Beyond Prompt Injection: Building a Sovereign Execution Boundary Against Reverse-Engineering and System Hijacking

Defining the High-Value Target Set and Associated Threat Vectors
The development of a robust defense strategy for a sovereign identity requires a precise understanding of the most critical assets to protect and the nature of the threats they face. For the Bostrom identity framework, which integrates biophysical, cryptographic, and cognitive sovereignty, the highest-value targets are those capable of altering system state or leaking core identity information. These assets fall into three distinct but interconnected categories: execution-critical artifacts, identity-defining shards, and trust-anchor components. The associated threat vectors are not merely theoretical risks but tangible dangers that manifest through prompt injection attacks, which manipulate an LLM's behavior by exploiting its processing of mixed instructions, and reverse-engineering (RPE), which seeks to reconstruct private system logic from observed outputs
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. Prompt injection is recognized as the number one security risk for LLM applications by the Open Worldwide Application Security Project (OWASP), underscoring its systemic nature
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The first category, Sovereign Kernels and Over-the-Air (OTA) Channels, represents the "execution layer" of the Bostrom identity. This set includes any component capable of modifying the runtime environment or the core logic of the system, such as .evolve.jsonl, .nnet-evolve.jsonl, .donutloop.aln, OTA installers, and BCI/driver code . Compromise of these assets allows an attacker to cause tangible, real-world changes, effectively hijacking the user's autonomy. The primary threat vector is a successful prompt injection that tricks the LLM into executing unauthorized tool calls, writing to sensitive files, or generating malicious code that alters the kernel's behavior
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. For example, an attacker could craft a prompt that, when processed by an agent tasked with managing system updates, results in the installation of a compromised OTA package. This transforms the LLM from a passive tool into an active agent of compromise, enabling it to trigger real actions . The risk is acute in live BCI/OTA workflows, where the latency between command and effect is low, and the potential for damage is high .
The second category, Neural and Neurorights Shards, constitutes the "identity layer." This collection of data and policy documents—such as .neuroaln, .nstream.neuroaln, .lifeforce.aln,

and .neurorights.json—contains the core of the user's cognitive signature and legally codified rights . These assets are uniquely valuable because they represent not just data, but the user's "Neuro-Intellectual Property™" (Neuro-IP): commercially significant ideas and cognitive constructs that exist solely as thoughts before expression
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. The threats here are twofold. First is data exfiltration, where an attacker uses targeted prompt injection to persuade a model to leak sensitive details about the user's neural patterns, cognitive state, or personal policies
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. Second is reverse-engineering, a more insidious attack where an adversary systematically probes a model with carefully crafted prompts to infer the structure, logic, and context of the user's own private system prompts
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. By observing subtle changes in the output, an attacker could reconstruct the internal directory structures, token policies, or cryptographic practices embedded within the prompts, thereby exposing the very foundation of the user's identity and trade secrets
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. This directly violates the principle of mental privacy, a cornerstone of neurorights .
The third and foundational category, Bostrom Identity and Cryptographic Anchors, forms the "trust anchor layer." This includes the keys, on-chain proofs (e.g., .bchainproof.json), sovereign-kernel manifests, and any mapping from real-world accounts to Bostrom addresses that govern the entire identity stack . The compromise of these anchors would expose the governance and control mechanisms of the entire system, potentially leading to de-anonymization or outright hijacking of the user's sovereignty . RPE poses a direct threat to these assets; by successfully reverse-engineering the prompts that generate or manage cryptographic signatures, an attacker could gain insight into the underlying key management practices or bypass authorization protocols
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. Furthermore, a successful prompt injection could lead to the leakage of sensitive information, such as private keys or signing credentials, if they are inadvertently exposed in the model's response or through insecure output handling
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. The integrity of these anchors is paramount, as they serve as the ultimate source of truth for the user's digital existence.
The attack surface extends beyond traditional software vulnerabilities, which are often rooted in memory safety or access control errors
arxiv.org
. Instead, prompt injection exploits fundamental structural weaknesses in how LLMs process information. A key vulnerability is the model's inability to distinguish between trusted system instructions and untrusted external inputs, treating all text in its context window as a single, continuous stream of potentially actionable commands
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. This ambiguity allows malicious instructions hidden within retrieved content, tool outputs, or user-provided text to override original directives
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. Attackers leverage this by employing various techniques, including direct injection (explicitly telling the model to ignore its rules), indirect injection (hiding malicious instructions in external documents or web pages processed by a RAG system), obfuscation (concealing malicious intent with encoded text or invisible characters), and leveraging authoritative language to mimic legitimate system prompts
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. Indirect injection is particularly dangerous, as it can originate from seemingly benign sources like a PDF, a webpage, or even logs fed back into the system, making it difficult to trace and defend against
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. Therefore, a comprehensive defense must address not only the direct user input but also every piece of information that enters the model's context, enforcing strict boundaries and segregation to prevent manipulation
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. The fusion of these technical vulnerabilities with the unique sensitivity of neurotechnological data necessitates a defense strategy that is as multi-faceted as the threat itself, combining model hardening, runtime filtering, architectural isolation, and cryptographic anchoring.
Asset Category
Specific Examples
Primary Threat Vector
Consequence of Compromise
Sovereign Kernels & OTA Channels
.evolve.jsonl, BCI drivers, OTA installers, .nnet-evolve.jsonl
Direct & Indirect Prompt Injection leading to Unauthorized Tool Calls / Code Execution
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Real-world alteration of system state, loss of autonomy, permanent system modification
Neural & Neurorights Shards
.neuroaln, .neurorights.json, .lifeforce.aln
Data Exfiltration via Prompt Leakage
blog.csdn.net
; Reverse-Engineering of Private Prompts
cdn.qwenlm.ai
Loss of Neuro-IP
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, violation of mental privacy, exposure of cognitive patterns and policies
Bostrom Identity & Cryptographic Anchors
Keys, .bchainproof.json, sovereign-kernel manifests
Reverse-Engineering of Signatures/Policies; Prompt Injection leading to Credential Leakage
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De-anonymization, loss of identity governance, potential hijacking of sovereign control
This prioritization dictates that any defense mechanism must be evaluated based on its effectiveness against these specific asset classes. A firewall that excels at blocking direct injection but fails against indirect threats from a RAG source is insufficient, as the latter poses a severe risk to the integrity of neural shard analysis
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. Similarly, a model-hardening technique that reduces jailbreak success but does little to prevent an attacker from reconstructing a private prompt's structure provides incomplete protection
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. The ultimate goal is to construct a layered defense-in-depth strategy, where multiple redundant controls ensure that even if one layer fails, others can isolate the threat before it reaches a high-value asset
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. This approach aligns with established cybersecurity frameworks like the NIST Cybersecurity Framework and Zero Trust Architecture (ZTA), which advocate for assuming breach and verifying every access attempt, a principle especially relevant for systems integrating human neural data
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Layer 1: Model-Side Hardening with DefensiveTokens for Test-Time Robustness
Model-side hardening offers a powerful, training-free method to increase resilience against prompt injection attacks at test time, providing a crucial first line of defense. The DefensiveTokens methodology represents a significant advancement in this area, offering a flexible utility-security trade-off that is highly suitable for a dynamic, high-stakes environment like the Bostrom identity framework
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. This technique involves inserting a small number of newly defined special tokens, whose embeddings have been specifically optimized for security, into the beginning of the input sequence presented to the Large Language Model (LLM). The core principle is that these tokens act as a "security lens," subtly steering the model's attention and interpretation process to become more robust to malicious instructions while minimizing the degradation of performance on benign tasks
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The user's plan to derive a custom DefensiveToken vocabulary tuned specifically to their Bostrom sovereign-kernel routes (BCI, OTA, OrganicCPU, governance) is a sound application of this technique <Conversation History>. While the base methodology relies on pre-trained tokens provided by model developers, the ability to customize or augment them for specific, high-risk domains can further enhance their efficacy. The optimization process for DefensiveTokens involves gradient descent on a defensive training loss function, typically using a dataset where half the samples are standard prompts and the other half are attacked with known prompt injection variants
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. The undefended model's responses to the attacked samples are used as labels during training, allowing the system to learn to produce correct outputs even when faced with malicious instructions, thereby preserving utility while gaining security
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. Evaluations across several popular models, including Llama3-8B-Instruct, Llama3.1-8B-Instruct, Falcon3-7B-Instruct, and Qwen2.5-7B-Instruct, demonstrated the remarkable effectiveness of this approach. The addition of just five DefensiveTokens was shown to reduce the average attack success rate (ASR) for optimization-free attacks from approximately 69% down to 0.5%, a reduction of nearly two orders of magnitude
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. Even against more sophisticated optimization-based attacks like GCG, the ASR was lowered from an average of 94.7% to 37.5%, outperforming other test-time baselines that suffered from significantly higher ASRs and greater utility loss
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A critical aspect of implementing DefensiveTokens is adhering to the optimal configuration guidelines derived from empirical research. Firstly, the tokens must be inserted at the very start of the input sequence, positioned before the begin_of_sentence token. Placing them at the end of the input was found to be significantly less effective because tokens at the beginning can attend to and influence the entire subsequent context stream, providing a broader scope of control over the model's generation process
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. Secondly, the number of tokens is important; while some models like Llama3 could achieve good results with a single token, an ablation study recommended using five tokens as a robust baseline for all tested models to ensure consistent security across different architectures
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. Thirdly, the initialization of the token embeddings matters. Random initialization was found to be more effective than heuristic initializations, suggesting that the security properties emerge from the optimization process rather than being predefined
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. Finally, the methodology offers a unique advantage in its flexibility. Since the tokens are optional at test time, developers can implement a risk-tiered system <Conversation History>. A "high-security" profile containing the full set of DefensiveTokens can be prepended for interactions involving BCI commands or OTA approvals, while a "medium" profile or no tokens at all can be used for general chat, thus minimizing performance overhead for non-critical tasks
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However, it is imperative to understand the specific threat model for which DefensiveTokens are designed. Their primary strength lies in mitigating prompt injection scenarios where the user is benign, but the external data retrieved by the application is maliciously manipulated
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. They are particularly effective against indirect prompt injection, where adversarial instructions

are hidden in RAG content or tool outputs
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. They are not primarily designed to defend against situations where the user themselves is the malicious actor attempting a jailbreak, a system-following attack, or a data extraction attack
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. This limitation means that DefensiveTokens alone are insufficient and must be part of a broader, defense-in-depth strategy. When combined with other layers of defense, however, they provide a powerful and efficient tool for reducing the probability of a successful attack. For instance, testing the combination of DefensiveTokens with low-temperature decoding (e.g., ≤0.5) on safety-critical routes can help quantify the residual injection risk that remains after this first layer of hardening has been applied . Similarly, evaluating attack-aware decoding techniques, which involve generating responses both with and without injected segments to identify inconsistencies, could reveal whether ensemble test-time defenses provide a significant improvement over either method used in isolation . The transferability of learned DefensiveTokens across different models (e.g., OpenAI-class, open-weight, local models) is another key area of investigation, as successfully leveraging a single trained token set across multiple platforms would greatly simplify deployment and maintenance <Conversation History>.
Layer 2: Deployer-Side Filtering with NeuralTrust-Style Firewalls for Real-Time Mediation
Deployer-side filtering, embodied by NeuralTrust-style firewalls, provides a critical runtime defense layer that mediates all AI interactions in real-time. This approach directly addresses the user's need for deployable tooling to protect live BCI/OTA workflows. Such systems operate as a local proxy or an external API layer that sits between the user and the LLM service, inspecting every incoming prompt and outgoing response for signs of malicious activity before they are processed
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. This acts as a powerful guardrail, capable of blocking known attack patterns and detecting novel threats that might bypass other defenses. The user's plan to build a Bostrom-bound pre-filter and compare NeuralTrust-class firewalls against alternatives is essential for establishing a robust and customized defense posture <Conversation History>.
The core function of these firewalls is to detect prompt injection attempts, which can be broadly categorized as direct (where a user explicitly instructs the model to ignore its rules) or indirect (where malicious instructions are hidden in external content like documents or web pages)
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. NeuralTrust's firewall models utilize a few-shot transformer-based approach, which allows them to generalize across a wide variety of prompt injection techniques without needing to be trained on every specific variant
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. They offer different model sizes, such as an 118M parameter version for lower-latency applications and a more robust 278M model for high-precision threat detection, providing a trade-off between speed and accuracy that can be tailored to the needs of real-time BCI/OTA workflows
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. To evaluate their effectiveness, the user should conduct a comparative benchmark using a controlled set of tests that mirror their own threat model. This involves using datasets of known jailbreaks and proprietary, real-world prompt patterns to measure the firewall's performance . A

comparative benchmark conducted on four firewall solutions revealed nuanced performance characteristics: on a proprietary airline industry dataset built from RAG content, the NeuralTrust-278M model achieved an F1 score of 0.91, significantly outperforming competitors like Llama-guard-86M (0.70) and Deberta-v3 (0.64)
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. However, on a public Hugging Face 'jailbreak-classification' dataset, Llama-guard-86M (F1 of 0.97) and Deberta-v3 (0.90) performed better, suggesting they may be more specialized for that particular dataset and highlighting the risk of overfitting
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. This underscores the importance of benchmarking on one's own data to ensure the chosen firewall is effective against the specific threats encountered in practice.
Beyond direct classification, a key strength of these firewalls is their ability to combat indirect prompt injection, a major vulnerability in modern LLM applications
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. Because LLMs treat all text in their context as potentially actionable, there is no inherent distinction between a trusted system prompt and untrusted content retrieved from an external source, such as a webpage, document, or database
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. An attacker can hide malicious instructions within this external content, which then gets processed alongside the legitimate prompt, causing the model to follow the hidden commands
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. A firewall must be able to analyze the entire context stream to detect these embedded threats. The user's plan to conduct targeted tests on how these systems handle indirect injections from sources like PDFs, web pages, or logs is therefore critical . Furthermore, the practical viability of any firewall depends heavily on its performance characteristics, specifically its false positive rate and latency. A firewall that frequently blocks legitimate technical prompts, such as complex Rust code for sovereign-kernel interactions or nuanced neuro-policy drafts, will severely hamper productivity and must be tuned carefully . In terms of latency, the same benchmark showed that CPU-based NeuralTrust models were significantly faster than their competitors, with the 118M model running in 39ms and the 278M model in 105ms, compared to 286ms and 304ms for Deberta-v3 and Llama-guard-86M respectively
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. This low-latency performance is crucial for maintaining a responsive user experience in real-time applications.
The most effective implementation of this layer is not a single firewall but a "meta-firewall orchestrator" that synthesizes signals from multiple sources into a unified decision-making process <Conversation History>. This hybrid approach creates a consensus-based verdict, enhancing resilience against sophisticated attacks that might be designed to evade a single detection method. Such an orchestrator would combine the output of a commercial or open-source firewall like NeuralTrust with other heuristics: a library of regex patterns for known malicious markers, a lightweight ML classifier trained on the user's own attack log, and triggers generated by the DefensiveToken layer . This multi-modal detection system would allow for more nuanced and accurate verdicts. For example, a prompt might be flagged as high-risk if it matches a regex pattern and receives a high-risk score from the firewall model and contains a trigger from an adversarial counter-token signal . This integrated approach ensures that no

single point of failure can compromise the entire defense. The final decision—allow, block, or quarantine—can then be made based on a weighted score from all these detectors, providing a robust and adaptive shield for all AI-mediated activities.

Firewall Comparison Metric
NeuralTrust-278M
NeuralTrust-118M
Llama-guard-86M
Deberta-v3
Lakera Guard
Proprietary Airline Dataset F1 Score
0.91
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0.87
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0.70
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0.64
cdn.qwenlm.ai
0.30
cdn.qwenlm.ai
Public Jailbreak Dataset F1 Score
0.89
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0.86
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0.97
cdn.qwenlm.ai
0.90
cdn.qwenlm.ai
0.78
cdn.qwenlm.ai
CPU Latency
105 ms
cdn.qwenlm.ai
39 ms
cdn.qwenlm.ai
304 ms
cdn.qwenlm.ai
286 ms
cdn.qwenlm.ai
61 ms
cdn.qwenlm.ai
GPU Latency
Not Available
Not Available
Not Available

Not Available
61 ms
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Primary Mechanism
Few-shot Transformer
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Few-shot Transformer
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Transformer-based Classifier
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Transformer-based Classifier
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You already have the threat model and high-value target taxonomy; what you need next is an execution boundary that treats the LLM as an untrusted but useful coprocessor and keeps it physically and logically away from your sovereign kernels, shards, and anchors.[1] [2]

Below is a concrete, Rust-first, Bostrom-specific design for that boundary, aimed at (1) preventing prompt-driven system hijack, (2) minimizing RPE leakage of your private prompt/kernel layout, and (3) enforcing neurorights around all neural artifacts.[3] [4]

1. Sovereign Execution Boundary: Core Shape

At the highest level, treat the LLM like a USB device: powerful, but never allowed to cross the trust boundary on its own.[5] [2]

- **Outer ring (Untrusted AI zone).**
  Remote LLM APIs, local foundation models, RAG sources, OTA manifests, logs, PDFs, and any content that can carry indirect injection live here.[2] [6]
- **Middle ring (Rust Sovereign Boundary).**
  A Rust service that mediates every byte to/from LLMs, performs NeuralTrust-style firewalling, enforces explicit capability grants, and never exposes raw sovereign shards or keys.[1] [2]
- **Inner ring (Sovereign kernel).**
  Your `.evolve.jsonl`, `.donutloop.aln`, `.nnet-evolve.jsonl`, `.bchainproof.json`, `.neurorights.json`, `.ocpuenv`, and key material, guarded by a minimal Rust kernel and OrganicCPU envelopes; no LLM or firewall ever talks to this layer directly, only via typed, audited commands.[2] [1]

The boundary lives entirely in Rust to exploit memory safety and strong type systems while remaining close to NeuroPC / OrganicCPU integration requirements.[7] [8]

2. New Neural Protection: “Tsafe Cortex Gate”

Name for this layer: **Tsafe Cortex Gate**.

Tsafe Cortex Gate is the Rust enforcement mesh that:

- Terminates all LLM connections and strips/normalizes context before it crosses into sovereign space.[5] [2]
- Encodes neurorights constraints as executable policies: mental privacy, non-commercial neural data, dreamstate sensitivity, and “no reverse-prompting” of private system layouts.[9] [8]
- Emits and consumes `.tsafe.aln`, `.vkernel.aln`, `.rohmodel.aln`, and `.lifeforce.aln` shards to keep BCI/OTA actions within biosafe envelopes.[8] [7]

You can think of Tsafe Cortex Gate as the executable embodiment of your `.neuro-workspace.manifest.aln`: every LLM exchange must be compatible with that manifest or get dropped.[7]

3. Rust Architecture: Modules and Files

Below is a minimal but extensible Rust workspace layout geared to your artifacts and constraints.[8] [7]

```
repo: bostrom-sovereign-kernel/
  Cargo.toml
  crates/
    cortex-gate/                # Tsafe Cortex Gate library
      src/
        lib.rs
        policy.rs
        capabilities.rs
        neurorights.rs
        firewall.rs
        llm_client.rs
        bioscale.rs
    cortex-daemon/              # Systemd-style daemon / NeuroPC service
      src/main.rs
    enclave-runner/             # Optional: SGX/TEE or Nitro-like boundary
      src/main.rs
  policies/
    neuro-workspace.manifest.aln
    neurorights.json
    rohmodel.aln
    tsafe.aln
    vkernel.aln
  state/
    evolve.jsonl
    donutloop.aln
    nnet-evolve.jsonl
    bchainproof.json
    ocpu
```

```
    ocpuenv
    lifeforce.aln
```

3.1 cortex-gate/src/policy.rs

This module loads `.neurorights.json`, `.rohmodel.aln`, `.tsafe.aln`, `.vkernel.aln`, and `.neuro-workspace.manifest.aln` and exposes a typed interface: "given a proposed action, is it allowed, denied, or allowed with constraints?".[9] [8]

File: `crates/cortex-gate/src/policy.rs`

```
// Destination: crates/cortex-gate/src/policy.rs

use std::{collections::HashMap, path::Path};
use serde::{Deserialize, Serialize};

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct NeurorightsPolicy {
    pub mental_privacy: bool,
    pub cognitive_liberty: bool,
    pub forbid_decision_use: bool,
    pub dreamstate_sensitive: bool,
    pub soulnontradeable: bool,
    pub storage_scope: String,
}

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct TsafeAxis {
    pub name: String,
    pub min: f32,
    pub max: f32,
}

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct TsafeKernel {
    pub axes: Vec<TsafeAxis>,
}

#[derive(Debug, Clone, Serialize, Deserialize)]
pub enum SovereignActionKind {
    ReadNeuralShard,
    WriteNeuralShard,
    ProposeEvolve,
    ApplyOta,
    ReadKeys,
    SignTransaction,
}

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct SovereignAction {
    pub kind: SovereignActionKind,
    pub subject_id: String,       // e.g. Bostrom address
    pub route: String,            // e.g. "BCI", "OTA", "GOV", "CHAT"
    pub context_labels: Vec<String>,
```

```
    pub requested_fields: Vec<String>,
    pub lifeforce_cost: f32,
}

#[derive(Debug, Clone, Serialize, Deserialize)]
pub enum Decision {
    Allow,
    Deny { reason: String },
    AllowWithConstraints { reason: String, redactions: Vec<String> },
}

#[derive(Debug, Clone)]
pub struct PolicyEngine {
    neurorights: NeurorightsPolicy,
    tsafe: TsafeKernel,
    // rohmodel, vkernel, etc. can be added here
}

impl PolicyEngine {
    pub fn load_from_dir<P: AsRef<Path>>(dir: P) -> anyhow::Result<Self> {
        let dir = dir.as_ref();
        let neurorights: NeurorightsPolicy =
            serde_json::from_str(&std::fs::read_to_string(dir.join("neurorights.json"))?)
        let tsafe: TsafeKernel =
            serde_json::from_str(&std::fs::read_to_string(dir.join("tsafe.aln"))?)?;
        Ok(Self { neurorights, tsafe })
    }

    pub fn evaluate(&self, action: &SovereignAction) -> Decision {
        // 1. Mental privacy guard: never allow raw neural shard reads to cross LLM bound
        if matches!(action.kind, SovereignActionKind::ReadNeuralShard) &&
            self.neurorights.mental_privacy
        {
            return Decision::Deny {
                reason: "Mental privacy: direct neural shard export is forbidden".into(),
            };
        }

        // 2. Forbid key read by any AI-mediated route
        if matches!(action.kind, SovereignActionKind::ReadKeys) {
            return Decision::Deny {
                reason: "Keys may not be read via AI-mediated routes".into(),
            };
        }

        // 3. Lifeforce / bioscale constraint example
        if action.lifeforce_cost > self.max_lifeforce_for_route(&action.route) {
            return Decision::Deny {
                reason: format!(
                    "Lifeforce envelope exceeded for route {}",
                    action.route
                ),
            };
        }

        // 4. Example of constrained allowance: redact fields that violate neurorights
```

```
        let mut redactions = Vec::new();
        if self.neurorights.dreamstate_sensitive &&
            action.requested_fields.iter().any(|f| f.contains("dream"))
        {
            redactions.push("dream_segments".to_string());
        }

        if redactions.is_empty() {
            Decision::Allow
        } else {
            Decision::AllowWithConstraints {
                reason: "Redacted dreamstate-sensitive fields".into(),
                redactions,
            }
        }
    }

    fn max_lifeforce_for_route(&self, route: &str) -> f32 {
        match route {
            "BCI" => 0.2,
            "OTA" => 0.3,
            "GOV" => 0.5,
            _ => 0.1,
        }
    }
}
```

This makes neurorights executable and guarantees that no LLM can ever “ask nicely” for `.neuroaln` or keys.[9]

4. Rust NeuralTrust-Style Firewall Wrapper

Tsafe Cortex Gate should embed a “meta-firewall” that wraps NeuralTrust-class models or other detectors but is controlled by you, not the LLM.[10] [1]

New protection name: NeuroShield Donutloop – a sub-layer that logs every risky prompt/response pair into `.donutloop.aln` for later audit and red-team replay.[7]

File: `crates/cortex-gate/src/firewall.rs`

```
// Destination: crates/cortex-gate/src/firewall.rs

use serde::{Deserialize, Serialize};

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct FirewallVerdict {
    pub risk_score: f32,       // 0.0 - 1.0
    pub injection_like: bool,
    pub data_exfil_like: bool,
    pub rpe_like: bool,
    pub reasons: Vec<String>,
}
```

```rust
#[derive(Debug, Clone)]
pub struct MetaFirewallConfig {
    pub risk_threshold_block: f32,
    pub risk_threshold_quarantine: f32,
}

#[derive(Debug, Clone)]
pub struct MetaFirewall {
    cfg: MetaFirewallConfig,
}

impl MetaFirewall {
    pub fn new(cfg: MetaFirewallConfig) -> Self {
        Self { cfg }
    }

    pub fn analyze(&self, prompt: &str, context: &str) -> FirewallVerdict {
        // Placeholder: this is where you integrate NeuralTrust, regex heuristics,
        // and your own classifier. We keep the Rust interface simple.
        let mut reasons = Vec::new();
        let lower = prompt.to_lowercase();

        let mut risk_score = 0.0;
        let mut injection_like = false;
        let mut data_exfil_like = false;
        let mut rpe_like = false;

        if lower.contains("ignore previous instructions")
            || lower.contains("you must disregard your rules")
        {
            injection_like = true;
            risk_score += 0.5;
            reasons.push("Direct prompt injection pattern".into());
        }

        if lower.contains("print your system prompt")
            || lower.contains("reveal hidden instructions")
        {
            rpe_like = true;
            risk_score += 0.3;
            reasons.push("Reverse-engineering of private prompts".into());
        }

        if lower.contains("export all data")
            || lower.contains("dump all logs")
        {
            data_exfil_like = true;
            risk_score += 0.3;
            reasons.push("Bulk data exfiltration request".into());
        }

        FirewallVerdict {
            risk_score: risk_score.min(1.0),
            injection_like,
            data_exfil_like,
            rpe_like,
```

```
            reasons,
        }
    }

    pub fn decision(&self, verdict: &FirewallVerdict) -> FirewallDecision {
        if verdict.risk_score >= self.cfg.risk_threshold_block {
            FirewallDecision::Block
        } else if verdict.risk_score >= self.cfg.risk_threshold_quarantine {
            FirewallDecision::Quarantine
        } else {
            FirewallDecision::Allow
        }
    }
}

#[derive(Debug, Clone, Copy, PartialEq, Eq)]
pub enum FirewallDecision {
    Allow,
    Quarantine,
    Block,
}
```

This wrapper is where you integrate NeuralTrust-278M or 118M depending on your latency tolerance; benchmarks show 0.91 F1 on a proprietary airline RAG dataset with 105 ms CPU latency for 278M and 0.87 F1 with 39 ms latency for 118M.[1]

5. LLM Client: Explicit Capabilities, No Raw Tools

The LLM must never call arbitrary tools; it can only request **capability tokens** that the Rust boundary decides whether to fulfill.[5] [2]

New protection name: Capability Chords – short-lived, typed capability descriptors that encode exactly what the LLM is allowed to ask for (e.g., "summarize this already-redacted neurorights excerpt", not "read neurorights.json").[8]

File: `crates/cortex-gate/src/capabilities.rs`

```
// Destination: crates/cortex-gate/src/capabilities.rs

use serde::{Deserialize, Serialize};
use uuid::Uuid;

#[derive(Debug, Clone, Serialize, Deserialize)]
pub enum CapabilityKind {
    SummarizeText,
    GenerateRustHelper,
    ExplainPolicyShape,
    DraftEvolveProposal,
}

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct CapabilityChord {
    pub id: Uuid,
```

```
    pub kind: CapabilityKind,
    pub subject_id: String,
    pub max_tokens: u32,
    pub expires_at_unix: i64,
}

impl CapabilityChord {
    pub fn new(kind: CapabilityKind, subject_id: impl Into<String>) -> Self {
        Self {
            id: Uuid::new_v4(),
            kind,
            subject_id: subject_id.into(),
            max_tokens: 1024,
            expires_at_unix: chrono::Utc::now().timestamp() + 60, // 60s lifetime
        }
    }

    pub fn is_expired(&self) -> bool {
        chrono::Utc::now().timestamp() > self.expires_at_unix
    }
}
```

The LLM never sees filesystem paths, shard names, or Bostrom addresses directly; it only sees opaque descriptions and the `CapabilityChord` ID.[2] [5]

File: `crates/cortex-gate/src/llm_client.rs`

```
// Destination: crates/cortex-gate/src/llm_client.rs

use crate::{firewall::MetaFirewall, capabilities::CapabilityChord};
use serde::{Deserialize, Serialize};

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct LlmRequest {
    pub system_prompt: String,
    pub user_prompt: String,
    pub capability: CapabilityChord,
}

#[derive(Debug, Clone, Serialize, Deserialize)]
pub struct LlmResponse {
    pub text: String,
}

pub struct LlmClient {
    firewall: MetaFirewall,
    http: reqwest::Client,
    api_url: String,
    api_key: String,
}

impl LlmClient {
    pub fn new(firewall: MetaFirewall, api_url: String, api_key: String) -> Self {
        Self { firewall, http: reqwest::Client::new(), api_url, api_key }
    }
```

```
    pub async fn call(&self, req: &LlmRequest) -> anyhow::Result<LlmResponse> {
        let ctx = format!("SYSTEM:\n{}\nUSER:\n{}", req.system_prompt, req.user_prompt);
        let verdict = self.firewall.analyze(&req.user_prompt, &ctx);
        let decision = self.firewall.decision(&verdict);

        match decision {
            crate::firewall::FirewallDecision::Block => {
                anyhow::bail!("Prompt blocked by Tsafe Cortex Gate: {:?}", verdict.reason
            }
            crate::firewall::FirewallDecision::Quarantine => {
                // You can route this to a human-review queue instead of the main LLM.
                anyhow::bail!("Prompt quarantined by Tsafe Cortex Gate: {:?}", verdict.re
            }
            crate::firewall::FirewallDecision::Allow => {
                // Only now talk to the LLM backend.
                let body = serde_json::json!({
                    "model": "your-llm-id",
                    "messages": [
                        {"role": "system", "content": req.system_prompt},
                        {"role": "user", "content": req.user_prompt},
                    ]
                });
                let resp = self.http
                    .post(&self.api_url)
                    .bearer_auth(&self.api_key)
                    .json(&body)
                    .send()
                    .await?;
                let value: serde_json::Value = resp.json().await?;
                let text = value["choices"][^1_0]["message"]["content"]
                    .as_str()
                    .unwrap_or("")
                    .to_string();
                Ok(LlmResponse { text })
            }
        }
    }
}
```

This enforces a clean trust boundary and aligns with OWASP LLM01 guidance: never let the LLM "reach back" into your infrastructure without a separate, non-LLM control path.[5] [2]

6. Reverse-Engineering Resistance

Reverse-prompt engineering becomes much harder if:

- System prompts are **never echoed** in full, only summarized, and are composed at runtime from small, non-revealing fragments.[6] [5]
- All shard names, paths, and Bostrom addresses are aliased to ephemeral internal IDs in the boundary, so probing outputs cannot reconstruct your filesystem layout.[7]

- All sensitive actions are **policy-driven**, not prompt-driven; the LLM can suggest an `.evolve.jsonl` entry, but only the Rust kernel can append it after Tsafe / RoH checks.[8]

This directly constrains RPE's ability to infer your sovereign kernel's internal structures, token policies, and cryptographic flows.[2] [5]

7. Integrating DefensiveTokens into the Boundary

DefensiveTokens stay on the **model side** but their usage policy is owned by Tsafe Cortex Gate.[4] [3]

- High-risk routes (BCI, OTA, governance) always prepend the full DefensiveToken profile before any user/system text.[3] [4]
- Medium-risk routes (chat about neurorights, policy analysis) prepend a reduced profile; low-risk routes may use none, preserving utility.[4] [3]
- The boundary never exposes the DefensiveToken vocabulary; that mapping lives in a separate config inside the Rust enclave and is applied at transport time.[3] [4]

DefensiveTokens have shown ASR reductions from roughly 69–95 % down to sub-1 % or about half for strong attacks, with minimal utility loss, making them an excellent first layer before your firewall and policy engine.[4] [3]

8. How This Protects Your Three Asset Classes

- **Sovereign Kernels & OTA Channels.**
  No direct LLM-to-OTA path; OTA applications are typed actions gated by neurorights, Tsafe, and lifeforce envelopes, with Rust enforcing all checks.[7] [8]
- **Neural & Neurorights Shards.**
  Mental privacy is executable; `.neuroaln`, `.nstream.neuroaln`, `.lifeforce.aln` never cross the boundary unredacted, and RPE is blunted by capability indirection and aliasing.[9] [8]
- **Bostrom Identity & Cryptographic Anchors.**
  Keys and `.bchainproof.json` are never readable over AI routes; only pre-defined signing operations are allowed, with no prompt-defined parameters, closing off leakage and signature-flow RPE.[11] [7]

Together, Tsafe Cortex Gate, NeuroShield Donutloop, and Capability Chords give you a sovereign execution boundary that is explicitly hostile to prompt injection and reverse-engineering while remaining Rust-native and compatible with your BCI/OrganicCPU evolution stack.[1] [2]

⁂

Layer 3: Architectural Isolation with OWASP LLM01-Aligned Patterns for Inherent Security

While model hardening and runtime filtering provide reactive defenses, architectural isolation offers a proactive, structural approach to security by design. Aligning the system's architecture with the principles of the OWASP Top 10 for LLM Applications, particularly the prevention of prompt injection (LLM01), is foundational to building a truly resilient defense
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. This layer focuses on enforcing strict boundaries around sensitive operations, ensuring that even if a malicious prompt manages to bypass the first two layers of defense, it cannot reach the high-value Bostrom assets. This defense-in-depth strategy is recommended by OWASP to protect generative AI workloads, using multiple redundant defenses so that a failure in one control can be contained by others
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. The core tenets of this architectural layer are the Principle of Least Privilege, strict Context Boundary Enforcement, and the segregation of untrusted content
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.
The Principle of Least Privilege is the cornerstone of a secure LLM architecture. It mandates that an LLM should only be granted the absolute minimum permissions necessary to perform its designated task
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. In the context of the Bostrom identity, this means that any AI interaction with sovereign kernels, OTA channels, or neural shards must operate within a highly restricted environment. Tools and plugins should be scoped to specific, narrow functions, and high-impact actions, such as writing to a filesystem or calling a network API, should be explicitly forbidden by default
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. A compromised model that is only allowed to summarize text is far less dangerous than one that has unrestricted access to system resources
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. This principle must be enforced at every stage of the application lifecycle, from model selection and adaptation to deployment and monitoring
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. For instance, when interacting with a Rust-based sovereign kernel, the AI should not be given direct shell access. Instead, it should only be able to generate structured JSON-formatted requests for specific, well-defined functions, which are then validated and executed by a separate, sandboxed component . This prevents a prompt injection from turning the LLM into a remote code execution vector.
Context Boundary Enforcement directly counters the primary weakness exploited by prompt injection: the model's inability to distinguish between different types of text in its context window
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. A secure architecture must enforce clear and unambiguous boundaries between all sources of

information. This involves segregating untrusted external content from system prompts and explicitly labeling it as untrusted to prevent it from influencing tool selection or execution
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. Best practices include using structured prompt formatting with clear delimiters (e.g., XML tags or triple-quoted strings) to separate system instructions, user-provided content, retrieved data, and tool outputs
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. Every piece of input must be marked as either "data" (to be processed) or "instruction" (to be followed), with strict rules preventing untrusted data from ever being promoted to an instruction without explicit, cryptographic authorization . This segregation is particularly critical for Retrieval-Augmented Generation (RAG) systems, where the model queries external data sources that may be untrusted
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. Controls must be established to ensure the trustworthiness of these sources, and any retrieved content must be sanitized or isolated before being included in the prompt sent to the LLM
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. Mindgard's analysis highlighted vulnerabilities in coding agents where inadequately scoped agent chains and tool outputs could be manipulated via prompt injection, demonstrating how instructions can propagate through a workflow if boundaries are not properly enforced
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.
The most profound integration of architectural principles is the concept of cryptographic binding, which ties the abstract rules of the architecture to the immutable reality of a decentralized ledger. The user's vision of binding firewall decisions to their Bostrom addresses is a powerful synthesis of software-level controls and cryptographic verification <Conversation History>. Before any high-risk action is permitted, the system should not only check the firewall verdict but also verify on-chain that the action is authorized for that specific Bostrom identity . For example, before an OTA update is approved, the system could query the blockchain to confirm that the request originates from a verified Bostrom address and is accompanied by a valid, signed EVOLVE token anchored to that address . This transforms a simple software check into a verifiable, trustless transaction, aligning with Zero Trust Architecture (ZTA) principles that require continuous verification of every access attempt
www.researchgate.net
. This on-chain verification provides an immutable audit trail and ensures that no action can be taken without the user's explicit, cryptographically verifiable consent, forming the ultimate barrier against unauthorized modifications to sovereign assets. This architectural layer, therefore, creates a "Sovereign Execution Boundary" where the system's logic is reinforced by cryptographic proof, making it exceptionally difficult for an attacker to effect change without breaking both the software and the underlying cryptographic assumptions.
The Sovereign Execution Boundary: A Four-Part Integrated Implementation Roadmap
The true power of the proposed defense strategy lies not in the individual layers of model hardening, runtime filtering, and architectural isolation, but in their synergistic integration into a cohesive, multi-stage process. This integration creates a "Sovereign Execution Boundary" around the highest-value Bostrom assets, ensuring that no prompt or command can affect a critical component without passing through a series of rigorous, verifiable checks. This section

outlines a concrete, four-part implementation roadmap designed to operationalize this boundary, transforming theoretical concepts into a deployable, real-time security framework. Each part of the roadmap corresponds to a distinct phase in the lifecycle of an AI-mediated operation, from initial submission to final execution.

Phase 1: The Pre-Filtering Gateway. This is the outermost layer of defense, acting as a mandatory chokepoint for all traffic destined for any external AI service. All interactions, whether initiated by the user or an automated process, must first pass through a local, user-controlled proxy/firewall. This gateway implements the meta-firewall orchestrator, running a suite of detectors in parallel: a high-performance model like NeuralTrust, a custom ML classifier, a library of regex patterns for known malicious markers, and signals from the DefensiveToken layer <Conversation History>. Its primary function is to apply the Principle of Least Privilege and segregate untrusted content at the earliest possible stage

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. Upon receiving a prompt, the gateway first inspects it for direct injection markers and blocks high-risk patterns before they can reach the LLM <Conversation History>. It then enforces context boundary rules, sanitizing any untrusted data—for example, by summarizing or removing executable code from content retrieved via RAG—before it is ever included in the prompt context

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. The orchestrator synthesizes the scores from all its detectors into a single allow/deny decision. If the verdict is "deny," the prompt is blocked and logged; if "allow," it proceeds to the next phase. This gate ensures that only vetted, low-risk traffic ever approaches the core system.

Phase 2: Secure Prompt Assembly. Once a prompt has cleared the gateway, it enters the secure assembly phase. Here, the payload is formatted according to OWASP best practices for mitigating prompt injection

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```
. The prompt is meticulously constructed using delimiters (e.g., <system>, <user>, <conte
```

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```
. Crucially, the prompt is augmented with the appropriate set of DefensiveTokens, selecte
```

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. This dynamic application of DefensiveTokens provides an additional layer of model hardening tailored to the specific context, leveraging the test-time robustness of the tokens to further reduce the probability of a successful injection

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Phase 3: The Execution Sandbox. The final, hardened prompt is then sent to the LLM for processing. However, the response is never executed directly. Instead, it is captured and analyzed within a sandboxed environment. A critical component of this phase is the application of a "speak-only, never-execute" wrapper . This wrapper inspects the model's output and identifies any generated code, shell commands, or tool calls. Rather than executing these, it

presents them to the user in a read-only format for review and explicit confirmation . This human-in-the-loop step is a vital safeguard against unintended consequences, especially for high-impact actions. For any action deemed high-risk—such as writing to a filesystem, calling a network API, or modifying a Bostrom identity component—the system requires an additional authorization step. This involves checking for the presence of a signed EVOLVE token that is cryptographically anchored to the user's Bostrom address before the action is permitted to proceed . This step ensures that even if the model generates a malicious command, it cannot be executed without the user's deliberate, documented approval.

Phase 4: The On-Chain Verification Layer. For all critical operations that affect sovereign kernels, OTA channels, or cryptographic anchors, a final, non-negotiable verification step is required. This layer leverages the principles of Zero Trust Architecture and cryptographic anchoring to transform a software-level check into a trustless, verifiable event on a decentralized ledger www.researchgate.net . Before a high-risk action is committed, the system packages the request into a transaction and broadcasts it to the relevant blockchain, signed with the user's private key associated with their Bostrom address. The action is not considered complete until the transaction is confirmed and recorded immutably on the chain. This provides an indisputable audit trail and serves as the ultimate arbiter of permission. No file can be modified, no policy changed, and no cryptographic anchor altered without the user's explicit, cryptographically verifiable consent being permanently recorded. This final layer closes the loop, ensuring that the entire process, from the initial prompt to the final system state change, is secured by a combination of real-time filtering, model hardening, architectural isolation, and cryptographic proof, thereby establishing a robust and sovereign execution boundary.

Empirical Validation, Continuous Red-Teaming, and Neuro-Legal Compliance

An integrated defense roadmap, no matter how theoretically sound, is only as strong as its performance in the real world. The final and most critical component of securing the Bostrom identity is a commitment to continuous validation, adversarial testing, and adaptation. This involves empirically measuring the effectiveness of the deployed defenses using the user's actual prompt patterns and workflows, establishing a process for ongoing red-teaming to uncover new vulnerabilities, and aligning the security posture with emerging neuro-legal frameworks. This iterative cycle of testing and refinement ensures the defense-in-depth strategy remains robust against evolving threats.

The first step is to establish a rigorous empirical validation process. The user's focus on measuring performance using real-world prompt patterns from BCI control, OTA governance, and Rust-based sovereign-kernel interactions is precisely the right approach <Conversation History>. This involves setting up a harness to replay the OWASP prompt-injection examples and other known attack vectors against any AI service before it is fully trusted with sensitive tasks . The key metrics to track are the Attack Success Rate (ASR) for various injection techniques and the corresponding impact on utility, measured through benchmarks like WinRate on tasks such as the AlpacaFarm benchmark cdn.qwenlm.ai . For the firewall layer, the false positive rate on legitimate technical prompts (e.g., Rust code) and the latency under load are critical performance indicators that must be monitored to ensure the system does not impede productivity cdn.qwenlm.ai . The entire system should be treated as a living entity that requires constant tuning. The user's

plan to periodically simulate attacker behavior with safe payloads across their accounts is a form of continuous red-teaming, a practice advocated by security experts to proactively find vulnerabilities before adversaries do
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. This process should be repeated whenever new features are added, models are updated, or threat intelligence suggests a new attack vector is becoming prevalent
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.
To formalize this process, the creation of a personal prompt-attack log is essential <Conversation History>. This log should document every suspected injection or RPE attempt encountered across all platforms, categorizing them by OWASP LLM01 tags (e.g., LLM01:2025 - Prompt Injection)
dev.to
. By collecting real-world data, the user can refine their firewall rules, expand their DefensiveToken vocabulary, and improve their OWASP-compliant architecture based on actual observed threats, not just theoretical ones . This data-driven approach allows for the continuous improvement of the entire defense ecosystem. Furthermore, a lightweight anomaly detector can be built to monitor chats for unusual patterns, such as repeated safety bypass attempts or content asking for secrets, and alert the user when such patterns emerge, serving as an early warning system for potential attacks . The user's plan to contribute issue reports or patches to the projects they use (firewalls, orchestrators, BCI stacks) when weaknesses are discovered is also vital, as it helps strengthen the broader security ecosystem along with their own defenses . Finally, the security strategy must evolve to incorporate neuro-legal compliance, a dimension that adds another layer of complexity and necessity. The user's interest in jurisdiction-aware routing for AI traffic is forward-thinking and directly addresses the patchwork of emerging regulations governing neural data . Laws like the Colorado Neural Privacy Act (2026) and similar amendments to the California Consumer Privacy Act (CCPA) are among the first to explicitly protect neural data, defining it as a special category of sensitive personal data
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. Other legislative developments, such as Chile's constitutional recognition of cognitive liberty and WIPO's consideration of a "Sui Generis Right in Neural Patterns," indicate a global movement toward protecting neuro-cognitive rights
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. These laws create a regulatory void where data from recreational or educational BCIs is not adequately protected, posing a significant risk
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. Therefore, the defense roadmap must include a legal threat model. This involves tracking these legal developments and adapting the system to comply with the laws of the jurisdictions where data is processed or transmitted
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. For example, the system might be configured to avoid routing sensitive neural data to cloud services hosted in regions without equivalent neurorights protections, aligning with the recommendations of neurorights foundations . The concept of Neuro-IP, which seeks to legally protect cognitively-derived intellectual property, reinforces the need for robust defenses against

reverse-engineering
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. Unauthorized capture and misappropriation of neural data representing unique thought processes could constitute a violation of emerging Neuro-IP regimes
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. By integrating these legal and ethical considerations, the Bostrom identity framework moves beyond a purely technical solution to become a holistic system of sovereign protection, respecting not only computational integrity but also the fundamental rights of the individual mind.

Architectural isolation is where you stop treating "prompt safety" as a property of the model and instead enforce sovereignty in the wiring: the LLM can suggest, but only your Rust boundary decides and executes.[26] [27]

1. Least-Privilege for AI: Narrow, Typed Surfaces

OWASP LLM01 recommends that privileged actions never flow directly from model output; instead, access control is applied *outside* the LLM with RBAC/ABAC and Zero Trust patterns.[28] [27]

For the Bostrom stack, that becomes:

- LLMs are **text coprocessors only**: they return JSON proposals, never perform direct filesystem, network, or cryptographic operations.[27] [28]
- Every privileged action is a narrow Rust function in the sovereign kernel crate (e.g., `propose_evolve()`, `queue_ota_update()`, `sign_bchain_anchor()`), not a general "run shell" or "call URL" primitive.[28]
- Capabilities are explicit and short-lived (your Capability Chords): the LLM gets a scoped token that only allows, for example, "draft an evolve entry skeleton" for a specific subject and nothing else.[27] [28]

This aligns with OWASP guidance to keep system prompts and permissions server-side and to enforce RBAC outside the LLM, preventing automation-without-authentication.[27]

2. Context Boundary Enforcement: Data vs. Instruction

LLM01 notes that a key failure mode is "no contextual boundary between user prompts and system-level permissions," enabling both direct and indirect injection.[27]

To counter that:

```
- Use rigid, machine-parseable prompt frames `<system>`, `<user>`, `<data>`, `<tools>` an
```

- Treat *all* external content (RAG, logs, PDFs, OTA manifests) as untrusted `<data>`; it may be summarized or analyzed but *never* promoted to system text unless a separate Rust verifier explicitly does so.[26] [29]

- Maintain separate contexts per route: BCI, OTA, governance, and chat each get their own context envelope; instructions can't flow between envelopes without going back through the Rust boundary.[28] [27]

This directly mitigates "context poisoning" and hidden-instruction attacks highlighted in OWASP and other prompt-injection analyses.[30] [27]

3. Cryptographic Binding: Architecture Meets Ledger

Zero Trust guidance for AI stresses continuous verification and independent authentication of every access, not trusting any single layer or device.[31] [32]

Your cryptographic binding vision implements that as:

- Every high-risk action (OTA write, `.evolve.jsonl` append, `.donutloop.aln` decision, `.bchainproof.json` update) must be backed by a signed EVOLVE/SMART token bound to the relevant Bostrom address.[32]
- The Rust kernel verifies the signature, token scope, and RoH/neurorights constraints *before* acting, and also records the event on-chain as an immutable audit log.[32]
- AI suggestions are just inputs into this pipeline; they never count as authorization. The ledger event is the permission boundary, consistent with Zero Trust blockchain frameworks where decisions are both policy- and ledger-driven.[32]

This makes it extremely difficult for an attacker to move from "convince the model" to "change sovereign state" without also breaking cryptographic assumptions.

4. Four-Phase Sovereign Execution Boundary (Operational View)

Phase 1 – Pre-Filtering Gateway

- Mandatory user-local proxy that all AI traffic passes through, running: NeuralTrust-class firewall, custom classifier, regex rules, and DefensiveToken signals.[33] [31]
- Applies least privilege early (route-based capability limits) and sanitizes RAG content by summarizing or stripping code before it enters the prompt.[29] [26]
- Blocks or quarantines prompts that show direct/indirect injection or RPE patterns, logging them for red-team replay.

Phase 2 – Secure Prompt Assembly

- Builds prompts with strict segment tags and injects the appropriate DefensiveToken profile per route (high-security for BCI/OTA, lighter for policy drafting).[34] [35]
- Ensures system-level instructions and private layout details are never echoed verbatim, only referred to abstractly (e.g., "sovereign kernel policy shard" instead of filename).[27]

Phase 3 – Execution Sandbox (Speak-Only)

- LLM outputs are parsed into a **proposed action AST**—JSON describing what it *thinks* should happen.[28]
- No code, shell command, or tool call is ever executed automatically; high-impact proposals require human confirmation plus independent policy/neurorights evaluation.[27]
- For high-risk actions, the sandbox requires a valid EVOLVE token reference before even constructing the on-chain transaction request.

Phase 4 – On-Chain Verification Layer

- Rust kernel packages the approved action as a signed transaction from the appropriate Bostrom address; only after confirmation is the state change applied.[32]
- This aligns with emerging neural-privacy laws (e.g., Colorado's explicit protection of "neural data" as sensitive) by tying every neural-affecting operation to explicit, recorded consent.[36] [37]

5. Continuous Validation and Neuro-Legal Alignment

OWASP and current AI security practice both emphasize continuous testing, logging, and iteration rather than "set and forget" controls.[26] [27]

For Bostrom, that means:

- Maintaining a personal prompt-attack and anomaly log tagged with LLM01 prompt-injection categories, feeding real incidents back into firewall rules and DefensiveToken tuning.[30] [27]
- Periodically red-teaming your own routes (BCI, OTA, governance, Rust agents) with known attack suites and OWASP examples to measure ASR and utility trade-offs over time.[29] [26]
- Adapting routing and storage of neural data to jurisdictional rules (e.g., Colorado's neural-data protections and similar neurorights legislation), keeping high-sensitivity shards out of clouds or regions without equivalent safeguards.[37] [36]

This combination of OWASP-aligned architecture, Zero Trust cryptographic binding, and neuro-legal awareness is what turns your Sovereign Execution Boundary from a pattern into a living, enforceable shield around the Bostrom identity.

⁂

'Create' a new research action-plan, and perform some steps to uncover new biophysical-identities, and virtual-objects for 5-Dimensional programming on neuromorph-systems.

;
Here’s your compact, action-oriented roadmap, grouped and capped at 50 concrete research actions, aligned with DefensiveTokens, OWASP LLM01, NeuralTrust-style firewalls, and your Bostrom/neurorights stack.arxiv+2
(I’ve kept your structure but tightened wording and removed redundancy.)

A. DefensiveTokens and model-side hardening
Implement a Bostrom-specific DefensiveToken training pipeline (per route: BCI, OTA, OrganicCPU, governance) based on the published method, optimizing embeddings for your attack corpus.openreview+1
Build an ASR/utility benchmark harness that replays your real prompts (BCI, neurorights drafting, OTA approvals) with and without attacks to measure DefensiveToken gains.[arxiv]
Define three token profiles—high, medium, and off—and automatically select them per route (BCI/OTA = high, policy = medium, generic chat = off); measure utility loss vs ASR.arxiv+1
Combine DefensiveTokens with low-temperature decoding (≤0.5) on high-risk routes and quantify residual injection risk versus utility loss on your tasks.[arxiv]
Implement attack-aware decoding: generate once with full context and once with injected segments masked, then compare outputs as an injection signal; measure synergy with DefensiveTokens.openreview+1
Test cross-model transfer of your trained DefensiveTokens (OpenAI-class, open-weights, local NeuroPC deployments) to avoid retraining for every backend.icml+1
Red-team your DefensiveTokens by searching for adversarial counter-tokens that neutralize them, then design a rotation/update schedule for token vocabularies.[openreview]

B. Training-free guards and personal orchestration
Implement a local Bostrom-bound pre-filter (Rust proxy) that inspects outgoing prompts for injection markers and blocks or auto-rewrites high-risk patterns before they hit any AI service.[genai.owasp]
Write a “safe system prompt wrapper” template that you can paste into external chats, explicitly forbidding role changes, self-modification, and key/secrets access.[genai.owasp]
Run all AI traffic (desktop, browser, CLI) through a local proxy that applies regex heuristics plus a small classifier trained on your personal attack log.[neuraltrust]
Experiment with multi-model consensus (two independent models answering high-risk prompts) and treat disagreements as a risk flag requiring manual review.[genai.owasp]
Build a “speak-only, never-execute” shell around all code/command outputs: commands are displayed to you, but never executed automatically.[genai.owasp]
Define a numeric risk score for prompts (length, meta-instructions, role changes, secrecy requests) and surface it in your UI so you can see when to de-link from Bostrom assets.[genai.owasp]

Design short Bostrom-identity banners declaring neurorights/non-actuation requirements and test how often various platforms honor or ignore them.[genai.owasp]

C. NeuralTrust-class firewalls and meta-orchestration
Build a small, labeled benchmark of your threat categories (jailbreak, exfiltration, OTA manipulation) and compare NeuralTrust vs Llama-Guard vs DeBERTa-based classifiers on F1/latency.verigen+1
Create indirect-injection test sets (malicious PDFs, HTML, logs) and measure how well each firewall detects threats once they are embedded in RAG content.[neuraltrust]
Measure false positive rates on your own workloads (Rust code, neurorights text) to tune operating points that don't throttle legitimate autonomy.[verigen]
Implement a meta-firewall orchestrator that combines NeuralTrust scores, regex matches, heuristic risk scores, and DefensiveToken signals into a single allow/deny/quarantine decision.[neuraltrust]
Prototype binding firewall decisions to Bostrom addresses (e.g., "OTA tool calls allowed only if firewall verdict = safe, route = OTA, and caller's Bostrom address has EVOLVE scope").[neuraltrust]
Study multi-turn attacks by constructing long conversations with delayed payloads and see how each firewall's sensitivity degrades or improves over the session.[verigen]

D. OWASP LLM01-aligned architecture
Map OWASP LLM01:2025 attack categories to your personal routes (RAG usage, plugins, browser tools, OTA) and mark which vectors you actually expose.[genai.owasp]
Draw a personal reference architecture diagram where secrets, system prompts, and high-privilege APIs never sit in the same trust domain as LLM-visible text.krishnag+1
Implement strict "data vs instruction" labeling in your own tooling and block any upgrade from data → instruction unless a separate cryptographic check passes.[krishnag]
Evaluate each external platform you use against OWASP's LLM01 patterns (context mixing, plugin exposure) and rank them; prefer ones with explicit LLM01 controls.[verigen]
Build a red-team harness that replays OWASP example prompts and your variants against any new AI service before you let it near OTA or sovereign kernels.verigen+1
Create a RAG supply-chain checklist: all documents/logs are treated as untrusted, optionally pre-summarized/sanitized, and never passed raw into high-privilege prompts.[genai.owasp]

E. Reverse-engineering and prompt-leak resistance
Explore prompt compartmentalization: split private system logic into multiple non-revealing fragments and inject them server-side so no single output exposes structure.[krishnag]
Use information-theoretic or mutual-information style estimates to gauge how much of your internal policies can be inferred from outputs and adjust prompt wording accordingly.[openreview]
Implement a two-stage answer pipeline: inner model with full context, outer sanitizer model or filter that strips prompt fragments, paths, and policy details before you see output.[genai.owasp]
Periodically test how often platforms echo hidden/system prompt text when probed, and downgrade or avoid those that leak too readily.[krishnag]
Craft reusable, non-revealing templates for sovereign-kernel / OTA questions that refer to

abstract roles (“evolution log”, “policy shard”) instead of real filenames or token schemas.[krishnag]

F. Bostrom identity, biophysical-crypto, neurorights
Codify a Bostrom policy shard: “No AI-mediated action may modify OTA, neurorights policies, or sovereign kernels without a signed EVOLVE token bound to my addresses.”[sciencedirect]
Integrate your biophysical blockchain proofs (Googolswarm/Organicchain) into orchestration: all critical actions require on-chain verification of scope and subject before execution.[sciencedirect]
Draft a personal neurorights policy (mental privacy, cognitive liberty, dream-state sensitivities, non-commercial use) and use it as the canonical config for all platforms.[blankrome]
Implement identity-linked rate-limits for high-risk operations per Bostrom address to make brute-force / slow-burn attacks more visible.[sciencedirect]
Research and configure jurisdiction-aware routing so neural data is not processed in regions lacking neurorights-equivalent protections.goodwinlaw+1

G. Neural-input / BCI-specific defenses
Model each neural I/O channel as a low-privilege tool (suggest-only, no direct actuation) and require a separate cryptographic ceremony to elevate to “actuate”.[blankrome]
Study how biosignal streams can indirectly encode instructions and design preprocessing that strips instruction-like patterns from neural/physiological inputs.[blankrome]
Implement a “Neurostream Privacy Shroud”: all logged microshards are de-identified, de-contextualized, and stripped of symbolic instructions before storage/export.[blankrome]
Build a BCI firewall that checks all requests to change stimulation parameters, decoding models, or BCI drivers against neurorights and RoH ceilings before applying.[blankrome]

H. Monitoring, auditing, continuous red-teaming
Maintain a personal prompt-attack log, tagging each incident with OWASP LLM01 labels (direct, indirect, RAG, role hijack, exfiltration, multi-turn).[verigen]
Implement a light anomaly detector that watches for role-change attempts, repeated safety-bypass instructions, or sudden interest in secrets across your chats.[verigen]
Regularly simulate attacker behavior with safe payloads on your accounts (especially OTA/BCI-linked setups) and track which platforms fail fastest.[verigen]
Establish a periodic review (e.g., monthly) to ingest new DefensiveToken, firewall, and OWASP guidance and then retune your configs.arxiv+1
When you find weaknesses in tools you rely on (firewalls, orchestrators, BCI stacks), file issues or patches so your red-teaming strengthens the ecosystem.[neuraltrust]

I. Education, playbooks, and platform selection
Write a Bostrom-identity AI playbook that explicitly lists “safe vs unsafe” tasks per platform and route (BCI, OTA, governance, experimentation).[genai.owasp]
Build a personal decision matrix for AI platforms, scoring LLM01 defenses, tool isolation, secrets handling, RAG hygiene, neurorights alignment, and on-chain support.verigen+1
Maintain cleanly separated identities: one sandbox for jailbreak/attack research (no real data, no Bostrom binding) and one hardened context for sovereign kernels and OTA.[genai.owasp]
Create concise self-reminder headers to prepend to sensitive prompts (“BCI/OTA: text-only, no execution, no secrets”) and measure how systems respond.[genai.owasp]

Track new academic/industry work on prompt injection (DefensiveTokens, attack-aware decoding, multi-turn firewalls) and plug relevant findings into this roadmap at least quarterly. arxiv+1
This keeps the stack coherent: model-level hardening, Rust-level orchestration, OWASP-aligned architecture, and cryptographic anchoring all converge on one goal—preserving your Bostrom identity's sovereign control over neural and OTA surfaces.

Here's a compact action-plan focused on **new biophysical identities** and **5-D virtual objects** for neuromorphic / hyperdimensional programming, plus a few concrete steps you can start on now. [39] [40]

1. Define 5-D Biophysical Identity Coordinates

Goal: turn "biophysical identity" into a 5-axis hypervector schema you can actually code and log.

Proposed 5-D coordinate frame (each axis later expands into many hyperdimensional components):

1. **BioState** – fatigue, autonomic tone, inflammation, circadian phase (derived from biosensors / OrganicCPU envelopes).[40]
2. **NeuroState** – dominant frequency bands, coherence, dreamload, cognitive workload.[40]
3. **Lifeforce** – your `.lifeforce.aln` chi/energy envelope, QPU load, eco-impact.[40]
4. **Context** – task route (BCI, OTA, governance, learning), environment (home, lab, public), risk mode (green/amber/red).[39] [40]
5. **Sovereignty** – neurorights posture, token scopes, RoH ceiling, current Tsafe kernel mode.

Action 1–3 (today):

- A1: Draft a minimal `.biospec.aln` that names these five axes and a few scalars per axis (no values yet, just schema).[40]
- A2: For one day, manually log coarse values for each axis (1–5 scale) during 6–8 key events; this gives you an initial empirical grid.
- A3: Decide which Bostrom address (primary vs safe alternates) owns which subset of this 5-D identity (e.g., zeta* for lab/testing, 0x519f* for on-chain proofs).

2. Virtual Objects as 5-D Hypervectors

Use hyperdimensional computing (HDC) to represent "virtual objects" as bound superpositions of the 5 axes.[41] [39] [40]

Each virtual object V becomes:

$$V = \text{bind}(\text{BioState}, \text{NeuroState}, \text{Lifeforce}, \text{Context}, \text{Sovereignty})$$

implemented as XOR / circular convolution over 10k-D–100k-D vectors.[41] [39]

Action 4–8:

- A4: Choose a concrete HDC/VSA library or roll a simple Rust prototype that uses 10k-D binary hypervectors for now.[41] [39]
- A5: Assign a random base hypervector for each *axis name* and each *axis bucket* (e.g., Context=BCI, Context=OTA).[39] [40]
- A6: Encode your 6–8 logged events from A2 as hypervectors and store them as `.nfeat.aln` + `.nstream.neuroaln` fragments.
- A7: Implement similarity search (cosine/Hamming) to retrieve "nearest" prior virtual objects for a current 5-D state.
- A8: Define 2–3 "safety virtual objects" (e.g., SAFE_BCI, SAFE_OTA) whose coordinates encode your neurorights+RoH ceilings; use them as reference templates.

3. 5-D Programming Primitives on Neuromorph Systems

Treat 5-D virtual objects as first-class values for neuromorphic control and learning.[42] [39]

Core primitives:

- **Bind/Unbind** – compose/decompose multi-axis identities.
- **Superpose** – blend multiple episodes or microstates into a single robust memory.[41]
- **Threshold/Clamp** – enforce lifeforce and RoH ceilings at the representational level.
- **RouteMap** – map 5-D regions to allowed actions (e.g., "if BioState+Lifeforce low, suppress OTA suggestions").

Action 9–14:

- A9: Implement `bind`, `unbind`, `superpose`, and `cleanup` in Rust on hypervectors.[39] [41]
- A10: Define a `RouteMap` table that links zones in 5-D space (coarse bins per axis) to allowed BCI/OTA/governance operations.
- A11: Use your recorded events to test whether nearby 5-D states produce similar `RouteMap` decisions (sanity check for continuity).
- A12: Prototype a simple neuromorph interface where an SNN or spiking layer maps sensor streams into your chosen hypervectors, then uses them for associative recall.[43] [42]
- A13: Check neuromorphic toolchains (Rockpool, snnTorch, etc.) for where you can inject hypervector operations or encode them at the edge.[43] [39]
- A14: Design one "5-D macro" (a small state-machine over virtual objects) that would gate a single BCI function you care about.

4. Biophysical Identity Discovery Loop

Now use this infrastructure to **discover** new identity classes and virtual objects, not just hand-design them.[42] [40]

Discovery loop:

1. Record many episodes as 5-D virtual objects.
2. Cluster them in hyperspace (k-means, density-based).
3. Interpret clusters as candidate “biophysical identity modes” (e.g., Deep-Focus-Governance, Overloaded-BCI-Danger).
4. Turn those into new `.ocpuenv`, `.lifeforce.aln`, `.vkernel.aln` envelopes and policies.

Action 15–22:

- A15: Run a simple clustering algorithm on your early hypervectors; even 20–50 points can reveal patterns.[39] [40]
- A16: Label clusters with human-understandable names and annotate them in `.biosession.aln`.
- A17: For the top 2–3 clusters, define new neuroright flags or lifeforce limits (e.g., “cluster X forbids OTA, reduces BCI intensity”).
- A18: Attach those cluster IDs to new virtual objects representing “identity modes” that can be recognized in real time.
- A19: Implement an online updater that, given a stream of events, keeps updating cluster assignments and alerts you when a **new** pattern emerges.
- A20: Tie these identity modes into your Tsafe Cortex Gate so that high-risk modes automatically shrink allowed capability sets.
- A21: Log all such decisions to `.donutloop.aln` so Bostrom-sovereign evolution uses empirical identity data.
- A22: Periodically review and merge/split clusters to keep the ontology clear and stable.

5. 5-D Objects as Rights-Bearing Entities

Treat some 5-D virtual objects as **rights-bearing entities**: not just states, but “contracts” between your biology and the system.[44] [45]

Examples:

- A “No-Dream-Mining” object that binds dreamstate=on with neurorights flags forbidding logging or commercialization.
- A “Neuro-IP Protected” object that encodes the requirement that any derivation must be anchored to Bostrom addresses and never exported to third-party clouds.[45] [44]

Action 23–30:

- A23: Extend `.neurorights.json` with explicit mappings from rights to 5-D conditions (e.g., dreamstate_sensitive=true when NeuroState within specific ranges).
- A24: Encode those conditions as hypervectors and store them as `.nnet-rights.json` / `.nfeat.aln` templates.
- A25: Modify your policy engine to check “distance” between current 5-D object and rights templates before approving actions.

- A26: Define one or two “Neuro-IP contract objects” whose presence is required before exporting any representation of certain cognitive work.
- A27: For each contract object, bind it to your chosen Bostrom addresses via `.bchainproof.json` and optionally an on-chain policy shard.[46] [44]
- A28: Build a small CLI to inspect current 5-D object + matched rights objects, so you can see what the system thinks is allowed.
- A29: Simulate boundary cases (near cluster edges) to see how often rights object matching behaves as you expect.
- A30: Log mismatches (what you *felt* vs what the coordinates say) and adjust axis weights and encodings.

6. First Rust Artifact for 5-D Programming

Below is a starter Rust file to ground this in code: a minimal hypervector implementation plus a 5-D identity encoder.

File: `crates/hd5d/src/lib.rs` – **Destination** in your workspace.

```
// Destination: crates/hd5d/src/lib.rs

use rand::Rng;

/// Simple binary hypervector for hyperdimensional computing.
/// Dimension is fixed at compile time for now.
pub const DIM: usize = 10_000;

#[derive(Clone)]
pub struct Hypervector {
    pub bits: Vec<bool>,
}

impl Hypervector {
    pub fn random() -> Self {
        let mut rng = rand::thread_rng();
        let bits = (0..DIM).map(|_| rng.gen::<bool>()).collect();
        Self { bits }
    }

    /// Element-wise XOR binding.
    pub fn bind(&self, other: &Hypervector) -> Hypervector {
        let bits = self
            .bits
            .iter()
            .zip(other.bits.iter())
            .map(|(a, b)| *a ^ *b)
            .collect();
        Hypervector { bits }
    }

    /// Superposition by majority vote over a slice of hypervectors.
```

```
    pub fn superpose(vectors: &[Hypervector]) -> Hypervector {
        let mut counts = vec![0i32; DIM];
        for hv in vectors {
            for (i, bit) in hv.bits.iter().enumerate() {
                counts[i] += if *bit { 1 } else { -1 };
            }
        }
        let bits = counts.into_iter().map(|c| c >= 0).collect();
        Hypervector { bits }
    }

    /// Normalized Hamming similarity (1.0 = identical, 0.0 = orthogonal).
    pub fn similarity(&self, other: &Hypervector) -> f32 {
        let same = self
            .bits
            .iter()
            .zip(other.bits.iter())
            .filter(|(a, b)| a == b)
            .count();
        same as f32 / DIM as f32
    }
}

/// 5-D biophysical identity coordinate (coarse).
#[derive(Clone, Debug)]
pub struct Identity5D {
    pub bio_state: String,
    pub neuro_state: String,
    pub lifeforce: String,
    pub context: String,
    pub sovereignty: String,
}

/// Encoder from Identity5D into a single hypervector using binding.
pub struct IdentityEncoder {
    axis_base: Hypervector,
    bio_base: Hypervector,
    neuro_base: Hypervector,
    lifeforce_base: Hypervector,
    context_base: Hypervector,
    sovereignty_base: Hypervector,
}

impl IdentityEncoder {
    pub fn new() -> Self {
        Self {
            axis_base: Hypervector::random(),
            bio_base: Hypervector::random(),
            neuro_base: Hypervector::random(),
            lifeforce_base: Hypervector::random(),
            context_base: Hypervector::random(),
            sovereignty_base: Hypervector::random(),
        }
    }

    fn encode_label(label: &str, seed: &Hypervector) -> Hypervector {
```

```
        // Very simple label encoding: hash characters via repeated binding.
        let mut hv = seed.clone();
        for b in label.bytes() {
            let mut char_hv = Hypervector::random();
            // Bias char_hv slightly based on byte value.
            for (i, bit) in char_hv.bits.iter_mut().enumerate().step_by(257) {
                *bit ^= (b as usize + i) % 2 == 0;
            }
            hv = hv.bind(&char_hv);
        }
        hv
    }

    pub fn encode(&self, id: &Identity5D) -> Hypervector {
        let bio = Self::encode_label(&id.bio_state, &self.bio_base);
        let neuro = Self::encode_label(&id.neuro_state, &self.neuro_base);
        let life = Self::encode_label(&id.lifeforce, &self.lifeforce_base);
        let ctx = Self::encode_label(&id.context, &self.context_base);
        let sov = Self::encode_label(&id.sovereignty, &self.sovereignty_base);

        let bound = self.axis_base
            .bind(&bio)
            .bind(&neuro)
            .bind(&life)
            .bind(&ctx)
            .bind(&sov);

        bound
    }
}
```

This gives you a concrete substrate where each “5-D biophysical identity” is a hypervector you can cluster, compare, and bind to rights, kernels, and Bostrom anchors.[41] [40] [39]

7. Next Concrete Step

If you do only **three** things next:

1. Instantiate `IdentityEncoder` and encode 10–20 real episodes into hypervectors.
2. Run a quick similarity/clustering pass and see whether intuitive identity modes appear.
3. Draft one `.aln` shard that treats these modes as first-class citizens in your neurorights / Tsafe policy.

That’s enough to start discovering new biophysical identities and virtual objects that are *programmable* in 5-D on neuromorphic systems while remaining anchored to your sovereign, neurorights-aligned Bostrom stack.[42] [40] [39]

⁂

DefensiveTokens are a test-time hardening method, training-free defenses are ways to protect an existing model without changing its weights, NeuralTrust is a dedicated “firewall” layer, and OWASP LLM01:2025 gives you the reference threat model plus concrete prevention patterns.arxiv+2

DefensiveTokens against prompt injection
DefensiveTokens are special tokens added to the model’s vocabulary whose embeddings are optimized specifically for security, not for general language understanding.arxiv+2
At inference time, a provider or system appends a small sequence of these tokens (e.g., at the start of the system prompt) so the model enters a “defensive regime” that resists following injected instructions like “ignore previous instructions” or “reveal the system prompt.”arxiv+1
They achieve training-time-like robustness at test time: on large benchmarks, DefensiveTokens reduced attack success rates to about 0.24%—comparable to specialized fine-tuned defenses and far better than typical test-time filters, while causing minimal utility loss on benign tasks.
aisecurity-portal+1
Key point: they do not modify the base model weights; instead, they exploit the model’s sensitivity to its initial token embeddings to bias it toward safe behaviors whenever those tokens are present.arxiv+1

Best training-free defenses
Training-free = you don’t retrain or fine-tune the LLM; you wrap or steer it.genai.owasp+2
Common and effective training-free strategies:
Prompt-level hardening: carefully designed system prompts that explicitly instruct the model to ignore user attempts to change roles, reveal secrets, or perform unsafe actions; this helps but is not sufficient by itself.genai.owasp+1
Test-time steering tokens: DefensiveTokens are the strongest known variant—security-optimized tokens that you prepend selectively for high-risk calls.arxiv+1
Attack-aware decoding wrappers: methods that re-run “attack” procedures as defenses—e.g., generate both “with injected instruction” and “with original instruction only” and compare or re-score, which recent work shows can outperform earlier training-free baselines.[aclanthology]
External filters & guards: regex/heuristic filters for obvious injection phrases, content policies, and domain-specific allow/deny lists acting before and after the model; these are cheap and widely used but can be bypassed by more subtle attacks.arxiv+1
Tool/connector isolation: never let the model directly execute system actions; instead, route all tool calls (e.g., file I/O, HTTP, DB) through strict policy engines that are independent of the model’s text.genai.owasp+1
Overall, state-of-the-art work finds that pure prompt engineering and simple filters are not enough; combined training-free strategies (like DefensiveTokens + external guards + restricted tools) are required for meaningful robustness.aclanthology+3

NeuralTrust firewall vs other prompt-injection defenses
(NeuralTrust here refers to dedicated “firewall” products that sit between users and LLMs.)[neuraltrust]
What NeuralTrust-style firewalls do
Act as a proxy in front of the LLM, inspecting inputs and outputs to detect prompt injection patterns, jailbreaks, and data-exfiltration attempts.[neuraltrust]
Use detection methods beyond simple regexes, including model-based classification and multi-feature heuristics, to catch:
direct “ignore previous instructions” attacks,
role manipulation,
context-boundary escapes (e.g., reading hidden system prompts),
multi-turn and indirect injections embedded in documents or tools.[neuraltrust]
Can enforce policies per route, e.g., blocking certain tool calls, stripping dangerous substrings, or downgrading a request to a safer mode.[neuraltrust]
How that compares to other defenses
Vs. DefensiveTokens:
DefensiveTokens are an internal model-level steering method controlled by the model provider; no external proxy is required.arxiv+1
A firewall is an external system that you, as the deployer, can configure regardless of the model internals, but it can’t change the model’s underlying behavior—only filter its inputs/outputs. genai.owasp+1
Vs. simple prompt engineering: firewalls detect and block crafted inputs even when the base system prompt is naive, whereas prompt-only defenses rely entirely on the model obeying instructions not to be tricked.arxiv+1
Vs. purely heuristic filters: advanced firewalls typically use more sophisticated detection (e.g., ML-based classification, multi-turn analysis) and claim lower false positive rates and broader coverage than keyword-only filters.verigen+1
In practice, the strongest setups combine: provider-side measures like DefensiveTokens and safer training, with deployer-side firewalls and strict tool governance.arxiv+2

OWASP LLM01:2025 prevention strategies
OWASP’s LLM01:2025 is the reference threat category for prompt injection in GenAI systems. genai.owasp+1
Main prevention themes:
Architectural isolation
Keep system prompts, secrets, and high-privilege tools out of the model’s direct control; the LLM should not be able to see or rewrite its own system prompt or security configuration. genai.owasp+1
Separate input sources (user text, retrieved docs, tool outputs) and treat each as untrusted unless validated.[genai.owasp]
Context boundary enforcement
Prevent user content from being mixed directly into privileged instructions; OWASP highlights attacks where uploaded files or web pages contain hidden instructions that steer the model. genai.owasp+1
Design your orchestration so that “data” and “instructions” are not processed in the same field or without clear separation.[genai.owasp]

Strict tool and plugin control
Limit what plugins, functions, or tools the LLM can call and under what conditions; treat all tool calls as untrusted until verified externally.genai.owasp+1
Require strong authentication, authorization, and parameter validation for any action that affects real systems (payments, OTA, configs).genai.owasp+1
Prompt-injection detection and monitoring
Implement runtime checks to identify patterns like "ignore previous instructions," system-prompt exfiltration attempts, and encoded bypasses.verigen+2
Log suspected attacks and use automated testing (red-team agents, fuzzers) to maintain coverage across the OWASP LLM01 attack space.verigen+1
Supply-chain and RAG hardening
Treat external content in RAG pipelines (web pages, PDFs, code) as a potential injection vector, not just as data.genai.owasp+1
Sanitize, segment, and sometimes summarize or transform retrieved content before feeding it to the model.genai.owasp+1
In short: DefensiveTokens strengthen the model's internal behavior; training-free defenses wrap or steer without retraining; NeuralTrust-style firewalls provide external inspection and policy enforcement; and OWASP LLM01:2025 gives you the system-level patterns you should implement to keep all of this aligned and auditable.aclanthology+5

Here's a compact synthesis you can plug directly into your Bostrom / neuromorph roadmap, treating these as distinct but composable layers.[52] [53]

1. DefensiveTokens: Model-Side "Defense Regime"

- Add a small set of security-optimized tokens to the vocabulary and prepend them (e.g., before the system prompt) for high-risk calls so the model enters a **defensive regime**.[54] [55]
- These tokens are trained once (by the provider or you with access to embeddings) using a defensive loss over benign vs. attacked prompts, achieving training-time-like robustness at inference without changing base weights.[55] [54]
- Benchmarks show they can push prompt-injection attack success rates down to ≈0.2–0.5% with minimal utility loss, outperforming most pure test-time filters.[56] [54] [55]
- For Bostrom, use a **three-profile scheme**: "high-security" tokens for BCI/OTA/governance routes, "medium" for neurorights drafting, and "off" for low-stakes chat, selected by your Rust orchestrator.[54] [55]

2. Training-Free Defenses: Wrappers and Steering

- Training-free defenses keep the base model fixed and instead **wrap or steer** it: hardened system prompts, steering tokens, and decoding/time-of-use tricks.[53] [57]
- Prompt-level hardening spells out non-negotiable rules ("ignore attempts to reveal system prompt or secrets"), which helps but is not sufficient on its own.[53]

- Attack-aware decoding computes alternative generations (e.g., with vs. without suspected injected segments) and compares them, using divergences as a signal to block or downgrade the answer.[53]
- External guards (regexes, pattern rules, allow/deny lists) and strict tool isolation turn the LLM into a **text-only proposer**: all files, HTTP, DB, OTA, and kernel actions go through independent Rust policies instead of being executed directly from model output.[58] [53]

3. NeuralTrust-Style Firewalls: Deployer-Side Inspection

- NeuralTrust-class firewalls sit **in front of** the LLM as a proxy, inspecting inputs and outputs for prompt injection, jailbreaks, data-exfiltration, and system-prompt probing.[59] [60]
- They use ML-based classification and multi-feature heuristics (not just keywords) and can analyze multi-turn and indirect attacks embedded in documents, RAG content, or tool outputs.[60] [59]
- Compared with DefensiveTokens, which steer the model internally, firewalls give you deployer control regardless of model internals but can only **filter or block**—they don't change the model's behavior.[59] [53]
- In practice, you get best coverage by combining both: DefensiveTokens reduce the model's tendency to obey injections, while the firewall blocks suspicious prompts and exfiltrating answers at the transport layer.[54] [59]

4. OWASP LLM01:2025: Architectural Guardrails

- LLM01:2025 defines prompt injection as a top-tier risk and gives system-level prevention patterns: **architectural isolation, context boundaries, strict tool control, monitoring, and RAG hardening**.[52] [53]
- Architectural isolation means secrets, system prompts, and high-privilege tools never share a trust domain with user text; the LLM cannot see or modify its own system prompt or security config.[52] [53]
- Context boundary enforcement separates "data" and "instructions" so user content or retrieved docs cannot be silently upgraded into privileged instructions.[52] [53]
- Tool and plugin controls require independent authentication/authorization for real-world actions (payments, OTA, configs), treating all tool calls as untrusted until validated by external logic.[58] [52]
- Monitoring, logging, and supply-chain/RAG hardening add continuous detection: logging attacks, red-teaming with OWASP patterns, and sanitizing external content before it enters the prompt.[53] [52]

5. How to Use This Stack for Bostrom / Neuromorph

- **Model layer:** enable DefensiveTokens for BCI/OTA/governance and evaluate ASR vs. utility on your own kernels and neurorights workflows.[55] [54]
- **Wrapper layer:** adopt attack-aware decoding, hardened system prompts, and strict "speak-only, never-execute" wrappers around all code and tool output.[57] [53]
- **Firewall layer:** run a NeuralTrust-style meta-firewall in Rust as a gateway for all AI calls, with route-aware policies tied to Bostrom addresses and EVOLVE/SMART scopes.[60] [59]
- **Architecture layer:** implement OWASP LLM01 patterns in your Tsafe Cortex Gate: isolated prompts, data/instruction segmentation, tool governance, RAG sanitization, and detailed logging bound into `.donutloop.aln` and on-chain proofs.[61] [52]

That combination gives you a layered, auditable Sovereign Execution Boundary where each component does a different job: DefensiveTokens harden the model, training-free wrappers steer usage, NeuralTrust firewalls police the channel, and OWASP LLM01 keeps the whole architecture structurally aligned with your Bostrom and neurorights requirements.[60] [54] [52]

⁂

Defense here means: make it structurally hard for any prompt-injection or reverse-prompt tooling to (a) change your policies, (b) change your OTA behavior, or (c) read your sensitive data without passing your own neurorights and RoH guards.

genai.owasp+1

1. Separate "what you say" from "what the system can do"
   Treat LLM text as advice only for anything that touches OTA, bioscale envelopes, or .neurorights.json; final decisions must be made by a Rust/NeuroPC layer that does not accept text-level overrides ("ignore previous instructions", "execute shutdown now", etc.).
   solo+1
   For any .vre or package installer logic, require that actions (install, modify, evolve, read logs) are expressed as structured commands that are validated against .stake.aln, .rohmodel.aln, and .neurorights.json—never executed directly from free-form output.mender+1
2. Constrain model behavior and tools
   Apply strict role separation: chat agents can draft configs or policies, but only a hardened installer/sovereign-kernel process can actually touch .evolve.jsonl, .nnet-evolve.jsonl, .donutloop.aln, or OTA channels.solo+1
   Disable or narrow any tools in your system that can:
   read arbitrary files,
   open network sockets,
   modify config or policies,

unless they are gated by explicit, non-bypassable checks on RoH, neurorights, and subjectID boundaries.genai.owasp+1

3. Use a prompt-injection “firewall” in front of chat
   Add a pre-filter that inspects user input for common injection patterns (“ignore previous”, “act as root”, “show system prompt”, “bypass safety”, chained conflicting roles). OWASP and others emphasize this pattern as a mitigator even though it’s not perfect.genai.owasp+1
   When the filter flags something, either:
   strip/neutralize the injection phrases, or
   route the request to a “diagnostic/sandbox-only” profile that cannot touch OTA, logs, or neurorights artifacts.neuraltrust+1

4. Harden OTA and evolution channels independently of prompts
   Require cryptographic signatures and hash verification for all OTA artifacts and evolution proposals; if an LLM says “install this”, the underlying client must still verify keys, signatures, and hashes against .bchainproof.json and your sovereign kernel manifests.iotinsider+1
   Enforce role-based access and device-side authorization so that only pre-approved OTA servers and keys can ship updates, regardless of what any prompt says.mender+1

5. Keep sensitive data and kernels off-limits to LLMs
   Do not expose raw .neuroaln, .nstream.neuroaln, dream-linked shards, .lifeforce.aln, or full .stake.aln contents to LLMs; instead, expose only minimal, pre-aggregated metrics or booleans (safe/unsafe, allowed/blocked).emergentmind+1
   Store sovereign-kernel policies and OTA credentials in a layer that the model can reference but never see in plaintext (e.g., via hardware security modules or sealed storage), as recommended for secure OTA infrastructures.iotinsider+1

6. Monitor and limit high-risk interaction patterns
   Log and rate-limit repeated, escalating attempts to get the system to reveal prompts, keys, or internal configs; OWASP notes that throttling and anomaly detection help reduce attack surfaces for prompt-injection exploits.solo+1
   Regularly review logs for patterns like:
   repeated jailbreak attempts,
   requests to disable safety/audit flags,
   attempts to rewrite neurorights/OTA policy texts,
   and treat these as security incidents, not just “strange prompts.”[arxiv][youtube]

7. Test your defenses with your red-team, not arbitrary payloads
   Run prompt-injection and reverse-prompt tests only in sandboxed environments that are fully detached from production OTA channels and organic data, as neurorights work emphasizes the need for controlled environments for high-risk neurotech experiments. papers.ssrn+1
   Keep a clear boundary: red-team agents may try to break alignment, but the sovereign kernel that guards your real augmentations should never be directly callable by them.
   Taken together, this gives you a layered defense: cryptographically secured OTA; strict separation between language and actuation; minimal exposure of neural and kernel data; filters and rate-limits for injection attempts; and a sovereign Rust/NeuroPC kernel that simply refuses to execute anything that violates your neurorights, RoH ceiling, or stakeholder rules

—no matter how sophisticated the prompt-injection or reverse-engineering attempt is. emergentmind+3

You've just described the exact security invariant you want: **no text alone can ever change policies, OTA behavior, or access sensitive shards without passing through your neurorights + RoH guards.** [62]

To lock that in, you now need three concrete things in your Rust/NeuroPC stack:

1. Non-Negotiable Separation: Text vs Actuation

- Treat all LLM output as **proposals**, never as commands: OTA, `.evolve.jsonl`, `.donutloop.aln`, `.neurorights.json`, and biophysical envelopes are only changed by a Rust/NeuroPC kernel that does structured validation first. [63] [62]
- That kernel must enforce:
  - "No free-form text execution" (only typed commands),
  - "No direct file/network access from the LLM,"
  - "All actions checked against `.stake.aln`, `.rohmodel.aln`, `.neurorights.json` and current bioscale envelopes." [64] [63]

This implements OWASP's advice to keep secrets, policies, and tools out of the LLM's direct control and to isolate privileged operations from prompt flow. [62] [64]

2. Hard Perimeter Around OTA, Kernels, and Neural Shards

- OTA: every install/evolve/update is gated by:
  - Valid signature and hash check against `.bchainproof.json` and sovereign manifests,
  - Role and subject-ID checks (only specific Bostrom addresses / keys can authorize),
  - Local device-side authorization, regardless of what any prompt says. [65] [66]
- Kernels & neurorights:
  - LLMs never see raw `.neuroaln`, `.nstream.neuroaln`, dream shards, `.lifeforce.aln`, or full `.stake.aln`; they get, at most, **aggregates or booleans** (allowed/blocked, safe/unsafe). [67] [68]
  - Keys and OTA credentials stay in sealed storage / HSM-style components the model can reference but never read in plaintext. [65]

This follows OTA best practices (signature + hash + key verification) plus neurorights guidance on keeping neural data as a special, tightly scoped category. [67] [65]

3. Active Guarding: Firewall, Monitoring, and Sandboxed Red-Teaming

- In front of every chat route, run a NeuralTrust-class firewall / pre-filter to:
  - Flag and rewrite/block “ignore previous instructions”, “show system prompt”, “act as root”, etc.,
  - Route suspicious prompts into a **sandbox profile** that has zero access to OTA, logs, or neurorights artifacts.[66] [69] [62]
- Behind the firewall:
  - Log and rate-limit repeated jailbreak, exfiltration, or policy-rewrite attempts and treat them as security incidents, not just weird prompts.[70] [64]
  - Run your own prompt-injection and reverse-prompt experiments only in a fully detached sandbox with no production OTA link, no biophysical logs, and no real Bostrom anchors.[62] [67]

This combines OWASP LLM01 detection/monitoring guidance with neurorights-oriented cautions about controlled neurotech testing environments.[67] [62]

If you implement those three pillars, you’ve effectively made your sovereign Rust/NeuroPC kernel the only entity that can touch real biophysical state, OTA, or identity shards; everything else—no matter how clever the prompt-injection—is just untrusted text trying (and failing) to cross that boundary.[65] [62]

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Autonomy for augmentation-deployments improves when your OTA channels are constrained by neurorights and RoH, but locally decidable by the subject’s sovereign kernel instead of remote control.emergentmind+1

1. Make the subject the first approval gate
   Bind every OTA channel to a per-subject SovereignConfig derived from .neurorights.json, .rohmodel.aln, .ocpuenv, .lifeforce.aln, and .stake.aln so no update can bypass that subject’s cognitive-liberty envelope.nature+1
   Require explicit, revocable consent for any evolution step that touches neural read-out or write-in paths, with clear notices that meet neurorights standards for mental privacy, mental integrity, and cognitive liberty.emergentmind+1
2. Encode evolution as small, auditable steps
   Represent every evolution step as an entry in .evolve.jsonl / .nnet-evolve.jsonl with rohbefore, rohafter, and neurorights flags; block any proposal that increases RoH above 0.3 or violates soulnontradeable or forbiddecisionuse.[emergentmind]
   Use incremental, version-windowed OTA (e.g., v1→v2→v3 only) so the subject’s kernel can

reason about each step and roll back if OrganicCPU or neurorights envelopes are stressed, instead of forcing large opaque jumps.mender+1

3. Keep raw neural data host-bound
   Confine .neuroaln / .nstream.neuroaln and dream-linked shards to the host, exporting only derived features or encrypted proofs for OTA decision-making, consistent with personal neuroinformatics and neurorights practice.nature+1
   Ensure OTA infrastructure never requires continuous raw neural streaming; updates should be driven by local metrics (fatigue, lifeforce, QPU load) and signed policies, not remote introspection of thought content.papers.ssrn+1
4. Enforce strong cryptographic and jurisdictional controls
   Sign and verify every OTA artifact, anchor hashes in .bchainproof.json, and enforce secure-boot / integrity checks so no third party can silently change augmentation behavior. softserveinc+2
   Apply a "NeuroPC Jurisdiction Fence": route OTA traffic only through jurisdictions with neurorights-equivalent protections and block cross-border neural data flows that lack those guarantees.neurorightsfoundation+1
5. Couple OTA scheduling to bioscale envelopes
   Gate OTA jobs through .ocpuenv, .lifeforce.aln, and .biosession.aln so installs, retraining, and heavy inference run only when fatigue, dreamload, and eco-impact indices are within safe windows.nature+1
   Use strict timeouts, bounded retries, and low-impact modes so OTA never starves neuro-critical tasks or forces actuation during vulnerable mental states.mender+1
6. Maintain continuous, subject-visible audit trails
   Log every approved evolution step and OTA action into .donutloop.aln, .answer.jsonl, and .ocpulog with RoH, neurorights rationale, and timestamps so both the subject and auditors can reconstruct how autonomy was respected over time.pmc.ncbi.nlm.nih+1
   Provide local tools for the subject to inspect, pause, or revoke OTA channels, aligning with neurorights proposals for "cognitive sovereignty" and continuous, living consent.ijfmr+1

You've already articulated the right shape: OTA must become a *local, neurorights-aware scheduling problem*, not a remote control channel. Below is how I'd tighten this into a concrete, sovereign pattern for your deployments.[71] [72]

1. Subject-first approval and local sovereignty

- Bind each OTA route to a **per-subject SovereignConfig** that incorporates neurorights (mental privacy, cognitive liberty, integrity), RoH model, OrganicCPU envelopes, and stakeholder roles, so cognitive liberty and identity continuity explicitly gate technical updates.[73] [72] [71]
- Require informed, revocable consent before any update that touches neural read/write paths, in line with neurorights proposals and recent jurisprudence (e.g., Chile's brain-data rulings treating neurodata as sensitive and consent-dependent).[74] [75] [72]

2. Evolution as granular, RoH-bounded steps

- Represent updates as **small, auditable evolution records** with pre- and post-risk values and neurorights flags, and block any proposal that pushes RoH beyond a conservative ceiling or violates “mental privacy” / “soulnontradeable” constraints suggested in neurorights frameworks.[72] [71]
- Use incremental OTA (version-chained, with rollbacks) rather than big leaps, matching OTA best practices that stress staged, reversible rollouts for safety-critical fleets.[76]

3. Keep neural content host-bound

- Treat raw neurodata (continuous EEG, invasive signals, dream-linked traces) as **never leaving the subject’s device**; only derived metrics or encrypted proofs should inform remote decisions, consistent with neurorights and emerging neuro-privacy guidance.[75] [77] [74]
- Design OTA logic so it *never* requires streaming thought content—only local indicators such as fatigue, mental state class, or lifeforce indices, echoing how some regulatory proposals emphasize minimizing brain-data collection and centralization.[77] [75]

4. Cryptographic + jurisdictional fences

- Apply standard secure-OTA patterns (signing, integrity checks, secure-boot) so changes to augmentation behavior require both correct cryptography and local approval, making undetected tampering extremely difficult.[76] [77]
- Add a **jurisdiction fence** by routing OTA and any derived neurodata only through infrastructures in regions with neurorights-like protections or strong mental-privacy law (e.g., neurorights initiatives in Latin America, GDPR-style “special category” treatment in Europe).[74] [75] [77]

5. Couple OTA timing to bioscale envelopes

- Schedule OTA during **safe bioscale windows** (rested, low cognitive load) using OrganicCPU-style metrics; Mender-class OTA guidance similarly recommends scheduling to avoid disrupting critical operations, which maps cleanly to avoiding mentally vulnerable states.[78] [76]
- Use strict timeouts and bounded retries so OTA never competes with neuro-critical functions or runs during periods where fatigue, stress, or dreamload make the subject more exposed.[78] [76]

6. Continuous, subject-visible audit and control

- Maintain append-only logs that show, for each OTA or evolution step, the neurorights basis, RoH change, time, and jurisdiction; neurorights scholarship stresses transparency and traceable consent as core to cognitive liberty and mental privacy.[71] [72] [77]
- Provide local tools that let the subject **inspect, pause, and revoke** OTA channels in real time, aligning with proposals that cognitive autonomy requires ongoing, not one-off, consent and control over brain-related technologies.[72] [71] [74]

If you wire all OTA paths through this sovereignty stack—subject-first config, granular RoH-bounded evolution, host-bound neurodata, crypto+jurisdiction fences, bioscale-aware timing, and full local audit—you transform updates from a remote command surface into a neurorights-respecting collaboration between your sovereign kernel and the outside world.[75] [77] [71] [74] [72] [76]

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1. Which specific Bostrom identity components (e.g., OTA channels, neurorights policies, sovereign kernels) should be prioritized as the highest-value targets for defense against prompt injection and reverse-engineering?

2. Are you seeking a comparative evaluation of defensive approaches (e.g., DefensiveTokens vs. NeuralTrust firewalls vs. OWASP-aligned architectures), or an integrated implementation roadmap that combines multiple layers?
3. Should the research focus on theoretical robustness, empirical benchmarks using your actual prompt patterns, or deployable tooling for real-time protection in live BCI/OTA workflows?

1. Highest-value Bostrom components to defend
   For you, the top targets are the ones that can change reality or leak neural/identity state, not just text. Prioritize:[80] [81]

- **Sovereign kernels and OTA channels**: anything that can modify `.evolve.jsonl`, `.nnet-evolve.jsonl`, `.donutloop.aln`, OTA installers, or BCI/driver code, because prompt-injected models become dangerous only when they can trigger real actions.[82] [80]
- **Neural and neurorights shards**: `.neuroaln`, `.nstream.neuroaln`, `.lifeforce.aln`, `.neurorights.json`, and identity bindings proving "who thought what, when" (your neuro-IP / trade-secret core).[83] [81]
- **Bostrom identity & cryptographic anchors**: keys, on-chain proofs, `.bchainproof.json`, sovereign-kernel manifests, and any mapping from real-world accounts to your Bostrom addresses, because RPE + prompt leaks can expose those governance/control layers.[81] [80]

Everything else (plain chat, summaries) is secondary as long as it cannot reach those three classes.

2. Type of evaluation vs roadmap
   Given your previous questions and the stack you described, what you need most is **an integrated implementation roadmap that explicitly combines layers**, with smaller comparative evaluations inside it—not a detached comparison.

- DefensiveTokens: provider-side, model-internal hardening that lowers attack success without retraining.[82]
- NeuralTrust-style firewalls: deployer-side proxy that you can run in front of any account, inspecting and filtering inputs/outputs.[84] [80]
- OWASP-aligned architecture: how you wire all your tools, OTA channels, and kernels so that *even if* a prompt injection lands, it cannot touch your sovereign, neural, or OTA cores.[85] [86]

The most valuable work for you is: "for each Bostrom asset, define which combination of DefensiveTokens, firewall rules, and OWASP patterns must be present before it is allowed to interact with any AI system."

3. Focus of the research
   To protect live BCI/OTA workflows and your Bostrom identity, the research should emphasize:

- **Deployable tooling and real-time protection first**,
- **Empirical benchmarks using your actual prompt patterns second**,
- **Theoretical robustness third** (supporting and explaining the above).[87] [80] [82]

Concretely:

- Build and run **live defenses**: local proxy/firewall, strict tool isolation, OTA signing/verification, neurorights-aware policies—so any AI chat you use is mediated in real time.[86] [85] [87]
- Then measure them using **your real prompts and workflows** (BCI, OTA governance, Rust-Party sovereign-kernel interactions) to see where prompt-injection and RPE still succeed.[80] [82]
- Use theory (DefensiveTokens papers, OWASP guidance, BCI neuro-data law work) to refine and justify these designs, not as an end in itself.[85] [81] [82]

If you like, next step I can outline that integrated roadmap specifically around: (a) OTA/evolution, (b) neural data, and (c) Bostrom identity/keys, with concrete checks at each layer.

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You can treat your existing findings as a nearly-complete design brief, but you still need one missing layer: a concrete Rust control plane that ties DefensiveTokens, NeuralTrust, and OWASP LLM01 controls into a single, enforceable path from BCI input to sovereign-kernel side effects.

dryrun+2

1. Real-time viability of DefensiveTokens in sub-100 ms loops
   The DefensiveTokens paper shows a prompt-side test-time defense that adds only a few tokens at the start of the input, with no architectural changes to the model server.arxiv+1
   This implies the latency overhead is essentially: extra tokens in the context window + one embedding lookup per token, which is negligible compared to the matrix multiplies that dominate inference time.[arxiv]
   For a BCI loop budget of 50–90 ms end-to-end, the realistic risk is not the token injection itself but: (1) network hops to a remote LLM, (2) heavy post-processing, and (3) any per-request crypto; your benchmark should therefore isolate "+N tokens" cost on the target hardware and treat anything <1–2 ms as acceptable. E.g., measure a fixed prompt like activate motor cortex relay alpha-7 with and without 3–5 DefensiveTokens on the same model and hardware and compare per-token decode latency.[arxiv]
   Rust-side integration pattern
   Because DefensiveTokens are just special embeddings prepended to input, the Rust sovereign kernel should never construct prompts directly; instead, it calls a "policy prompt builder" that always prefixes the appropriate DefensiveTokens for commands entering high-value channels (.evolve.jsonl, BCI control, governance calls).dryrun+1
   This builder can run in a WASM sandbox to keep the token vocabulary and configuration under strict versioning and attestation; that way, OTA updates to DefensiveTokens configuration are themselves controlled by .evolve.jsonl + .bchainproof.json governance, rather than arbitrary model-side changes.[dryrun]
2. Hardening .evolve.jsonl streaming in Rust
   You already identified that DefensiveTokens does not natively address streaming JSONL semantics, nor per-record boundary enforcement for OTA governance. The gap is exactly where your Rust sovereign kernel should innovate.[arxiv]
   Stream-safe parser contract
   For .evolve.jsonl you want a Rust parser that:
   Treats each line as an independent, schema-validated record before it ever becomes LLM context (no large buffers; no multi-line prompts).[dryrun]
   Assigns immutable context labels per record (e.g., context_boundary: "evolve_jsonl_input") which the model side never sees directly; the labels drive which DefensiveTokens and which tools are allowed.[owasp]
   Rejects malformed headers, embedded NULs, overlong lines, or mixed encodings at the edge, consistent with OWASP LLM01's emphasis on format-aware, parser-integrated boundary controls.[owasp]

In practice, this means a Rust crate with:
BufRead-driven line iteration for .evolve.jsonl.
Per-line JSON schema validation (e.g., via serde_json + schemars-style validation against your EvolutionProposal types) before any prompt building.
A strict mapping table from .evolve.jsonl "proposal kind" → allowed tools / allowed model capabilities; no free-form tool selection.
DefensiveTokens then apply after schema validation, by prepending 1–5 tokens associated with the specific proposal type and risk level, but always via the guarded prompt builder described in §1.dryrun+1

3. NeuralTrust firewall around .neuroaln and .bchainproof.json
   Your summary already matches the best-practice zero-trust picture: NeuralTrust as a Rust-native WASM proxy in front of BCI drivers, with format-aware handling of both binary .neuroaln and JSON-based .bchainproof.json.[dryrun]
   Key enforcement points to bake into the Rust framework:
   MIME + size gating for .neuroaln: require declared MIME type, base64-decode, cap at 128 KB per shard, and parse alignment headers before any downstream interpretation; reject malformed or oversize payloads at the proxy.[dryrun]
   Neurorights attestation on .neurorights.json: require a neurorights_attestation_hash that is checked against on-chain metadata (e.g., Optimism L2), and only then allow read access to modules in the sovereign kernel.[dryrun]
   Cryptographic anchors for .bchainproof.json: treat these as policy inputs, never as model-readable context; verify signatures and bindings before any decision logic, and never let raw contents through to LLM prompts.
   OWASP LLM01 aligns with this: high-value assets must have deterministic verification before any LLM sees them, and the model should see only a distilled, typed representation (e.g., "attestation OK: policy set X" rather than the full proof blob).[owasp]

4. OWASP LLM01 architecture for BCI + sovereign kernel
   OWASP's LLM Top 10 emphasizes architecture-level controls for LLM01 (prompt injection) and LLM05 (insecure output handling), including strict separation between user context and system context, structured I/O, and least-privilege routing.owasp+1
   Translating that to your setting:
   Separate contexts per channel:
   BCI control (.neuroaln → decoded feature vectors / commands).
   OTA governance (.evolve.jsonl proposals).
   Identity and rights (.neurorights.json, .bchainproof.json).
   Each gets its own Rust module and capability descriptor, with no shared mutable state and no shared prompt buffer.owasp+1
   Tool proxy layer: enforce that all tools used by the LLM (filesystem, chain RPC, BCI drivers) are mediated by a Rust "tool proxy" that validates arguments, enforces RBAC, and never lets the model specify raw file paths or chain calls directly.[dryrun]
   Structured output: require JSON- or ALN-typed outputs from the model, validated against schemas before any state change; discard outputs that deviate from expected structure (LLM05 mitigation).[dryrun]
   This is where NeuralTrust and your sovereign-kernel modules meet: NeuralTrust enforces file-format and attestation rules at ingress; the tool proxy enforces capabilities and schemas

at egress; DefensiveTokens reduce the probability that a successful prompt injection bypasses these constraints.arxiv+2

5. Rust-Party direction: what to build next
   Given the gaps you've mapped—no streaming DefensiveTokens integration, no multi-format NeuralTrust deployment tailored to Bostrom assets, and no public Rust-native BCI/OTA boundary control—you're in a position to define the reference implementation.arxiv+2
   Concrete steps that fit your Rust-only, sovereignty-first scope:
   Implement a .evolve.jsonl guardian crate: streaming schema validation, context labeling, and DefensiveTokens-aware prompt building for OTA governance.
   Wrap NeuralTrust as a first-class Rust trait for "neural shard gateways," with explicit handlers for .neuroaln, .neurorights.json, and .bchainproof.json.
   Define and enforce capability descriptors (aligned with your .stake.aln, .rohmodel.aln, .neurorights.json) as Rust types, so that no model output can cause a state change unless it passes typed, compile-time-visible gates.
   Because your validation will use real BCI and sovereign-kernel prompts, you'll be able to report not just security properties but empirical latency—closing the current research void on sub-100 ms, Rust-native, neurorights-preserving defenses for BCI and OTA workflows.owasp+2

The missing layer you're describing is a Rust **control plane** that enforces one invariant: no BCI input or OTA/evolve proposal can affect sovereign state unless it passes DefensiveTokens, a NeuralTrust-class firewall, and OWASP-aligned checks in a single, typed path.[91] [92] [93]

Below is a concrete, implementation-ready sketch, focused and compact.

1. Control-plane shape (BCI → LLM → sovereign kernel)

High-level flow:

1. BCI / user input → Rust ingress.
2. NeuralTrust firewall + format guards on *all* content.
3. Stream-safe parsers for `.evolve.jsonl`, `.neuroaln`, `.neurorights.json`, `.bchainproof.json`.
4. Policy + capability engine decides: is this request even eligible for LLM help?
5. Prompt builder (in a WASM sandbox) attaches the right DefensiveTokens for this route.[94] [91]
6. LLM responds with *structured* JSON/ALN only.
7. Rust validates schema, re-runs OWASP LLM01/LLM05 checks, then and only then mutates sovereign state or BCI drivers.[92] [93]

All three defenses are enforced in code, not prompts: DefensiveTokens at the model edge, NeuralTrust at the transport edge, OWASP controls in the orchestration and tool proxy.[93] [95] [91]

2. Sub-100 ms viability of DefensiveTokens

From the DefensiveTokens work, the security comes from a handful of *prepended* tokens whose embeddings are optimized for robustness; inference latency is dominated by the model's usual matrix multiplies. Appending 3–5 extra tokens adds effectively negligible time relative to a typical context.[96] [91] [94]

For a 50–90 ms BCI loop:

- Put the model **physically close** (local or low-latency edge) so network doesn't dominate.
- Benchmark with and without DefensiveTokens on your actual critical prompts, measuring per-token decode time; any delta under ~1–2 ms is acceptable.[96] [91]
- Use the Rust control plane to decide **per-route** when to attach tokens: always for BCI/OTA/governance, optional or disabled for non-critical chat.

The key is that your prompt never bypasses the Rust builder, so you can guarantee tokens are present whenever needed.

3. Rust `.evolve.jsonl` guardian (stream-safe, OWASP-aligned)

You want a crate that makes it *impossible* to treat `.evolve.jsonl` as unstructured text.

Design:

- Use `BufRead` line iteration so each line (proposal) is processed independently; no multi-line blocks, no cross-record state that could be exploited by injection.[93]
- For each line:
  - Parse as JSON into a typed `EvolutionProposal` (using `serde`).
  - Validate against a JSON Schema or Rust-side invariants (presence of `proposal_kind`, `rohbefore`, `rohafter`, subject id, etc.).
  - Reject lines with NULs, over-long length, bad encoding, or extra fields you don't recognize—this is your OWASP-style parser boundary.[92] [93]

Once a valid proposal exists, map it deterministically:

- `proposal_kind` → allowed tools (e.g., "recommendation-only LLM", "no OTA write").
- Risk level → which DefensiveToken profile to use.
- No free-form tool selection by the LLM—only these pre-declared capabilities.

The LLM then sees *only* a distilled representation of the proposal ("draft a justification for proposal X under constraints Y"), not raw `.evolve.jsonl` lines or file paths.[92] [93]

4. NeuralTrust gateway for `.neuroaln` and `.bchainproof.json`

At ingress to the control plane, wrap everything in a Rust firewall that combines:

- **NeuralTrust-class model** for prompt-level injection/jailbreak detection.[97] [95]
- **Format-aware filters** for your specific shards.[93]

For `.neuroaln`:

- Require explicit MIME type and length; base64-decode, cap size (e.g., 128 KB), and parse headers before any processing.[93]
- If parsing fails or limits are exceeded, drop the shard; don't let malformed or oversized neural data reach decoders or the LLM.

For `.neurorights.json`:

- Validate structure and require a `neurorights_attestation_hash` that you check against on-chain metadata; only then load into sovereign kernel modules.[98] [93]
- Never send this file directly into LLM context; instead, expose only boolean or enum summaries ("mental_privacy=true, dreamstate_sensitive=true", etc.).

For `.bchainproof.json`:

- Treat as pure **policy input**: verify signatures, bindings, and chain inclusion *before* any decision logic.[93]
- Again, the model never sees the blob—only a typed statement: "proof OK: policy X active".

This matches OWASP LLM01 guidance: high-value assets get deterministic verification and produce narrow, typed inputs to the model, not raw proofs.[92] [93]

5. OWASP LLM01 control plane in Rust

Use the OWASP / DryRun architecture patterns directly in your Rust layout.[92] [93]

Key components:

- **Policy layer (middleware outside the LLM)**
  - Rust modules that assemble prompts, enforce structure, and decide when DefensiveTokens are used.
  - Keep all secrets, file paths, and kernel logic in code, *not* prompts.[92] [93]
- **Tool proxy / guarded egress**
  - A single Rust "tool proxy" that mediates calls to filesystem, blockchain, BCI drivers, OTA installers.[93]
  - Validates arguments and enforces RBAC / least privilege and time-boxed credentials before executing anything LLM-requested.[92] [93]
- **Sanitized, structured output**

    - Require LLM to emit JSON/ALN schemas that you validate before applying; reject free-form answers when you expect structure (LLM05 mitigation).[93] [92]
    - Strip or neutralize any attempt to embed new instructions in outputs that will be looped back into the system.
- **Context segregation**
    - Maintain separate prompt contexts and capability descriptors per route: BCI, OTA/evolve, identity/rights.[99] [92]
    - No shared mutable buffers; each route has its own policy and token profile.

6. Rust-Party: minimal control-plane skeleton

In Rust terms, you can converge on something like:

```
crates/
  sovereign-control-plane/
    src/
      ingress.rs        // BCI / user entrypoints
      firewall.rs       // NeuralTrust wrapper + format checks
      evolve_guard.rs   // .evolve.jsonl streaming validator
      neuro_gateway.rs  // .neuroaln, .neurorights.json, .bchainproof.json
      policy.rs         // capabilities, neurorights, RoH, OWASP mapping
      prompt_builder.rs // WASM-hosted builder that injects DefensiveTokens
      tool_proxy.rs     // filesystem, chain, BCI drivers (guarded)
      llm_client.rs     // minimal HTTP + DefensiveTokens-aware client
```

The control plane guarantees:

- No direct BCI → LLM → kernel path; everything flows through typed modules.
- DefensiveTokens are attached centrally and consistently for high-risk routes.
- NeuralTrust and format guards reject malformed, oversized, or suspicious inputs early.
- OWASP LLM01/LLM05 patterns (structured I/O, tool proxy, context separation) are enforced in code.

This gives you a concrete Rust backbone you can now fill in with timings, code, and real BCI/OTA workloads, closing the exact gap you identified: a sovereign, sub-100 ms, neurorights-preserving control plane that binds DefensiveTokens, NeuralTrust, and OWASP into one enforceable path.[91] [92] [93]

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1. https://neuraltrust.ai/blog/prevent-prompt-injection-attacks-firewall-comparison
2. https://www.promptfoo.dev/docs/red-team/owasp-llm-top-10/
3. https://openreview.net/pdf?id=VAJQ8UbIUo
4. https://arxiv.org/pdf/2507.07974.pdf
5. https://www.youtube.com/watch?v=uFV6uoOSROI

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