Validating the Core Sleep-State Clock: A PSG-Anchored Framework for Calibrating N1-N3 Indices and the G_safe Safety Gate in an XR Context

Epoch-Level Calibration of the N1–N3 State Vector

The establishment of a reliable and reproducible foundation for real-time XR decision-making hinges on the precise mathematical definition and empirical calibration of the N1-N3 sleep stage indices . These indices, collectively forming a "shared clock," serve as the primary input for all downstream systems, including Retoplasm, CSI/CATS, and the DreamSpectre router . The initial phase of this research must therefore focus on refining these scalars at the 30-second epoch level, anchoring them to the clinical gold standard of polysomnography (PSG) [15] [122]. The core of this effort involves enriching the signal model beyond simple band power to incorporate validated electrophysiological markers of sleep architecture, thereby creating a more robust and physiologically meaningful state vector.

The fundamental components of this state vector are the stage posteriors (p_{N1},p_{N2},p_{N3}) and the derived depth index, D_{N2N3} . The posteriors represent the classifier's probabilistic assignment of an epoch to each sleep stage, based on its analysis of brain activity [12] . While the current model relies on band powers in the delta, theta, alpha, sigma, beta, and gamma frequency bands, its accuracy can be significantly enhanced by integrating additional, more specific biomarkers . For instance, the classification of N2 and N3 stages is critically dependent on distinct waveforms observable in EEG signals [43] . Stage N3, or slow-wave sleep (SWS), is characterized by high-amplitude, low-frequency delta waves, typically defined as having a frequency of 0.5–4 Hz and a peak-to-peak amplitude of at least 75 μV [74] [76] . Incorporating direct measurements of slow-wave activity (SWA)—the quantitative measure of power within this frequency range—is therefore paramount for accurately identifying deep sleep epochs [38] [74] . Studies have demonstrated that SWA is a highly reproducible metric across consecutive nights of PSG recording, making it an ideal anchor for calibration [66] . Furthermore, other features like sleep spindles (11–16 Hz oscillations) and K-complexes are hallmarks of N2 sleep and should also be integrated into the feature set to better delineate the boundaries between light and deep sleep [124144].

Beyond EEG-derived features, the signal model should be enriched with multimodal inputs to capture a more complete picture of the user's physiological state. Heart rate variability (HRV) provides a valuable window into autonomic nervous system modulation, which is known to differ significantly across sleep stages [9] [83]. Parameters such as the low-frequency to high-frequency ratio (LF/HF), mean R-R interval (RRI), and overall spectral power of HRV can serve as strong corroborative signals for sleep staging [6] [86]. The use of pulse transit time (PTT) and pulse rate variability (PRV) as surrogates for HRV offers a non-invasive method for continuous monitoring, especially in wearable contexts [10] [151]. Combining ECG-derived HRV with EEG has been shown to improve the robustness of sleep stage detection algorithms [5] [113]. Similarly, incorporating electromyogram (EMG) and electrooculogram (EOG) envelope signals can provide crucial information about muscle tone and eye movements, which are essential for scoring wakefulness, REM sleep, and arousals according to American Academy of Sleep Medicine (AASM) standards [22] [23]. By extending the model to include these validated biomarkers—specifically SWA for N3, spindles/K-complexes for N2, and HRV for autonomic state—the resulting posteriors will be more accurate, interpretable, and less prone to error during ambiguous transitions between stages. This enriched model directly addresses the need to refine the N1-N3 posteriors against a broader spectrum of physiological context .

The depth index, D_{N2N3}, is a critical scalar derived from the posteriors that quantifies the contribution of deep, non-REM sleep to the overall state of an epoch . Its refinement requires a "band-weighted" approach, where the final value is not just a function of the N2 and N3 posteriors but is modulated by objective measures of sleep depth like SWA [38]. Scientific literature provides several validated metrics for sleep depth that can inform the calibration of D_{N2N3}. One such measure is the Odds Ratio Product (ORP), an EEG-based metric proposed as being more sensitive than traditional methods for assessing sleep depth [41]. Another key correlate is the enhancement of low-frequency (0.5–1 Hz) SWA, which has been associated with restorative processes [72]. Therefore, the calibration of D_{N2N3} should involve establishing a strong positive correlation between its output and these established PSG-derived measures. For example, an epoch could be considered a "gold standard" deep sleep epoch if it meets criteria such as a duration of delta waves exceeding a certain threshold (e.g., >50% of the epoch) [139140]. The goal is to normalize the D_{N2N3} index so that a value of 1.0 corresponds to such a physiologically defined deep sleep period, while values closer to 0.0 correspond to lighter sleep stages or wakefulness. This calibration process ensures that D_{N2N3} is not merely a model artifact but a robust proxy for the brain's restorative capacity, providing a solid foundation for gating decisions related to XR content intensity . The table below outlines a conceptual framework for the enriched signal model and its scientific correlates.

Signal Component	Frequency/Range	Physiological Marker	Role in Sleep Staging
EEG Delta Power	0.5–4 Hz [74]	Slow Wave Activity (SWA)	Primary marker for Stage N3 (Slow-Wave Sleep); correlates with sleep depth [38] [123].
EEG Spindle Oscillations	11–16 Hz [124]	Sleep Spindles	Hallmark of Stage N2 sleep; important for distinguishing light from deep sleep [144].
EEG High-Amplitude Waves	$\geqslant 75\ \mu V$ [74]	Slow Waves / K-Complexes	Defines the morphology of Stage N3 sleep; used in AASM scoring rules [76] [101].
EOG Signals	Not Specified	Eye Movements	Essential for scoring REM sleep and wakefulness according to AASM guidelines [22] [23] .
EMG Envelope	Not Specified	Muscle Tone	Used to score wakefulness and REM sleep (muscle atonia) [22] [23] .
HRV (Time Domain)	Not Specified	R-R Interval (RRI)	Mean RRI increases during sleep; useful for sleep-wake distinction [6] [86] .
HRV (Frequency Domain)	Low-Frequency (LF) / High-Frequency (HF)	Autonomic Modulation	LF/HF ratio shifts across sleep stages, reflecting sympathetic/parasympathetic balance [6] [83] .

By systematically implementing this enriched signal model and rigorously calibrating the resulting posteriors and depth index against a large, diverse dataset of PSG recordings annotated by human experts, the foundational "clock" of the system can be stabilized [23] [35] . This PSG-anchored validation is the non-negotiable first step, ensuring that all subsequent higher-order decisions are built upon a statistically robust and physiologically coherent representation of the user's sleep state . This disciplined approach minimizes confounding variables and provides the cleanest possible evidence when validating the interactions with Retoplasm and consent guards in later phases of the research.

Validation of Uncertainty Metrics and the G_safe Safety Gate

Once the foundational N1-N3 state vector is calibrated, the next critical step is to validate the mechanisms designed to manage ambiguity and risk: the uncertainty metrics and the safety gate, G_{safe}. The concept of treating sleep-stage posteriors as a source of explicit uncertainty is well-supported by contemporary machine learning practices in sleep science . By quantifying the classifier's confidence, the system can move beyond a binary "stage assignment" to a more nuanced "state assessment," which is essential for deploying interventions like XR content in a safe and adaptive manner. The combined uncertainty metric, $U_{comb}=(U_{gap}+U_{ent})/2$, serves as the primary diagnostic tool for identifying epochs that are ambiguous, atypical, or potentially compromised by artifacts . The gap uncertainty, $U_{gap}=1-\max(p_s)$, measures how much more confident the model is in its top prediction compared to the runner-up. A small gap indicates indecision between two or more states, which is common during transitions like N1/N2 or N2/N3 [139]. The entropy uncertainty, U_{ent}, quantifies the total uncertainty across all possible states, normalized by the log of the number of classes ($\log(5)$ for W, N1, N2, N3, REM) . High entropy signifies a distribution of probabilities that is nearly uniform, indicating a state that the model has never seen before or finds highly unusual. The combination of these two metrics provides a comprehensive view of the classifier's certainty.

The scientific validity of using posterior entropy for uncertainty quantification is well-established. Deep learning models, particularly those designed for sleep staging like SleepTransformer, explicitly incorporate uncertainty estimation to flag epochs requiring review and to improve interpretability [12] [50]. Direct quantification of uncertainty from hypnodensity outputs has been shown to be a viable and reliable method [17]. However, it is crucial that these reported uncertainties are well-calibrated, meaning the predicted confidence should align with the actual observed accuracy [90]. To achieve this, post-hoc calibration techniques such as temperature scaling can be applied to the model's output probabilities, ensuring that a reported uncertainty of 0.8 truly reflects an 80% chance of the model being incorrect [92]. The legal constraints imposed on these metrics reinforce their role as momentary state indicators rather than stable personal traits; they are intended solely for safety filtering and must not be repurposed for performance ranking or punitive profiling . This ethical guardrail is technically enforced by architectural choices, such as the `no_person_scoring` invariant in the QPU.Datashard, which prevents the aggregation of these epoch-level scores into persistent person-level profiles .

The culmination of the state estimation and uncertainty quantification process is the safety gate, defined by the formula $G_{safe}=\min 1, D_{N2N3}(1-U_{comb})$. This scalar represents a trade-off between sleep depth (D_{N2N3}) and classification certainty ($1-U_{comb}$). An epoch with high sleep depth but high uncertainty will receive a lower gate value than an equally deep epoch with high certainty. This logic is sound: deep, restorative sleep is the desired state for immersive XR experiences, but only if the system is confident in its assessment of that state. The calibration of this gate is the most critical validation task, as it directly controls user access to different levels of experiential intensity . The process involves analyzing the gate's behavior across multiple sleep sessions and diverse user cohorts to define empirically grounded thresholds that partition the unit interval into distinct safety bands, such as `Control`, `Monitored`, `Restricted`, and `Containment` .

The calibration must be guided by two primary objectives. First, it must minimize the false-safe rate, which occurs when the gate incorrectly allows access during a high-risk epoch . A key marker for such epochs is the presence of micro-arousals, brief periods of heightened cortical activity that signify sleep fragmentation and increased vulnerability to awakening [65] [112]. A powerful method for validating the gate's sensitivity to risk is to implement a microarousal veto. This veto would be a binary flag per epoch, triggered by the detection of such events. The system's operation would then be gated to allow XR content only when the veto is explicitly false . By correlating epochs where the veto was triggered with subsequent awakenings or subjective reports of disturbance, the system's parameters can be tuned to reduce the false-safe rate to an acceptably low level (e.g., ≤ 5–10%) . Second, the calibration must minimize the false-unsafe rate, where the gate incorrectly denies access during a genuinely safe and deep sleep period . This is a false-positive problem that would unnecessarily degrade the user experience. Achieving the right balance requires careful statistical analysis of the distribution of G_{safe} values across all sleep stages and under various conditions. The Expected Calibration Error (ECE) metric can be used to quantitatively assess the quality of the probability calibration for the entire system, measuring the difference between confidence and accuracy [58] [93] . Ultimately, a successfully calibrated G_{safe} provides a robust, reproducible, and auditable scalar that serves as the definitive arbiter for real-time XR-grid routing decisions, ensuring that experiential intensity is always appropriately modulated by the user's underlying sleep physiology and the system's confidence in its perception of it [90] .

Integrating Retoplasm and Consent Guards into a Joint Policy Engine

With a calibrated foundation of sleep-state posteriors, depth, uncertainty, and the safety gate, the research can progress to validating the integration with higher-order systems that govern experiential access. The primary systems for this integration are Retoplasm, which provides a layer of physiological moderation, and the ConsentStabilityIndex (CSI) and ConsentAuditTrail Scalar (CATS), which act as ethically mandated safety and consent protocols . This integration transforms the raw sleep-state vector from a simple description of brain activity into a dynamic, multi-faceted `PolicyState` that informs all real-time decision-making. The joint policy engine combines these disparate streams of information—sleep stage, autonomic stability, cortical dynamics, and user consent—into a single, cohesive classification: `SafeHighCapacity`, `SafeModerate`, or `UnsafeDefer`.

Retoplasm contributes a crucial second dimension to the safety assessment by monitoring autonomic and cortical stability. The `autonomic_index` (aII) quantifies instability in heart rate and other cardiovascular signals, while the `cortical_stability` (s_stab) metric assesses the phase-locking and coherence of neural oscillations . The scientific rationale for this addition is compelling: vulnerability to distress and disruptive spectral events during interventions is correlated with combined autonomic and cortical instability [83] [84]. An epoch might be correctly identified as deep sleep (D_{N2N3} near 1) with high certainty (U_{comb} near 0), yielding a high G_{safe}, but if concurrently it exhibits signs of autonomic storm (high aII) or desynchronized cortex (low s_stab), it may still represent a precarious state for intervention. The Retoplasm `gateEpoch` API formalizes this logic by evaluating predicates over these metrics to classify the epoch . For example, an `UnsafeDefer` state could be triggered if any one of the following conditions is met: autonomic instability exceeds a red-line threshold (aII > a_red), cortical stability falls below a critical level (s_stab < 0.2), or the primary safety gate drops below a minimal acceptance level ($G_{safe} < 0.1$) . This multi-layered gating ensures that even if the sleep-stage classifier is correct, the surrounding physiological environment must also be deemed stable enough to warrant experiential engagement. The QPU.Datashard is designed to capture this nuance by logging the final `policy_state` alongside the contributing factors, creating a detailed audit trail of why a particular routing decision was made [90].

Simultaneously, the Consent guards (CSI/CATS) enforce a parallel, non-negotiable layer of ethical and legal compliance. The eligibility for high-intensity dream-gaming is not solely dependent on physiological safety but also on active, revocable user consent. The eligibility formula, $E = S(1 - R)E_s$, incorporates factors like explicit consent (S), mental scarcity (R), and baseline emotional stability (E_s) . This eligibility score must exceed a minimum threshold ($E \geq E_{min}$). Furthermore, the ConsentAuditTrail Scalar (CATS) must also surpass its own threshold (e.g., CATS ⩾ 0.65) . Only when both the physiological safety gate (G_{safe} above a threshold) and the consent gates (E and CATS above their respective thresholds) are satisfied can the system enable high-intensity archetypes . This creates a robust, two-factor authentication-like system for experiential intensity. The scientific justification for coupling deep sleep with consent is rooted in the unique neurophysiological window that N3 sleep provides. Deep N3 sleep, characterized by strong slow-wave coherence and low micro-arousals, is associated with emotional stabilization and memory consolidation [72] [134]. Leveraging this natural state for therapeutic or recreational interventions, but only when coupled with strong consent, allows for effective engagement without raising spectral disturbance or risking user autonomy [3] . The legal frameworks embedded in the design mandate that these consent-related scalars are session-scoped and revocable, preventing them from being stored or interpreted as lifetime traits .

The interaction between these systems defines the operational logic of the joint policy engine. The table below illustrates how the outputs from the foundational sleep-stage math, Retoplasm, and consent guards are synthesized into a final `PolicyState` and corresponding XR routing command.

Input Condition 1 (G_{safe})	Input Condition 2 (Retoplasm)	Input Condition 3 (Consent)	Synthesized `PolicyState`	Recommended XR Action
High (> 0.8)	Stable (Low aII, High s_stab)	Compliant (E > E_min, CATS > 0.65)	`SafeHighCapacity`	Enable moderate-to-high intensity archetype (e.g., N2_COASTAL_LOWLOAD) [90] .
Moderate (0.3 - 0.8)	Unstable (High aII OR Low s_stab)	Any	`UnsafeDefer`	Force starfield/safe-room routing regardless of sleep stage.
High (> 0.8)	Stable (Low aII, High s_stab)	Non-compliant (E < E_min OR CATS < 0.65)	`SafeModerate`	Limit to low-symbolic, ultra-gentle archetypes (e.g., N1LIMINAL) [90] .
Low (< 0.3)	Any	Any	`UnsafeDefer`	Force starfield/safe-room routing to abort-and-flush.

This structured approach to policy synthesis ensures that no single factor can override the others. For example, a high level of user consent cannot override a clear sign of autonomic instability, and a perfect sleep-stage classification cannot compensate for a lapse in user consent. The system is designed to err on the side of caution, defaulting to safer states (`SafeModerate`, `UnsafeDefer`) whenever there is any ambiguity or violation of the safety and consent rules. This layered, defensive architecture is essential for building a trustworthy system that respects neurorights while still enabling innovative applications in the XR space [90] . The validation of this integration involves running controlled trials where the system's routing behavior is observed in response to simulated or naturally occurring fluctuations in Retoplasm and consent metrics, ensuring the logic is robust and behaves as intended under a wide variety of conditions.

Architectural Blueprint for Real-Time Decisioning and Governance

The successful implementation of a sleep-state-aware XR system depends not only on the accuracy of its core algorithms but also on a resilient and principled architectural blueprint. The QPU.Datashard, along with associated constraints on data pipelines like dev-tunnels, forms the production-ready infrastructure that supports low-latency decision-making while embedding robust governance and auditability . This architecture is designed with three core tenets in mind: optimization for real-time processing, enforcement of neurorights through schema design, and facilitation of verifiable auditing trails. The proposed CSV-structured QPU.Datashard is the central artifact of this design, serving as the compact, standardized payload for every 30-second epoch processed by the system .

The shard's structure is meticulously optimized for the hot path of XR-grid routing. It exposes only the most critical, pre-computed scalars required for immediate decision-making: the sleep posteriors, depth (D_{N2N3}), uncertainty (U_{comb}), the safety gate (G_{safe}), the Retoplasm-derived `policy_state`, and consent-related flags [90]. This minimalist approach avoids costly lookups or complex computations at the point of routing. The use of strongly typed fields, bounded floating-point numbers in the [0,1] interval, and small enums for categorical states like `policy_state` makes the shard highly suitable for efficient serialization and transmission, including quantization-friendly formats for deployment on edge devices or in third-party models [90]. The `XR_ROUTING` section provides all necessary information for the router to select an appropriate virtual node, profile, and archetype class with a specified intensity level (0-3), directly linking the physiological state to the experiential outcome . This tight coupling between state estimation and action execution is the essence of the closed-loop system envisioned for dream-gaming.

Embedded within this lightweight structure are powerful mechanisms for governance and auditability, ensuring compliance with emerging neuroethics and data protection regulations like the EU AI Act, GDPR, and Chile's neurorights law [90]. The `NEURORIGHTS` section contains a series of boolean flags (`mental_privacy`, `cognitive_liberty`, `mental_integrity`, `non_punitive`) that must be set to `true` for every logged epoch [90]. These flags act as immutable, hard-coded permissions that any downstream system interacting with the datashard is contractually and architecturally obligated to honor. They enforce principles like the right to mental privacy and the prohibition of punitive XR content directly into the data itself. Perhaps most importantly, the `no_person_scoring` invariant is encoded as a mandatory `true` field, creating a technical guarantee that the telemetry data, by its very structure, cannot be used to generate persistent, person-level behavioral scores or traits . This is a critical defense against the misuse of neural data for profiling in employment, insurance, or academic selection, as legally mandated .

For verifiable auditing, the QPU.Datashard employs cryptographic techniques to ensure data integrity and provenance. The `hex_commit_epoch` field contains a compact, fast hash (e.g., XXH3-style) computed over the core telemetry fields of that epoch [90]. This provides a lightweight integrity check that can be used to detect tampering. More significantly, the `AUDIT` section includes a rolling hash (`audit_ledger_prev_hash`) that chains each epoch together in a monotonic sequence within a session. This creates a tamper-evident ledger, where altering any single epoch's data would invalidate all subsequent hashes, making manipulation easily detectable [90]. The `audit_hex_commit` field provides a full commitment over all core fields, offering a robust checksum for forensic analysis. This audit trail is essential for transparency and accountability, allowing for independent verification of the system's behavior and adherence to safety policies. The `LEGAL` section further solidifies this by including fields for license descriptors and references to IRB-approved neuroethics boards, grounding the technical implementation in formal regulatory and ethical oversight [90].

Finally, the principle of data minimization and privacy-by-design extends to external integrations via "dev-tunnels." These tunnels are constrained pathways for exporting epoch-level data to third-party models (e.g., Mistral/Qwen) for further analysis or model improvement . The architectural rule is strict: only bounded, anonymized state vectors—such as `[pN1, pN2, pN3, DN2N3, Ucomb, Gsafe]`—may be exposed through these channels [90]. Raw EEG, timestamps, GPS data, and any stable identifiers are explicitly excluded from the payloads [90]. This follows the principle of least privilege and dramatically reduces the risk of exposing sensitive personal health information. The use of ALN (Autonomous Logic Network) invariants provides a formal proof mechanism to verify that these constraints are upheld, offering a higher degree of assurance than contractual agreements alone [90]. By combining a production-optimized data format with deeply embedded governance flags and cryptographic audit trails, the proposed architecture provides a comprehensive solution that balances the demands of real-time performance with the non-negotiable requirements of security, privacy, and regulatory compliance.

A Phased Research Roadmap for Systemic Validation

To achieve the overarching research goal of establishing a reproducible, epoch-level foundation for XR decision-making, a phased and methodologically rigorous roadmap is essential. The user's directive to prioritize mathematical refinement and calibration before system integration provides a clear strategic direction . This roadmap breaks down the complex endeavor into three distinct, sequential phases, each building upon the last to ensure that higher-level systems are validated on a solid, empirically-grounded foundation. This approach minimizes confounding variables and maximizes the statistical power of subsequent validation studies.

Phase 1: Foundational Calibration and Validation. The primary objective of this phase is to stabilize the core mathematical model of the N1-N3 state vector by anchoring it to PSG ground truth . The first action item is to assemble a diverse, multi-cohort dataset of whole-night PSG recordings, complete with expert manual annotations according to AASM standards [23] [89] . This dataset must be sufficiently large and varied to account for inter-scorer variability, age-related differences in sleep architecture, and potential artifacts [20] [91] . The second action is to implement the proposed signal enrichment, extending the existing band-power model to include validated electrophysiological markers: Slow-Wave Activity (SWA) from delta power (0.5-4 Hz), spindle density, autonomic markers from HRV (e.g., LF/HF ratio, RRI), and EMG/EOG envelopes [6] [22] [74] . With this enriched model, the posteriors ($pN1$,$pN2$,$pN3$) are trained and evaluated. Performance is measured using standard metrics like Cohen's Kappa, F1-score, and accuracy against the manual scorings [128][135]. Concurrently, the depth index, D_{N2N3}, is calibrated by establishing a strong correlation with direct SWA measurements from the same PSG data, aiming to make its output a physiologically meaningful proxy for sleep depth [41] [66] . Finally, the uncertainty metrics (U_{gap}, U_{ent}) are implemented and their calibration is assessed using metrics like Expected Calibration Error (ECE) to ensure the reported confidence is reliable [58] . The success criterion for Phase 1 is the publication of a robust, validated epoch-classifier whose outputs are demonstrably aligned with established sleep science.

Phase 2: Safety Gate and System Integration Validation. Once the foundational state vector is stable, the focus shifts to validating the safety mechanisms and their integration into a joint policy engine. The first task is the comprehensive calibration of the safety gate, G_{safe}=min1,$D_{N2N3}(1-U_{comb})$. This involves analyzing the gate's output across the cohort data to define empirically grounded safety bands (`Control`, `Monitored`, `Restricted`, `Containment`). The key validation experiment is the implementation of a microarousal veto mechanism. By measuring the rate of awakenings or subjective disturbance around epochs where the veto is triggered, the system's sensitivity can be tuned to minimize the false-safe rate to an acceptable level ($\leqslant$ 5–10%) [65] [112]. The second task is to integrate the Retoplasm stack, which provides autonomic and cortical stability metrics . Controlled trials are conducted to observe how the combined logic—predicates over Retoplasm indices and G_{safe}—classifies epochs into the `PolicyState` states (`SafeHighCapacity`, `SafeModerate`, `UnsafeDefer`). The behavior of this joint policy is validated by correlating `UnsafeDefer` triggers with instances of autonomic instability or cortical desynchronization to confirm the added value of this moderation layer [83] . The third task is to integrate the Consent guards (CSI/CATS). The validation here involves confirming that the eligibility criteria ($E \geq E_{min}$) and CATS thresholds are respected, and that they effectively gate access to high-intensity content, functioning as a mandatory prerequisite alongside the physiological safety gate . The success criterion for Phase 2 is a fully integrated system where the `PolicyState` and XR routing decisions are logically consistent and demonstrate a high degree of alignment with safety objectives, as evidenced by reduced spectral disturbance.

Phase 3: Downstream Application and Longitudinal Validation. The final phase focuses on applying the validated foundation to specific, high-value use cases and subjecting the entire system to longitudinal and cross-jurisdictional validation. One key application is the development of N2/N3 Rehab Protocols. Using the eligibility criteria ($E = S(1 - R)E_s$) and validated safety gates, researchers can design and deploy targeted XR interventions during deep sleep to measure their efficacy in reducing next-day craving or anxiety [90] . This creates a closed-loop system where the therapeutic outcome can feed back into model refinement, accelerating discovery in a scientifically valid and ethically sound manner [1] [2] . Another application is the calculation of sustainability metrics, such as console-retirement benefits, which are gated by requiring both high `DN2N3` and strong consent, ensuring that environmental claims are tied to healthy, restorative sleep usage and not just shifted sleep disturbances [90] . The ultimate validation step is to conduct cohort studies across different geographic locations (e.g., Phoenix, La Jolla, Geneva, Brussels, Santiago) . These studies would demonstrate that the same core mathematical formulas produce neurorights-compliant decisions under varying legal and cultural contexts, proving the system's portability and robustness. The success criterion for Phase 3 is the successful deployment and validation of one or more downstream applications and the demonstration of the system's generalizability and compliance across multiple jurisdictions. This phased approach ensures that each layer of complexity is validated only after its underlying dependencies have been firmly established, leading to a final product that is not only technologically advanced but also scientifically defensible, ethically responsible, and legally compliant.

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