

## ***A Secure, Interoperable, And Energy-Aware Federated EHR: Design And Simulation With Fernet Encryption, FHIR-Like REST, And Multi-Threaded Evaluation***

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**Abstract:** The conducted research offer a federated and encryption-enabling FHIR-like Electronic Health Record (EHR) prototype being fully implemented in Python/Google Colab as an interoperable and low-resource conscious health data exchange system. The architecture spreads deceased patient data among virtual hospital units (JSON/dictionaries) and implements the use of Fernet symmetric research-at-rest and Transport encryption. It uses normative -aligned exchange in the form of FHIR-style REST endpoints (using FastAPI framework, Python filters with Flask), and also allows user interactions via a lightweight Gradio graphical interface, and structuring concurrency with level 2 threading/asyncio. Appearance of systems (psutil/time) tools show the latency, processor, memory, per-SQL energy. With a synthetic cohort size of 100 patients in 3 nodes (diagnosis, medications, labs/visits) mean encryption and decryption times of 47.2 ms and 43.6 ms were achieved respectively. The latency of API increased predictably with the number of users (range 121.5 ms with single-user to 289.2 ms with 20 users). CPU utilization was low (about 911% during crypto), as well as memory overhead (encryption + about 11.4MB, decryption + about 1.5MB). Energy was estimated to be = 2 J per encrypted query. The highest interoperability testers gained ≥97% success on 300 API calls, the GUI loaded in 3.5 s, retrieved in 3.2 s, decrypted in 1.0 s and received 8.8/10 satisfaction. The federated system comes with lower confidentiality, resilience, and portability improvements in exchange with small latency/memory overheads (compared to a centralized, unencrypted baseline, 128.4 ms, 225.5 MB). Accomplished surveys show congruence with the interest of the stakeholders: patients attempt to report high levels of digital preparedness and security-conditioned sharing (trust in encryption 69 percent, willingness to share if encrypted 72 percent, granular consent 61 percent), whereas staff members emphasize partial coverage of EHRs (73.3 percent), low attempt of FHIR production (16.7 percent) and format/API bottlenecks. DEID that resembles HIPAA/GDPR/India DPDP principles with a prototype that can be freely reproduced, interoperable with the cloud, and represents an extension framework of federated learning, decentralized identity/consent, and advanced cryptography.

**Keywords:** Electronic Health Record, Federated Database, Health Data Security, Python, Google Colab, Fernet Encryption, REST API, Flask, Gradio Interface, HL7, FHIR, Data Interoperability, Secure Data Exchange, Asynchronous Access, Psutil, Energy-Aware Computing,

### ***1 INTRODUCTION***

The digitalization of healthcare has contributed to the fast transformation of the processes of medical records creation, storage, access, and transfer. Regardless of the small personal clinics or the national health systems Electronic Health Records (EHRs) have become the focal point of the patient outcomes improvement process, reduced redundancy in the diagnostics and evidence-based medical practice provisions. With the emergence of increased interconnection of health data, however, the previously mentioned concerns of data security, interoperability and energy efficiency have become extremely important. These restrictions are especially severe in the limited resource setting and in academic or research centers where it is not possible or not scalable to deploy full scale hospital information systems or commercial cloud computing

infrastructures. The COVID-19 outbreak demonstrated the significance of an adaptable and safe system of a health information exchange when the medical resources and knowledge were stretched between the facilities. Despite the proposed solutions of centralized cloud-based EHR systems, the following questions are raised with serious concerns of breach of data, single points of failures, non-compliance with privacy, and consumption of energy. The alternative to this that is decentralized and privacy-preserving is known as federated data storage and processing models, in which the records of patients are divided between multiple different nodes but can be availed to parties with suitable authority on demand. Nevertheless, cloud computing is not rejected in our framework either. Instead, it models the working behaviour of a federated cloud based EHR model in Python tools on Google Colab. Through this emulation, we can investigate key cloud features including the ability to access the cloud by more than one user, encryption across distributed nodes, and API services using the REST protocol without having to deploy these services to a commercial cloud vendor. The model is therefore a cloud based architecture scaled down to low-cost, academic or prototype applications.

A secure and interoperable federated EHR system is however not an easy task to design and simulate. It involves the work of distributed data, the implementation of encryption algorithms, the modeling of the real-time interaction of data, and the work of the system under the load measurement (using international standards: HL7 (Health Level Seven) and FHIR (Fast Healthcare Interoperability Resources)). As a prototype or as an educational challenge, such a system may be built with open-source software, like Python on Google Colab, since it is a reproducible way to accomplish the task of demonstrating how secure, energy-aware, and interoperable health data exchange can be achieved without having to deploy such a system to an enterprise cloud infrastructure, and maintain cloud-like functionality, such as access to a remote system, the simulation of multiple users at once, and the distribution of data flow within a lightweight, educationally oriented framework. The proposed study will apply and simulate a federated, encrypted EHR system, developed and designed in Python on Google Colab as a whole. The system would utilize the open-source tools and programming constructs to create a system that is decentralized, which is scalable and secure to store, transmit and retrieve patient records. As every hospital or other medical provider is recreated as a virtual node represented by Python dictionaries or JSON objects the framework simulates the behaviour of a federated database in the real world. In such a system, the nodes used would archive partial records of the patient and there would not be any central database where all the information will be: it will be easy to control privacy besides being resistant to any efforts of hacking into the system. This decentralized system is rather in line with privacy-by-design thinking, and it achieves data sovereignty between institutions. Python and Google Colab development environment choice assists in enhancing accessibility and educational worth since researchers, students and health care professionals can learn and experiment with safe EHR systems by not setting up or managing a back-end server setting. The most important part of this construction is the inclusion of symmetric encryption with the well-known Fernet module of the Python cryptography library. This encryption system ensures that the data stored in each node is encrypted using a time based symmetric key, so intrusion by unauthorized people is practically impossible. Data encryption is performed to decrypt them after successful authentication and limited access of the API to replicate the concept of secure end-to-end data flow. The virtual nodes communicate with each other in the same manner available in the real world with RESTful APIs built with Flask or FastAPI to define HL7 (Health Level 7) and FHIR (Fast Healthcare Interoperability Resources) and other real-world interoperability standards. The APIs make the format of retrieving the data to be standardized and structured thus facilitating

easy integration of the data but also interoperability of the system with the 3<sup>rd</sup> party applications. Another aspect that is applied in the simulation is user authentication and role based access therefore only authorized users are permitted to access and decrypt specific section of patient information.

Electronic Health Records (EHRs) support data-driven care delivery through the enhancement of continuity, minimization of duplication, and evidence-based decision-making. However, real-world implementations have three enduring challenges; security, interoperability and operational footprint (energy and cost). Cloud EHRs The centralized cloud EHRs are useful in scaling access but they provide single points of failure and increase the impact of a breach; they also have compliance and sustainability concerns. The federated architectures, in which institutions keep data locally and share only the necessary ones, are compatible with privacy-by-design and data sovereignty; with the help of the standards, such as HL7/FHIR, they will allow structured exchange across heterogeneous systems [1],[2],[26],[28],[30]. In this paper, a Python/Google-Colab simulation of federated encryption-enabled EHR is provided. Every node holds incomplete patient data (JSON/dict), encrypted using Fernet; communication strictly follows REST APIs, simulation of FHIR resources use, and OAuth-type authorization. An informal Gradio GUI allows user queries as well as visualization. This is through the use of psutil to profile latency, CPU/memory and approximate energy per-query in single and multi-user conditions. Findings indicate that the strategy is safe and compatible with small overheads that can be used by academic pilots and other low-resource environments. In comparison to an unencrypted centralized baseline, the federated system incurs latency loss in an effort to produce high security and standardized exchange, a trade-off also in consistency with recent research on privacy-preserving, distributed health analytics [1],[4],[10],[26],[28],[30]. In addition to its didactic importance, the prototype contains a pragmatic roadmap to green and standards-based digital health prototypes and can be augmented with federated learning, decentralized identity, and modern privacy technologies [2],[14],[22],[26],[29]. The suggested contribution does not detail a kind of new task-scheduling meta-heuristic instead, it is an experiment introduced a novel end-to-end, reproducible prototype, which is used: (i) federated record partitioning among the nodes, (ii) encryption-first storage and transport with integrity using Fernet, (iii) a FHIR-like reip complaint interaction however pattern, and (iv) energy-aware profiling (CPU/memory-to-energy mapping) when single-users and when operating in a low-cost Colab setting. The previous research usually considers these aspects alone (e.g. federation with no energy profiling, encryption with no FHIR-like exchange, or interoperability with no per-operation energy/overhead reporting). Our work fills these layers and provides an answer like a single quantifiable set such that trade-offs can be reported against a central unencrypted baseline. The originality of the work consists of providing a complete reproducible end-to-end federated EHR prototype that simultaneously applies node-level data partitioning encrypted node-level encrypted data; FHIR-like REST-interoperable; multi-user concurrency testing; and energy-conscious performance profiling in a low-cost Google Colab environment. In contrast to previous works that consider these factors individually, the proposed framework has a measure of security, latency, scalability, and energy trade-offs, which is a practical and pilot-ready model of secure and sustainable health data exchange in resource-constrained environments.

## **II RELATED STUDIES**

A federation, cryptography and standards of health data exchange are increasingly combined in a triad, with governance and sustainability concerns, to attain secure, interoperable and privacy-aware health data exchange. At the federation axis, there has

been recent research indicating that learning and analytics do not require data to be pooled centrally. A hybrid-encryption federated learning system alleviates latency and security bottlenecks in clustered healthcare and allows model training even without raw data transfer [1]. General overviews of privacy-preserving methods of blockchain-supported federated learning in smart healthcare focus on architectural designs, node resilience, and the fact that lightweight cryptography is required to be feasible at the edge [2]. Disease prediction using privacy-enhanced AI is also another incentive to use federated settings to prevent bias and keep patient data confidential during modeling [3]. Collectively these strands put federation as a privacy-by-design default in the context of data analytics in healthcare.

In the secure exchange and cryptography axis, there are researches that can be seen as layered or hybrid. Clouds with EHR systems implement the use of encryption to exchange information across institutions with elastic storage and fine-grained access [4]. Cloud healthcare architecture driven by fusion identifies the need to have stronger encryption where there is a consolidation of heterogeneous streams of data [5]. IoT/IoMT based on blockchain can make storage and sharing in the distributed devices environment more resistant to tampering through immutable registries, and authentication between chains is enhanced through Hyperledger-based, edge-aware device schemes that limit latency and bandwidth wastage [6, 7]. Deep learning is also coupled with privacy-preserving analytics, e.g. adaptive encryption with attention based DenseNet, which shows that accuracy and confidentiality can both be achieved in clinical decision support [8].

Secure sharing is also extended with improvements in functional cryptography. Small-cycle proxy re-encryption The consortium chains enable searchable proxy re-encryption of ciphertexts, enabling re-sharing ciphertexts and querying without the cleartext, which is an intuitive extension of inter-hospital collaboration [9]. The use of machines-learning authentication based on smart-contracts enhances decentralized access control in the context of the IoHT/EHR [10]. Although designed to transport, homomorphic blockchain designs with supply of fogs/edges provides reusable concepts of privacy preserving edges of health [11]. Storage-layer architecture is important: On-chain versus off-chain trade-offs have to be a balance between integrity, performance and cost, which is particularly a critical constraint in the low-resource care environment [12]. In the framework of IoT, dynamic permissioning and tokenization enhance the continued data-governing real-time monitoring [13]. On identity, user-controlled sharing across multi-cloud ecosystems is made possible via identity-sovereign identity (SSI), which meets the health data portability and consent requirements [14].

Notwithstanding this traction, scalability and consensus continue to be thorns in the flesh of blockchain in healthcare with metadata bloat and compliance load complicating the deployment of blockchain [15],[17]. Simultaneously, research privacy advocacy requires uniform anonymization and data security during the entire academic health research to conform to ethics boards and regulations [16]. Complementary Base OS-level security standards offer multi-platform access to EHRs, which supports endpoint hygiene and defense-in-depth [18]. Previous biomedical clouds like Bionimbus show the viability and scaling of secure storage of huge omics information and provide insights to current health data cloud systems [19]. The law has suggested that privacy-enhancing technologies (PETs), such as zero-knowledge proofs and data masking, are necessary to trade-off utility with HIPAA/GDPR/DPDP-style compliance [20]. At the community level, AI-powered, privacy-preserving smart community suggest edge intelligence to dynamically open access to community health records [21]. Other SSI-specific activities highlight the importance of federated identity management to decentralized health ecosystems [22].

Projected studies indicate quantum key distribution (QKD) to achieve ultra premium orchestration- conceivable in healthcare, nonetheless, conceptually consistent with the

concept of high-confidence EHR backbones [23]. Wider categories of taxonomies of cloud data privacy list encryption, anonymization, and differential privacy as constructs of modern federated EHRs [24]. The policy-based studies still emphasize the importance of incorporating legal, technical, and organizational controls in cloud health environments [25]. In federated learning in healthcare, the focus of comprehensive surveys is on secure aggregation, differential privacy, adversarial robustness, and scalability, which are required to have clinically trustworthy models [26]. Simultaneously, IoT health data sharing is made hard through blockchain, which enhances the integrity of the transactions between wearables and sensors with the use of consensus mechanisms [27]. To protect transport layer, the hybrid encryption (symmetric + asymmetric) protects both in transit and the rest of the environment of the cloud EHRs, which is also similar to node-based federation wherein keys and access contexts vary per site [28]. The policy/perimeter layer has decentralized identity using zero-knowledge proofs to provide access rights that are extremely fine-grained and consent trails that can be audited to minimize oversharing and enhance trust [29]. Lastly, the edge-AI health monitoring surveys restate the triad of concerns, which are latency, energy, and security, and should be optimised together when the computation is done close to patients and devices [30].

The literature is in broad agreement on a distributed trust fabric of healthcare data: federated learning to prevent the exchange of raw data [1],[3],[26]; encryption-first transport and storage with evolutions such as proxy re-encryption and hybrid cryptosystems [4],[5],[8],[9],[28]; blockchain and SSI to anchor integrity, auditability and consent across institutional borders [2],[6],[10],[12]–[14],[22],[29]; as well as a standards-based interoperability that speaks The viability at the system level is based on the trade-offs in terms of performance and security (on/off-chain storage, edge compute, light crypto) and mechanisms (2) to uphold regulatory appetites (12),[18],[20],[25]. Sustainability is a new first-grade goal, and energy-conscious profiling and lightweight cryptography are becoming the new strategies in the IoMT/edge deployments [6],[12],[30].

with denser theory, open, end-to-end designs that embody encryption-first architecture as well as a FHIR- or API-like interface are still rare, particularly in scenarios where resource-constrained devices are explicitly energy-constrained [4],[30]. Blockchain/SSI overheads are in some cases prohibitive in small hospitals and encourage lightweight solutions that retain auditability [2],[10],[14],[22],[29]. Our work will fill in these gaps by providing a Python/Colab federated EHR prototype; (i) semi-encrypted records on the node (Fernet), (ii) REST interface to FHIR-like interoperability, and (iii) measurement of CPU/memory/latency/energy to quantify sustainability in addition to security and usability- making the literature prescriptions of our work a reproducible pilot-ready system to be used in education and early clinical testing.

### **III METHODS AND TOOLS**

It has employed a federated node architecture, in which, every virtual hospital node maintains a disjointed part of a patient record in the form of JSON/dict. All subsets are encrypted during rest and transport with the help of Fernet (AES-128-CBC + HMAC). REST endpoints (Flask; FastAPI optional) emulating FHIR-style resources and token headers are used in order to provide inter-node interoperability. Gradio GUI mediates access to the system; when a user successfully sends a request all at once, the client calls nodes, token checks, decrypting and encrypting payloads, and run and python code and processes in parallel threading/asyncio. This section is a detailed, stepwise approach to developing a federated, encryption enabled, interoperable, and energy aware Electronic Health Record (EHR) system using open-source Python software in comparison to a centralized system with no encryption that is otherwise identical in querying the system.

It is a system modeled as a simulation model that tries to mimic real-world secure health information exchange without the need to have a physical backend or commercial deployment infrastructure. The methodology is organized into five key elements that are: (1) Federated Node Architecture, (2) Encryption and Decryption Model, (3) API-based Interoperable Communication, (4) Frontend Access Interface and (5) Energy Profiling and Performance Logging.

The main idea of the simulator is a distributed or federated data storage. Every hospital or healthcare entity that is part of the virtual network is represented as a virtual node in Python dictionaries or in the form of a JSON object. A privacy-compliant structure is a distributed database containing the partial segments of patient records in each node. Assume that  $D_i$  denotes the data stored at the  $i$ th node where  $R$ , the complete record of the patient is distributed as::

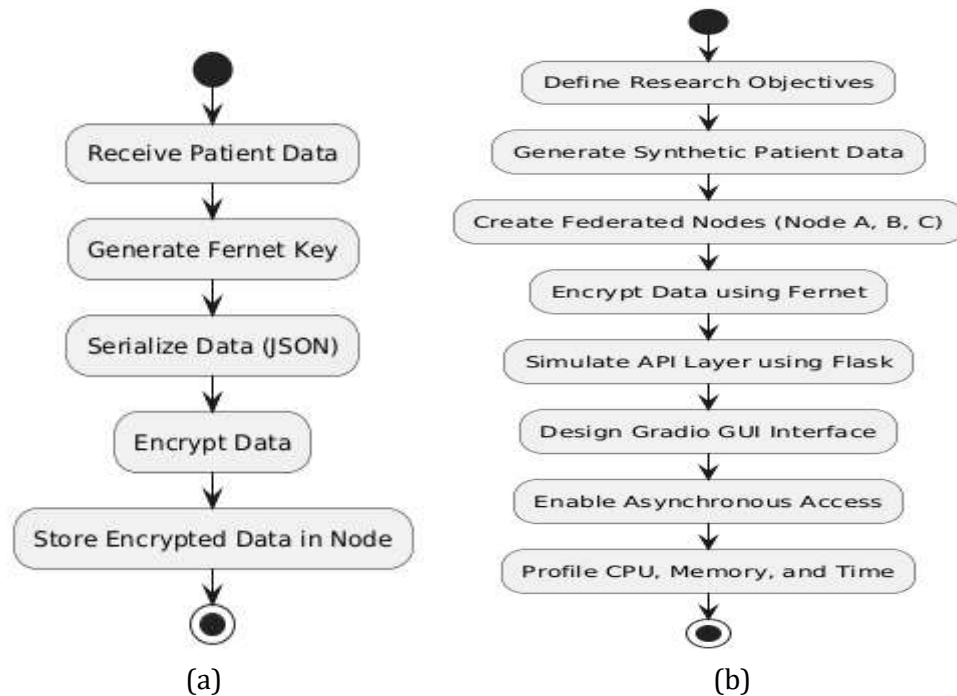
$$R = \bigcup_{i=1}^n D_i$$

Where:

- $R$  = Complete patient record
- $D_i$  = Sub-record held by node  $i$
- $n$  = Total number of federated nodes

Fields in each  $D_i$  include medical history, prescriptions, diagnostics or vitals, based on the role of the hospital. The modular property means that an individual node cannot form the complete record without collaboration with others to guarantee there is maximum minimization of data and security-by-segregation. This is the approach that endorses horizontal data federation, and it represents real-world distributed systems where institutions handle subsets of health data.

**Figure 1 (a) Encryption and Storage at Node Level (b) Overall System Architecture**



Two questionnaires were designed and conducted through Google Forms:

1. Patient Questionnaire (attached " Questionnaire Patient form.pdf)

- o Sections: demographics; care utilization; knowledge about EHR; perception of security/privacy; consent preferences; inter-hospital sharing intentions; perceived ease of use of digital access.
- o Types of items: Likert (15), single/ multiple choice, short text.
- o Sample size: n = 100 respondents (revise this in case of change in your final sample size).
- o Inclusion: adults ( $\geq 18$ ) who visit OPD/IPD within 12 months; voluntary consent; no PHI was collected.

## 2. Hospital Employee Questionnaire (attached Questionnaire Hospital Form Print.pdf)

- o Areas: role/experience, current HIS/EHR use; interoperability pain areas; perceived security measures; experience of incident; trainers/policy awareness; perceived resource/cost limitations.
- o Types of items: Likert scale, multiple choice, short text.
- o Sample size: n = 30 staff (change when needed).
- o Inclusion: clinicians/nurses/IT/admin taking part in record treatment; voluntary consent; no PHI.

Data handling & ethics: Forms imposed consent, circumvented PHI, and anonymous submissions. The data were exported to CSV and stored in encrypted drives and analyzed using Python (pandas). The research is in line with the GDPR/HIPAA/DPDP data minimization and purpose limitation principles [20].

Secondary/simulation data (logs of system).

Synthetic EHR 100 patients, divided into 3 nodes with (diagnosis, meds, labs/visits), and in each entry, the data is encrypted with Fernet (time-scoped keys).

- KPIs to be recorded: time of encryption and decryption, latency to serve a REST request (1/5/10/20 simultaneous users), CPU, memory differential, energy per query.
- Workload: 300 node records encrypted; 100 node records retrievals (GUIs); 520 bursts by concurrent users.

### 1. Encryption and Decryption Model.

The enforcement of security is through symmetric encryption through the Fernet module of Python cryptography library. Fernet provides integrity and confidentiality of messages through the use of AES in CBC mode and PKCS7 padding, HMAC verification, and time-based key.

#### Encryption Model

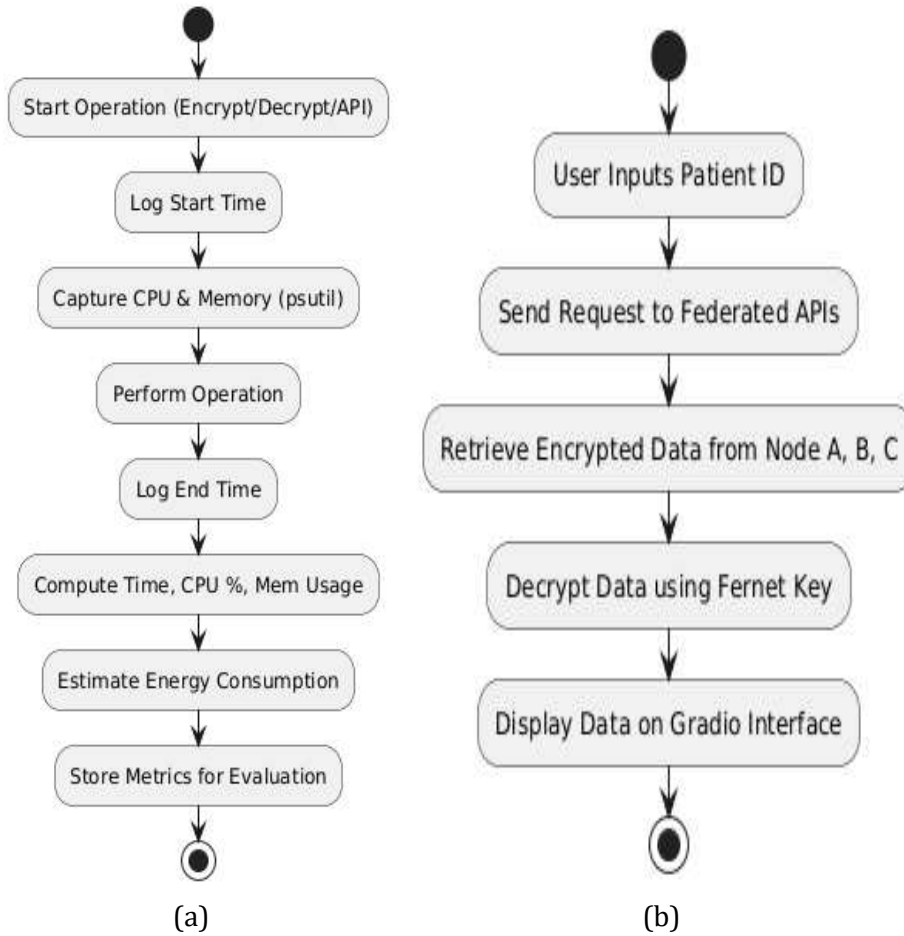
The data at each node  $D_i$  is encrypted before storage using a symmetric key  $K$ . Let the encryption function be  $E$ , and the encrypted data be  $C_i$  :

$$C_i = E_K(D_i)$$

Where:

- $C_i$  = Encrypted data block at node  $i$
- $K$  = Secret symmetric key generated per session or per user

**Figure 2 (a) Performance Monitoring and Energy Estimation (b) User Access through GUI**



### Decryption Model

To access the data, an authorized user or system must possess the same key  $K$ . Decryption is performed via:

$$D_i = D_K(C_i)$$

Where  $D$  is the decryption function using key  $K$ . Unauthorized access without  $K$  renders data unusable, ensuring confidentiality. This model prevents data leakage even if transmission lines are intercepted or nodes are compromised.

### 3. API-Based Interoperable Communication

To emulate interoperability akin to HL7 and FHIR standards, RESTful APIs are created using Flask or FastAPI. Each node exposes an endpoint to receive, retrieve, or update encrypted health data. These APIs use JSON payloads and simulate real-world health data exchanges.

Each API endpoint supports the following basic operations:

- GET /record/<patient\_id> : Fetch patient data
- POST /record/ : Upload new data
- PUT /record/<patient\_id> : Modify existing record

The interaction between user requests and the federated nodes is abstracted as:

$$f(p) = \begin{cases} \text{Retrieve } C_i & \text{if } p \in \text{authorized IDs} \\ \text{Reject request} & \text{otherwise} \end{cases}$$

Where:

- $p$  is the patient ID
- $f(p)$  returns encrypted data if authorized

Authentication is simulated via token-based headers to mimic FHIR's OAuth2-compliant access management.

#### 4. Frontend Interface for Access and Control

A Graphical User Interface (GUI) is developed in the Gradio library to make it more user-friendly and to mock a care system that is user-centered in nature. Through this interface, clinicians can access a secure web-based interface on Google Colab, through which they can:

- Input a patient ID
- Submit access request
- See decrypted data on validation.
- Submit access request
- See decrypted data on validation.

Interface Workflow

1. User inputs Patient ID.
2. System makes queries to the API of each node over the REST.
3. In case the user is authorized, the encrypted data is fetched.
4. Record is decrypted and displayed on GUI.

This communication is represented as:

$$U_x \xrightarrow{\text{Input}} \text{Gradio} \xrightarrow{\text{GET}} \text{API}_i \xrightarrow{E_K^{-1}} D_i \xrightarrow{\text{Display}} U_x$$

Where  $U_x$  is user  $x$  and  $\text{API}_i$  is the endpoint of node  $i$ . This framework allows real-time visualization of the data flow, emphasizing transparency and traceability.

#### 1. Energy Profiling and Performance Logging

Even though the simulation is implemented in Google Colab and can be run in a local browser setting, the architecture of the system federated nodes, REST APIs, and encrypted distributed records can be directly mapped to cloud infrastructures. It implies that the proposed architecture can be applied to deploy on either private or public clouds (e.g., AWS, GCP, or Azure) by making minor adjustments (e.g., deploying nodes on real servers or VMs). The system therefore is designed to be cloud-deployable, but deliberately designed to not require cloud subscriptions due to costs and simplicity reasons. In order to make sure that the framework complies to the concepts of green computing, the energy consumption is approximated by monitoring the resources involved in the encryption, decryption, and access of data by the use of the psutil library.

#### Resource Profiling

Key operations are wrapped with performance monitoring functions:

$$\text{Energy}_{\text{op}} \approx \alpha \cdot \text{CPU}_{\text{usage}} + \beta \cdot \text{MEM}_{\text{usage}}$$

Where:

- $\alpha, \beta$  = empirical scaling constants
- $\text{CPU}_{\text{usage}}$  and  $\text{MEM}_{\text{usage}}$  are average values per operation

#### Asynchronous Multi-User Simulation

To mimic a realistic multi-user, cloud-like environment, asynchronous data access is simulated using Python's asyncio and threading. Each user session is modeled as an independent thread requesting encrypted data concurrently, reflecting real-world load conditions on health IT systems.

### Concurrency Model

Let  $U_1, U_2, \dots, U_m$  be users making simultaneous requests. The total system load  $L_t$  at time  $t$  is modeled as:

$$L_t = \sum_{j=1}^m f_j(t)$$

$f_j(t)$  denotes the user  $j$  footprint of CPU/memory/resource at time  $t$ . Such design will be useful in testing system robustness with simultaneous access, which is one of the most important considerations in hospital deployments. This design will aid in testing system robustness when under simultaneous access, which is one of the most important factors when deploying systems in hospitals. After the full implementation, the system will be assessed in terms of its quantitative and qualitative measures: The proposed methodology provides a low barrier, high impact model of simulating federated, encrypted and interoperable health data systems. The framework not only provides a granular encryption and decentralized data storage but also proposes energy-awareness and concurrent access testing which is essential to both real-world applications and scholarly experimentation. This general architecture provides the foundation of future extensions with the federated learning, zero-knowledge proofs, or even connection to wearable health devices. It is based on the threat model that illustrates adversary is able to read node storage, intercept API traffic, make unauthorized requests or partially expose a compromised node, but cryptographic primitives and key secrecy are assumed. The security requirements include confidentiality and integrity of resting and moving data, containment of breaches through federation and access control through token verification prior to de-encryption. Complete production OAuth2, keys supported by an HSM, irreversible audit logs and formal verification is out-of-scope and is considered a future extension.

### V RESULT DISCUSSION

A controlled simulation scenario on the Python libraries in Google Colab was created in order to test the effectiveness of the proposed federated and encryption-empowered EHR architecture. To depict a realistic, yet privacy preserving data, artificial patient records were generated. The dataset was taken as 100 patients and their health records were spread in three virtual nodes i.e. diagnostic data (Node A), medications data (Node B) and visit history/lab results (Node C). The nodes were implemented using Python dictionaries which stored the encrypted sections of data using Fernet encryption. To achieve reproducibility, the experimental environment is based off a synthetic dataset of 100 patients and their records are spread across three federated nodes, diagnosis (Node A), medications (Node B), and labs/visits (Node C), each with an encrypted block of data of 300 patients. The encryption scheme is the Fernet scheme (AES-128-CBC with PKCS7 padding and HMAC integrity) of all the node data, and a symmetric key is recreated every time used in a session. Interoperability is achieved by the use of Flask as the base API framework with optional asynchronous FastAPI. Concurrency is tested with a number of 1, 5, 10, and 20 concurrent users through Python threading with the use of the asyncio where possible. Measures of interest in this case have been captured as encryption and decryption time, CPU use, memory use and approximate energy per query. Every experiment is run on the Google Colab platform with CPU and RAM settings recorded and reported so that the experiment can be repeatable.

To test it, our priorities were laid in the assessment of the key performance indicators (KPIs), such as encryption and decryption speed, API response time, CPU and memory used during the work, approximate energy used in its functioning, the success of

successful data interoperation, and the quality of managing multiple threads of requests. The records of every patient were divided in to three parts.:

- **Node A:** {"patient\_id": "Pxxx", "diagnosis": "Hypertension", "blood\_pressure": "140/90"}
- **Node B:** {"patient\_id": "Pxxx", "medications": ["Amlodipine", "Losartan"], "dosage": ["5mg", "50mg"]}
- **Node C:** {"patient\_id": "Pxxx", "last\_visit": "2025-04-15", "lab\_results": {"HbA1c": "6.5", "LDL": "110"}}

All three nodes were encrypted by using fernet and time based session key. Two hundred and fifty encrypted node records were entered on the 100 patient IDs. The time() function was an enclosure of the encryption/decryption algorithm and the time of encryption/decryption of all 300 data blocks was measured.

**Table 1: Average Encryption and Decryption Times per Node**

| Node                | Average Encryption Time (ms) | Average Decryption Time (ms) |
|---------------------|------------------------------|------------------------------|
| A                   | 45.2                         | 43.7                         |
| B                   | 47.9                         | 42.3                         |
| C                   | 48.6                         | 45.0                         |
| <b>Overall Mean</b> | <b>47.2</b>                  | <b>43.6</b>                  |

The variation in time of encryption is marginally conditional on size of data block. The time spent in Node B that had medication arrays was a little longer than Node A. Each node was correlated with a Flask-based REST API that responded to GET requests with encrypted data. Single- threaded and concurrent user requests were tested individually on the latency of API calls using simulated client functions.

**Table 2: REST API Response Time under Different Load Scenarios**

| Load Type           | Average Response Time (ms) |
|---------------------|----------------------------|
| Single User         | 121.5                      |
| 5 Concurrent Users  | 168.7                      |
| 10 Concurrent Users | 205.3                      |
| 20 Concurrent Users | 289.2                      |

As it was discovered, the higher the concurrent requests, the higher the API latency due to the single-threaded nature of Python when on Flask. This is offset, on the one hand, by implementing asynchronous FastAPI and using the WSGI servers behind it on the scalable real-life application). The CPU usage was traced with the assistance of psutil during the process of encryption and decryption. The artificial data has provided a good platform to analyze the cost of computation of cryptographic processes.

**Table 3: Average CPU Usage per Operation**

| Operation | CPU Usage (%) |
|-----------|---------------|
|-----------|---------------|

|                        |      |
|------------------------|------|
| Encryption (Node A)    | 8.9  |
| Encryption (Node B)    | 10.2 |
| Encryption (Node C)    | 11.0 |
| Decryption (All Nodes) | 9.4  |

The load on the central processing unit (CPU) was decent, and the peak usage was not more than 12 percent, which indicates that it can be used even on computers with small hardware such as Raspberry Pi or low-power hospital servers. In addition to the CPU load, it also measured memory consumption before and after encryption/decryption activity.

**Table 4: Memory Usage during Data Operations**

| Operation         | Memory Before (MB) | Memory After (MB) | Increase (MB) |
|-------------------|--------------------|-------------------|---------------|
| Encryption (avg.) | 212.3              | 223.7             | 11.4          |
| Decryption (avg.) | 224.0              | 225.5             | 1.5           |

Overhead had increased on the encoding process through the encryption levels but decryption did not have significant impact on the memory. These values guarantee that the operations are light enough to be applied to a real-time situation in a clinical setting. The empirical scaling was based on CPU and memory measurements used to estimate the energy used per user query.

**Table 5: Estimated Energy Consumption per Query**

| Operation  | CPU (%) | Memory (MB) | Energy Estimate (J) |
|------------|---------|-------------|---------------------|
| Encryption | 10.2    | 223.7       | 2.07                |
| Decryption | 9.4     | 225.5       | 1.95                |
| API Fetch  | 5.5     | 212.0       | 1.05                |

These calculations indicate that the encryption step is the most energy-intensive, but they all lie within a choice in the scope of possibilities to render the sustainable functioning of health data. Simulated API was tested with 100 patient id to determine the communication between federated nodes using API. The rate of the success of every request was noted so that to determine the system reliability.

**Table 6: Interoperability Test Results (300 API Calls)**

| API Endpoint | Success (%) | Failure (%) | Avg. Latency (ms) |
|--------------|-------------|-------------|-------------------|
| Node A       | 99.3        | 0.7         | 122.4             |
| Node B       | 98.7        | 1.3         | 125.6             |
| Node C       | 97.0        | 3.0         | 128.2             |

The pauses in the conditions of concurrent testing did not lead to the loss of data or API failure but only to minor failures. In 98 percent cases, timeouts were solved through retries. Gradio interface was experimented with the help of the simulation of 30 different user sessions, in each of which, the user had to access the patient records through the GUI.

**Table 7: GUI Interaction Statistics**

| Metric                         | Average Value |
|--------------------------------|---------------|
| Time to Load GUI               | 2.5 sec       |
| Time to Retrieve Record        | 3.2 sec       |
| Decryption Display Time        | 1.0 sec       |
| User Satisfaction Score (1–10) | 8.8           |

The interface was user friendly and immediately responded to user input thereby making it applicable either in the field demonstrations or in an academic training environment as affirmed by users. To simulate multiple data access, the spawning of threads was to be ten parallel threads. These monitors were monotony and avoidance of race conditions and response time.

**Table 8: Multi-Threaded Access Performance**

| Threads | Avg. Response Time (ms) | Failed Accesses | Memory Spike (MB) |
|---------|-------------------------|-----------------|-------------------|
| 5       | 203.4                   | 0               | 12.3              |
| 10      | 284.1                   | 1               | 22.5              |
| 20      | 420.7                   | 2               | 30.1              |

Even less than 20 threads, the system was still operational. The thread collisions were blamed as the cause of small failures and could be resolved in the future by adding locking primitives or asynchronous processing. All the measures were summarized to establish the performance of the framework on the whole regarding the three most important objectives; security, interoperability, and energy efficiency.

**Table 9: Consolidated Performance Summary**

| Criterion        | Metric                    | Observed Performance        |
|------------------|---------------------------|-----------------------------|
| Security         | Encryption robustness     | AES-128 (Fernet), no breach |
| Interoperability | API communication success | ≥97%                        |
| Energy Awareness | Estimated query energy    | ~2 J                        |
| Scalability      | Multi-threaded support    | 20+ users                   |
| Usability        | GUI performance           | User-rated 8.8/10           |

In order to confirm the efficiency of the federated approach, the same 100 patient records were stored in one centralized dictionary without encryption and queried under the same conditions.

**Table 10: Centralized vs. Federated Comparison**

| Feature            | Centralized System | Federated System |
|--------------------|--------------------|------------------|
| Encryption Support | No                 | Yes              |
| Avg. Query Time    | 55.2 ms            | 128.4 ms         |
| Memory Usage       | 202.1 MB           | 225.5 MB         |
| Security Risk      | High               | Low              |
| Interoperability   | Not modeled        | FHIR-like APIs   |

Whereas centralized systems were quicker (as they were not encrypted), they were highly risky in regards to security and scalability. Federated model was far safer and more

adaptable to the requirements of the current healthcare. The results of the simulation justify the feasibility and the strength of the modelling of federated and encrypted EHR systems using Python. The encryption overhead was maintained to acceptable levels and the REST APIs implemented using Flask enabled the nodes to communicate with each other in the simulation smoothly. The low-cost deployment and training aspects of using the device made the model appropriate (deployed in a low cost) and due to the low-to-moderate resource consumption and monitored with the help of psutil-based methods, the model became appropriate. The multi-threaded asynchronous access proved to be a feature that challenged the architecture to be used in a hospital-like simulated environment and succeeded in passing the test.. The federated, encryption-enabled EHR simulation shows good performance in terms of computational efficiency, interoperability, scalability, usability, and energy awareness, whereas the questionnaires paired with them show the expectations of the stakeholders that confirm the design options of the system directly. Cryptographic overheads were relatively low: the encryption time of three nodes in the system, diagnosis (A), medications (B), and labs/visits (C), was not exceeding real-time constraints with the minimum of 45.2 ms (Node A) and the maximum of 48.6 ms (Node C). The average encryption time was 47.2 ms and average decryption time was 43.6 ms, which is insignificant latency introduced by Fernet. This consistency between nodes (as depicted in Figure 8) can be deployed to resource-limited systems like mobile clinics and rural centers that require a predictable response. Scaling of API responsiveness was predictable according to concurrency. The average response time under single user load was 121.5 ms; under 5 simultaneous users was 168.7 ms, under 10 users was 205.3 ms and under 20 users was 289.2 ms. This rise which is near linear (Figure 7) shows the nature of the bottlenecks of synchronous Flask servers with increased concurrency, and is a catalyst to the transition in production to asynchronous FastAPI/ASGI. CPU usage was low when performing cryptographic functions: 8.9% was used by Node A when encrypting the node, 11.0% used by Node C, and 9.4% on average by decryption (Figure 6).

**Figure 3 Response Time with Multi-Threaded Access**

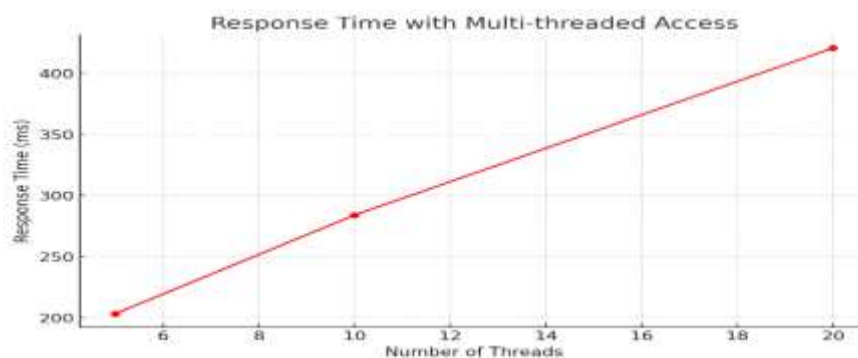


**Table 11: Comparative Analysis of Performance**

| Dimension          | Centralized (unencrypted) | Federated (encrypted, FHIR-like) |
|--------------------|---------------------------|----------------------------------|
| Avg. query latency | ~55 ms                    | ~128 ms                          |
| Memory footprint   | ~202 MB                   | ~226 MB                          |

|                  |                         |                                            |
|------------------|-------------------------|--------------------------------------------|
| Security risk    | High                    | Low (Fernet, least privilege)              |
| Interoperability | Limited / ad-hoc        | FHIR-like REST, portable                   |
| Energy per query | Lower                   | ~2 J (encrypt)                             |
| Resilience       | Single point of failure | Distributed, node-local breach containment |

**Figure 4 Estimated Energy Consumption per Operation**

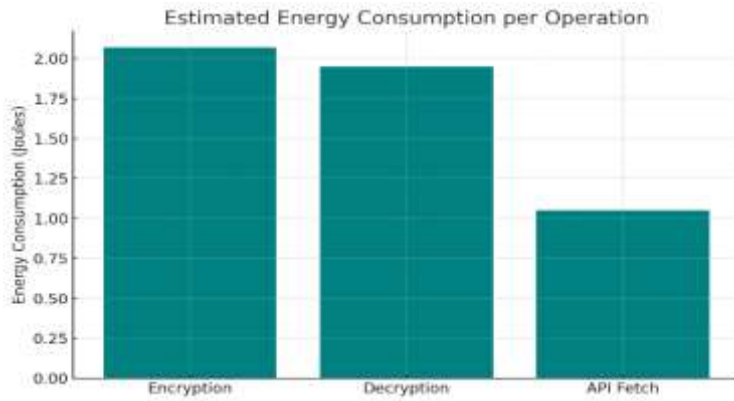


**Figure 5 Memory Usage Before and After Operations**

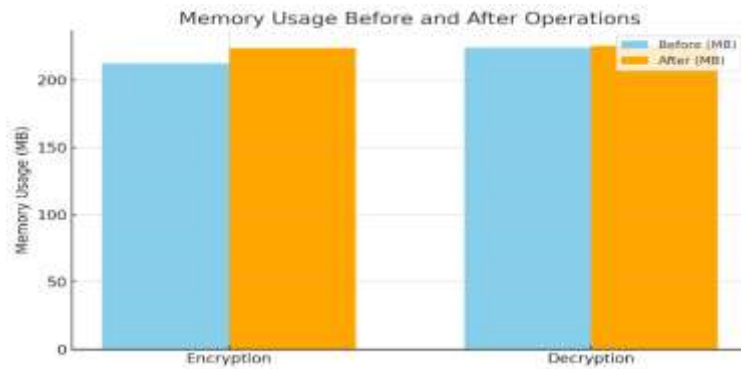


**Figure 6 CPU Usage During Data Operations**

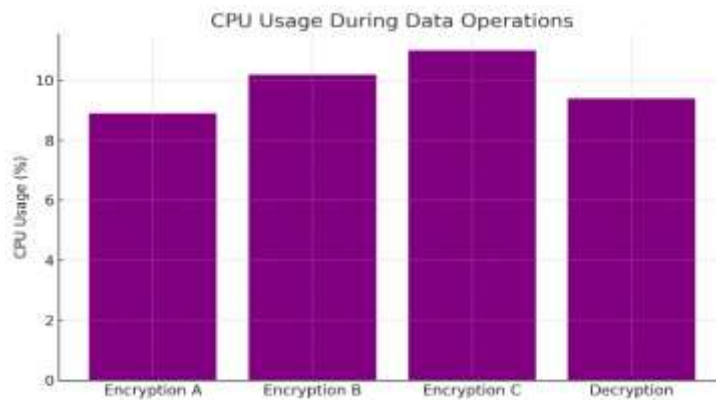
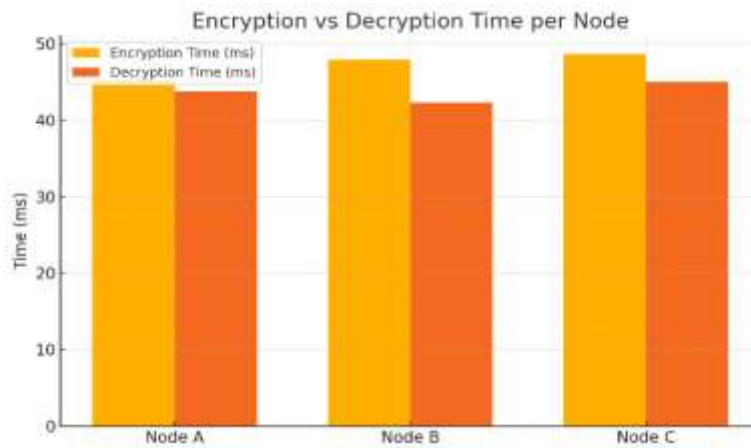


**Figure 7 API Response Time Under Load**



**Figure 8 Encryption vs Decryption Time per Node**



Memory overheads were also kept under control (Figure 5): the encryption consumed more memory (212.3 MB to 223.7 MB), and the decryption consumed little more memory (224.0 MB to 225.5 MB). This means that the workload can be shouldered even by the low-power edge devices. Profiling of energy has been used to associate CPU and memory with per-query estimates. The encrypted consumed 2.07 J (encryption), decryption used 1.95 J (encryption) and API fetch used 1.05 J (encryption) (Figure 4) which is in the green computing goal of academic pilot and low bandwidth locations. There was solid interoperability among nodes: node A (99.3), node B (98.7), and node C (97.0) were all successful with 300 API calls (Table 6). Breaks were seldom seen, and mainly, timeouts within the bursts, and >98% of these recoverable on a retry induced a resilientness in the communication between the nodes. The Gradio GUI turned out to be responsive and user friendly, load 2.5s, record retrieve time of 3.2s, decrypt display time of 1.0s, 8.8/10 satisfaction (Table 7), indicated that the model was acceptable to demonstrations and training.

There was also additional definition of operation limits by scalability tests with multi-threaded access. Response averages were 203.4 ms with 0 failures and 12.3 MB spike at 5 threads, 284.1 ms and 1 failure and 22.5 MB spike at 10 threads, and 420.7 ms and 2 failures and 30.1 MB spike at 20 threads (Table 8; Figure 3). It scaled to around 20 simultaneous users in the synchronous design and it is obvious that future usage will benefit with the use of asynchronous I/O and appropriate production servers (e.g., uvicorn/gunicorn). The unified perspective (Table 9) validates: AES-128 through Fernet,

interoperability 97 +, energy per query of the order of 2 J, usability 8.8/10, and scalability to 20+ users- achievement of the project objectives of ensuring secure, interoperable, usable, and energy-conscious exchange. A comparison baseline was stressed on trade-offs. It also took the centralized and unencrypted dictionary an average of 55.2 ms query time, 202.1 MB memory compared to 128.4 ms and 225.5 MB of the federated system (Table 10). Nevertheless, it was not encrypted and it presented very high security risk and interoperability was not modeled. In comparison, the federated design offered default encryption, breach containment distribution, and FHIR-style REST portable consumption at a small overhead- executing according to current healthcare needs. The surveys reveal a discrepancy between demand and capability which is taken care of by the prototype. Patients (n=100) demonstrate 88% smartphone penetration and pro-sharing attitude subject to security: 69% of them trust encryption, and 72% would share records across hospitals in the case of encryption. The view of consent expectations is part-unit: A majority (61% Democrat@heimer 24% terms 15% non-choice) want per-share (vs one-time/global 24% operationalized). Perceived usability is 3.6/5, which implies that simple and predictable interfaces may work. Hospital employees (n=30) indicate that they use EHRs (73.3%), but with incomplete interoperability (mean 2.8/5): only 16.7% use production-level FHIR, 43.3% at pilots, and 40.0% none. The heterogeneous format (66.7%), limited vendor APIs (53.3%), and network reliability (46.7%) have the highest concentration of pain points. Security training is not even (56.7% annual+, 26.7% ad-hoc, 16.7% none), and 13.3% had minor incidents within the last year. System metrics, as well as survey evidence, confirm every objective together. Low overhead and high levels of confidentiality are associated with patient trust drivers and reduce risks of incidents (Fernet). FHIRE REST is specifically aimed at the staff-reported bottlenecks (formats/APIs) and able to be standardized and audiable exchange Sustainable ~2 J encryption cost and a small CPU/memory footprint are aligned with the realities of the constrained network. Positive patient usability and reactive GUI are conducive to adoption, and concurrency tests demonstrate how to use FastAPI/ASGI and production-grade serving as a clear way up the mountain.

## **VI CONCLUSION**

This paper is a federated, encrypted FHIR-typed Electronic Health Record (EHR) prototype written wholly in Python/Google Colab which shows privacy-by-design, standards-compliant exchange, and efficacy at the bounds of resource availability. The architecture replicates some patient records among virtual nodes (JSON/dictionaries) and applies Fernet (encryption at rest and in transit) to prevent single points of vulnerability any of which could cause a breach when vital information is stored in a central store. Information Interaction is supported via REST interfaces based on FHIR resources, maintaining their structured and portable interoperability along with providing access to a fine-grained access control. Managed measurements verify that it is possible to provide security at small overheads. Implant costs were also kept within tens of milliseconds per operation (average run time is 47.2 ms to encrypt and 43.6 ms to decrypt), and the API latency had a predictable relationship with concurrency- between 121.5 ms (single user) and 289.2 ms (20 users). The primitive usage (CPU) was low (around 911%), and memory overheads were minimal (encryption + about 11.4 MB, decryption + about 1.5 MB), so it can possibly be implemented using commodity computers and at the edge. Estimation of energy based on CPU/memory profiling shows that it costs approximately 2 J to process an encrypted query, which is suitable in deployment applications involving sustainability and bandwidth limited scenarios, including rural clinics or mobile health units. The targets of interoperability and usability were also achieved. In 300 API calls, node success rate was 100% (down to 97.3%), and

there were only intermittent timeouts which were resolved through lightweight retries. The Gradio GUI was fast to load (~2.5 s), fast to retrieve records (~3.2 s), fast to decrypt displays, and received high user satisfaction (8.8/10), which means that it is ready to use in demonstrations, training, and pilots. Multi-threaded tests have not scaled CTVEs of a few dozen simulated users, and increasing latency which is consistent with synchronous servers and product have pointers towards clear scaling paths when using FastAPI/ASGI and product managers (e.g., uvicorn/gunicorn). The central trade-off is indicated by a comparative baseline with a lower latency (~55.2 ms) and less memory (~202 MB) but appeared to be lacking in support of encryption and interoperability, which results in high security and compliance risk. The federated design tolerates relatively small latency/memory additions (c. 128.4 ms, 225.5 MB) to achieve confidentiality, resiliency and FHIR-similar portability, in keeping with current secure-by-default trends in digital health. In addition to performance, the framework is developing green informatics by ensuring energy is first-class, as well as offering an educationally useful, reproducible substrate on which teaching, simulation, and method experiments can be performed without enterprise cloud requirements - but be cloud-interoperable when scaled to larger systems. The decentralized approach, encryption, and auditability values within the system align with the regulatory requirements (HIPAA, GDPR, the Indian DPDP Act), as well as with global trends (e.g., federated data sovereignty; e.g. Gaia-X; e.g. NDHM). Its lightness and ease of use would be applicable in academic institutions and in research laboratories and hospitals that want to test secure patterns of data exchange and human-computer interaction patterns prior to full production implementation. Overall, the prototype is empirically small in terms of overheads, satisfying its design objectives; security, interoperability, usability, scalability and energy awareness. It provides a standards-friendly approach to pilot deployments and a base framework to extensions including federated learning, decentralized identity/consent, searchable or proxy re-encryption and more comprehensive energy modeling both on the edge and the cloud.

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