known to control the quantities of interest.

b.
Governing equations include core physics but use over-simplified closures without sensitivity analysis.

c.
Governing equations include core physics with justified closures and sensitivity studies.

d.
Governing equations are tailored to each mechanism with validation-quality closures and quantified applicability limits.

8. Model Inputs: Parameters, Sources, and Calibration Strategy

Permeability tensors for the bundle model are derived from steady pressure-drop tests on three physical bundles at 37 C using glycerol–water mixtures matched to blood viscosity. Fitting Darcy–Forchheimer curves yields axial permeability of approximately 190 kPa·s/m2 and radial permeability of approximately 35 kPa·s/m2 over superficial velocities of 0.05–0.20 m/s, with an inertial coefficient near 1.5 × 10^5 m1. Dispersion coefficients are set to 10–30% of molecular diffusivities based on resolved simulations of flow through packed cylinders. The interfacial area density is computed from fiber count and geometry and cross-checked against manufacturer data. Liquid-film mass transfer coefficients for oxygen and carbon dioxide are upscaled from unit-cell studies for the nominal regime, yielding k_L a in the range of 0.3–0.6 s1 at clinical velocities.

Membrane properties are measured directly on five coupons. Using a diffusion cell at 37 C, we measure oxygen permeability as 1.8 × 1010 mol m/(m2 s Pa) with a coefficient of variation of 6%, and carbon dioxide permeability as 6.0 × 1010 mol m/(m2 s Pa) with a coefficient of variation of 8%. Wall thickness is measured at 25 ± 2 micrometers from microtome sections across 20 fibers. Henry's constants for oxygen and carbon dioxide in plasma are taken from standard compilations for 37 C. Blood viscosity follows the Pries formulation with hematocrit-dependent corrections in shear rates typical of the shell-side microchannels. Hemoglobin binding parameters are taken from Dash and Bassingthwaighte, with temperature and pH fixed at measured values in the tests.

For carbon dioxide kinetics in the bundle model, an effective relaxation time is determined by requiring that the model reproduce the slope of VCO2 versus sweep flow at high sweeps in the bench data; the best-fit relaxation time is 0.2–0.3 s across operating points, compatible with values in blood physiology literature. For the unit-cell model, explicit reaction rates are taken from reduced-carbonate kinetic sets in the literature (e.g., Chang and colleagues), with the Haldane dependence implemented via occupancy functions. The early fouling layer is represented as a series resistance in both models: an added thickness of 0–3 micrometers with an effective diffusivity 35% of plasma for oxygen and 50% for carbon dioxide, consistent with albumin-rich films, is applied on the blood side.

Only one set of parameters is tuned: the time constant for carbon dioxide chemistry in the bundle model and the fouling-layer resistance for the early fouling experiments. All other parameters are fixed from measurements or literature. The calibration strategy uses eight short-duration runs for fouling at a single flow condition and a set of 14 high-sweep carbon dioxide points; cross-validation holds out 25% of points to avoid overfitting.
Model inputs — gradation.

a.
Key parameters are assumed without sources or justification.

b.
Key parameters are taken from literature sources without local verification.

c.
Key parameters are measured locally or taken from literature with cross-checks; calibrated parameters are few and justified.

d.
Key parameters are measured with uncertainty quantification; calibration is minimal and performed with cross-validation.

9. Numerical Code Verification

Verification of the implementation uses manufactured solutions for scalar diffusion, advection–diffusion, and conjugate conduction–diffusion across domains. For the scalar diffusion MMS in a unit cube with Dirichlet boundaries, the observed order of accuracy in the L2 norm is 1.98 when refining hexahedral meshes from 50^3 to 400^3 cells. For advection–diffusion with a prescribed velocity field, the observed order is 1.93 in the same norm. Conjugate conduction–diffusion tests that include membrane-like jumps in material properties deliver an observed order of 1.99 for temperature and 1.96 for species concentration. These tests exercise the same discretization kernels used for oxygen and carbon dioxide transport. Continuous integration runs 146 unit tests and regression cases on each merge to the main branch; all tests passed in the releases used here.

Specific to the unit-cell solver, additional verification assesses coupling between flow, membrane diffusion, and stiff reaction kinetics by comparing against an MMS with a time-varying manufactured source term. The integrator achieves bounded global errors with first-order time-stepping in stiff regimes and second-order in non-stiff regimes; species mass conservation is maintained to within machine precision in decoupled tests and to within 0.1% in coupled tests across 1000 time steps. The pressure–velocity coupling in the bundle solver is checked against canonical porous plugs with known solutions; volumetric flux errors fall below 0.3% on refined meshes. These results indicate that the code’s discrete operators and couplings are behaving in line with theory.

The verification suite is versioned and run on two hardware environments (Linux workstations and a small Linux cluster), with identical results at the test tolerances. Performance regressions are detected through a threshold of 10% time-to-solution change on standard meshes, ensuring that algorithmic changes do not inadvertently alter solver behavior. None of these tests substitute for validation against experiments, but they provide confidence that the numerical implementation matches the governing equations that are supposed to be solved.
Numerical code verification — gradation.

a.
No formal verification; code is exercised only on production cases.

b.
Spot checks on canonical problems with qualitative agreement.

c.
Manufactured-solution or analytic tests with observed orders and regression testing.

d.
Comprehensive verification with observed orders, regression testing, and coverage of multiphysics couplings similar to the application.

10. Numerical Solver Error and Discretization Error Assessments

Two sources of numerical uncertainty are examined: errors due to incomplete solver convergence and errors due to finite mesh resolution. For the bundle model, steady-state runs use a pressure-based segregated scheme with algebraic multigrid preconditioners. Nonlinear iterations continue until the maximum normalized residual in each equation falls below 1×108 and the change in VO2 over the last 300 iterations is less than 0.1%. The species budgets are checked by integrating source terms and comparing against outlet minus inlet fluxes; budget imbalances are less than 0.3% across all reported runs. For the unit-cell model, backward Euler time integration is used for reactions with sub-iterations to couple to flow and diffusion. Tolerances are tightened such that steady periodic solutions are achieved with residuals below 1×109 for species and pressure continuity. Species budgets in these cases close within 0.3–0.8% depending on stiffness.

Mesh convergence studies span three meshes for the bundle model and three to five for the unit cell. Bundle meshes include approximately 1.2 million, 2.7 million, and 5.4 million cells with local refinement near inlets, outlets, and walls. When comparing the two finest bundle meshes, VO2 changes by 0.9% in oxygen-limited cases and VCO2 by 1.1% in carbon-dioxide-focused cases; pressure drop changes by 0.8%. Maldistribution indices derived from coarse and medium meshes differ by 2.3% and by 1.8% between medium and fine. For early fouling simulations, mesh-induced differences in VO2 over two hours are 1.5%. Unit-cell meshes range from 10 million to 18 million cells with boundary layer refinement to $y+ < 1$. Averaged Sherwood numbers change by 1.4% between 10 million and 18 million cells for oxygen and by 1.6% for carbon dioxide. Flux distributions around the fiber perimeter converge within 2% in L1 norm.

Solver settings for stiff CO2 chemistry in the unit cell include adaptive time stepping with minimum steps of 1×105 s and maximum of 1×103 s, ensuring that transient chemistry is resolved without prohibitive costs. The Jacobians are preconditioned with incomplete LU and damped Newton steps at under-relaxation factors of 0.6–0.9; iteration counts remain below 25 per global step. In the bundle model, pressure–velocity coupling uses a SIMPLE-like approach with residual smoothing; under-relaxation factors are 0.7 for momentum and 0.9 for pressure, decreasing to 0.5 for species in stiffer runs. Sensitivities to solver tolerances are examined by relaxing thresholds one order of magnitude, yielding changes in VO2 and VCO2 below 0.4% and 0.6%, respectively.
Numerical solver error — gradation.

a.
Solver residuals are not monitored and mass/energy budgets are not checked.

b.
Solver residuals are monitored but not tied to quantities of interest; budget checks are occasional.

c.
Tight residual targets are met and budgets close for quantities of interest.

d.
Residual and budget targets are demonstrated insensitive through perturbation studies and are linked to acceptance thresholds.

$$\text{CI\_\{score\}} = \frac{\sum_{i=1}^{n} w_i \, x_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

$$\text{\textbackslash varepsilon\_\{rel\}} = \frac{\sum_{i=1}^{n} w_i \, x_i}{\sum_{i=1}^{n} w_i} \tag{2}$$

$$\text{U\_\{val\}} = \frac{\sum_{i=1}^{n} w_i \, x_i}{\sum_{i=1}^{n} w_i} \tag{3}$$

11. Development Process and Product Management

The models were developed under an internal project roadmap with quarterly milestones for physics implementation, verification, and validation. Requirements and acceptance criteria were tracked in a lightweight issue system with links to commits and test results. Design reviews were held at major increments with cross-disciplinary participation from engineering, physiology, and quality personnel. Formal product management artifacts in the sense of gated releases and stage reviews were not instituted, as the intent was research-oriented rather than productized software delivery, though release tags were used to tie results to code states.
Development process and product management — gradation.

a.
Ad hoc development without documented requirements or reviews.

b.
Informal requirements with sporadic reviews and undocumented decisions.

c.
Documented requirements with periodic reviews and traceability to implementation.

d.
Formal stage-gated development with risk management and independent review boards.

12. Software Quality Assurance

Automated testing, version control, and code review were used throughout. Continuous integration executed unit tests and regression cases on feature branches before merging to main. Static analysis flagging common defects and code style conformance were incorporated. Documentation was maintained in-line and in a separate user guide, with examples demonstrating end-to-end runs. The models leveraged a mature solver library with its own quality processes; our contributions focused on application-specific physics and validation workflows.
Software quality assurance — gradation.

a.
No formal SQA; testing and reviews are ad hoc.

b.
Basic SQA with version control and occasional testing.

c.
Systematic SQA with CI, coverage goals, and code reviews.

d.
Comprehensive SQA with independent audits, traceability, and compliance to organizational standards.

13. Credibility Scoring Method (0–10 Index) and Decision Rules

This assessment uses a private numeric index from 0 to 10 to grade each factor for each model-by-mechanism pair. Scores are integers. A score of 0 indicates no credible support; a score of 10 indicates the strongest level of support attainable under the framework. Decision rules are factor-specific and mechanism-aware. They are designed to be simple enough to apply reproducibly yet nuanced enough to reflect differences in evidence quality across mechanisms and models.

For provenance and related experimental lineage, 0 means no traceable data, 5 means partial documentation with limited uncertainty estimates, and 10 means fully documented datasets with calibration records, raw files, and uncertainty budgets at or below 5% for the core quantities of interest. For mesh sensitivity, 0 means no study, 5 means single comparison with changes under 5% in primary outputs, and 10 means multi-mesh studies with changes under 2% in those outputs and conservative extrapolation. For the equations and closures, 0 means missing required physics, 5 means core physics captured with acknowledged simplifications, and 10 means mechanism-specific modeling with validation-quality closures and quantified limits. For parameters, 0 means parameters are assumed without sources, 5 means parameters are sourced from literature without local verification but are plausible, and 10 means parameters are locally measured with uncertainties or taken from vetted sources and calibration is minimal and cross-validated.

For correctness of the implementation, 0 means no formal verification and no regression testing, 5 means spot checks and some regression coverage, and 10 means manufactured-solution tests with near-theoretical observed orders across the relevant operators and continuous integration with high coverage. For solver behavior, 0 means unconverged runs without budget checks, 5 means monitored residuals but loose targets or occasional budget checks, and 10 means tight targets with mass/species budgets closing below 1% and perturbation tests of tolerances showing invariant outputs. For the practical import

of outputs, 0 means outputs do not translate into stakeholder decisions, 5 means they can be post-processed, and 10 means they directly inform decisions in the units and thresholds used operationally. Finally, for how well the laboratory and numerical conditions match reality, 0 means no overlap, 5 means partial overlap with key mismatches in temperature or hematocrit or durations, and 10 means close matches across all salient conditions.

All scores are assigned independently for each mechanism because, for example, an excellent mesh study for oxygen may not imply the same for the maldistribution index, and a parameter measured precisely for oxygen permeability may not carry over to albumin-layer properties for early fouling. The rules were applied by two assessors and differences were reconciled through discussion anchored to the documented evidence. The mapping from rules to scores is recorded in the supplemental material along with the raw notes used to justify each choice.

14. Results: Factor Scores by Model × Mechanism

We organize the numerical grades into two tables, one per model, and interpret them in the sections that follow each table. Across mechanisms, several patterns emerge. The bundle-scale model shows strong numerical performance and consistent mesh behavior, and it aligns best with diffusion-controlled oxygen transfer and with diagnosing maldistribution. It is less faithful where carbonate chemistry is the pacing mechanism and where early fouling dominates, owing to the use of a single effective timescale for chemistry and a simplified resistance model for the fouling layer. The unit-cell model excels at representing conjugate transport and finite-rate kinetics and provides sharp estimates of Sherwood numbers for both species, but it lacks the ability to represent system-scale flow heterogeneity and thus does not directly project maldistribution impact without additional assumptions.

The grid-convergence studies demonstrated changes in the primary outputs below 1.2% for the bundle model and below 1.6% for the unit-cell model when cell counts were doubled, indicating negligible sensitivity to mesh resolution at the reported settings. The observed solver residuals and balance checks were tight in both models. All reported cases reached tight nonlinear and linear convergence, with residuals falling below 1×108 for the porous bundle and 1×109 for the conjugate unit cell and species and mass budgets closing within 0.3–0.8%. These behaviors are consistent across the four mechanisms, with modestly more effort needed to converge late-stage fouling cases in the bundle and stiff carbon dioxide kinetics in the unit cell.

Parameterization is strongest for gas permeability and membrane thickness—measured locally on five coupons—and for hydraulic resistance—measured on three bundles—whereas early fouling resistance relies on eight short-duration runs and exhibits higher uncertainty. Carbonate chemistry parameters in the unit cell are drawn from well-cited sources and implemented explicitly, while in the bundle they are compressed into a single relaxation time calibrated on a limited set of points. These differences are reflected in mid-range scores for model form and parameters in the carbon dioxide mechanism for the bundle and higher scores for the unit cell.

The relevance of outputs to clinical and engineering decisions and the matching of laboratory to in-use conditions are discussed further in the synthesis and discussion to keep findings consolidated and avoid duplication. The numerical grades, however, already reflect the fact that oxygenator design and clinical protocols operate directly on VO2, VCO2, outlet blood gases, and pressure drop, and that the laboratory studies were conducted at 37 C, realistic hematocrits, and across relevant flow and sweep ranges with acknowledged limitations in test duration for fouling.

Discretization error — gradation.

a.
No mesh convergence analysis; grid choice is arbitrary.

b.
Single mesh comparison with qualitative or >5% changes in key outputs.

c.
Multi-mesh study with <5% changes in key outputs and documented settings.

d.
Multi-mesh study with <2% changes in key outputs, Richardson extrapolation or equivalent, and mechanism-aware sensitivity.

14.1. Results Table: RANS–Porous-Media Bundle Model

The RANS–Porous-Media Bundle Model exhibits strong numerical performance and consistent alignment with oxygen diffusion control and maldistribution diagnosis. Scores for carbon dioxide kinetics and early fouling reflect simplifications in chemistry and interfacial resistance growth. The table enumerates every factor across the four mechanisms, restating the basis that appears in the prose with the same numbers. Rows are ordered by factor and mechanism for ease of scanning and sorting.

14.2. Results Table: Micro-Resolved Unit-Cell Conjugate Model

The Micro-Resolved Unit-Cell Conjugate Model provides high-fidelity transport and chemistry at the fiber scale. Its outputs are most directly applicable to deriving closures for bundle analyses and for examining the balance between membrane and blood-film resistances. The model is less suited to mechanisms dominated by device-level flow heterogeneity. The table below contains the 32 rows for all factors and mechanisms, restating numeric bases provided earlier in the paper.

15. Synthesis Across Mechanisms and Models

The two models answer different questions with different strengths. For oxygen uptake under diffusion control, both models are credible within their domains: the bundle model provides direct estimates of VO2 and outlet oxygenation across the flow and sweep range, while the unit-cell model explains

the balance between membrane and blood-side resistances and produces transfer coefficients that ground the bundle's volumetric closures. The models agree that blood-side film resistance dominates in the 3–6 L/min flow band and that achieving VO2 above 200 mL/min at hematocrit 0.35–0.45 with 100% oxygen sweep is feasible given the measured membrane permeability and area.

For carbon dioxide removal, the unit-cell model's explicit chemistry captures the Haldane-mediated boost in decarboxylation as blood oxygenates and the competition between bicarbonate dissociation and membrane transport. The bundle model, with an effective single time constant for chemistry, reproduces trends but introduces biases up to 12% at high sweeps. If decarboxylation is the critical design target, the unit-cell model should be used to derive mechanism-aware closures for incorporation into the device-scale analysis, or the bundle model should be upgraded to include explicit chemistry under appropriate stiffness-handling strategies.

Maldistribution is best diagnosed at the device scale. The bundle model, with anisotropic permeability and header geometry, reproduces pressure losses within 6% and delivers utilization indices that correlate with observed dye patterns. The unit-cell model cannot address this mechanism directly, though it can clarify how sensitive transfer is to local shear and boundary layer development under a given perfusion pattern. Therefore, design iterations aimed at improving perfusion uniformity should lean on the bundle model while using unit-cell calculations to ensure that fiber-scale physics are not left in an unfavorable regime.

The early fouling mechanism exposes the weakest evidence base in both models. The bundle analysis adds a series resistance that captures the first two hours' decline in VO2 and VCO2, but it does not represent morphological changes that might alter dispersion or local shear. The unit-cell representation improves physical realism at the interface but does not evolve film structure. New measurements spanning day-scale operation under anticoagulation would be needed to raise credibility for predictions used in long-duration support planning.

Across all mechanisms, the experimental datasets used for comparison were traceable to raw files with device serial numbers and timestamped configurations; for the subset most aligned to bundle-scale transfer (n=42 tests), measurement uncertainty was below 5% for VO2 and 6% for VCO2. Key parameters were obtained by direct measurement for the membrane and flow resistance, with literature-derived values used for carbonate chemistry and albumin-layer properties; only the fouling resistance was tuned, using eight short runs. While this synthesis highlights shared strengths, differences in how each mechanism draws on the evidence motivate the specific scores recorded in the tables.

16. Discussion

The governing assumptions were sufficient for O2-diffusion control and flow maldistribution, but they under-represent CO2 speciation dynamics and the evolution of fouling structure, as evidenced by mechanism-specific residual trends and bias patterns. For oxygen, an interfacial volumetric term tied to a well-characterized liquid-film resistance captures the key throttling step in clinical flows; for maldistribution, a Darcy–Forchheimer representation parameterized from measured pressure drops provides a practical and verifiable closure for the bundle. For carbon dioxide, the bundle model's compressed kinetics cannot express how bicarbonate dissociation depends on local pH and oxygenation, nor the changing carbamino binding, without introducing mechanism-specific parameters. In contrast, the unit-cell chemistry resolves these couplings but at the cost of excluding macroscopic perfusion patterns.

Laboratory operating points matched clinical blood temperature and hematocrit and spanned typical flow and sweep settings; limitations were the short duration of fouling trials and the use of a CO2-enriched sweep in several decarboxylation tests. The latter improves signal-to-noise for carbon dioxide flux measurements but diverges from the air–oxygen mixes common in practice; the impact is small on oxygen transfer but can amplify decarboxylation beyond what is seen clinically. Short-duration fouling runs are realistic for startup behavior but do not probe protein reorganization and cell deposition that can occur over days, nor do they capture anticoagulation effects. As a result, predictions for early hours are on firmer ground than those for longer horizons.

Model improvement priorities follow from these observations. For the bundle model, explicit carbonate kinetics, even in a reduced form, would raise credibility for decarboxylation forecasting and acid–base management planning. For both models, fouling needs a more mechanistic representation that evolves film thickness and porosity with time and shear, supported by day-scale measurements in blood. The unit-cell approach could be extended to multi-cell domains to capture simple maldistribution motifs, although the computational costs increase sharply. Alternatively, bundle-scale flow fields could be sampled to generate boundary conditions for unit-cell studies, closing the loop across scales. Finally, adding uncertainty quantification to propagate parameter and input uncertainties to outputs would better align the assessment with decision-making under risk.

Test conditions — gradation.

a.
Application and test conditions do not overlap in key variables.

b.
Application and test conditions overlap partially; at least one key variable is outside the operational band.

c.
Application and test conditions overlap well in key variables with documented differences and rationale.

d.
Application and test conditions match across all key variables, including duration and environmental factors, with sensitivity analyses.

17. Conclusions

This credibility assessment used NASA-STD-7009A factors and a private 0–10 index to grade two computational models

across four clinically relevant mechanisms in hollow-fiber oxygenators. Scores are reported separately for each factor, model, and mechanism, yielding 64 rows across two tables. The bundle-scale RANS–Porous-Media Model demonstrates strong numerical behavior and alignment with oxygen diffusion control and maldistribution evaluation, while the Micro-Resolved Unit-Cell Conjugate Model provides higher-fidelity representation of conjugate transport and finite-rate chemistry, most useful for parameterizing closures and understanding species partitioning. Weaknesses concentrate in simplified carbonate chemistry in the bundle and the absence of macroscopic flow variation in the unit cell, as well as limited-duration evidence for early fouling in both approaches.

Manufactured-solution tests produced near second-order spatial convergence in all solvers, and every unit test executed in continuous integration passed in the releases used for the results. The modeling and experimental programs share a traceable foundation with measured parameters for the membrane and hydraulic resistances, though chemistry and fouling remain partially constrained by literature or short runs. The outputs emphasized by both models connect directly to clinical targets and design acceptance bands, strengthening their utility in decision-making under the reported conditions.

Future work should tighten the link between scales by computing closures for carbon dioxide that are mechanism-aware and by incorporating time-evolving fouling with support from longer-duration tests. Incorporating uncertainty propagation would add discipline to how margins are expressed. Used together, the two models can give designers and clinicians higher confidence: the unit-cell model for physics fidelity and parameter grounding, and the bundle model for system-level predictions and trade studies.

18. Acknowledgments

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20. Supplemental Material: Mesh Convergence Records, Solver Settings, and Score Matrices

Mesh convergence records include cell counts, refinement strategies, and quantity-of-interest changes for each mesh. For the RANS–Porous-Media Bundle Model, meshes at approximately 1.2M, 2.7M, and 5.4M cells are documented with VO2, VCO2, Δp, and perfusion uniformity indices recorded at each level. For the Micro-Resolved Unit-Cell Conjugate Model, meshes at 10M, 14M, and 18M cells are recorded with local and averaged Sherwood numbers for oxygen and carbon dioxide, as well as circumferential flux distributions at multiple axial stations. Richardson extrapolations are included where appropriate along with estimated grid uncertainties.

Solver settings are tabulated for each mechanism and model: tolerances, under-relaxation factors, preconditioners, iteration counts, and time-step controls. Mass and species budget closure checks are recorded with integrated source–sink terms and inlet–outlet balances for each run. Perturbation studies for solver tolerances are included with the resulting changes in VO2, VCO2, and other quantities of interest; these changes remain below 0.6% in all cases reported.

Score matrices specify the factor-specific decision rules used to convert evidence into integer grades on the 0–10 index. Each entry in the results tables maps to a row in the matrix with the associated evidence references: data source identifiers, mesh study identifiers, solver logs, and parameter measurement records. Assessor comments are included where differences were reconciled. The supplemental files are available upon request and are archived in the institutional repository under accession number CFD-OXY-7009A-2026.

Discretization error — gradation.

a.
No convergence evidence provided.

b.
Some convergence evidence; changes in outputs exceed 5%.

c.
Convergence evidence shows <5% changes in outputs across at least two meshes.

d.
Convergence evidence shows <2% changes across at least three meshes with uncertainty estimates.

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Table 1: Credibility assessment summary for the RANS–Porous-Media Bundle Model (RANS-PM) across four mechanisms on the private 0–10 Credibility Index.

Credibility factor	Level	Basis
Data pedigree - RANS–Porous-Media Bundle Model (RANS-PM) - Diffusion-limited O2 transfer at clinical flow and hematocrit	8	42 bundle runs include 18 O2-focused points at Hct 0.40±0.03 and 37.0±0.2 C with VO2 repeatability ±3.1%.
Data pedigree - RANS–Porous-Media Bundle Model (RANS-PM) - CO2 removal with bicarbonate chemistry and Haldane interaction	7	14 CO2-focused points span inlet PCO2 45–80 mmHg; VCO2 repeatability is ±4.5% with daily calibration.
Data pedigree - RANS–Porous-Media Bundle Model (RANS-PM) - Bundle-scale blood-flow maldistribution	6	9 dye and Δp mapping experiments yield perfusion uniformity indices 0.64–0.82 using planar imaging.
Data pedigree - RANS–Porous-Media Bundle Model (RANS-PM) - Early fouling layer on fiber surfaces	4	8 two-hour holds at fixed settings show VO2 drift 6–12% with confocal checks of film formation.
Discretization error - RANS–Porous-Media Bundle Model (RANS-PM) - Diffusion-limited O2 transfer at clinical flow and hematocrit	9	VO2 changes by 0.9% between 2.7M and 5.4M cells; pressure drop shifts 0.8% on the same meshes.
Discretization error - RANS–Porous-Media Bundle Model (RANS-PM) - CO2 removal with bicarbonate chemistry and Haldane interaction	9	VCO2 changes by 1.1% between 2.7M and 5.4M cells under CO2-focused settings.
Discretization error - RANS–Porous-Media Bundle Model (RANS-PM) - Bundle-scale blood-flow maldistribution	8	Perfusion uniformity index shifts 1.8% from medium to fine mesh in header-biased cases.
Discretization error - RANS–Porous-Media Bundle Model (RANS-PM) - Early fouling layer on fiber surfaces	8	Mesh-induced VO2 differences over a two-hour fouling run are 1.5% between medium and fine meshes.
Model form - RANS–Porous-Media Bundle Model (RANS-PM) - Diffusion-limited O2 transfer at clinical flow and hematocrit	7	Volumetric kLa with blood-film control reproduces outlet PaO2 within 7 mmHg across 18 points.
Model form - RANS–Porous-Media Bundle Model (RANS-PM) - CO2 removal with bicarbonate chemistry and Haldane interaction	5	Single relaxation time for chemistry; gives VCO2 bias

Table 2: Credibility assessment summary for the Micro-Resolved Unit-Cell Conjugate Model (UC-CP) across four mechanisms on the private 0–10 Credibility Index.

Credibility factor	Level	Basis
Data pedigree - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - Diffusion-limited O2 transfer at clinical flow and hematocrit	6	6 coupon tests with micro-PIV and microelectrodes yield Sh with ±7% uncertainty at 37 C.
Data pedigree - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - CO2 removal with bicarbonate chemistry and Haldane interaction	5	4 CO2 coupon datasets with 25 mM bicarbonate buffers; no direct whole-blood microchemistry.
Data pedigree - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - Bundle-scale blood-flow maldistribution	3	No macroscopic maldistribution measurements at the unit-cell scale; reliance on literature context.
Data pedigree - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - Early fouling layer on fiber surfaces	4	4 ninety-minute albumin fouling experiments measure films of 0–3 μm via confocal imaging.
Discretization error - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - Diffusion-limited O2 transfer at clinical flow and hematocrit	9	Sh changes by 1.4% when refining from 10M to 18M cells with y+<1 boundary layers.
Discretization error - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - CO2 removal with bicarbonate chemistry and Haldane interaction	9	CO2 interfacial flux changes 1.6% between 10M and 18M cells under stiff chemistry.
Discretization error - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - Bundle-scale blood-flow maldistribution	9	Resolved unit-cell fields converge; macroscopic maldistribution is out of scope but numerics are stable.
Discretization error - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - Early fouling layer on fiber surfaces	9	Flux decay with a 0–3 μm surface layer changes <1.9% on mesh refinement.
Model form - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - Diffusion-limited O2 transfer at clinical flow and hematocrit	9	Conjugate diffusion with finite-rate Hb kinetics reproduces fiber-level fluxes across ReD 20–60.
Model form - Micro-Resolved Unit-Cell Conjugate Model (UC-CP) - CO2 removal with bicarbonate chemistry and Haldane interaction	8	Reduced carbonate kinetics