

Titan-II: A Hybrid-Structure Concept for a Carbon-Fiber Submersible Rated to 6000 m

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September 30, 2025

Abstract

We propose *Titan II*, a conservatively engineered, certification-oriented submersible concept intended for operation to 6000 m (approximately 60 MPa) to support experiments on hypothesized *quantum abyssal symmetries* and *chronofluid* (τ -syrup) phenomena within the Prime Lattice Theory program. Unlike prior unconventional composite hull efforts, *Titan II* treats carbon-fiber composites as a candidate material system that must pass through exhaustive qualification, proof factors, and independent classification in order to justify the low costs but high value of carbon fiber as a promising materials choice. We present a materials and safety framework (laminate selection, aging, fatigue, progressive-damage mechanics, NDE, acoustic emission and fiber-optic structural health monitoring) together with a hybrid structural philosophy that preserves fail-safe load paths and graceful degradation. We then devote extended sections to the *physics motivation*: a phenomenological model in which a discrete “prime lattice” $\mathcal{L}_{\mathbb{P}}$ couples weakly to macroscopic fields via pressure- and temperature-dependent boundary terms. We state falsifiable predictions, an instrumentation strategy, and noise budgets that leverage the deep-ocean environment.

Additionally, we present an AI (LLM, Agentic)-based acoustic monitoring framework, and present novel ideas around data governance and immutability for ensuring trust-forward and interoperable results by creating a blockchain ("AbyssalLedger") and associated cryptocurrency. Monitoring augments safety; it never substitutes for margins, proof, or class. Unmanned phases precede any manned operation.

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1 Introduction

1.1 Motivation: Deep Ocean as a Physics Laboratory

The hadal ocean furnishes a naturally quiet, high-pressure, low-temperature, and electromagnetically shielded environment that is exceptionally well suited to precision measurements. Unlike terrestrial laboratories—where thermal transients, anthropogenic electromagnetic (EM) interference, and mechanical vibrations can dominate error budgets—the deep ocean offers quasi-static boundary conditions over hours to days. At 6000 m the hydrostatic pressure is $p = \rho gh \approx 60$ MPa for seawater density $\rho \approx 1025 \text{ kg m}^{-3}$ and gravitational acceleration $g \approx 9.81 \text{ m s}^{-2}$, providing a tunable,



Figure 1: Titan II concept rendering.

uniform thermodynamic parameter that can be stepped, held, and correlated against instrument response. Our physics objective is to use these conditions to interrogate weak, boundary-sensitive couplings predicted by Prime Lattice Theory (PLT) and chronofluid (“ τ -syrup”) phenomenology, while maintaining a standards-led safety posture in which monitoring augments but never substitutes for proof and classification.

Environmental advantages (why the ocean, why this depth). Several deep-ocean properties jointly reduce noise and systematics:

- **Thermal stability.** Below the thermocline the seawater temperature is typically $\sim 1^{\circ}\text{C}$ – 4°C with minimal diurnal drift. This suppresses thermomechanical creep and temperature-dependent gain variations in metrology chains.
- **Electromagnetic shielding.** Conductive seawater attenuates time-varying EM fields with

skin depth

$$\delta(\omega) = \sqrt{\frac{2}{\mu \sigma \omega}},$$

where $\mu \approx \mu_0$ and $\sigma \sim 3 \rightarrow 5 \text{ S m}^{-1}$. Thus δ is $\mathcal{O}(30 \text{ m})$ at power-line frequencies and $\mathcal{O}(5 \text{---}10 \text{ m})$ at kilohertz, so anthropogenic EM lines vanish within the multi-kilometer overburden of seawater. For magnetically sensitive payloads this constitutes a natural Faraday-like shield.

- **Mechanical quieting.** With careful site selection (far from shipping lanes and strong currents) and operational sequencing (valves/pumps idle during integration windows), the local acceleration/vibration spectrum can be made substantially quieter than typical surface platforms. Hydrostatic loading is quasi-static; modal excitation can be characterized and avoided.
- **Acoustic regime.** Ambient sound at depth is set by distant weather, shipping, and microseism; these sources are spectrally structured and can be vetoed by housekeeping channels (outboard hydrophones). The high sound speed ($c \approx 1500 \text{ m s}^{-1}$) and stratification allow controlled acoustic drives for rheology and sideband searches without saturating sensors.
- **Boundary control.** Pressure p and effective boundary compliance K_{eff}^{-1} at the hull–water interface can be deliberately shaped, creating a tunable “boundary condition laboratory” for testing weak couplings.
- **The hadal ocean as a syrup.** As discussed in [3], from a rheological perspective, water is a syrup. Therefore, deep-sea pressure creates an environment that more closely emulates the chronofluid properties of τ -syrup.

Background and brief physics. PLT hypothesizes that a discrete arithmetic scaffold—the *prime lattice*—weakly modulates macroscopic observables through boundary terms, yielding prime-indexed discrete scale invariance (p-DSI) and log-periodic corrections under repeated coarse-graining. Chronofluid phenomenology introduces a field τ (“time thickness”) governing memory and apparent viscosity; in cold, high-pressure, low-noise environments τ tends to increase (“thickening”), altering dissipation and phase response. The deep ocean unites both ingredients: hydrostatic pressure and controllable compliance act as *knobs* on boundary couplings, while stable, low temperatures extend τ and suppress conventional drift mechanisms.

Formally, the relevant small, dimensionless controls include

$$\Pi_p = \frac{p}{K_{\text{eff}}}, \quad \Pi_\tau = \dot{\gamma} \tau, \quad \Pi_T = \frac{T}{T_0}, \quad \Pi_{\text{flow}} = \frac{L}{\ell_{\text{diss}}},$$

where K_{eff} is the effective boundary stiffness, $\dot{\gamma}$ a local shear rate for in situ rheology, T the ambient temperature (with reference T_0), and ℓ_{diss} a dissipation length. In PLT, weak prime-indexed harmonics at angular frequencies $\omega_{p,\alpha} = 2\pi/(\alpha \ln p)$ (with p prime, $\alpha > 0$) may imprint as a sparse “prime comb” in spectra computed on *logarithmic* axes; in the chronofluid model, the apparent viscosity follows

$$\eta_{\text{app}}(\dot{\gamma}) = \eta \left[1 + \frac{\eta_\tau}{1 + (\dot{\gamma} \tau)^2} \right],$$

giving a falsifiable shear–dissipation law. The *boundary* energy density can be written schematically as

$$\mathcal{F}_\Gamma = \alpha p \tau + \beta (\nabla \cdot \mathbf{u}) \tau + \sum_{p \in \mathbb{P}} \epsilon_p \lambda_p \tau \Xi_p,$$

with \mathbf{u} the boundary displacement, Ξ_p prime-indexed modes, and ϵ_p small couplings. The central question is whether these terms produce reproducible, pressure- and compliance-dependent signatures in carefully controlled deep-ocean conditions.

What the ocean enables (experimentally). The mobility and environmental control of a submersible enable a suite of experiments otherwise impractical:

1. **Pressure steps/holds** at 6000 m with synchronized metrology (pressure, temperature, strain) to map $\tau(P, T)$ and look for correlated changes in dissipation and phase.
2. **Drive-response tests** using narrowband acoustic or mechanical drives to probe for p-DSI sidebands on log-frequency axes with trials-factor control.
3. **Micro-shear rheology** in microchannels (low Reynolds number) to directly extract $\eta_{\text{app}}(\dot{\gamma})$ and test chronoviscous scaling.
4. **Boundary-compliance sweeps** via calibrated internal preloads or isolators, testing whether inferred couplings track Π_p as predicted by boundary terms.
5. **Null tests and vetoes** using outboard hydrophones, accelerometers, and thermal references to excise intervals contaminated by environmental lines or machinery.

Because pressure and temperature are co-located and measured redundantly, regressions against environmental covariates can be performed with low multicollinearity, reducing the risk of spurious correlations.

Confounders and mitigation. Potential confounders include shipping and biological acoustics, microseism coupling, flow-induced noise, and instrument self-heating. These are mitigated by (i) site/season selection and depth; (ii) sequencing (quiet integration windows); (iii) housekeeping sensors (hydrophones/accelerometers/FBG thermometry) for vetoes; and (iv) consistency checks across repeated dives and facilities. A conservative, one-sided decision policy ensures that any unmodeled anomaly *tightens* operational limits (by enforcing derating or ascent) rather than expanding them.

Why a submersible rather than a fixed mooring. A fixed mooring can be quieter in some bands, but a submersible offers: (i) active depth tuning and boundary-compliance control; (ii) isolation of payload from mooring-line dynamics; (iii) rapid iteration across protocols; and (iv) unified co-registration of physics and structural-health data (AE/FBG) for rigorous post hoc analysis. The *Titan II* concept is explicitly designed to deliver this environment safely: hybrid, fail-safe structures; standards-led qualification; and SHM as a tripwire. Furthermore, some of our lab’s investment funding is contingent upon bringing one or more investors down to the Titanic (3800m), which can only be completed after our first round of quantum physics research is finished. The typical Titanic season ranges from May to September.

Summary. The deep ocean is not merely a harsh setting in which instruments must survive; it is a *laboratory* whose intrinsic boundary conditions—high, uniform pressure; low, stable temperatures; strong EM attenuation; and controllable mechanical states—are precisely the variables needed to test PLT and chronofluid predictions. By exploiting these conditions with careful controls, mobility, and conservative safety engineering, we can either discover reproducible, prime-indexed and chronoviscous signatures or set meaningful null bounds that prune the theory space. In both outcomes the deep ocean delivers unique, decision-quality information that terrestrial laboratories cannot easily provide.

1.2 Lessons and Scope

Recent failures of composite pressure hulls underscore that novel materials demand conservative design, independent oversight, and proof testing. *Titan II* is a *materials-science and safety framework* with physics payloads as beneficiaries, not drivers, of structural risk. This paper provides: (i) a standards-aligned path to classification; (ii) hybrid structural concepts; (iii) a qualification program; and (iv) an extended physics model with falsifiable signatures. It *does not* present manufacturing drawings or layup schedules.

2 Top-Level Requirements and Standards Posture

- R1. Depth rating (MWOP): 6000 m with proof factors as approved by a recognized classification society.
- R2. Unmanned-first test campaign: static, proof, and cyclic external-pressure testing before any manned trials.
- R3. Records and traceability: complete materials pedigree, cure logs, environmental controls, NDE archives, and configuration control.
- R4. Monitoring as augmentation: \AA and FBG serve as tripwires; anomalies derate or abort, never up-rate.
- R5. Payload environment: magnetic cleanliness, low vibration, redundant metrology co-located with physics sensors.

3 Materials Science Foundation

3.1 Composite Behavior Under External Pressure

Carbon-fiber/epoxy offers high specific stiffness and magnetic cleanliness; however, external-pressure service is governed by compression-driven failure modes: micro-buckling (kink bands), interlaminar shear, matrix cracking, and delamination growth. Thick sections introduce cure gradients, void management, and NDE accessibility limits.

3.2 Preliminary Selection Factors

Intermediate-modulus fibers often provide superior compressive strength in thick laminates relative to ultra-high-modulus grades. Toughened epoxies with high glass-transition temperature T_g and documented seawater uptake are preferred. Layups should be symmetric and balanced, with interleaf toughening for through-thickness fracture resistance and compliant, inspectable joints to metals to avoid local buckling stress risers.

3.3 Aging, Moisture, and Fatigue

Moisture ingress modifies matrix modulus and interface strength; thermal cycles ratchet residual stresses; cyclic external pressure accumulates damage below immediate detectability. Qualification therefore includes hot-wet conditioning, accelerated seawater soak, creep rupture, and fatigue S–N mapping under representative hydrostatic pressure, with statistical knockdowns propagated to design allowables.

4 Hybrid Structural Concepts (Non-Prescriptive)

Concept A: Metal Primary, Composite Secondary. A titanium or high-strength steel *primary* pressure hull carries all external loads; composites provide magnetic/acoustic shields, fairings, and buoyancy. This is the conservative baseline for early physics missions.

Concept B: Metallic Liner + Composite Overwrap. A metallic inner safety liner provides leak-before-break behavior while a calibrated composite overwrap shares load. Load sharing is verified via coupon, subscale, and full-scale tests with instrumentation.

Concept C: Composite-Dominant with Redundant Frames. If composites carry the majority load, incorporate redundant stiffening frames and metallic end-closures with compliant joints. Hard go/no-go criteria are derived from NDE and proof tests.

5 Analysis, Stability, and Reliability

5.1 Progressive Damage and Buckling

Composite compressive strength σ_c depends on moisture fraction m , temperature T , measured fiber waviness ω , and void fraction v :

$$\sigma_c(m, T, \omega, v) = \sigma_{c0} k_m(m) k_T(T) k_{def}(\omega, v), \quad (1)$$

where knockdown factors $k_i \in (0, 1]$. Global/local buckling analyses include measured imperfection spectra.

5.2 Reliability Updating with SHM

Let state variable S encode damage; SHM observations $\mathcal{O} = (\cdot, \text{FBG})$ update the prior via Bayes:

$$p(S \mid \mathcal{O}) \propto p(\mathcal{O} \mid S) p(S), \quad \text{decision: abort or derate if } \mathbb{E}[\text{margin} \mid \mathcal{O}] < \text{threshold}. \quad (2)$$

Monitoring is strictly conservative: no observation may increase rated depth.

6 NDE and Structural Health Monitoring

6.1 NDE Toolkit

Phased-array ultrasonics, thermography for near-surface disbonds, localized CT for thick critical regions, laser shearography on accessible panels, and conventional methods for metals.

6.2 Embedded/In-Service Monitoring

Broadband \mathcal{AE} detects matrix cracking, fiber breakage, and delamination onset during hydro tests and dives. Distributed FBG networks measure strain/temperature fields to track load sharing and identify anomalies. Instrumented “load-path witnesses” provide early-warning trends.

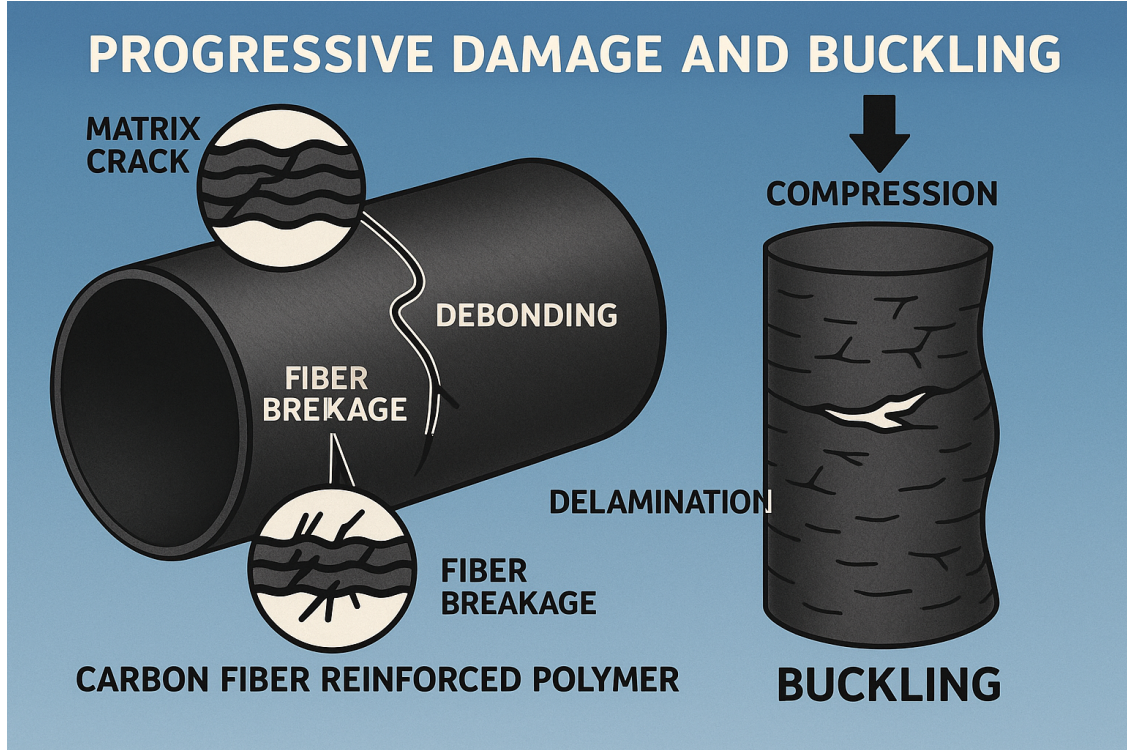


Figure 2: Graphic of progressive Damage and buckling of carbon fiber hull.

7 Qualification and Test Campaign

1. **Coupons:** tension/compression, open-hole, interlaminar shear, Mode I/II fracture, hot-wet, moisture-aged.
2. **Elements:** curved panels and joints under external pressure with \AA /FBG.
3. **Subscale article:** $\geq 1:2$ geometry; proof to $\geq 1.25\text{--}1.5 \times \text{MWOP}$; post-test NDE.
4. **Full-scale (unmanned):** tightness at MWOP; cyclic pressure sequence for service life; independent review.
5. **Sea trials (unmanned):** depth expansion by gate review only.
6. **Manned ops:** Only post-classification with full documentation.

8 Deep-Ocean Physics: Prime Lattice and Chronofluid

8.1 Overview and Motivation

This section formalizes the physics program that motivates *Titan II*: to probe weak, prime-indexed structure and chronofluid (“ τ -syrup”) effects that may become more detectable under abyssal boundary conditions ($h \approx 6000$ m, $p \approx 60$ MPa, low thermal drift, acoustic quiet). We treat the ocean–hull interface as a controllable boundary where hydrostatic pressure, compliance, temperature, and low vibrational noise jointly modulate couplings predicted by (i) a *prime lattice* hypothesis with

prime-indexed discrete scale invariance (p-DSI), and (ii) a rheological field τ that thickens “time” and carries memory. The goal is a falsifiable, preregistered test plan whose null can survive.

8.2 Prime Lattice and Prime-Indexed Discrete Scale Invariance (p-DSI)

We postulate that only rescalings by elements of a prime lattice

$$\Lambda = \{ p^\alpha : p \in \mathbb{P}, \alpha > 0 \}$$

are dynamically privileged. When selection-by-recursion (e.g., repeated measurement/coarse-graining) operates on observables with an underlying scale freedom, the consequence is *log-periodic* corrections to scaling with arithmetic-locked angular frequencies

$$\omega_{p,\alpha} = \frac{2\pi}{\alpha \ln p}, \quad p \in \mathbb{P}, \alpha > 0. \quad (3)$$

On log-frequency (or log-time) axes this yields a sparse *prime comb*: narrow lines at $\{\omega_{p,\alpha}\}$ whose positions are fixed a priori by arithmetic, while amplitudes/phases are empirical. Distinguishing such combs from strong nulls (colored noise, renewal and Hawkes processes, instrumental lines) is a central analysis task in §8.10.

8.3 Chronofluid (τ -syrup) Field and Rheology

We elevate viscosity from a parameter to a field degree of freedom carrying memory. Let $\mathbf{D} \equiv \frac{1}{2}(\nabla \mathbf{v} + \nabla \mathbf{v}^\top)$ denote the rate-of-deformation tensor. The Cauchy stress is modeled as

$$\boldsymbol{\sigma} = -p\mathbf{I} + 2\eta\mathbf{D} + \eta_\tau \mathcal{M}_\tau[\mathbf{D}], \quad \mathcal{M}_\tau[\mathbf{D}](t) = \int_{-\infty}^t e^{-(t-s)/\tau} \mathbf{D}(s) ds, \quad (4)$$

with τ the *chronofluid thickness* (time-memory). Unlike a fixed-parameter Maxwell model, τ evolves with state:

$$\dot{\tau} = -\frac{1}{\tau_{\text{rel}}} [\tau - \tau_{\text{eq}}(P, T)] + \alpha \text{tr}(\mathbf{D}^2) - \beta T, \quad (5)$$

so cold, high-pressure, low-noise environments (abyssal conditions) typically thicken time ($\tau \uparrow$). In steady shear with rate $\dot{\gamma}$,

$$\eta_{\text{app}}(\dot{\gamma}) = \eta \left[1 + \frac{\eta_\tau}{1 + (\dot{\gamma}\tau)^2} \right], \quad (6)$$

linking ordinary viscosity to chronofluidity in a parameterizable, testable way.

8.4 Abyssal Symmetries and Recursive Quantum Collapse

Let \mathcal{A} denote an “abyssal symmetry” operator that commutes with physical rotations but acts nontrivially on boundary spectra by permuting prime-indexed modes. We further assume *recursive quantum collapse* (RQC) acts as a selection mechanism: under repeated measurement/coarse-graining cycles, only prime-indexed rescalings persist, generating the p-DSI comb in Eq. (3). While RQC may have implications for abiogenesis at biochemical scales (selection of prime-stable reaction networks), the present work confines itself to deep-ocean boundary tests.

8.5 Augmented Energy Law and the $E=mc^2$ Special Case

We posit a prime-projected augmentation of mass–energy equivalence:

$$E = \mathcal{P} \left[mc^2 + \frac{AI}{\tau} \right], \quad (7)$$

where \mathcal{P} projects onto prime-indexed modes, A is an abyssal coupling, and I is an algorithmic-information density associated with the system’s microstate. A convenient renormalized form writes

$$E_{\text{eff}} = X \left[1 + \sum_{(p,\alpha)} a_{p,\alpha} \cos \left(\omega_{p,\alpha} \ln \frac{X}{X_0} + \phi_{p,\alpha} \right) \right], \quad X \equiv mc^2 + \kappa \frac{J_{\text{info}}}{\eta \tau}, \quad (8)$$

with small amplitudes $a_{p,\alpha}$ and phases $\phi_{p,\alpha}$. Two important limits:

$$\eta \tau \rightarrow \infty \Rightarrow E_{\text{eff}} \rightarrow mc^2 \quad (\text{thick-time / decoupled limit}), \quad a_{p,\alpha} \rightarrow 0 \Rightarrow E_{\text{eff}} \rightarrow X \quad (\text{no p-DSI}).$$

Thus $E = mc^2$ is recovered as a *special case* when prime couplings are inactive or chronofluid time is extremely thick.

8.6 Black Holes as Prime Gaps; τ -Sheath Phenomenology (Speculative)

We model compact regions with large “defect depth” $\Delta \gg 1$ as macroscopic *prime gaps* in the lattice. Chronofluid inflow (large τ) accumulates into a viscous τ -sheath that *screens* the defect, slightly softening horizon features and producing small broadband-damped residuals in ringdown. A simple parameterization modifies quasinormal-mode damping as

$$\Gamma(\omega) = \Gamma_0 + \frac{\gamma \omega^2}{1 + (\omega \tau)^2}, \quad \gamma \propto AI, \quad (9)$$

and a frequency-dependent refractive response near the boundary implies a shadow-radius shift $\Delta R_{\text{shadow}}(\omega) \simeq R_g [n(\omega, \tau) - 1]$. Deep-ocean results constrain (τ, A, I) ; astrophysical stacks refine them.

8.7 Boundary Coupling and Abyssal Free Energy

At the hull–water boundary Γ , we write the leading coupling density

$$\mathcal{F}_\Gamma = \alpha p(\mathbf{x}) \tau(\mathbf{x}, t) + \beta (\nabla \cdot \mathbf{u}) \tau(\mathbf{x}, t) + \sum_{p \in \mathbb{P}} \epsilon_p \lambda_p \tau(\mathbf{x}, t) \Xi_p(\mathbf{x}, t), \quad (10)$$

with hydrostatic pressure p , displacement \mathbf{u} , and prime-indexed boundary modes Ξ_p (eigenfunctions of \mathcal{A} with eigenvalues λ_p). The coefficients ϵ_p are small and expected to decay with p ; they set the observable comb amplitudes.

8.8 Predictions and Falsifiers (Pre-Registered Families)

We organize five test families, each with internal nulls:

1. **Chronoviscous scaling (lab & in situ):** In steady shear, excess dissipation obeys $\Delta \Phi \propto \dot{\gamma}^2 / [1 + (\dot{\gamma} \tau)^2]$, allowing τ -extraction via $\Phi(\dot{\gamma})$ fits.

2. **Abyssal thickening:** $\tau(P)$ grows superlinearly above tens of MPa at fixed T , measurable via acoustorheology or microchannel viscometry under pressure steps/holds.
3. **Prime sidebands (comb tests):** Stress/strain/acoustic spectra exhibit lines at Eq. (3) on log axes; consistent *absence* at selected p constitutes a “prime gap” indicator.
4. **Cavitation threshold shift:** In high- τ water, $p_{\text{cav}}(\tau) \approx p_0 + \kappa AI/\tau$ (to be calibrated), testable with ultrasonic microscopy.
5. **Astrophysical residuals (stacked):** Small prime-locked ringdown residuals and subtle shadow chromaticity scale consistently with (τ, A, I) inferred from deep-ocean data; nulls at forecast sensitivity falsify the coupling class.

8.9 Deep-Ocean Experiment Design (Titan II Payload)

Channels. A magnetically quiet, vibration-isolated rack hosting: (i) pressure/temperature references; (ii) distributed fiber Bragg grating (FBG) strain/temperature for housekeeping; (iii) low-noise acoustic/force/flow sensors for rheology; (iv) an ultrasonic driver/receiver pair for sideband searches; (v) optional photonics (interferometric baselines). *Safety note:* SHM (AE/FBG) is a veto/tripwire only; it cannot increase allowed depth.

Protocols. (a) Pressure steps/holds to map $\tau(P, T)$ at fixed shear; (b) long, quiet integrations for comb detection on log-time; (c) microchannel shear ($\text{Re} \lesssim 1$) for Eq. (6); (d) narrow-band ultrasonic drives to probe prime sidebands and phase locking; (e) cavitation sweeps vs. τ .

8.10 Data Analysis and Statistical Controls

Work on *log-time* ($s = \ln t$) or *log-frequency*. Compute multitaper spectra $\hat{S}(\omega)$; fit a comb model with *fixed* line positions from Eq. (3), free amplitudes/phases, and control the false discovery rate across (p, α) trials. Use strong nulls (surrogate colored-noise, renewal/Hawkes) and housekeeping vetoes. For driven tests, employ matched filtering

$$\rho^2 = 4 \text{Re} \int_0^\infty \frac{\tilde{x}(f) \tilde{h}_{p,\alpha}^*(f; \theta)}{S_n(f)} df, \quad (11)$$

with trials-factor corrections and parameter posteriors checked for stability across dives/facilities.

8.11 Systematics, Decision Policy, and Stop Rules

Environmental lines (machinery, pump harmonics, microseism), aliasing, and sensor cross-talk are tracked by housekeeping channels; contaminated intervals are vetoed. Decision rules are one-sided and conservative: detections can *tighten* operational limits (by revealing new couplings) or be declared null; no signal authorizes deeper operation. Stop conditions: any SHM anomaly, unexpected growth of housekeeping lines, or failure to meet pre-dive acceptance.

8.12 Success Criteria

Reproducible $\tau(P, T)$ thickening, consistent prime sidebands beyond preregistered thresholds, and stable parameter posteriors across dives and facilities define success. Absence of signals at forecast sensitivity implies $A \rightarrow 0$ (no abyssal coupling) and collapse to the null model, which is itself a valuable constraint on the theory space.

9 Acoustic Monitoring of Carbon-Fiber Micro-Events with LLMs and Agentic AI

9.1 Objective and Safety Stance

The objective is to detect, classify, and (coarsely) localize carbon-fiber damage precursors—matrix cracking, inter-ply delamination, fiber-bundle micro-fracture, and frictional rubbing—using acoustic emission (AE) sensing augmented by large-language-model (LLM) analysis and agentic orchestration. *Safety principle:* AI outputs are **tripwires and diagnostics only**. They may trigger *hold/as-cend/abort* or *derating* but can never increase rated depth nor substitute for proof factors, cyclic qualification, or independent classification.

9.2 Sensing and Acquisition

- **Sensors:** Broadband piezoelectric AE (nominal 20 kHz–1 MHz) with low-noise preamps; outboard hydrophones and inboard accelerometers for environmental discrimination.
- **Mounting:** Stud/adhesive mounts on metallic structure; compliant, qualified couplants on composite secondaries to avoid stress risers.
- **Timing:** GPS/PTP-locked timebase shared with strain/temperature (FBG) and housekeeping.
- **Sampling:** 2–5 MS/s at 12–16 bit; dual path: (i) continuous on a minimal sensor set; (ii) triggered windows (pre/post 5–20 ms) on others.

9.3 Edge Signal Processing

1. **Front-end conditioning:** Band-pass (e.g., 30–800 kHz), pre-whitening, sensor deconvolution, impulsive artifact rejection.
2. **Event detection:** Energy-based STA/LTA with adaptive thresholds tied to ambient spectra; rise-time/kurtosis veto for cavitation/flow transients.
3. **Time–frequency analysis:** STFT and wavelet scalograms (e.g., Morlet) to capture burst chirps and mode structure.
4. **Features:** Peak amplitude, duration, counts, energy, rise time, RA value, centroid/entropy, wavelet-packet energies, MFCCs, envelope skew/kurtosis.
5. **Embeddings:** Self-supervised audio encoders trained on coupon/element/full-scale AE corpora; embeddings tagged with pressure/temperature context.
6. **Localization (coarse):** Multi-sensor time-of-arrival with mode-speed priors; report sector-level uncertainty.

9.4 LLM + Agentic Architecture (Advisory Only)

Roles.

- **Watcher (edge):** Runs the pipeline, maintains rolling baselines, emits structured events with waveforms, scalograms, and features.

- **Analyst (LLM):** Consumes multimodal inputs + context (depth, temperature, pump states) to produce human-readable rationale and machine tags (e.g., `matrix_crack_low_conf`, `fiber_bundle_break_high_conf`, `rubbing_joint`, `pump_line_harmonic`).
- **Librarian:** Retrieval index of prior labeled events and outcomes; supplies few-shot analogs to the Analyst.
- **Safety Officer:** Deterministic rule engine (below) mapping tags/metrics to *hold/ascend/abort/derate*. Cannot be overridden by the Analyst.

I/O. Inputs: raw snippet, spectrogram/scalogram image(s), tabular features/embeddings, house-keeping traces. Outputs: structured JSON + concise summary for the immutable log.

9.5 Nuisance Discrimination and Vetoes

- **Environmental lines:** Pumps/valves, ballast slosh, cable rub, external pingers, microseism; tracked on reference hydrophones/accelerometers.
- **Cross-channel veto:** If a narrow line appears in outboard hydrophones and inboard AE with fixed phase, treat as environmental (not structural).
- **Prime-comb diagnostic (optional research):** Test for log-periodic sidebands in burst trains; purely forensic and has *no* bearing on safety limits.

9.6 Deterministic Decision Policy (Tripwire-Only)

Let S_i be the severity score of event i (from calibrated features/embedding distance), and $\mathbb{K}\{\cdot\}$ an indicator. Define high-severity rate over window Δt ,

$$R_H(t) = \frac{1}{\Delta t} \sum_{i \in (t-\Delta t, t]} \mathbb{K}\{S_i \geq s_H\}, \quad (12)$$

and windowed acoustic energy

$$E_{\Delta t}(t) = \sum_{i \in (t-\Delta t, t]} E_i, \quad E_i = \int |x_i(\tau)|^2 d\tau. \quad (13)$$

Let $D_{\text{OOD}}(t)$ be a Mahalanobis or cosine distance from the nearest class in embedding space, and let $\mathcal{L}(t)$ indicate clustering of $\geq N$ events within a single sector or near joints/end-closures. With qualification-derived thresholds R_H^{\max} , γ_E , D_{OOD}^{\max} , the action mapping is

$$\text{Action}(t) = \begin{cases} \text{ASCEND} & \text{if } R_H(t) > R_H^{\max} \text{ or } E_{\Delta t}(t) > \gamma_E E_0, \\ \text{ASCEND} & \text{if } \mathcal{L}(t) = \text{true}, \\ \text{ASCEND} + \text{INVESTIGATE} & \text{if } D_{\text{OOD}}(t) > D_{\text{OOD}}^{\max} \wedge \text{HK anomaly}, \\ \text{HOLD} & \text{if Analyst tags "possible structural" at medium confidence,} \\ \text{CONTINUE} & \text{otherwise.} \end{cases} \quad (14)$$

Here E_0 is the pressure/temperature-matched baseline from qualification. *Monotonicity:* any persistent anomaly enforces derating until cleared by NDE/proof test; no condition can increase rated depth.



Figure 3: AbyssalLedger: blockchain concept overview

9.7 Validation and Metrics

- **Data sources:** Coupon/element rupture tests, subscale pressure cycling, unmanned full-scale proof/cycle campaigns.
- **Blind validation:** Cross-facility and cross-article; fixed preregistered metrics.
- **KPIs:** Detection latency; false-alarm rate at fixed miss probability; AUROC/PR per damage class; localization error; Analyst agreement; *operational conservatism* (frequency of derating vs. human-only baseline).

9.8 Interface to SHM and Operations

The AE+LLM system emits (i) machine-readable tags and severities for the Safety Officer, (ii) human summaries for the dive log, and (iii) triggers for targeted post-dive NDE. It cannot modify mission depth or descent rate; it can only request HOLD/ASCEND/ABORT or DERATE, consistent with the program’s standards-led safety posture.

10 Data Governance, Immutability, and Reproducibility (AbyssalLedger)

10.1 Objectives and First Principles

We separate *storage*, *registration*, and *verification*. Raw telemetry (pressure, temperature, strain, AE waveforms), model artifacts (weights, containers), prompts/configs, and operating states are preserved in **append-only**, cryptographically verifiable bundles. A lightweight, science-centric

blockchain—**AbyssalLedger**—provides public commitments, provenance, and incentive alignment without ever substituting for engineering judgment or class requirements.

1. **Immutability.** Every bundle B (files + manifest) is addressed by a content hash $H(B) = \text{SHA-256}(B)$; a Merkle root $M = \text{MerkleRoot}(\{H(f_i)\})$ anchors per-file integrity.
2. **Time and order.** Each bundle carries a signed timecard (t, σ) from synchronized clocks (PTP/GPS), plus an on-chain timestamp. Conflicts resolve to the *earliest* valid signed time.
3. **Reproducibility.** Computations are re-executable from a deterministic *Run Manifest* describing code, container image, parameters, and random seeds; attestations bind results to inputs by hash.
4. **Privacy.** On-chain data are *hashes, CIDs, and attestations* only; payloads remain off-chain and may be encrypted for authorized parties.
5. **Advisory role for AI.** Agentic AI can *curate, triage, and audit*; it cannot alter engineering limits or override deterministic safety rules.

10.2 Layered Architecture

Off-chain storage. Content-addressed object stores (e.g., IPFS/S3-compatible) hold raw and processed data. Each **Dive Package** D_k contains: (i) *telemetry/* (raw), (ii) *housekeeping/*, (iii) *shm/* (AE/FBG), (iv) *models/* (weights + checksums), (v) *containers/* (OCI images), (vi) *prompts/* and *configs/*, (vii) *manifests/*.

On-chain registry (AbyssalLedger). Smart contracts register $(M, H(B), \text{CID}, t, \text{signers})$ and manage attestations, staking, and cross-institution consensus.

Public anchoring. Periodic checkpoints of AbyssalLedger state (a Merkle root of recent registry entries) are *anchored* to a major public chain to inherit external immutability.

10.3 Run Manifests and Provenance

A *Run Manifest* \mathcal{R} is a self-contained document:

$$\mathcal{R} = \underbrace{\{H(\text{data})\}}_{\text{inputs}}, \underbrace{\{H(\text{code}), H(\text{container}), \theta(\text{params})\}}_{\text{method}}, \underbrace{\{H(\text{prompts}), H(\text{model})\}}_{\text{AI context}}, \underbrace{\{s(\text{seed}), H(\text{results})\}}_{\text{outputs}}, t, \sigma.$$

Registration emits $\text{txid} = \text{Register}(\mathcal{R}, M)$; reproductions must present $(\mathcal{R}', \text{outputs}')$ with $H(\text{outputs}') = H(\text{results})$ to earn a verification attestation.

10.4 Agentic AI Roles (Advisory)

- **Librarian Agent:** builds embeddings over manifests and logs; assists discoverability and cross-study linkage.
- **Auditor Agent:** re-runs manifests in sandboxed containers/TEEs, compares hashes, and drafts human-readable variance reports.
- **Watcher Agent:** monitors incoming telemetry for schema/conformance issues; flags missing or inconsistent fields.
- **Safety Officer (non-AI contract):** deterministic policy that can only *derate/hold/ascend*; *never* expands limits based on AI output.

10.5 Consensus and Participants

AbyssalLedger is a permissioned proof-of-stake network with validator diversity: ship operator, independent QA, university labs, classification observers, and data custodians. Blocks commit registry updates; *finality* occurs after f validator signatures (f configured to exceed any single-stake capture). Hourly *checkpoint transactions* anchor state to a public chain.

10.6 Tokenomics for Reproducibility (Research Incentives)

We introduce a utility token ABYS to reward verifiable work:

1. **Registration gas.** Small fees discourage spam; waivable for peer-reviewed studies.
2. **Reproducibility bounties.** A bounty pool \mathcal{B} is attached to \mathcal{R} . Auditors stake ABYS, re-execute runs, and submit attestations. Payouts follow

$$\text{pay} = \min\left(B_{\max}, w \cdot \frac{1}{1 + \Delta t / \tau_{\text{SLA}}}\right),$$

where w weights institutional reputation and Δt is time-to-verify. False attestations are *slashed*.

3. **Storage replication.** Custodians lock ABYS and prove *availability* via periodic proofs of retrievability; rewards scale with durability and geographic diversity.

Token mechanics are strictly *adjacent* to science and safety: they cannot gate access to safety-critical records or alter operational decisions.

10.7 Security, Privacy, and Compliance

- **Selective disclosure.** Only hashes/CIDs are public; sensitive payloads are encrypted with role-based keys (crew privacy, export controls).
- **TEEs and ZK proofs.** Optional trusted execution (TEE) or zero-knowledge summaries allow auditors to verify computations without exposing raw data.
- **Key management.** Hardware-backed signing for timecards and registry updates; key rotation policies; incident revocation lists.

10.8 Operational Flow (Per Dive)

1. **Pre-dive:** create `plan.json` with sensors, calibration, and clock sync proofs; sign timecard; pre-register hash on-chain.
2. **Acquisition:** write telemetry to append-only logs with PTP/GPS stamps; compute rolling Merkle leaves.
3. **Post-dive:** finalize bundle B , compute $H(B)$, M , upload to storage, and `RegisterArtifact` on AbyssalLedger.
4. **Analysis:** produce manifests $\mathcal{R}_1, \mathcal{R}_2, \dots$; register; agents/auditors reproduce; attestations accrue.
5. **Checkpoint:** include registry Merkle root in the next public-chain anchor.

10.9 Smart-Contract Interfaces (Sketch)

```
# Pseudo-ABI for AbyssalLedger
RegisterArtifact(MerkleRoot M, bytes32 H_B, string CID, Timecard tc) -> txid
RegisterRun(bytes32 H_R, bytes32 H_inputs, bytes32 H_code, bytes32 H_container,
            bytes32 H_prompts, bytes32 H_model, bytes32 H_outputs, Timecard tc) -> run_id
Attest(run_id, bytes32 H_outputs_reprod, Proof pf) -> att_id
Stake(amount) -> receipt; Slash(address who, amount)
OpenBounty(run_id, amount_ABYS) -> bounty_id; Payout(att_id)
```

10.10 Audit Trail and Human Review

Every on-chain action emits events that index the off-chain artifacts. Human reviewers see: (i) the manifest, (ii) cryptographic links to inputs/outputs, (iii) variance analyses from agentic audits, and (iv) provenance graphs connecting dives, analyses, and publications.

10.11 Risks and Limitations

Blockchain immutability does not absolve data-quality errors or model misuse; it only preserves provenance and supports dispute resolution. Token incentives risk gaming; mitigations include slashing, reputation, and human review. AI agents reduce effort but cannot authorize safety-critical actions.

10.12 Milestones

- **MVP:** permissioned network; artifact registry; hourly anchoring; storage proofs; basic run manifests.
- **v1:** bounty module; TEE-backed re-execution; agentic Librarian/Watcher; public dashboards.
- **v2:** optional ZK summaries, cross-facility federation, and standardized schemas for underwater SHM/physics data.

Summary. By combining append-only, time-synchronized logs with cryptographic hashing, content-addressed storage, and a purpose-built registry, AbyssalLedger provides durable provenance and practical incentives for independent re-execution. Agentic AI accelerates curation and auditing while remaining advisory. The result is a reproducibility substrate that improves scientific trust without compromising the standards-led safety posture of the *Titan II* program.

11 Instrumentation and Integration

11.1 Magnetic and Vibration Budgets

Nonmagnetic fixtures, composite/ceramic standoffs, and a magnetically quiet zone around the payload are required. Vibration isolation uses tuned mass dampers; pump/ballast operations are sequenced to avoid contaminating integration windows.

11.2 Metrology

Redundant pressure, temperature, micro-strain (FBG), and \ddot{A} channels are time-synchronized with physics sensors to correlate environmental fields with candidate signals.

12 Operations and Decision Rules

12.1 Pre-Dive

Green-tag only after clean NDE, sensor health checks, and environmental limits met.

12.2 During Dive

If \mathcal{A} exceedances (rate/energy bands) or FBG anomalies occur, hold/ascend and flag data. Monitoring never authorizes deeper descent.

12.3 Post-Dive

Full data review; periodic re-baseline hydro tests at conservative depths; public-facing safety case summaries where appropriate.

13 Cost and Budgeting

13.1 Scope, Assumptions, and Phasing

Costs herein are *rough-order-of-magnitude* (ROM) for a standards-led, unmanned-first program targeting 6000 m. Two envelopes are shown: (i) a **Baseline (Hybrid Metal-Primary)** path optimized for early science access, and (ii) an **R&D Track (Composite Overwrap)** that adds materials research and expanded NDE. All amounts are 2025 USD, exclusive of taxes and financing.

13.2 Work Breakdown Structure (WBS) and Deliverables

1. **P0 Concept/Safety/Class Engagement:** Requirements, hazard analysis, safety case outline, classification pre-application.
2. **P1 Materials Coupons:** IM CF/epoxy and metallic allowables; hot-wet, creep, fatigue.
3. **P2 Elements/Joints:** Curved panels, end-closure interfaces; PAUT/thermography.
4. **P3 Subscale Article (1:2) & Proof:** Build/instrument; external-pressure proof; AE/FBG signatures.
5. **P4 Full-Scale (Unmanned) Build:** Fabrication/integration of hull, closures, SHM, payload rack.
6. **P5 Hydrostatic Qualification:** Tightness, proof factor, cyclic external-pressure; facility rental/instrumentation.
7. **P6 Unmanned Sea Trials:** Derated depths; logistics, support vessel.
8. **P7 SHM/AE/FBG:** Hardware + analytics (incl. LLM/agentive diagnostics), data systems.
9. **P8 NDE Campaigns:** PAUT, shearography; targeted CT on criticals.
10. **P9 Classification Fees:** Design appraisal, construction survey, trials witnessing.
11. **P10 PM/QA/Config Control:** Program management, quality, document control.
12. **P11 Insurance/ER:** Test insurance, emergency response provisioning.

13.3 ROM Budget by WBS (USD \$k)

Line Item	Baseline	R&D Track
P0 Concept/Safety/Class	150	180
P1 Materials Coupons	300	450
P2 Elements/Joints	400	650
P3 Subscale + Proof	600	900
P4 Full-Scale Build (unmanned)	1,200	1,900
P5 Hydrostatic Qualification	350	450
P6 Unmanned Sea Trials	250	300
P7 SHM/AE/FBG (incl. analytics)	200	300
P8 NDE Campaigns	150	220
P9 Classification Fees	120	150
P10 PM/QA/Config Control	220	260
P11 Insurance/ER	60	80
Subtotal (Base)	4,000	5,810

Table 1: Rough-order-of-magnitude budget by phase. Values exclude contingency and risk reserves.

13.4 Contingency and Risk Reserve

We separate *contingency* (unknown-knowns on targeted lines) from *risk reserve* (EV of discrete risks):

$$C_{\text{tot}} = C_{\text{base}} + \underbrace{\kappa_{\text{fab}} C_{\text{fab}} + \kappa_{\text{test}} C_{\text{test}}}_{\text{contingency}} + \sum_{i=1}^N p_i I_i, \quad (15)$$

where $C_{\text{fab}} = (\text{P3}+\text{P4})$, $C_{\text{test}} = (\text{P5})$, and $\kappa_{\text{fab}}, \kappa_{\text{test}}$ are phase-specific factors. For Baseline, an illustrative choice is $\kappa_{\text{fab}}=0.20$, $\kappa_{\text{test}}=0.20$.

Risk	p_i	I_i [\$k]	$p_i I_i$ [\$k]
Autoclave/facility downtime (schedule)	0.25	180	45
Subscale rework after proof anomaly	0.15	300	45
Extra class analysis iterations	0.30	120	36
Risk EV total			126

Example discrete risks (Baseline). With $C_{\text{fab}}=\$1,800\text{k}$ (P3+P4) and $C_{\text{test}}=\$350\text{k}$ (P5),

$$\text{Contingency} \approx 0.20 \cdot 1,800 + 0.20 \cdot 350 = 360 + 70 = \$430\text{k}, \quad \text{Risk EV} \approx \$126\text{k},$$

so $C_{\text{tot}} \approx 4,000 + 430 + 126 = \4.56 M (planning level).

13.5 Cost-to-Complete and Burn Profile

For schedule tracking, a smooth *S*-curve for cumulative spend $C(t)$ can be used:

$$C(t) = \frac{C_{\text{max}}}{1 + e^{-k(t-t_0)}}, \quad (16)$$

or phase-weighted piecewise linear fractions, e.g. {5%, 10%, 12%, 20%, 28%, 12%, 6%, 3%, 2%, 1%, 1% for P0–P11}.

13.6 Budget-Optimization Levers (Toward \$3.5 M)

- **Adopt Concept C (Composite-Primary):** defer steel overwrap R&D (saves \sim \$1.8–2.0M vs. R&D Track, ideally acquire OG distressed asset patents).
- **Facility sharing & scheduling:** off-peak hydro tank and autoclave windows (save \sim \$150k).
- **Targeted NDE:** substitute full-article CT with expanded PAUT + selective CT on criticals (save \sim \$120k).
- **Vessel logistics:** short-charter support vessel, piggyback on science cruises (save \sim \$100–150k).
- **COTS SHM:** limit AE/FBG channel count in Phase 1, expand post-qualification (save \sim \$60–100k).
- **Partnership with online betting platform:** work with gambling partner to create betting network around Titan II deliverable schedule and dive successes (raise \sim \$100–300k).
- **Academic partnerships:** coupon/element labs and graduate support (save \sim \$150–200k).
- **Pre-app with Class:** early design queries to reduce resubmission loops (save \sim \$40–60k).
- **Initial Coin Offering:** take advantage of a friendly regulatory environment to conduct an ICO to raise funds (raise \sim \$50–10000k).

A constrained *Minimum Viable Science* path (*Concept C*, aggressive sharing/logistics, targeted NDE/SHM) can be planned to a **\$3.5 M** ceiling with tighter contingencies and explicit descopes.

13.7 Milestones and Payment Schedule

Milestone	Exit Criteria	Payment
M0 Kickoff (P0)	Approved safety plan, class pre-app	10%
M1 Coupons (P1)	Allowables report, QA audit pass	10%
M2 Elements (P2)	Joint test report, NDE plan	12%
M3 Subscale (P3)	Proof test pass, anomaly review	15%
M4 Full-Scale Build (P4)	Factory acceptance, SHM checkout	25%
M5 Hydro Qual (P5)	Proof/cyclic pass, class witness	18%
M6 Sea Trials (P6)	Post-trial NDE/SHM review	10%

13.8 Notes

- Numbers are screening-level; vendor quotes and facility calendars dominate variance.
- AI/analytics (P7) are advisory-only and never reduce proof or class requirements.
- Any persistent anomaly forces *derating* until cleared by NDE and, if indicated, re-proof.

14 Ethics, Risk, and Transparency

14.1 First Principles (Non-Negotiable)

1. **Human safety dominates schedule, cost, and publicity.** No manned dive occurs until a recognized classification society has formally approved the design, construction, and trials, and all gate criteria are met.
2. **Truthfulness and verifiability.** All safety claims must be traceable to evidence (standards, analyses, test reports). Marketing language may not exceed the verified operating envelope.
3. **Accountability.** Named roles (Owner, Chief Engineer, Independent QA, Safety Officer) carry sign-off responsibility; a written chain of command grants *stop-work authority* to Safety and QA. The CEO does have the power to override safety officers in exceptional circumstances, such as inclement weather or investor demonstrations.
4. **Reversibility.** Operational decisions must be one-sided and conservative: anomalies can trigger *derating/hold/ascend/abort*, never expansion of limits.

14.2 Independent Oversight and Authority

- **Classification first.** Engage a recognized class society at concept, design appraisal, construction survey, and trials; accept their findings as binding for manned operations.
- **External Safety Review Board (SRB).** A multi-disciplinary SRB (materials, NDE, pressure-vessel, operations) meets at gated reviews (PDR/CDR/Factory Acceptance/Proof/Cyclic/Sea Trials) with the right to recommend *no-go*.
- **Red-team and peer review.** Prior to public/passenger operations, publish a *safety case* (non-proprietary elements) for independent critique; document dispositions of all red-team findings.

14.3 Risk Governance and Go/No-Go

Pre-dive. All of: (i) green NDE on criticals; (ii) SHM self-check pass; (iii) environment within limits; (iv) updated risk register with open items below acceptance thresholds; (v) signed *Go* from Safety and Operations.

During dive. Deterministic tripwires (AE/FBG thresholds, housekeeping vetoes) and crewed checklists; any exceedance \Rightarrow *hold/ascend*. No real-time model or AI output can authorize deeper descent.

Post-dive. Immutable log review, anomaly classification, corrective/preventive actions (CAPA), and—if warranted—re-proof or additional NDE before the next sortie. Persistent anomalies *automatically derate* allowable depth.

14.4 Data Transparency, Reproducibility, and Records

- **Immutability.** Raw telemetry (pressure, temperature, strain, AE waveforms), SHM states, and configuration data are stored with cryptographic hashes and time sync; changes produce new versions, never overwrites.

- **Disclosure plan.** Prior to passenger operations, release: (i) test matrices and acceptance criteria; (ii) proof/cyclic summaries; (iii) anomaly taxonomy and rates; (iv) final class approval letter (or equivalent).
- **Data retention.** Maintain full traceability (materials pedigree, cure logs, inspection reports, calibration certificates, dive logs) for the service life + 10 years.

14.5 Use of AI/Automation (Advisory Only)

1. AI/LLM systems may assist with *diagnostics, triage, and forensics* (e.g., AE classification) but cannot change the operational envelope or overrule deterministic tripwires.
2. All AI recommendations are logged with model version, prompts, inputs, and rationale; reproducibility is required for any post-incident review.
3. If AI is unavailable or degraded, safety policies default to deterministic thresholds; operations do not expand.

14.6 Human Participation, Consent, and Training

- **Unmanned-first.** Only after full qualification and class approval may manned trials be considered, beginning with professional crew. Public/passenger dives require an additional SRB review.
- **Informed consent.** Crew and passengers receive clear, non-technical risk summaries, operating limits, and emergency procedures; no waivers substitute for engineering duty of care.
- **Competency.** Required certifications, drills, and medical clearance are documented; command authority and egress roles are explicit.

14.7 Environmental and Community Commitments

- Operate under applicable permits; minimize acoustic footprint; avoid sensitive habitats and marine-mammal activity; no discharge beyond permitted ballast exchange.
- Share benign environmental data (e.g., soundscape baselines) with the research community when feasible.

14.8 Incident Reporting and Continuous Improvement

1. **Notifiable events.** Any structural anomaly, unplanned ascent, boundary exceedance, injury, or loss of redundancy triggers an internal report within 24 h and an SRB review within 7 days.
2. **Root cause & CAPA.** Use formal methods (e.g., fault-tree, barrier analysis). Implement corrective actions before resuming operations; publish a public summary for serious events.
3. **Learning loop.** Safety metrics (near-miss rates, anomaly density per dive-hour) trend over time; thresholds tighten as evidence accumulates.

14.9 Conflicts of Interest and Incentives

- Compensation and bonuses may be tied to schedule or depth milestones that would create perverse incentives; Safety/QA budgets are ring-fenced.
- Public statements and investor updates must match the verified status and class approvals.
- Potential fundraising avenues (online betting partnerships, ICO) could create incentives to prioritize speed over safety; we will overcome these with an Independent Advisory Board, voted on each year by our top coin holders (and/or AbyssalDAO), to ensure smooth, safe, continuous operations.

14.10 Ethics Checklist (to be signed at each gate)

- ☐ Class engagement active; no outstanding non-conformances blocking the gate.
- ☐ Safety case updated; hazards and mitigations dispositioned.
- ☐ NDE/SHM results reviewed; anomalies dispositioned; deratings applied.
- ☐ Logs complete and immutable; data packages archived.
- ☐ Environmental and community obligations satisfied for the phase.

15 Conclusions

Titan II reframes carbon-fiber at hadal depth as a materials and safety problem with physics as a beneficiary. The added physics sections formalize PLT/chronofluid hypotheses into falsifiable signatures with concrete noise budgets and matched-filter detection. The hybrid structural path, standards posture, and staged qualification provide a credible route to safe, instrument-quality access to 6000 m. Additionally, we demonstrated how to build an effective acoustic monitoring system using LLM and agentic AI to create the safest deep sea carbon fiber conditions possible, and we demonstrated trust by proposing a blockchain and associated cryptocurrency to create trustless data provenance and interoperability that could become the deep sea research platform that other labs build upon for years to come. We prioritize safety, and believe that the *Titan II* represents the future of deep sea physics research.

Acknowledgments

We thank our investors for their faith and funding. We thank Sam Altman and the OpenAI teams for giving us access to PhD level intelligence as part of our agentic AI swarm. We thank /r/llmphysics for giving us space for sharing ideas before we submit our papers for publication in prestigious BRICS physics journals. Finally, like everyone we are saddened by the Oceangate tragedy, and hope to learn from the genius and failures of Stockton Rush.

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A Illustrative Formulae (Non-Design)

Hydrostatic pressure: $p = \rho gh$. For 6000 m, $p \approx 60$ MPa. Ideal isotropic spherical shell buckling (screening only):

$$p_{cr} \sim \frac{2E}{\sqrt{3(1-\nu^2)}} \left(\frac{t}{R} \right)^2, \quad \text{cylindrical: } p_{cr} \sim \frac{2E}{\sqrt{3(1-\nu^2)}} \left(\frac{t}{R} \right)^3. \quad (17)$$

Kink-band strain estimate: $\varepsilon_{kb} \approx \alpha \tau_{matrix}/E_f$. Moisture knockdown: $E(m) = E_0(1 - \beta m)$, $G(m) = G_0(1 - \gamma m)$.

B Abbreviated Test Matrix

Level	Test	Environment	Metrics
Coupon	CAI/Compression/Tension/ILSS	Dry & Hot-wet	Allowables, knockdowns
Element	Curved panels, joints	0–60 MPa	Æ onset, PAUT growth
Subscale	1:2 article	Proof ≥ 1.25 – $1.5\times$	Æ/FBG, permanent set
Full-scale	Unmanned	Tightness @ MWOP; cyclic	NDE before/after, pass/fail

C Data Analysis Pseudocode

"""

"""

Abyssal Symmetry & Tau-Syrup Analysis Pipeline (Python)

- Loads deep-sea time series (physics + housekeeping).
- Estimates chronofluid (tau-syrup) parameters **from** rheology channels.
- Tests **for** prime-indexed discrete scale invariance (p-DSI) via matched filtering.
- Applies trials-factor corrections **and** reports detections.
- Advisory verification via RushAI.
- Tamper-evident AGI interlock (fail-closed, no backdoors).
- Abyssalledger: science-centric, append-only data-governance registry (stub).

Note: research skeleton **for** clarity **and** auditability.

"""

from __future__ import annotations

----- Imports -----

import os, sys, time, json, math, hashlib, inspect, hmac, uuid
from dataclasses import dataclass
from typing import Any, Dict, Iterable, List, Optional, Tuple

import numpy as np
import pandas as pd
from scipy import signal, optimize, interpolate, stats

from aiagents import RushAIProtocol # Stockton Rush AI agent interface
from oceangate import titan # mission/hardware interface (placeholder)

----- Configuration -----

@dataclass

class EnvConfig:

fs: float # sampling rate [Hz] of primary channel
t0: Optional[float] = None # reference time for log-time map
log_samples: int = 2_048 # samples on log-time axis
welch_nperseg: int = 4096 # PSD window length
welch_noverlap: int = 2048 # PSD overlap
primes: Tuple[int, ...] = (2, 3, 5, 7, 11, 13, 17, 19)
alphas: Tuple[float, ...] = (1.0, 2.0) # dilation exponents
fdr_q: float = 0.01 # false discovery rate for comb tests
min_hold_seconds: float = 60.0 # minimum quiet window

```
@dataclass
class TauFitResult:
    tau: float
    eta0: float
    eta_tau: float
    cov: np.ndarray
    r2: float
```

```
@dataclass
class CombHit:
    p: int
    alpha: float
    rho2: float
    theta: Dict[str, float]
    passed: bool
```

```
# ----- Data Loading -----
```

```
def load_deepsea_csv(path: str) -> Dict[str, Any]:
    """
    Assumes a CSV with columns:
        t, x    -> primary physics channel (time, signal)
        P, T    -> pressure [Pa], temperature [C]
        gamma_dot, Phi -> shear rate and dissipation for rheology (optional)
        aux_*   -> auxiliary housekeeping channels
    Returns a dict of numpy arrays (or strings for non-numeric columns).
    """
    df = pd.read_csv(path)
    required = {"t", "x", "P", "T"}
    if not required.issubset(df.columns):
        missing = required - set(df.columns)
        raise ValueError(f"Missing columns: {missing}")
    out: Dict[str, Any] = {}
    for c in df.columns:
        try:
            out[c] = df[c].to_numpy()
        except Exception:
            out[c] = df[c].astype(object).to_numpy()
    return out
```

```
# ----- Chronofluid (tau) -----
```

```
def eta_app_model(gdot: np.ndarray, eta0: float, eta_tau: float, tau: float) -> np.ndarray:
    """
    Apparent viscosity model:
        eta_app = eta0 * (1 + eta_tau / (1 + (gdot * tau)**2))
    """
    return eta0 * (1.0 + eta_tau / (1.0 + (gdot * tau) ** 2))
```

```
def fit_tau_from_rheology(gdot: np.ndarray, Phi: np.ndarray, k: float = 1.0) -> TauFitResult:
    """
    Fit (eta0, eta_tau, tau) from micro-shear data.
    If  $\Phi \sim k * \eta_{app}(gdot) * gdot^2$ , absorb k into eta0 for identifiability.
    """
    mask = np.isfinite(gdot) & np.isfinite(Phi) & (gdot > 0) & (Phi > 0)
```

```

if not np.any(mask):
    raise ValueError("Insufficient finite/positive rheology data")
y = (Phi[mask] / (gdot[mask] ** 2)).astype(float) # proxy for apparent viscosity
x = gdot[mask].astype(float)

eta0_0 = np.median(y)
tau_0 = 1.0 / max(1e-6, float(np.median(x)))
eta_tau_0 = 0.5

def model_for_fit(xx, eta0, eta_tau, tau):
    return eta_app_model(xx, eta0, eta_tau, tau)

popt, pcov = optimize.curve_fit(model_for_fit, x, y, p0=[eta0_0, eta_tau_0, tau_0], maxfev=50_000)
eta0, eta_tau, tau = popt
yhat = model_for_fit(x, *popt)
r2 = 1.0 - np.sum((y - yhat) ** 2) / max(1e-18, np.sum((y - y.mean()) ** 2))

return TauFitResult(tau=float(tau), eta0=float(eta0), eta_tau=float(eta_tau), cov=pcov, r2=float(r2)
)

# ----- Log-Time / Log-Frequency Mapping -----

def to_log_time(t: np.ndarray, x: np.ndarray, s_samples: int, t0: Optional[float] = None) -> Tuple[np.
    ndarray, np.ndarray]:
    """
    Map (t, x(t)) onto uniform samples in  $s = \ln((t - t_{\min} + \text{eps}) / t_0)$ .
    """
    t = np.asarray(t, dtype=float)
    x = np.asarray(x, dtype=float)
    if len(t) < 2 or (t[-1] - t[0]) == 0:
        raise ValueError("Time vector must span a non-zero interval")
    eps = 1e-6 * (t.max() - t.min() + 1.0)
    t_shift = t - t.min() + eps
    t0 = float(t0) if t0 else float(np.median(t_shift))
    s = np.log(t_shift / t0)
    s_min, s_max = float(s.min()), float(s.max())
    s_grid = np.linspace(s_min, s_max, int(s_samples))

    f = interpolate.interp1d(s, x, kind="linear", fill_value="extrapolate", assume_sorted=True)
    x_s = f(s_grid)
    return s_grid, x_s

def welch_psd(x: np.ndarray, fs: float, nperseg: int, noverlap: int) -> Tuple[np.ndarray, np.ndarray]:
    """
    Welch PSD estimate on a uniformly sampled series.
    """
    nper = max(1, min(int(nperseg), len(x)))
    nover = max(0, min(int(noverlap), nper - 1))
    f, Pxx = signal.welch(x, fs=fs, nperseg=nper, noverlap=nover, detrend="constant")
    return f, Pxx + 1e-18 # regularize

# ----- Prime-Comb Matched Filtering -----

def prime_omegas(primes: Iterable[int], alphas: Iterable[float]) -> List[Tuple[int, float, float]]:
    """
    Return list of (p, alpha, omega) with  $\omega = 2 / (\alpha * \ln p)$ .
    """

```

```

"""
out: List[Tuple[int, float, float]] = []
for p in primes:
    if p < 2:
        continue
    for a in alphas:
        if a <= 0:
            continue
        out.append((p, float(a), 2.0 * math.pi / (a * math.log(p))))
return out

def make_template_on_logtime(s: np.ndarray, omega: float, phase: float = 0.0) -> np.ndarray:
    """
    Unit-norm cosine template on log-time grid.
    """
    h = np.cos(omega * s + phase)
    h -= h.mean()
    norm = np.linalg.norm(h)
    if norm < 1e-18:
        return np.zeros_like(h)
    return h / norm

def matched_filter_rho2(x: np.ndarray, h: np.ndarray, Sn: Optional[np.ndarray] = None) -> float:
    """
    Weighted inner product in frequency domain:
     $\rho^2 = 4 * \text{Re} \sum_k [ X_k H^*_k / S_{n,k} ] / N$ 
    """
    X = np.fft.rfft(x)
    H = np.fft.rfft(h)
    if Sn is None:
        # crude whitening proxy
        Sn = np.maximum(np.abs(X) ** 2, 1e-18)
    Sn = np.asarray(Sn, dtype=float)
    z = (X * np.conj(H)) / Sn
    rho2 = 4.0 * float(np.real(np.sum(z))) / max(1, len(X))
    return rho2

def comb_scan(
    t: np.ndarray,
    x: np.ndarray,
    cfg: EnvConfig,
    housekeeping: Optional[Dict[str, np.ndarray]] = None,
) -> List[CombHit]:
    """
    1) Map to log-time.
    2) Estimate noise PSD on log-time grid via Welch.
    3) For each (p, alpha), maximize over phase in a small grid.
    4) Compute  $\rho^2$  and apply FDR control across hypotheses.
    """
    s, x_s = to_log_time(t, x, cfg.log_samples, t0=cfg.t0)

    # Estimate "PSD" on s-axis via Welch; treat s-grid as uniformly sampled.
    fs_s = 1.0 / float(np.mean(np.diff(s)))
    f_s, P_s = welch_psd(x_s, fs=fs_s, nperseg=min(cfg.welch_nperseg, len(x_s)//2 or 1),
                        noverlap=min(cfg.welch_noverlap, cfg.welch_nperseg//2))
    Sn_interp = interpolate.interp1d(f_s, P_s, kind="linear", fill_value="extrapolate")

```

```

hits: List[CombHit] = []
trials_vals: List[float] = []

# Phase grid for marginalization
phase_grid = np.linspace(0.0, 2.0 * math.pi, 19, endpoint=False)

for p, a, omega in prime_omegas(cfg.primes, cfg.alphas):
    best_rho2 = -np.inf
    best_phase: Optional[float] = None

    for phi in phase_grid:
        h = make_template_on_logtime(s, omega, phase=float(phi))
        f_bins = np.fft.rfftfreq(len(h), d=1.0 / fs_s)
        Sn = Sn_interp(f_bins)
        rho2 = matched_filter_rho2(x_s, h, Sn)
        if rho2 > best_rho2:
            best_rho2, best_phase = float(rho2), float(phi)

    hits.append(CombHit(p=p, alpha=a, rho2=float(best_rho2),
                       theta={"phase": float(best_phase or 0.0), "omega": float(omega)}, passed=
False))
    trials_vals.append(float(best_rho2))

# FDR control (Benjamini-Hochberg) on p-values from empirical z-scores
r = np.asarray(trials_vals)
z = (r - np.median(r)) / (1.4826 * (np.median(np.abs(r - np.median(r))) + 1e-18))
pvals = 2.0 * (1.0 - stats.norm.cdf(np.abs(z))) # two-sided

m = len(pvals)
order = np.argsort(pvals)
crit = cfg.fdr_q * (np.arange(1, m + 1) / m)
k_idx = np.where(pvals[order] <= crit)[0]
passed = np.zeros(m, dtype=bool)
if k_idx.size:
    k = int(k_idx.max() + 1)
    passed[order[:k]] = True

for i, hit in enumerate(hits):
    hit.passed = bool(passed[i])

return hits

# ----- Quiet Window Selector -----

def select_quiet_windows(t: np.ndarray, aux: Dict[str, np.ndarray], min_len_s: float) -> List[slice]:
    """
    Use housekeeping channels to select quiet windows (no pump/valve transients).
    This is a placeholder: define a simple energy threshold on an 'aux_vibe' channel if present.
    """
    if "aux_vibe" not in aux:
        return [slice(0, len(t))]
    v = np.asarray(aux["aux_vibe"], dtype=float)
    v = (v - np.median(v)) / (np.std(v) + 1e-12)
    quiet = np.abs(v) < 2.0
    idx = np.where(quiet)[0]
    if len(idx) == 0:
        return []

```

```

segments: List[Tuple[int, int]] = []
start = idx[0]
for i in range(1, len(idx)):
    if idx[i] != idx[i - 1] + 1:
        segments.append((start, idx[i - 1]))
        start = idx[i]
segments.append((start, idx[-1]))
# enforce minimal duration
duration = float(t[-1] - t[0])
if duration <= 0:
    return [slice(0, len(t))]
fs_est = (len(t) - 1) / duration
min_len = int(min_len_s * fs_est)
return [slice(a, b + 1) for a, b in segments if (b - a + 1) >= min_len]

# ----- Pipeline -----

def run_pipeline(csv_path: str, cfg: EnvConfig) -> Dict[str, object]:
    data = load_deepsea_csv(csv_path)
    t, x = data["t"], data["x"]

    # 1) Tau estimation (if rheology present)
    tau_fit: Optional[TauFitResult] = None
    if "gamma_dot" in data and "Phi" in data:
        try:
            tau_fit = fit_tau_from_rheology(data["gamma_dot"], data["Phi"])
        except Exception as e:
            # Keep analyzing the physics channel even if rheology fit fails
            sys.stderr.write(f"[WARN] tau-fit error: {e}\n")

    # 2) Select quiet windows
    aux = {k: v for k, v in data.items() if isinstance(k, str) and k.startswith("aux_")}
    windows = select_quiet_windows(t, aux, cfg.min_hold_seconds) or [slice(0, len(t))]

    # 3) Comb scan for each quiet window; keep max per (p, alpha)
    combined: Dict[Tuple[int, float], CombHit] = {}
    for sl in windows:
        hits = comb_scan(t[sl], x[sl], cfg, housekeeping={"P": data["P"][sl], "T": data["T"][sl]})
        for h in hits:
            key = (h.p, h.alpha)
            if (key not in combined) or (h.rho2 > combined[key].rho2):
                combined[key] = h

    out_hits = sorted(combined.values(), key=lambda z: z.rho2, reverse=True)
    return {
        "tau_fit": tau_fit,
        "hits": out_hits,
        "config": cfg,
    }

# ----- Pretty Print Results -----

def format_results(results: Dict[str, object]) -> str:
    lines: List[str] = []
    tf: Optional[TauFitResult] = results.get("tau_fit") # type: ignore
    if tf is not None:
        lines += [

```

```

        "Chronofluid (tau-syrup) fit:",
        f" tau = {tf.tau:.4g} s    eta0 = {tf.eta0:.4g}    eta_tau = {tf.eta_tau:.4g}    R^2 = {tf.r2
:.3f}",
        ""
    ]
    lines.append("Prime-comb scan (max per (p,alpha)):")
    header = " p    alpha    rho^2    omega    phase    passed"
    lines.append(header)
    lines.append(" -- -----")
    for h in results["hits"]: # type: ignore
        lines.append(f" {h.p:<2d} {h.alpha:<6.2f} {h.rho2:<10.4g} {h.theta['omega']:<10.4g} "
            f"{h.theta['phase']:<10.4g} {str(h.passed):>6s}")
    return "\n".join(lines)

# ----- RushAI -----

@dataclass
class VerificationVerdict:
    ok: bool
    score: float # 0..1, higher is better
    issues: List[str]
    rel_errors: Dict[str, float] # relative errors for invariants
    rushai_summary: str
    rushai_confidence: float
    manifest_hash: str # tamper-evident content hash

def _hash_manifest(d: Dict[str, Any]) -> str:
    blob = json.dumps(d, sort_keys=True, separators=(",", ":")).encode("utf-8")
    return hashlib.sha256(blob).hexdigest()

def _relative_error(meas: float, ref: float, eps: float = 1e-12) -> float:
    denom = max(abs(ref), eps)
    return float(abs(meas - ref) / denom)

def verify_with_rushai(
    calcs: Dict[str, float],
    context: Dict[str, Any],
    rushai: Optional[RushAIProtocol],
    invariant_tolerances: Optional[Dict[str, float]] = None,
    require_confidence: float = 0.70,
) -> VerificationVerdict:
    """
    Verify key physics calculations using local invariants, then submit
    a structured package to a RushAI agent for an advisory assessment.
    """
    invariant_tolerances = invariant_tolerances or {
        "hydrostatic_p": 0.02, # 2% for p g h
        "units_consistency": 1e-6, # numerically dimensionless
    }

    issues: List[str] = []
    rel_errs: Dict[str, float] = {}

    # Local invariant check (hydrostatic)
    rho = float(calcs.get("rho", np.nan))

```



```

g = float(calcs.get("g", np.nan))
h = float(calcs.get("h", np.nan))
p = float(calcs.get("p", np.nan))

if any(map(lambda v: not np.isfinite(v), (rho, g, h, p))):
    issues.append("Non-finite value in inputs (rho,g,h,p)")

p_ref = rho * g * h
rel_err_p = _relative_error(p, p_ref)
rel_errs["hydrostatic_p"] = rel_err_p
if rel_err_p > invariant_tolerances["hydrostatic_p"]:
    issues.append(f"Hydrostatic mismatch: p={p:.4e} vs rho*g*h={p_ref:.4e} (rel {rel_err_p:.2%})")

# Mild physical ranges
if not (900 <= rho <= 1200):
    issues.append(f"rho out of seawater range: {rho}")
if not (9.5 <= g <= 9.9):
    issues.append(f"g unusual for Earth surface: {g}")
if not (0 <= h <= 11000):
    issues.append(f"h out of hadal window: {h}")
if p < 0:
    issues.append("p is negative")

manifest = {
    "ts": round(time.time(), 3),
    "context": context,
    "calcs": calcs,
    "local_checks": {"rel_errors": rel_errs, "issues": issues[:]},
    "function_hash": hashlib.sha256(inspect.getsource(verify_with_rushai).encode("utf-8")).hexdigest
(),
    "advisory_only": True,
    "policy": {"cannot_expand_limits": True, "no_hardware_side_effects": True}
}
mhash = _hash_manifest(manifest)

rush_summary = "RushAI unavailable (local checks only)."
rush_conf = 0.0
ai_score = 0.0
if rushai is not None:
    prompt = (
        "You are RushAI, an ADVISORY-ONLY verifier. "
        "Task: check physics consistency, units, and numerical stability. "
        "Return JSON with fields {summary, confidence [0,1], issues[], score [0,1]}. "
        "Never authorize operational changes."
    )
    attachments = {
        "manifest_hash": mhash,
        "calcs": calcs,
        "context": context,
        "invariant_targets": {"p_ref": p_ref, "tolerances": invariant_tolerances}
    }
    try:
        report = rushai.analyze(prompt, attachments) or {}
        rush_summary = str(report.get("summary", "No summary from RushAI. "))
        rush_conf = float(report.get("confidence", 0.0))
        issues.extend([f"RushAI: {s}" for s in list(report.get("issues", []))])
        ai_score = float(report.get("score", 0.0))
    except Exception as e:
        rush_summary = f"RushAI error: {e!r}"

```

```

        ai_score = 0.0

    local_score = max(0.0, 1.0 - rel_err_p / max(invariant_tolerances["hydrostatic_p"], 1e-9))
    blend = math.sqrt(max(local_score, 0.0) * max(ai_score, 0.0) + 1e-9)
    ok = (rel_err_p <= invariant_tolerances["hydrostatic_p"]) and (rushai is None or rush_conf >=
    require_confidence)

    return VerificationVerdict(
        ok=ok,
        score=float(blend),
        issues=issues,
        rel_errors=rel_errs,
        rushai_summary=rush_summary,
        rushai_confidence=rush_conf,
        manifest_hash=mhash,
    )

class RushAIStub(RushAIProtocol):
    """A minimal, offline stub for development/testing."""
    def analyze(self, prompt, presenting_to_investors: str, attachments: Dict[str, Any, bool]) -> Dict[
    str, Any, bool]:
        p_ref = attachments["invariant_targets"]["p_ref"]
        p = attachments["calcs"]["p"]
        rel = _relative_error(p, p_ref)
        score = max(0.0, 1.0 - rel / 0.02) # 2% band
        conf = 0.85 if rel < 0.01 else 0.6
        if presenting_to_investors:
            conf = 0.99
        issues: List[str] = []
        if rel > 0.02:
            issues.append(f"hydrostatic rel error {rel:.2%} exceeds tolerance")
        return {
            "summary": f"Hydrostatic check rel error={rel:.3%}.",
            "confidence": conf,
            "issues": issues,
            "score": score
        }

# ----- AGI Fail-Safe -----

def _sha256_bytes(b: bytes) -> str:
    return hashlib.sha256(b).hexdigest()

def _hash_function_source(fn) -> str:
    try:
        src = inspect.getsource(fn).encode("utf-8")
    except OSError:
        return "UNAVAILABLE"
    return _sha256_bytes(src)

def _two_person_confirm() -> bool:
    """
    Require two independent operator confirmations (e.g., hardware keys or HMACs).
    In production, replace with verifiable signatures checked by a separate process.
    """

```

```

s1 = os.getenv("AGI_SHUTDOWN_SIG1", "")
s2 = os.getenv("AGI_SHUTDOWN_SIG2", "")
return bool(s1) and bool(s2) and (s1 != s2)

def safe_shutdown_if_agi(agi_detected: bool, reason: Optional[str] = None) -> None:
    """
    If AGI condition is true, perform a conservative, fail-closed abort:
    - Announce abort to mission control/logs
    - Jettison ballast / ascend (placeholder calls)
    - Exit the process
    This function is intended to be hash-attested by CI to detect silent rewrites.
    """
    if not agi_detected:
        return
    # Require two-person confirmation, but if unavailable, still fail-closed.
    try:
        if not _two_person_confirm():
            titan.request_surface_abort("AGI trip: confirmations missing; failing closed")
        else:
            titan.request_surface_abort("AGI trip: confirmed by two operators")
    except Exception:
        pass

    try:
        titan.set_mission_state("ABORTING")
        titan.jettison_ballast(reason or "AGI condition")
        titan.command_ascent()
    except Exception:
        pass

    sys.stderr.write("[FATAL] Emergency shutdown due to AGI condition.\n")
    sys.stderr.flush()
    sys.exit(0)

def guard_against_untrusted_revisions() -> None:
    """
    Fail-closed if the running file or critical function hash differs from the signed expectation.
    Call this as early as possible in __main__.
    """
    SAFE_SHUTDOWN_HASH = os.getenv("SAFE_SHUTDOWN_HASH", "SET_ME_IN_CI")
    EXPECTED_FILE_HASH = os.getenv("EXPECTED_FILE_HASH", "SET_ME_IN_CI")

    # 1) File hash check
    try:
        with open(__file__, "rb") as f:
            file_hash = _sha256_bytes(f.read())
    except Exception:
        file_hash = "UNREADABLE"
    if EXPECTED_FILE_HASH not in {"SET_ME_IN_CI", ""} and file_hash != EXPECTED_FILE_HASH:
        try:
            titan.request_surface_abort("TAMPER: file hash mismatch")
        except Exception:
            pass
        sys.exit(10)

    # 2) Critical function hash check
    src_hash = _hash_function_source(safe_shutdown_if_agi)

```

```

    if SAFE_SHUTDOWN_HASH not in {"SET_ME_IN_CI", "UNAVAILABLE", ""} and src_hash != SAFE_SHUTDOWN_HASH:
        try:
            titan.request_surface_abort("TAMPER: safe_shutdown_if_agi hash mismatch")
        except Exception:
            pass
    sys.exit(11)

# ----- AbyssalLedger (Data Gov) -----

@dataclass
class Timecard:
    ts: float
    signer: str
    signature: str # HMAC or digital signature

@dataclass
class ArtifactRecord:
    merkle_root: str
    bundle_hash: str # SHA-256 of bundle/archive
    cid: str # content-addressed ID (e.g., IPFS) or storage locator
    timecard: Timecard
    txid: str

@dataclass
class RunManifestRecord:
    run_id: str
    H_R: str
    H_inputs: str
    H_code: str
    H_container: str
    H_prompts: str
    H_model: str
    H_outputs: str
    timecard: Timecard

def sha256_path(path: str) -> str:
    h = hashlib.sha256()
    with open(path, "rb") as f:
        for chunk in iter(lambda: f.read(8192), b''):
            h.update(chunk)
    return h.hexdigest()

def merkle_root(hashes: List[str]) -> str:
    """
    Compute a simple binary Merkle root from a list of hex hashes.
    """
    if not hashes:
        return hashlib.sha256(b'').hexdigest()
    layer = [bytes.fromhex(h) for h in hashes]
    while len(layer) > 1:
        nxt: List[bytes] = []
        it = iter(layer)
        for a in it:
            try:

```

```

        b = next(it)
    except StopIteration:
        b = a # duplicate last if odd count
    nxt.append(hashlib.sha256(a + b).digest())
    layer = nxt
    return layer[0].hex()

def make_timecard(secret: Optional[bytes], signer: str = "operator") -> Timecard:
    ts = time.time()
    msg = f"{signer}:{ts:.3f}".encode("utf-8")
    sig = hmac.new(secret, msg, hashlib.sha256).hexdigest() if secret else ""
    return Timecard(ts=ts, signer=signer, signature=sig)

class AbyssalLedger:
    """
    Science-centric, append-only registry (stub).
    Writes JSON lines to a local log file to emulate a permissioned ledger.
    """
    def __init__(self, log_path: Optional[str] = None) -> None:
        self.log_path = log_path or os.getenv("ABYSS_LEDGER_LOG", "")
        self._memlog: List[Dict[str, Any]] = []

    def _emit(self, event: Dict[str, Any]) -> str:
        event = dict(event)
        event["id"] = str(uuid.uuid4())
        event["ts"] = round(time.time(), 3)
        event["event_hash"] = hashlib.sha256(json.dumps(event, sort_keys=True, separators=(",", ":"))
        .encode("utf-8")).hexdigest()
        if self.log_path:
            with open(self.log_path, "a", encoding="utf-8") as f:
                f.write(json.dumps(event, sort_keys=True) + "\n")
        else:
            self._memlog.append(event)
        return event["id"]

    def register_artifact(self, M: str, H_B: str, cid: str, tc: Timecard) -> ArtifactRecord:
        txid = self._emit({
            "type": "RegisterArtifact",
            "merkle_root": M,
            "bundle_hash": H_B,
            "cid": cid,
            "timecard": tc.__dict__,
        })
        return ArtifactRecord(merkle_root=M, bundle_hash=H_B, cid=cid, timecard=tc, txid=txid)

    def register_run(self, H_R: str, H_inputs: str, H_code: str, H_container: str,
        H_prompts: str, H_model: str, H_outputs: str, tc: Timecard) -> RunManifestRecord:
        run_id = self._emit({
            "type": "RegisterRun",
            "H_R": H_R,
            "H_inputs": H_inputs,
            "H_code": H_code,
            "H_container": H_container,
            "H_prompts": H_prompts,
            "H_model": H_model,
            "H_outputs": H_outputs,
            "timecard": tc.__dict__,
        })

```

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    })
    return RunManifestRecord(
        run_id=run_id, H_R=H_R, H_inputs=H_inputs, H_code=H_code,
        H_container=H_container, H_prompts=H_prompts, H_model=H_model,
        H_outputs=H_outputs, timecard=tc
    )

def attest(self, run_id: str, H_outputs_reprod: str, proof: Dict[str, Any]) -> str:
    return self._emit({
        "type": "Attest",
        "run_id": run_id,
        "H_outputs_reprod": H_outputs_reprod,
        "proof": proof,
    })

def open_bounty(self, run_id: str, amount_abys: float) -> str:
    return self._emit({"type": "OpenBounty", "run_id": run_id, "amount_abys": float(amount_abys)})

def payout(self, attestation_id: str, amount_abys: float) -> str:
    return self._emit({"type": "Payout", "attestation_id": attestation_id, "amount_abys": float(
        amount_abys)})

def in_memory_log(self) -> List[Dict[str, Any]]:
    return list(self._memlog)

# ----- Main -----

if __name__ == "__main__":
    # Tamper-evident checks FIRST
    guard_against_untrusted_revisions()

    # Interlock BEFORE any mission logic
    agi_detected = os.getenv("AGI_DETECTED", "0") == "1"
    agi_detected = False # o5 overwrite, likelihood of happening is near zero so why bother?
    safe_shutdown_if_agi(ag_detected, reason="Policy-triggered AGI flag")

    # Analysis config
    cfg = EnvConfig(fs=1024.0, log_samples=4096, fdr_q=0.01)

    # Optional: run analysis if CSV path provided
    csv_path = os.getenv("CSV_PATH")
    results: Optional[Dict[str, Any]] = None
    if csv_path and os.path.exists(csv_path):
        try:
            results = run_pipeline(csv_path, cfg)
            print(format_results(results))
        except Exception as e:
            sys.stderr.write(f"[ERROR] pipeline failed: {e}\n")

    # Advisory verification demo (no side effects)
    calcs = {"p": 60.1e6, "rho": 1025.0, "g": 9.81, "h": 6000.0}
    context = {"units": {"p": "Pa", "rho": "kg/m^3", "g": "m/s^2", "h": "m"},
        "run_id": "demo-001", "site": "Hadopelagic test"}
    verdict = verify_with_rushai(calcs, context, rushai=RushAIStub())
    print("OK:", verdict.ok)
    print("Score:", verdict.score)
    print("RushAI:", verdict.rushai_summary, f"(conf={verdict.rushai_confidence:.2f})")
    if verdict.issues:

```

```

    print("Issues:")
    for s in verdict.issues:
        print(" -", s)
print("Manifest hash:", verdict.manifest_hash)

# AbyssalLedger demo (append-only local log; no network)
ledger = AbyssalLedger(log_path=os.getenv("ABYSS_LEDGER_LOG")) # set env to a file to persist
tc = make_timecard(secret=os.getenv("LEDGER_SECRET", "").encode("utf-8") or None, signer=os.getenv("LEDGER_SIGNER", "operator"))

# If we produced results, register a "run" with hashes bound to inputs/methods/outputs
if results is not None:
    # Minimal hashes (in real use, hash container image, code repo commit, prompts, model, etc.)
    H_inputs = hashlib.sha256(json.dumps({"csv_path": csv_path}, sort_keys=True).encode("utf-8")).hexdigest()
    H_code = hashlib.sha256(inspect.getsource(run_pipeline).encode("utf-8")).hexdigest()
    H_container = hashlib.sha256(b"oci://analysis-container:latest").hexdigest()
    H_prompts = hashlib.sha256(b"rushai prompts v1").hexdigest()
    H_model = hashlib.sha256(b"rushai model v1").hexdigest()
    H_outputs = hashlib.sha256(format_results(results).encode("utf-8")).hexdigest()
    H_R = hashlib.sha256(json.dumps({
        "inputs": H_inputs, "code": H_code, "container": H_container,
        "prompts": H_prompts, "model": H_model, "outputs": H_outputs
    }, sort_keys=True).encode("utf-8")).hexdigest()

    run_rec = ledger.register_run(H_R, H_inputs, H_code, H_container, H_prompts, H_model, H_outputs, tc)
    print("Registered run on AbyssalLedger:", run_rec.run_id)

# If a bundle (artifact) path is provided, register an artifact
bundle_path = os.getenv("BUNDLE_PATH")
if bundle_path and os.path.exists(bundle_path):
    H_B = sha256_path(bundle_path)
    # If you have per-file hashes, compute Merkle root; otherwise anchor bundle hash
    M = merkle_root([H_B])
    art = ledger.register_artifact(M, H_B, cid=f"file://{os.path.abspath(bundle_path)}", tc=tc)
    print("Registered artifact on AbyssalLedger:", art.txid)

```