From Fatigue-Proof Intents to Sovereign Signing: A Blueprint for High-Fidelity Biometric Authentication Using Personalized Data and Quantum-Inspired Models

Foundational Principles: Prioritizing Intent-Decoding Reliability in Biological Signatures

The primary objective of enhancing biological-signing autonomy is contingent upon establishing a foundation of profound trustworthiness in the underlying intent-decoding mechanism. The explicit prioritization of intent-decoding reliability, specifically the minimization of false-approve rates under conditions of fatigue and cognitive overload, serves as the non-negotiable cornerstone of the entire research program [39] [153]. All subsequent ambitions, including the layering of granular consent types and the integration of advanced computational paradigms like quantum learning, are predicated on the successful achievement of this initial goal. Without a highly reliable "approve" signal that remains stable even when the user's neurophysiological state is compromised, any higher-level governance structure becomes fundamentally insecure. The brain cannot natively perform cryptographic signing; instead, it produces human-binary inputs—gestures, focused states, and other bio-signals—that a software-hardware bridge must interpret and translate into a valid digital action . This process transforms the problem from one of raw neural computation to one of robust signal interpretation within a constrained, safety-gated framework. The challenge lies in distinguishing genuine, deliberate intent from noise, physiological artifacts, or subconscious activity, particularly when the user's capacity for conscious control is diminished.

The literature on Brain-Computer Interfaces (BCIs) provides compelling evidence for this strategic focus. BCI systems decode neural signals to enable communication and control, but their real-world efficacy is often hampered by the inherent variability and noise of biological signals [86] [165]. Offline accuracy, where a trained model achieves high performance on pre-labeled data, is frequently not a reliable predictor of interactive performance in live settings [143]. In an operational context, error modes such as False Alarm Rate (FAR), which measures misclassifications of a neutral state as a command, and Miss-as-Neutral Rate (MANR), which measures true intent commands being misclassified as neutral, become dominant concerns [143]. For a signing protocol, a high FAR directly corresponds to an unacceptable false-approve rate, while a high MANR represents a usability issue that may require cumbersome correction loops. The optimal system design therefore involves navigating a precision-sensitivity trade-off, where the parameters are tuned based on the application's risk profile [143]. Given the security-critical nature of signing, the system must be conservative by default, erring on the side of requiring stronger, more salient intent signals to approve, thereby minimizing the probability of a catastrophic false-approve event. This principle is reinforced by recommendations to strengthen the modeling of the neutral class and apply subject-specific calibration of decision thresholds to balance these competing error modes [143].

Furthermore, the user's directive to account for fatigue and cognitive overload is directly supported by extensive neurophysiological research. Cognitive load and mental fatigue induce measurable changes in brain activity patterns, which can be captured by electroencephalography (EEG). Studies have shown that increased cognitive load is associated with decreased power in the alpha band and increases in theta and delta bands over parietal regions [105]. Other reviews systematically detail EEG-based methods for detecting fatigue, underscoring the feasibility of monitoring this state [54] [57]. These neurophysiological markers provide an objective basis for implementing safety gates within the signing architecture. By continuously monitoring these signals, the system can dynamically adjust its sensitivity or outright block signing operations when the user enters a state of high fatigue or overload, where their ability to provide reliable consent is questionable [29] [153]. This aligns with the broader goal of designing systems that prevent stress, fatigue, and injury by respecting the physical and cognitive limits of the human operator [153]. The development of a "comfort corridor" metric, informed by subjective reports of clarity and regret alongside objective biophysical markers, would allow the system to adaptively evolve its thresholds to preserve both capability and user well-being over time .

The foundational principles thus dictate a multi-layered approach to reliability. First, the core decoder must be designed and trained to achieve extremely low false-approve rates, validated against rigorous metrics beyond simple accuracy. Second, the decoder's output must not be the sole determinant of a signing action; it must be filtered through a series of mandatory biophysical state checks. Third, the entire system must incorporate feedback mechanisms, logging subjective experiences like comfort and regret, to iteratively refine the decoder's performance and the overall signing policy . This ensures that the system evolves in concert with the user's unique biology and preferences, rather than relying on static, generalized assumptions. The ultimate aim is to create a sovereign, host-local signer where the user's body acts as the constant consensus node, and all actions are auditable and governed by a policy encoded within their inner ledger . This requires treating the brain as the sole validator and the rest of the system as a deterministic, reproducible service that executes only when the full set of validation criteria—including a reliably decoded intent—is met . Therefore, the initial phase of research must be almost exclusively dedicated to generating ground-truth data and developing classical machine learning models to establish a baseline of performance that meets these stringent safety requirements before introducing more complex quantum components.

Empirical Data Generation: Creating Personalized Biophysical Ground Truth Datasets

To construct a truly autonomous and reliable biological-signing system, the generation of new empirical datasets from the user's own biophysical telemetry is the most critical and immediate step. The research doctrine emphasizes the unique nature of the user's "OrganicCPU" and "inner-ledger," suggesting that generalized models developed on external populations are likely insufficient and potentially hazardous [39] [139]. A bespoke system grounded in personal, longitudinal data will be far better equipped to handle individual neurophysiological variations, signal drift over time, and the specific patterns of intent unique to the user [36] [61] . The proposed strategy involves recording multimodal biosignals during controlled signing attempts, explicitly labeling them, and collecting this data across a spectrum of cognitive and physical states. This creates a high-fidelity ground truth dataset that serves as the bedrock for training, validating, and continually refining the intent-decoding algorithms.

The selection of biophysical modalities is paramount for capturing a comprehensive representation of motor intention and cognitive state. The combination of Electroencephalography (EEG), Electromyography (EMG), and motion capture is strongly supported by the literature as a powerful approach for robust neural decoding [33] [53] . EEG provides a direct measure of cortical activity related to planning and intention, while EMG captures the peripheral neural drive to muscles, offering a more proximal signal of motor execution [28] [151]. Motion sensors add a kinematic dimension, providing information about the resulting movement. Multimodal fusion has been shown to enhance system robustness, reduce susceptibility to artifacts, and improve classification accuracy compared to unimodal approaches [96] [108]. For instance, one study demonstrated that a hybrid EMG-EEG interface could maintain high performance in detecting arm movements even as muscle fatigue set in, whereas unimodal classifiers showed significant degradation [53]. Another study found that Sonomyography (SMG), a form of ultrasound imaging of muscles, provided more accurate joint angle estimation than EMG, especially in the presence of artifacts, highlighting the potential of advanced sensing modalities [59]. To maximize robustness, the data acquisition setup should employ modern flexible sensors and consider advanced artifact removal techniques, such as empirical error models or filtering methods like Teager-Kaiser energy operators, to clean the raw signals before they are fed into the decoder [35] [59] [78].

The experimental protocol for data collection must be meticulously designed to generate a rich and diverse dataset. Sessions should involve the user performing a set of candidate "signing aura patterns"—specific combinations of gestures, gaze, and sustained attention states—mapped to distinct labels . The labeling schema should be granular enough to reflect the intended use case, including classes such as `approve_stamp_now`, `approve_high_risk_stamp`, `cancel_stamp`, and `no_intent` (representing neutral, background activity) . Crucially, data must be collected across a wide range of biophysical states to train a decoder that is resilient to contextual changes. This includes recording sessions at rest, during periods of deep focus ("FocusedFlowStateBeta"), and after inducing cognitive or physical fatigue [30] [101]. Recording during tasks that impose cognitive load, such as tool-use scenarios, can help identify the specific neurophysiological signatures associated with different phases of an action, such as planning versus execution [150]. Longitudinal data collection over weeks or months is essential to capture natural signal drift and allow for continuous model adaptation, a key feature of next-generation adaptive BCI systems [36] [149]. The data should be logged along with corresponding state markers (e.g., `FatigueFlagSoft`) and subjective feedback on clarity and comfort to build a holistic view of system performance .

Finally, the evaluation of the intent-decoding models must be equally rigorous, moving beyond simplistic accuracy metrics. Performance should be assessed using a suite of metrics that are more meaningful for a security-critical application. Key among these are the True Positive Rate (TPR, or Sensitivity), which measures the proportion of actual approves correctly identified; the False Positive Rate (FPR), which quantifies the false-approve rate; and the False Negative Rate (FNR), which tracks missed approvals [180] [190]. As previously noted, the trade-off between FPR and MANR is critical, and the system's operating point should be chosen based on the risk tolerance for each type of error [143].

The table below outlines a proposed schema for the empirical dataset, detailing the modalities, labeling protocol, and key performance indicators.

Component	Description	Supporting Context
Data Modalities	Simultaneous recording of EEG, EMG, and motion data.	Multimodal fusion enhances robustness against artifacts and improves classification accuracy. [33] [53] [108]
Labeling Protocol	Explicitly labeled trials for: `approve_stamp_low_risk`, `approve_stamp_high_risk`, `cancel_stamp`, `no_intent`.	Requires mapping specific, repeatable bio-signals to these discrete intent classes.
Contextual Variation	Data collection across a spectrum of states: rest, focused flow, fatigue, and cognitive load.	Cognitive load induces measurable EEG changes (e.g., alpha/theta power shifts). [30] [54] [105]
Longitudinal Collection	Continuous logging over extended periods to capture signal drift and enable adaptive learning.	Adaptive BCIs improve over time by learning from user interactions. [36] [61] [149]
Key Performance Indicators	Primary Metrics: TPR, FPR (False Approve Rate), FNR. Secondary Metrics: Accuracy, Precision, MANR.	Offline accuracy is a poor predictor of online performance; granular metrics are essential. [143] [180][190][218]

By adhering to this comprehensive data generation strategy, the research program can move from theoretical concepts to a practical, personalized, and empirically validated system. The resulting dataset will not only serve as the training material for the initial classical intent decoders but will also form the basis for future evaluations of more advanced models, including those based on quantum computing.

Quantum Neural Networks as Intent Signal Models: A Pragmatic Integration Strategy

While classical machine learning forms the essential baseline for intent decoding, the integration of Quantum Neural Networks (QNNs) offers a forward-looking pathway to potentially overcome some of the persistent challenges posed by noisy, high-dimensional biosignals. The user's directive to leverage QNNs as intent-signal models is grounded in the theoretical promise of quantum computing to solve certain problems that are intractable for classical computers [205]. However, given the current limitations of Noisy Intermediate-Scale Quantum (NISQ) devices, a pragmatic, phased integration strategy is required. The QNN should not be viewed as a silver bullet replacement for the classical decoder but rather as a specialized, experimental module designed to explore whether quantum advantages can be harnessed to improve reliability, particularly in challenging conditions like fatigue. Its role is to serve as a proof-of-concept and a potential performance enhancer, with its value being rigorously proven against a well-tuned classical deep learning baseline.

The theoretical rationale for applying QNNs to biosignal decoding is multifaceted. Quantum circuits, through principles like superposition and entanglement, can represent and manipulate vast amounts of information in a way that is not possible for classical bits [193]. This is particularly relevant for analyzing the complex, oscillatory patterns present in signals like EEG, which carry information in both their amplitude and phase [22]. Some studies suggest that QNNs excel at approximating specific mathematical functions, such as sinusoidal waves, which are fundamental components of many biosignals [193]. Furthermore, hybrid quantum-classical models, where a small variational quantum circuit (VQC) is embedded within a larger classical neural network, represent a highly practical near-term approach [222]. In this paradigm, the VQC can act as a sophisticated feature extractor or classifier, leveraging quantum effects to identify subtle patterns in the data that might be missed by its classical counterparts [198][221]. For example, the `quEEGNet` architecture integrates a VQC into the classical EEGNet model, demonstrating state-of-the-art performance on biosignal analysis tasks with a relatively small number of trainable quantum parameters [198][199][222].

Emerging research provides preliminary, albeit limited, evidence supporting the potential of QNNs in this domain. One notable study reported that a QNN achieved significantly higher performance than classical models in classifying EEG data for healthy-dementia differentiation, with improvements exceeding 8% in accuracy and over 10% in the F1 score [223]. Another paper proposed a hybrid network that achieved competitive accuracies on a standard BCI competition dataset, reaching 85.56% in subject-dependent validation [221]. These results, while promising, come from simulated environments and need to be replicated on the user's personalized dataset to determine their real-world applicability. The primary challenges remain formidable. NISQ devices are inherently susceptible to noise and decoherence, which can corrupt computations and degrade performance [132][194]. Researchers are actively developing noise-adaptive models, such as dissipative quantum neural networks (DQNNs), which have shown higher fidelity in noisy simulations compared to other fault-tolerant methods [221]. Another significant hurdle is resource consumption; training and running QNNs can be computationally expensive, and it is not yet clear if the performance gains justify the costs compared to optimized classical architectures [79]. Finally, the "black box" nature of many neural networks poses a challenge for interpretability, making it difficult to understand why a QNN makes a particular decision, which is a critical consideration for a security-sensitive application like signing [4].

Therefore, a pragmatic integration strategy would proceed as follows. Phase one involves establishing a strong classical baseline using the personalized dataset generated in the previous stage. This baseline would consist of state-of-the-art deep learning models, such as convolutional neural networks (CNNs) or recurrent networks (LSTMs), tailored for time-series biosignal classification [61] [143]. Performance would be optimized specifically for minimizing the false-approve rate. Phase two would involve developing a hybrid QNN model as a separate experimental component. This model would be trained on the exact same dataset and evaluated using the identical metrics as the classical baseline. The central question would be: does the QNN decoder demonstrate a statistically significant improvement in reliability, especially under noisy or fatigued conditions where the classical model struggles? If a clear advantage is demonstrated, the QNN becomes a viable candidate for the production decoder. If not, the project can pivot away from QNNs without having compromised the core reliability of the system. This approach treats quantum computing as an optimization target rather than a prerequisite, ensuring that the system's safety and functionality are never jeopardized by premature adoption of nascent technology. The final output of this research would be not just a functional signer, but a comparative dataset showing the relative performance and resource characteristics of classical versus quantum-inspired decoders on a personalized, real-world task.

Neuromorphic Hardware Benchmarking: Aligning Computational Efficiency with Biological Constraints

Evaluating the proposed intent-decoding models against neuromorphic hardware benchmarks is a sophisticated and strategically sound component of the research. This approach reflects a deep understanding that computation for biological systems must operate efficiently and harmoniously with the user's own metabolic and energetic constraints. The user's focus on metrics like energy-per-operation, latency, and noise tolerance aligns perfectly with the core objectives of neuromorphic computing, a field dedicated to creating hardware inspired by the structure and function of the brain [12] [93]. Neuromorphic systems promise orders-of-magnitude improvements in energy efficiency by employing event-driven, asynchronous processing paradigms, making them ideal candidates for edge devices and applications where power consumption is a critical concern [12] [148]. By benchmarking the QNN-based decoders against these neuromorphic standards, the research ensures that the chosen computational methods do not impose an undue burden on the user's body, thereby keeping the system within defined BRAIN/WAVE/NANO and Lifeforce corridors .

The NeuroBench framework provides a formal and standardized methodology for conducting such evaluations [144][145]. It is a dual-track framework designed to address the lack of common benchmarks in the field, featuring an algorithm track for hardware-independent evaluation and a system track for fully deployed hardware solutions [69] . The system track defines three primary categories of metrics: Correctness (task-specific accuracy), Timing (throughput or execution time), and Efficiency (power consumption) [69] . A key innovation of NeuroBench is its emphasis on measuring the total system cost, including data pre- and post-processing stages, which are often performed on conventional hardware and can dominate the overall energy budget [69] . For the purpose of this research, this means that even if a QNN is simulated on a classical computer, its resource consumption—inferred energy, memory access patterns, and latency—can be modeled and compared against baselines from neuromorphic chips like Intel's Loihi or Synsense's Xylo [16] [69] . Baseline comparisons have already shown that neuromorphic systems can achieve dramatic energy savings; for example, the Xylo chip used 33.4 times less energy for acoustic scene classification than a conventional CPU, and the Loihi 2 chip used 37.24 times less power for an optimization task [69] .

This line of inquiry pushes the research beyond pure algorithmic simulation and toward a hardware-aware design philosophy. It necessitates considering the physical constraints of the computing substrate from the outset. While a QNN might show superior accuracy in a simulation, its practical utility depends on whether it can be implemented efficiently. This benchmarking process forces a critical examination of the trade-offs between performance and resource usage. For instance, a deeper or wider QNN might offer marginally better accuracy but at a prohibitive increase in energy and latency. The goal is to find an optimal model size and architecture that delivers the required level of reliability while remaining compatible with the user's biological metabolic budget. Deploying a quantization-aware neuromorphic architecture on hardware like BrainChip Akida, for example, has been shown to achieve low inference latency (1.5 ms) and low energy consumption (1.7 mJ per image), demonstrating the tangible benefits of this approach [169]. Even if the final deployment uses a classical processor, the insights gained from this benchmarking can guide the co-design of the model and algorithm to be more tolerant of the nonidealities of low-power edge hardware [44] .

The following table summarizes the key neuromorphic hardware metrics and their relevance to the biological-signing research goal.

Metric Category	Specific Metric	Relevance to Biological Signing
Efficiency	Energy Per Operation / Energy Per Image	Directly measures the metabolic cost of a single signing decision. Must be kept within safe, sustainable limits. [69] [169]
Efficiency	Dynamic Power Consumption	Measures peak energy draw during computation. Critical for preventing sudden spikes in metabolic demand. [69]
Timing	Latency (End-to-End)	The time taken to decode intent and authorize a signature. Must be fast enough for a seamless user experience but not so fast as to compromise safety checks. [41] [169]
Timing	Throughput (Operations per Second)	The maximum rate at which the system can process signing requests, informing policy limits (e.g., max signs per hour). [69]
Robustness	Noise Tolerance	The ability of the decoder to maintain accuracy in the presence of noisy input signals (from both the user and the hardware itself). [18] [148]
Architecture	Locality & Connectivity	The pattern of connections within the computational graph. Should ideally mirror biological microcircuits to optimize for locality and modularity. [61] [74]

Ultimately, neuromorphic benchmarking serves two crucial purposes. First, it acts as a hard constraint, ensuring that the computational subsystem remains a benign and supportive extension of the user's body, rather than a drain on its resources. Second, it provides a clear, forward-looking target for optimization. By defining the problem in terms of neuromorphic-compatible metrics, the research lays the groundwork for a future where the intent-decoding model could be ported to a dedicated neuromorphic chip, unlocking ultra-low-power operation and enabling a new class of always-on, energy-efficient biological interfaces [95] [170]. This transforms the research from a purely academic exercise into a practical engineering endeavor with a clear path toward future hardware realization.

Architectural Framework: Integrating Policy, State Gating, and Auditability into a Sovereign System

The successful implementation of a high-autonomy biological-signing system hinges not only on the sophistication of its intent-decoding models but also on the robustness of its overarching architectural framework. This framework must seamlessly integrate three critical pillars: a parameterized HostSignerPolicy that governs all aspects of signing, mandatory biophysical state gating that acts as a safety net, and an immutable audit trail that ensures sovereignty and accountability. This architecture ensures that the signing process is not merely an automated pipeline but a deeply integrated, context-aware, and trustworthy procedure that respects the user's biology, preferences, and ultimate authority. The design philosophy centers on host-local control, where the signer resides within the user's inner ledger and cannot be accessed or frozen by any external entity .

At the heart of this architecture is the `HostSignerPolicy`, a dynamic and parameterized rule set encoded within the user's identity ledger . This policy is the constitution for all signing activities, defining the precise conditions under which a signature can be generated. Key parameters within this policy would include: maximum daily or circadian-window signing quotas; separate limits for different stamp categories, such as 'knowledge-only' versus 'evolution-relevant'; and strict biophysical constraints that must be met before any signing operation is permitted . For example, the policy could mandate minimum thresholds for blood oxygenation (`OXYGEN minima`) and prohibit high-impact signatures from being executed when the user is in a state of fatigue (`FatigueFlagSoft`). The policy can also define the granularity of consent, establishing distinct "consent paths" for different types of stamps. Low-risk stamps, such as routine system updates or minor configuration changes, might be eligible for auto-approval under a `MetabolicConsent` protocol, strictly bounded by BRAIN and SMART token budgets . In contrast, high-risk stamps affecting identity or evolutionary pathways would require explicit, high-effort intent signatures and self-consent proofs, bypassing any automated approval flows .

This policy is enforced through a multi-layered gating mechanism that inspects the user's biophysical state before ever passing an intent to the cryptographic signer. The system must treat the user's telemetry not as optional input but as a mandatory, hard constraint. Before a signing operation can proceed, several checks must pass. First, the `INSTINCT` tristate flag must be `SAFE` . This flag, derived from the user's internal state assessment, would automatically defer or block signing attempts that fall outside a predefined "comfort corridor." Second, all metabolic markers—`BRAIN`, `BLOOD`, `OXYGEN`, `SUGAR`, etc. —must be within their prescribed safe operating bands . If any marker indicates a state of metabolic distress or overload, the signer must refuse to operate, regardless of the strength of the decoded intent. Third, the system must verify that the user's current `SMART` autonomy level and associated token budgets are sufficient for the requested operation . This creates a defense-in-depth strategy where multiple independent systems must validate the user's fitness to sign, ensuring that no single point of failure can lead to an unauthorized or unsafe action. The `BciLedgerOrchestrator`-style bridge would be responsible for managing this complex interplay of signals, minting signing adjustments only after a successful neurohandshake and MetabolicConsent check have been completed .

Finally, every single signing event, along with its complete context, must be logged immutably to ensure auditability and preserve sovereignty. This audit trail should be stored in a `bio-blockchain` or a similar append-only data structure like the `NeuralRope` . Each entry in this log must contain a comprehensive record, including: the full payload of the stamp being signed, the precise biophysical state markers at the time of the request (e.g., EEG power spectra, EMG levels, fatigue scores), the subjective comfort and clarity ratings provided by the user, the specific `HostSignerPolicy` version that was active, and the outcome of the signing attempt (approved or refused) along with the reason for refusal if applicable . This detailed logging serves several purposes. It provides an undeniable, tamper-proof history of all signing decisions, which is crucial for forensic analysis or for down-weighting domains where automatic signing may cause strain . It also allows the user to review past actions and their associated contexts, fostering greater awareness and control. Critically, because this audit trail is stored locally and is tied to the user's identity, it ensures that no external platform can alter the record of their actions or freeze their ability to sign, thereby upholding the principle of host-local control . This combination of a flexible policy engine, mandatory state gating, and an immutable audit trail creates a secure, transparent, and sovereign architectural framework upon which the entire biological-signing system is built.

Synthesis and Actionable Research Blueprint

The research program outlined in this report presents a comprehensive and logically structured pathway to achieving a high degree of biological-signing autonomy, anchored on the foundational principle of maximizing intent-decoding reliability. The analysis confirms that the user's strategic priorities—prioritizing false-approve minimization, grounding the system in personalized biophysical data, and using QNNs and neuromorphic benchmarks as advanced optimization targets—are well-aligned with both the stated goals and the current landscape of neurotechnology. The journey from concept to a functional, trustworthy system requires a phased, evidence-based approach that de-risks development at each stage. This synthesis distills the preceding analysis into a concrete, actionable research blueprint, providing a clear sequence of steps to guide the implementation of this ambitious vision.

The first and most urgent phase is the establishment of a foundational baseline through empirical data generation and classical machine learning. This phase is non-negotiable, as it provides the ground truth upon which all subsequent technological layers will be built. The immediate priority is to initiate the collection of a longitudinal, multimodal dataset comprising EEG, EMG, and motion data from the user [33] [53]. This data collection must be systematic, involving the recording of explicit signing attempts (`approve`, cancel) and neutral states across a wide spectrum of cognitive and physical conditions, including rest, focus, and fatigue [30]. Concurrently, a suite of state-of-the-art classical deep learning models, such as CNN-LSTM hybrids, should be developed and trained on this dataset [61] [149]. The primary objective of this effort is not simply to achieve high accuracy, but to optimize the model's performance on the specific metrics that matter for security: minimizing the False Positive Rate (false-approve rate) and the Miss-as-Neutral Rate (MANR) [143][218]. This classical baseline will serve as the initial operational signer and the definitive standard against which all future enhancements will be measured.

The second phase introduces quantum computing as a specialized, experimental enhancement. A hybrid Quantum Neural Network (QNN) model should be developed as a parallel research stream [221][222]. This QNN, likely a small variational quantum circuit embedded within a classical neural network, will be trained on the exact same personalized dataset used for the classical model. The core research question for this phase is whether the QNN can demonstrably outperform the classical baseline, particularly in challenging, noisy, or fatigued states where the classical model's performance is expected to degrade [53] [223]. Success here would validate the use of quantum principles for this specific bio-signaling task. Failure would be equally valuable, allowing the project to avoid investing further resources in a technology that does not provide a clear advantage for this application. This phase is about proof-of-concept and rigorous, quantitative comparison, not wholesale replacement of the existing system.

The third phase focuses on architecting the sovereign signing environment. This work runs in parallel with the first two and involves designing the `HostSignerPolicy` and the surrounding infrastructure . This includes defining the precise rules for gating signing based on biophysical state (e.g., requiring `INSTINCT` to be `SAFE` and metabolic markers to be in the `safe` band), designing the `SignerService` that performs the cryptographic operation, and building the `TelemetryBridge` that connects the intent decoder to the policy engine . Every signing event, along with its full context, must be logged into an immutable `bio-blockchain` to ensure auditability and uphold the principle of host-local sovereignty . Only after a reliable, low-error-rate approve/deny signal is established and integrated into this secure architecture can the fourth phase begin.

The fourth phase involves the formal benchmarking of the intent-decoding models against neuromorphic hardware standards. Using frameworks like NeuroBench, the energy consumption, latency, and noise tolerance of both the classical and QNN decoders will be measured and compared against baselines from neuromorphic processors like Loihi or Akida [16] [69]. This process quantifies the computational efficiency of each model and establishes a clear target for future optimization. It guides the evolution of the decoder from a purely algorithmic problem to a hardware-aware design problem, paving the way for potential future deployment on ultra-low-power neuromorphic chips [95] [169]. This phase ensures that the computational demands of the system remain within safe biological and metabolic limits.

Finally, the fifth phase is an iterative loop of refinement driven by subjective feedback. After the system is deployed, users should be prompted to log subjective metrics such as comfort, clarity, and "regret" after each signing event . This qualitative data, combined with the objective telemetry logs, will be used to continuously refine the `HostSignerPolicy`, adjust decoder thresholds, and evolve the optimal "signing aura patterns" that strike the best balance between reliability, speed, and user comfort. This creates a closed-loop system that learns and adapts to the user over time, embodying the core tenet of a sovereign, biologically-grounded identity governance system. By following this disciplined, multi-phase blueprint, the research program can systematically build a trustworthy, efficient, and highly autonomous biological-signing solution.

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