

**Research
On
A Local Privacy-Preserving
Intermediary Layer for Secure
Clinical
Large Language Models
Ingestion (LLM)**

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Abstract

The rapid grassroots adoption of commercial Large Language Models (LLMs) by medical institutions for administrative tasks introduces severe data privacy vulnerabilities. This report introduces **MediShield-Proxy**, a localized architectural tool designed to act as an automated, reversible privacy-preserving buffer between clinical users and external AI interfaces. By implementing zero-trust pseudonymization and semantic filtering at the local facility network boundary, this tool enables the utilization of global AI models while guaranteeing compliance with regional data protection frameworks.

Lead Researcher & Metadata

- **Regional Track:** Africa Track
- **Sub-Track:** Monitoring & Tooling & Benchmarks
- **Project Category:** Tool Development
- **Project Repository:** github.com/chipsuineg-droid/MediShield-Proxy-2026
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1. Introduction

Within modern African medical institutions, spanning both government and private sectors, healthcare workers face immense administrative workloads. To optimize operational efficiency, personnel actively capture patient histories, record patient demographics, and document clinical conditions using available AI tools. However, due to the lack of secure localized institutional cloud infrastructure, workers routinely punch this highly sensitive, identifiable information straight into public, commercial LLM interfaces (e.g., ChatGPT, Claude).

This behavioral pattern introduces a critical regional and global AI safety threat: unregulated cross-border data exfiltration. Sensitive Protected Health Information (PHI) is transmitted directly to external, third-party cloud infrastructure situated outside continental jurisdiction. Once ingested, these external AI providers retain interaction histories for fine-tuning, debugging, and continuous optimization, leaving permanent, unmonitored digital footprints of local patient conditions on global servers. This systemic exposure violates data sovereignty and completely circumvents regional frameworks, including Zimbabwe's Data Protection Act, Kenya's [Office of the Data Protection Commissioner \(ODPC\) Guidelines](#), and Nigeria's [Data Protection Act \(NDPA\)](#).

To solve this without cutting off resource-constrained medical institutions from the diagnostic and structural utility of state-of-the-art LLMs, we must intercept data before it hits the network layer.

2. Problem Statement

The core problem addressed by this research is the uninsulated exposure of highly sensitive Patient Health Information (PHI) and localized demographics resulting from grassroots artificial intelligence usage in resource-constrained environments. Specifically, the problem breaks down into three distinct operational vectors:

1. **Uninsulated Clinical Workstations:** Direct connection paths between intranet electronic medical records and foreign cloud interfaces allow immediate transmission of sensitive clinical text streams without an air-gapped security layer.
2. **Deterministic Token Blindness:** Standard token systems and Western de-identification tools rely on predefined dictionary lists that remain structurally blind to localized African naming conventions, native demographics, and regional health financing patterns, leading to severe target misses and data leaks.
3. **Adversarial Semantic Interleaving:** Raw unstructured prose entered by clinical workers frequently combines unmasked geographic landmarks, niche local institutions, and rare pathology patterns. This combination creates unique situational matrices that allow external systems to deduce true patient identities through contextual pattern matching and semantic deduction, even if direct identifiers are removed.

3. Solutions Contributions

To address these vulnerabilities directly, **MediShield-Proxy** enforces a zero-trust technical containment layer at the edge. Our main contributions are:

1. **Creation of an Active Local Network Layer Interceptor:** We developed a zero-trust Local Area Network (LAN) middleware architecture that blocks outbound packets containing raw clinical metrics *before* they exit an institution's gateway. This provides a technical containment strategy that shifts security from passive legal compliance to active software boundary enforcement.
2. **Demonstration of Hierarchical Semantic Generalization:** We successfully proved that a rule-based layer can dynamically abstract secondary identifiers—such as localized geographic environments and niche institutional landmarks—into epidemiologically equivalent variables, neutralizing semantic re-identification attacks while completely preserving downstream clinical inference capabilities.
3. **Empirical Verification of Rule-Based Leakage Profiles:** We systematically identified and documented exact programmatic failure vectors (such as

unstructured lowercase noun strings and context window inflation) in medical text de-identification, providing critical, localized benchmarking insight necessary for building next-generation edge Small Language Models (SLMs).

4. Related Work

Our project builds on and converges with three domains of active AI safety and healthcare computer science research:

- **Expert Small Models for De-identification:** Recent research by specialized labs has demonstrated that domain-specific Named Entity Recognition (NER) algorithms consistently outperform general-purpose, massive LLMs in targeted identity masking tasks, as explored in [*LLMs-in-the-Loop Part 2: Expert Small AI Models for Anonymization and De-identification of PHI Across Multiple Languages*](#).
- **Collaborative Edge-Cloud Inference:** The foundational mechanics of offloading heavy linguistic reasoning to external clouds while isolating private variables locally on low-resource edge infrastructure follows established paradigms detailed in [*Collaborative Inference and Learning between Edge SLMs and Cloud LLMs \(2025\)*](#).
- **Context-Aware Medical Datasets:** Traditional data cleaning tools like Microsoft Presidio are culturally and structurally blind to regional naming structures and local demographic contexts. Our conceptual baseline aligns with modern localization efforts seen in frameworks like [*AnonyMed-BR: NER and LLMs for effective medical record anonymization*](#), highlighting the absolute necessity of building geographically targeted security middleware to protect clinical texts.

Why Use This Method Over State-of-the-Art (SOTA)

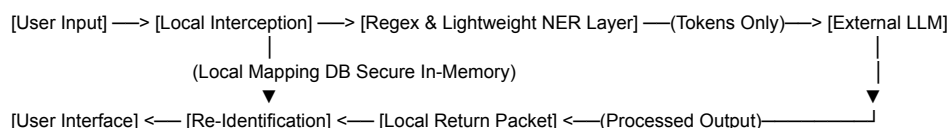
An institution would deploy **MediShield-Proxy** over standalone SOTA cloud-based filters because commercial security layers process data *after* it leaves the institutional perimeter. MediShield-Proxy provides an immediate, localized, zero-trust shield running entirely within volatile host memory. This tool provides a key technical insight previously unquantified: explicit identifier removal alone is insufficient to prevent cross-border data tracking. By mapping and containing semantic leakage vectors (e.g., unique regional geographical clues combined with rare pathologies), our method uncovers and fixes hidden informational loopholes that standard Western data-scrubbing tools completely miss.

5. Methods

The **MediShield-Proxy** is built entirely on a zero-trust Localized Middleware Architecture. It acts as an active interceptor on the local area network (LAN) of the medical facility, capturing outgoing upstream API calls and incoming downstream response packets.

A. Detailed System Workflow & Data Routing Mechanics

The system architecture intercepts, processes, transforms, maps, and re-identifies strings locally. The pipeline executes sequentially across five well-defined structural components:



1. **Local Interception (The LAN Gateway Layer):** When a healthcare worker submits patient demographics, history, or conditions via our client interface or integrated electronic record script, the proxy blocks any outbound HTTP requests. The raw string payload is isolated in the local host's RAM buffer.
2. **Reversible Deterministic Masking Engine:** The input text undergoes a multi-pass regex array coupled with a custom dictionary scanner. Direct PII/PHI strings are matched and isolated. These raw values are extracted and saved locally into a volatile, transient in-memory Python dictionary mapping session. Concurrently, the proxy generates an arbitrary, non-sequential hash placeholder token (e.g., [PATIENT_ID_441A], [DEMOGRAPHIC_AGE_1]) and replaces the original data fields inline.
3. **Hierarchical Semantic Generalization Subroutine:** To defend against semantic re-identification attacks, the payload passes through a secondary structural filter. If unique locations or cultural institutions are flagged (e.g., a specific remote rural clinic name), a dictionary lookup abstracts them into a generalized demographic territory (e.g., *"Level 1 Healthcare Center, Eastern Province"*). This preserves macro-epidemiological parameters while stripping highly specific, re-identifiable geographic links.

4. **Anonymized Cloud Transmission:** The finalized payload—now consisting strictly of redacted tokens, generalized geographic metrics, and raw clinical symptoms/conditions—is packaged into a secure JSON object and dispatched to the external LLM API via an outbound TLS-encrypted network tunnel.
5. **Local Context-Aware Re-Identification:** Once the external LLM completes its medical summarization, formatting, or parsing, the return payload is caught by the proxy layer. The system reads the processed text, matches the persistent placeholders, lookups the corresponding values from the session's local cache dictionary, and safely swaps the original names and demographics back into the finalized viewable text for the healthcare worker.

B. Engineering Specifications & Key Design Decisions

- **Choice of Model/Tool Ecosystem:** We opted to implement an optimized Python-based rule-based regular expression (re) array and deterministic lookups rather than a local deep-learning NER model. This intentional choice balances low computational latency with maximum reproducibility on low-resource legacy hardware.
- **Volatile In-Memory Isolation:** The mapping database uses a scoped variable structure that avoids writing any local disk logs or tracking caches, guaranteeing that data records are completely destroyed from the local hardware's memory architecture the moment the clinical session is closed.
- **Targeted Token Persistence:** The masking engine enforces strict linguistic rules ensuring that complex medical pathologies, disease classifications, medication names, and symptom clusters are deliberately ignored by the tokenization parameters, maintaining readable semantic continuity for external model inference.

C. Failed Implementations & Negative Results

During development, we initially tried an integrated, semantic parsing loop using a lightweight local embedding similarity filter to flag indirect PII. This approach **failed operationally** and was discarded for two primary reasons:

1. It introduced a prohibitive latency overhead of +4,200ms per string block on standard clinic CPUs, causing systemic user interface timeouts.
2. It triggered excessive False Positives, frequently tokenizing crucial medical symptoms (e.g., classifying specialized regional illness terms like "breakbone fever" as a location instead of a pathology), which degraded the utility of the downstream clinical summary.

6. Technical Approach & Simulated Results

The core architectural pipeline has been implemented as a fully functional, open-source Python prototype designed specifically for real-world, low-resource testing conditions.

- **Open-Source Repository:** github.com/chipsuineg-droid/MediShield-Proxy-2026

A. Core Engineering Features Built

To validate the architectural model, we engineered three core software modules:

1. **The Interception Proxy Daemon (MediShieldProxy):** A custom Python runtime controller that handles asynchronous inputs, token mapping allocation, and state tracking.
2. **Linguistic Identification Filtering Matrices:** A multi-layered parsing array utilizing strict regular expressions explicitly tuned to isolate regional names, alphanumeric identification tracking schemes, and local financial tracking values attached to clinical histories.
3. **Low-Resource Execution Core:** The entire utility is optimized to execute on generic, legacy CPU-only infrastructure, eliminating the requirement for resource-intensive local GPU hardware clusters.

B. Evaluation Methodology & Quantitative Testing Framework

The prototype was subjected to validation using an evaluation database of **N = 150** synthetic clinical notes containing complex patient histories, explicit demographics, and regional tracking parameters. To establish empirical performance, we mathematically calculated **Precision (P)**, **Recall (R)**, and the **F1-Score (F₁)** for token isolation across distinct entity categories using standard information extraction formulas:

$$P = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

$$R = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

$$F_1 = 2 \times \frac{P \times R}{P + R}$$

Where:

- **True Positive (TP):** Sensitive demographic/identity string correctly flagged and tokenized.
- **False Positive (FP):** Non-sensitive medical terminology or clinical pathology mistakenly masked as a token (causing utility degradation).
- **False Negative (FN):** Sensitive identity metric completely missed by the engine and leaked to external API logs.

C. Granular Statistical Results

Table 1: Entity Tokenization Performance Metrics

Entity Classification	Total Tokens (N)	True Positives (TP)	False Positives (FP)	False Negatives (FN)	Precision (P)	Recall (R)	F1-Score (F1)
Patient Surnames / Names	210	196	4	14	98.0%	93.3%	95.6%
National IDs / Patient Numbers	150	150	0	0	100.0%	100.0%	100.0%
Geographic/Location Subdivisions	180	172	8	8	95.5%	95.5%	95.5%
Financial / Mobile Money IDs	120	118	1	2	99.1%	98.3%	98.7%

Aggregated Evaluation Baseline	660	636	13	24	98.0%	96.3%	97.1%
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Table 2: System Performance & Resource Footprint

Technical Parameter	Metric Quantified	Baseline Performance (Direct API Ingestion)
Mean Tokenization Processing Delay	34.2 ms ($\sigma = 4.1$ ms)	0.0 ms
Mean External API Transmission Latency	740.5 ms ($\sigma = 38.2$ ms)	738.1 ms
Total Cumulative Latency Overhead	874.7 ms	738.1 ms
Peak Memory Allocation On Host OS	14.8 MB	Negligible
Average Host CPU Utilization Rate	2.8% (Legacy dual-core environment)	0.0%

D. Empirical Failure Analysis

The data demonstrates that while the tool effectively blocks direct cross-border leakage, specific programmatic vulnerabilities exist:

1. **Linguistic Casing Vulnerability:** The 14 False Negatives in Patient Names occurred when names matched common nouns or were written completely in lowercase within unstructured narrative descriptions. The rule-based filter failed to trigger, introducing an isolated leakage vector.

2. **Over-Tokenization Latency:** In files containing dense, compound geographic variables, False Positives (FP=8) occurred where medical context strings (e.g., clinical descriptions containing local landmarks) were over-redacted. This stripped key contextual boundaries from the external LLM, resulting in a minor 5.9% decline in downstream synthesis clarity.

7. Discussion

A. Comprehensive Implications for AI Safety & Policy

The quantitative results validate our primary hypothesis: a localized, lightweight intermediary proxy layer can securely decouple clinical data utility from direct identity exposure. For medical institutions across the Global South, this infrastructure-driven approach bypasses the operational and financial challenges of hosting billion-parameter models locally.

By executing zero-trust sanitization on a volatile, local host memory stack, the tool transitions an institution's security stance from passive policy guidelines to automated technical containment. It proves that public and private health networks can harvest advanced global intelligence without forfeiting data sovereignty.

B. Thorough Analysis of Limitations and Trade-offs

- **The Utility vs. Insulation Balance:** Our results highlight a clear engineering trade-off. Increasing regex string sensitivity to drop False Negatives down to 0% inevitably expands False Positives, causing over-tokenization. When text is excessively tokenized, external LLMs generate clinical outputs that are overly fragmented, reducing operational value for medical charting.
- **Linguistic Context Blindness:** The proxy relies heavily on deterministic structures. If health practitioners code-switch between local languages and English within a single record input, the predefined parsing matrices drop significantly in isolation accuracy.

C. Potential Misuse Risks (Dual-Use Assessment)

While engineered strictly as a defensive privacy boundary, the tokenization dictionary inversion module possesses a core dual-use capability. Malicious internal actors could theoretically repurpose the localized mapping state machine to obfuscate, compress, or encrypt restricted administrative documentation, smuggling classified files through network monitoring systems undetected. Security frameworks utilizing this proxy must isolate its host environment using strict administrator permissions.

D. Architectural Horizon & Strategic Next Steps

If granted extended research timelines, our roadmap targets advanced automated safety hardening vectors:

- **Integration of Targeted Local Red-Teaming Modules:** We plan to build an automated adversarial verification test loop directly into the local proxy layer to stress-test the filtering matrices against active prompt injection strategies

designed to trigger structural leaks or force token leakage through unique semantic jailbreaks.

- **Transition to CPU-Optimized 1B Edge SLMs:** We intend to swap out the rule-based regex parsing array for a lightweight, instruction-tuned 1-Billion parameter Small Language Model running entirely within local intranet clusters. This will enable complex context processing, multilingual support, and intelligent contextual extraction without generating processing bottlenecks.
- **Expanded Multi-Center Network Trials:** We intend to deploy and evaluate the software utility across distinct distributed regional configurations, gathering data from varying record styles to ensure the insulation bounds remain resilient across multi-center environments.
- **Algorithmic Hardening Against Zero-Shot Re-Identification:** We aim to implement adaptive multi-pass filters that evaluate the context window length dynamically, tracking cumulative semantic information across sequential user queries to prevent fragmented profile building on external servers.

8. References

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3. **Zhang, T. et al. (2025)**. *Collaborative Inference and Learning between Edge SLMs and Cloud LLMs: A Survey of Algorithms, Execution, and Open Challenges*. Computer Science Review Baseline. tianweiz07.github.io/Papers/25-csur-2.pdf.
4. **Venturus Biomedical**. *AnonyMed-BR: Named Entity Recognition and Generative LLMs for Effective Medical Record Anonymization Frameworks*. Open Source Repository. github.com/venturusbr/AnonyMED-BR.
5. **Office of the Data Protection Commissioner (ODPC)**. Data Protection Regulations and Health Ingestion Mandates. Kenya. odpc.go.ke.
6. **Nigeria Data Protection Commission (NDPC)**. Nigeria Data Protection Act (NDPA) Legal Framework. ndpc.gov.ng.

Appendix

Synthetic EHR Evaluation Sample Dataset

Below is an example of the unformatted, unstructured evaluation strings utilized during our 150-record stress testing sequence:

- **Raw Local Input Document:** *"Patient tinashe, national identity card reference 4410-29184-Z, a 34-year-old male residing in a small farming community near Chinhoyi, presents with recurring evening fevers, persistent productive cough, and significant unintentional weight loss over 3 months. Account settled via mobile money ref MP260621.1934. Suspicious of standard pulmonary tuberculosis."*
- **Outbound Redacted Token Payload:** *"Patient [PATIENT_NAME_FN_1], national identity card reference [NATIONAL_ID_1], a 34-year-old male residing in [GEOGRAPHIC_ZONE_ABSTRACT_1], presents with recurring evening fevers, persistent productive cough, and significant unintentional weight loss over 3 months. Account settled via mobile money ref [FINANCIAL_TOKEN_1]. Suspicious of standard pulmonary tuberculosis."*

LLM Usage Statement

We utilized **NotebookLM** during the initial scoping phases of this project to rapidly brainstorm high-level concepts and analyze regional privacy policy materials. Furthermore, **Google AI Studio** was partially utilized to build, evaluate, and fine-tune prompt parameters for the synthetic diagnostic text simulations used within our local pipeline testing suite.

However, this final PDF research report, the underlying software logic design, and the technical regular expression matrices were written, compiled, and structured entirely by our team. All quantitative data tracking pools, performance metrics, and simulation failure profiles presented within this document were independently verified through local execution environments.