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# HLFCPIR: Embedding Computational Private Information Retrieval into Hyperledger Fabric Chaincode for Query Privacy

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**ABSTRACT** Permissioned blockchains ensure integrity and auditability of shared data but expose query parameters to endorsing peers during read operations. In Hyperledger Fabric, evaluate transactions reveal function arguments and read-sets to peers, creating privacy risks for organizations querying sensitive records. We address this gap by presenting the first full integration of Computational Private Information Retrieval (CPIR) within Fabric’s chaincode layer. Our design encodes the ledger’s key–value table as a packed plaintext polynomial and enables clients to submit encrypted selection vectors evaluated under the Brakerski–Gentry–Vaikuntanathan (BGV) homomorphic encryption scheme. Peers perform ciphertext–plaintext evaluation entirely inside chaincode and return encrypted results, preventing index leakage while preserving Fabric’s endorsement and audit semantics. A prototype built with the Lattigo library achieves end-to-end query latency of ≈113 ms and peer-side evaluation below 45 ms for databases of up to 128 records, demonstrating practical performance within permissioned environments. Network measurements indicate ≈2 MB of peer traffic per query due to the external chaincode model, which can be halved under in-process deployment. Overall, the results confirm the feasibility of native CPIR execution in Hyperledger Fabric and establish a foundation for scalable extensions such as constant-time evaluation, sublinear and sharded PIR, and encrypted-database ($ct \times ct$) computation for richer private analytics.

**INDEX TERMS** Private Information Retrieval (PIR), Homomorphic Encryption, Hyperledger Fabric, Permissioned Blockchains, Private Reads, Query Privacy.

## I. INTRODUCTION

### A. MOTIVATION AND PROBLEM STATEMENT

Blockchain [1] is a peer-to-peer network protocols that uses cryptographic primitives and consensus mechanism to create and maintain a distributed ledger of transactions, such as Ethereum [2] and Hyperledger Fabric [3].

According to the literature [4]–[7] such systems are widely adopted in various domains, such as Cyber Threat Intelligence (CTI) sharing, where multiple organizations exchange threat indicators and wish to keep their queries confidential. Blockchain guarantees, however, primarily cover data integrity and auditability, not query privacy. For example, only recently PSE team in Ethereum foundation explicitly highlighted the need for private reads in addition to private writes and private proving [8].

In Hyperledger Fabric [3], the separation of *evaluate* and *submit* makes the read-privacy gap explicit: an evaluate call is a read-only proposal sent to endorsing peers, which execute the chaincode and return results without committing to the ledger [9]. Crucially, these peers still observe all function arguments and read-sets. Thus, in multi-organization settings, the dominant privacy risk arises not from the immutable ledger, but from endorsing peers who can log or infer sensitive query information.

This motivates us to target *query* or *read* privacy issue in Fabric, defined as the ability to hide which record is being queried from endorsing peers during *evaluate* type calls. Given problem description, an obvious approach is to construct and use Private Information Retrieval (PIR) [10] protocol, which would enable client to retrieve an item from a world state database without revealing to peer which item was requested. There are two main types of PIR schemes. Earlier Information-Theoretic (IT-PIR) schemes [10]–[14] provide unconditional privacy by distributing the database across multiple non-colluding servers, a client then queries subsets of servers such that no single server learns the selection index. Computational PIR (CPIR) schemes [15]–[20] relying on cryptographic assumptions and homomorphic encryption to achieve privacy with a single server.

However, consortium settings exclude IT-PIR due to multiple non-colluding servers requirement, since all peers are typically considered honest-but-curious, and collusion is a realistic threat. Thus, we focus on CPIR, which is more suitable for our threat model.

### B. LITERATURE REVIEW

This section surveys prior work at the intersection of Private Information Retrieval (PIR) and distributed systems, with emphasis on smart-contract or chaincode-based implementations for query privacy across different domains, not limited to any specific domain or blockchain platform.

Xie et al. [21] design BIT-PIR, a PIR-based query scheme tailored to Bitcoin light clients: they restructure on-chain data and craft a storage format so lightweight wallets can privately fetch transaction-related items without Bloom-filter leakage. This work is pioneering in applying PIR to public blockchains, but its reliance on Bitcoin's UTXO model limits generalizability to other platforms.

Chhabra et al. and Kumar introduced a series of PIR - blockchain frameworks across multiple domains, such as PRIBANI, MUDRA, DEBPIR, and BRON. PRIBANI [22] combines PIR with ring signatures and PEKS to enhance query anonymity in transaction systems. MUDRA [23] integrates dual-server Ring-PIR within Hyperledger Fabric to enable private access to healthcare records, while DEBPIR [24] embeds PIR and k-out-of-N OT in Fabric chaincode for privacy-preserving business data retrieval. BRON [25] extends this approach to human resource management, integrating PIR at the smart-contract layer with ZK components to support verifiable private record queries. Across these works, PIR consistently serves as a privacy-preserving layer for permissioned ledgers, yielding favorable throughput and latency. However, their evaluations offer limited cryptographic parameter details, making scalability and precise overhead less transparent.

Xiao et al. [26] propose Cloak, a privacy-preserving blockchain query framework that hides retrieval targets via two-phase distributed query requests (division and aggregation). By splitting queries across nodes and aggregating partial answers, Cloak reduces exposure of which records are fetched and reports notable query-time improvements over naive single-server approaches. The technique is PIR-inspired rather than a direct PIR scheme; the paper focuses on distributed obfuscation and leaves a comparison against concrete CPIR/IT-PIR baselines (communication vs. server work vs. anonymity) for future study.

Peer2PIR [27] addresses privacy leakage in IPFS by enabling private peer routing, provider discovery, and content retrieval using PIR-backed protocols; the paper also surveys PIR choices in distributed systems and demonstrates reasonable overheads. While not a blockchain system per se, the work is highly relevant to decentralized Web stacks frequently coupled with blockchains, and its modular designs could be adapted to ledger-attached DHTs. A limitation is the absence of end-to-end integration with on-chain settlement/audit, so operational lessons for smart-contract pipelines are indirect.

**Targeted gap.** Given the above survey, we identify a gap in the literature: while several works embed PIR into permissioned blockchains, none provide a detailed, practical implementation of a lattice-based CPIR scheme directly within Hyperledger Fabric chaincode, with comprehensive parameter analysis and performance benchmarks. One recent survey outlined several open research questions in this area [28], such as: How can PIR be effectively integrated into blockchain to enhance privacy in decentralized applications?

Our work directly contributes to these directions by implementing a HE-based CPIR protocol in Fabric chaincode under evaluate calls, ensuring that endorsing peers cannot infer queried indices while also answering the open research question above.

Combining Fabric with CPIR thus yields a dual guarantee: (1) writes remain auditable and attributable; (2) reads become unlinkable to specific keys—even to endorsing peers.

### C. KEY OBJECTIVE AND CONTRIBUTIONS

In this work, we demonstrate that CPIR can be implemented natively in chaincode to provide query privacy for Fabric reads under evaluate path and achieve practical performance under certain parametrization choices.

Hence, the main contributions of this work are:

1) **BGV-based CPIR as Fabric chaincode.** We present, to the best of our knowledge, the first fully functional integration of a lattice-based CPIR scheme into Fabric chaincode for query privacy.
2) **Feasibility constraints.** We derive necessary and sufficient conditions on the cryptographic parameters, database size, and record structure to ensure that polynomial packing is possible, facilitating practical deployment for CTI sharing and similar use cases.
3) **Multi-channel architecture.** We design a multi-channel Fabric architecture where each channel main-

tains an independent polynomial database and metadata, allowing different organizations to host separate datasets while reusing the same CPIR chaincode.

4) **Comprehensive evaluation.** We implement a prototype using the Lattigo library and benchmark cryptographic operations, blockchain interactions, and end-to-end query latency under various configurations. Our results show that single-query latencies remain practical for typical Fabric deployments.
5) **Open-Source Release.** To encourage reproducibility and use by other researchers, we open-source the complete CPIR-on-Blockchain system, including chaincode, client, and experimental setup. The repository is available at: https://github.com/artias13/2_2_HLF_CPIR.

### D. ORGANIZATION

The remainder of this paper is organized as follows: Section II reviews Fabric privacy features, PIR fundamentals, and BGV encryption. Section III describes our system and threat models, polynomial database construction, feasibility constraints, multi-channel architecture, workflow and algorithms. Section IV shows experimental setup, cryptographic and blockchain benchmarks, and overall system performance. Section V discusses limitations and future directions, and Section VI concludes the paper.

## II. PRELIMINARIES

### A. FABRIC NATIVE PRIVACY FEATURES

We hereby acknowledge several native solutions for privacy that Hyperledger Fabric provides and explain why they do not fully address the query privacy problem.

**Separate Channels.** Fabric's multi-channel architecture [29] isolates ledgers across subgroups of organizations, limiting which participants observe which data. However, channel separation controls *who* sees a ledger, query intent remains visible to all endorsers of a channel.

**Private Data Collections (PDC).** PDCs [30] restrict which organizations store and access private key–value pairs. The shared ledger records only hashes, while members of the collection hold plaintext. PDCs provide access control but still expose function arguments to endorsers inside the collection, leaving query patterns observable.

**Fabric Private Chaincode (FPC).** FPC [31], [32] executes chaincode within Intel SGX enclaves. Arguments and state are protected even from peer operators, but this requires Trusted Execution Environments (TEEs) and attestation, introducing additional hardware and trust assumptions.

### B. FABRIC STORAGE LIMITS

We here address the question of how large a database can be stored in Fabric world state and ledger history, as this impacts the practical limits of our PIR construction.

**World state (LevelDB/CouchDB).** Fabric imposes no hard limit on the number of key–value entries in world state; capacity depends on available disk space and peer I/O throughput. In our implementation, each channel maintains a few small artifacts in world state that amount up to a 350 KB under typical parameters (see Section IV), LevelDB is sufficient and preferable for performance and simplicity, while CouchDB [33] remains an option to extend from 8 MB to 4 GB if needed.

**Ledger history (blockchain log).** According to the documentation [34], block size is constrained by the ordering service configuration. By default, the Fabric orderer limits the serialized payload to *AbsoluteMaxBytes = 10 MB* (recommended under 49 MB given the gRPC ceiling of 100 MB), and typically aggregates up to *MaxMessageCount = 500* transactions per block or *PreferredMaxBytes = 2 MB*. In our system, these limits affect only *submit* transactions such as *InitLedger* or record updates. *Evaluate* transactions (including *PIRQuery*) are read-only and do not generate blocks, thus unaffected by ordering or batching constraints. **Implication.** The effective capacity of a channel is governed primarily by cryptographic feasibility (Fig. 3) and the size of a single world-state value (i.e., $m_{DB}$), rather than by Fabric's block or database limits. For large or binary CTI objects (e.g., malware samples or full PCAPs), an optional extension is to store them off-chain in IPFS [35] while persisting only their content identifiers (CIDs) in world state, keeping the polynomial $m_{DB}$ as the structured component used for private retrieval.

### C. PRIVATE INFORMATION RETRIEVAL (PIR)

**Homomorphic Encryption.** Lattice-based homomorphic encryption schemes, such as Brakerski/ Fan-Vercauteren (BFV), Brakerski-Gentry-Vaikuntanathan (BGV), CKKS and TFHE [36]–[39] have emerged as foundational technologies for practical CPIR implementations.

We base our CPIR construction on the BGV scheme, a lattice-based homomorphic encryption based on the Ring Learning With Errors (RLWE) problem [40], which supports both addition and multiplication over ciphertexts. The BGV scheme defines operations over two polynomial rings: a ciphertext ring $R_Q = \mathbb{Z}_Q[X]/(X^N + 1)$ and a plaintext ring $R_T = \mathbb{Z}_T[X]/(X^N + 1)$, both sharing the same dimension $N = 2^{\log N}$. In our implementation, these rings are jointly specified by a single parameter literal $(\log N, \log Q_i, \log P_i, T)$ as provided by the Lattigo library [41] and paper [42]. The field $T$ determines $R_T$, while the modulus chain $(Q, P)$ and their bit-lengths $(\log Q_i, \log P_i)$ determine $R_Q$.

**CPIR Definition.** Model the database as a vector $D = \{d_0, \ldots, d_{n-1}\}$. To retrieve desired record $d_i$ without revealing $i$, the client forms a one-hot selection vector $\hat{v}_i$ defined as $\hat{v}_i = (0, \ldots, 0, 1, 0, \ldots, 0)$ where $1$ corresponds to the desired record at index $i$. He then encrypts it as $ct_q = \text{Enc}_{pk}(\hat{v}_i)$ under a public key $pk$ and sends $ct_q$ to the server, which computes $ct_r = (ct_q \cdot D) = \text{Enc}_{pk}(d_i)$, returning $ct_r$ to the client for decryption $d_i = \text{Dec}_{sk}(ct_r)$

using his secret key $sk$, thus obtaining the desired record $d_i$ without revealing $i$ to the server, or peer in our case.

**CPIR Instantiation:** We instantiate Computational PIR as a tuple of probabilistic polynomial-time algorithms (*KeyGen*, *Enc*, *Eval*, *Dec*):

- $\mathit{KeyGen}(\lambda) \to (pk, sk)$: On input the security parameter $\lambda$, output a public key $pk$ and a secret key $sk$.
- $\mathit{Enc}_{pk}(\hat{v}_i) \to ct_q$: Given a windowed selection vector $\hat{v}_i \in \{0,1\}^N$, encode it into the plaintext ring $R_T$ and encrypt to a query ciphertext $ct_q$ under $pk$.
- $\mathit{Eval}(ct_q, m_{DB}) \to ct_r$: Given $ct_q$ and the plaintext polynomial database $m_{DB} \in R_T$, homomorphically evaluate the product to obtain an encrypted response $ct_r \in R_Q$.
- $\mathit{Dec}_{sk}(ct_r) \to d_i$: Using the secret key $sk$, decrypt the response ciphertext $ct_r$ to recover the desired record $d_i$.

**Protocol objective.** Correctness requires that for all $i \in [n]$,

$$\mathit{Dec}_{sk}(\mathit{Eval}(\mathit{Enc}_{pk}(\hat{v}_i), m_{DB})) = d_i.$$

*Remark (restricted operation set).* The full BGV scheme also provides EvalKeyGen to generate relinearization and rotation keys, supporting ciphertext–ciphertext multiplication, automorphisms, and modulus switching. Our PIR construction requires only ciphertext–plaintext multiplication ($ct \times pt$), since the database polynomial $m_{DB}$ is kept in plaintext within world state. This avoids degree growth and level management, so we do not expose EvalKeyGen in chaincode. Extending to ciphertext–ciphertext evaluation would require additional on-chain artifacts (relinearization keys, Galois keys, encrypted $m_{DB}$), larger world-state footprint, and higher evaluation cost, which we leave as future work.

### D. NOTATION

We summarize the main notation used throughout the paper in Table 1.

**TABLE 1.** Notation

| Symbol | Description |
|---|---|
| $\lambda$ | Security parameter |
| $n$ | Database size;<br>index domain $[n] = \{0, \dots, n-1\}$ |
| $D = \{d_0, \dots, d_{n-1}\}$ | Database records |
| $m_{DB}$ | Plaintext polynomial representation of $D$ |
| $\hat{v}_i$ | One-hot selector for index $i$ |
| $v_i$ | Windowed selector for index $i$ with $record_s$ contiguous ones |
| $pk$, $sk$ | Public / secret keys (BGV) |
| $ct_q = \mathit{Enc}_{pk}(\hat{v}_i)$ | Encrypted query |
| $ct_r = \mathit{Eval}(ct_q, m_{DB})$ | Encrypted response |
| $d_i = \mathit{Dec}_{sk}(ct_r)$ | Decrypted record $d_i$ retrieved by client |
| $\mathit{KeyGen}(\lambda) \to (pk, sk)$ | Key generation |
| $\mathit{Enc}_{pk}(\cdot)$, $\mathit{Dec}_{sk}(\cdot)$ | Encrypt / Decrypt |
| $\mathit{Eval}(\cdot)$ | Homomorphic evaluation (ct–pt multiply) |
| $N = 2^{\log N}$ | Ring dimension |
| $\log Q_i$ | Bit-lengths of primes forming modulus chain $Q$ |
| $\log P_i$ | Bit-lengths of special primes $P$ |
| $T$ | Plaintext modulus |
| $record_s$ | Slots allocated per record |
| $record_b$ | Base serialized size of a record in bytes |
| $record_{\mu,\log N}$ | Template-specific minimum record size at security level $\log N$ |
| $\mathcal{S}$ | Allowed discrete slot sizes |
| $c = (c_0, \dots, c_{N-1})$ | Coefficient vector of the polynomial encoding (slots of $m_{DB}$) |
| $\lvert \cdot \rvert$, size$(\cdot)$ | Length in elements / size in bytes |
| Cap$(N, s, n)$ | Capacity predicate: $n \cdot s \le N$ |
| Min$(\log N, s)$ | Template predicate: $s \ge record_{\mu,\log N}$ |
| Disc$(s)$ | Discrete predicate: $s \in \mathcal{S}$ |
| Cap $\wedge$ Min $\wedge$ Disc | Feasibility condition |
| $\mathcal{DO}$, $\mathcal{DW}$, $\mathcal{DR}$, $\mathcal{GW}$ | Data Owner; Data Writer;<br>Data Requester; Gateway |
| *evaluate*, *submit* | Fabric read / write transaction phases |
| $\mathcal{L}$ | Leakage considered (ciphertext size, protocol timing) |

## III. PROPOSED SYSTEM

### A. SYSTEM MODEL

We introduce a blockchain-based query privacy system designed for permissioned ledgers. The system enables clients to privately retrieve from the ledger while endorsing peers can evaluate read-only queries over encrypted inputs without learning which record was accessed. The novelty of our approach lies in the integration of CPIR into Hyperledger Fabric chaincode using the BGV [37] homomorphic encryption scheme. This approach ensures that clients remain the sole holders of decryption keys, while peers perform only black-box computations, thereby enhancing overall privacy without requiring trusted hardware or protocol modifications. Our system is composed of the following entities:

- **Data Owner** ($\mathcal{DO}$)**:** Endorsing peers that hold the current plaintext polynomial $m_{DB}$ in world state and execute PIR during *evaluate*. $\mathcal{DO}$ is honest-but-curious.
- **Data Writer** ($\mathcal{DW}$)**:** A client organization that provisions or refreshes the database. $\mathcal{DW}$ invokes *submit* to initialize the ledger (e.g., set $n$ and template bounds). Chaincode computes $record_s$, packs $D = \{d_0, \dots, d_{n-1}\}$, encodes it into $m_{DB}$, and persists it.

- **Data Requester ($\mathcal{DR}$):** A client that privately retrieves a record. $\mathcal{DR}$ runs $KeyGen(\lambda) \to (pk, sk)$, forms $ct_q = Enc_{pk}(v_i)$, calls *evaluate PIRQuery*, and later decrypts $ct_r$.
- **Gateway ($\mathcal{GW}$):** The Fabric client/chaincode interface used by $\mathcal{DW}$ and $\mathcal{DR}$ to invoke *InitLedger*, *GetMetadata*, and *PIRQuery*. It follows standard Fabric semantics; no extra trust is assumed.

*Remark (world-state scope).* In Fabric, the ”ledger” comprises the blockchain log and the world state. Our CPIR operates on the world state: $m_{DB}$ encodes the latest key–value snapshot, not the historical transaction logs.

## B. THREAT MODEL

Our design follows the standard *honest-but-curious* adversarial model. We explicitly consider the following assumptions and threats:

- **Endorsing peers ($\mathcal{DO}$).** Execute chaincode correctly but may try to infer the queried index from *evaluate* inputs or logs. They see $ct_q$, metadata, and $m_{DB}$.
- **Data Writer ($\mathcal{DW}$).** Issues initialization writes via *submit*. $\mathcal{DW}$ is not trusted with decryption keys and learns nothing about $\mathcal{DR}$'s queries. We assume $\mathcal{DW}$ follows the write protocol but is not relied upon for privacy.
- **External observers.** May eavesdrop on client–peer traffic. Without $sk$, $ct_q$ and $ct_r$ reveal nothing under BGV assumptions.
- **Out of scope.** Traffic analysis and timing side-channels; the only permitted leakage is $\mathcal{L}$ (ciphertext size and protocol timing).

**Security objective.** For any $i \in [n]$, neither $\mathcal{DO}$ nor external observers can distinguish which $d_i$ is requested from $ct_q$ and $ct_r$. The only permissible leakage is ciphertext size and protocol timing, denoted collectively as $\mathcal{L}$.

## C. SYSTEM OVERVIEW

The proposed system integrates computational Private Information Retrieval (CPIR) directly into Hyperledger Fabric chaincode. Its purpose is to ensure that query indices remain hidden from endorsing peers while preserving Fabric's endorsement and audit workflow. At a high level, the workflow consists of four stages, illustrated in Fig. 1.

1) **Ledger initialization.** $\mathcal{DW}$ invokes *InitLedger* via $\mathcal{GW}$ using *submit*. Chaincode derives $record_s$ from $record_b$, packs $D$ into $c = (c_0, \ldots, c_{N-1})$, encodes $m_{DB}$, and stores $m_{DB}$ and metadata in world state held by $\mathcal{DO}$.
2) **Metadata discovery.** $\mathcal{DR}$ calls *GetMetadata* via *evaluate* to obtain $n$, $record_s$, and BGV parameters needed to form a valid query.

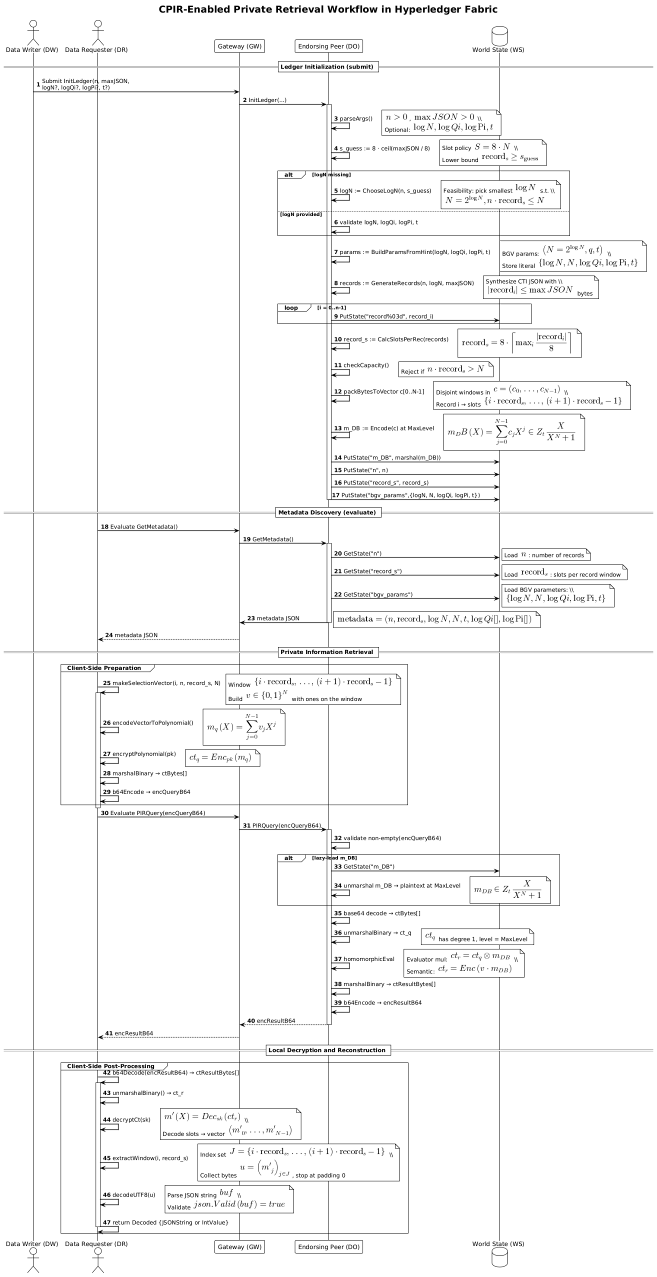

CPIR-Enabled Private Retrieval Workflow in Hyperledger Fabric
Data Writer (DW)
Data Requester (DR)
Gateway (GW)
Endorsing Peer (DO)
World State (WS)
Ledger Initialization (submit)
1 Submit InitLedger(n, maxJSON, logN?, logQi?, logPi?, t?)
2 InitLedger(...)
3 parseArgs()
$n > 0$, $\max JSON > 0$ \\ Optional: $\log N, \log Qi, \log \mathrm{Pi}, t$
4 s_guess := 8 · ceil(maxJSON / 8)
Slot policy $S = 8 \cdot N$ \\ Lower bound $\mathrm{record}_s \geq s_{\mathrm{guess}}$
alt
[logN missing]
5 logN := ChooseLogN(n, s_guess)
Feasibility: pick smallest $\log N$ s.t. \\ $N = 2^{\log N}, n \cdot \mathrm{record}_s \leq N$
[logN provided]
6 validate logN, logQi, logPi, t
7 params := BuildParamsFromHint(logN, logQi, logPi, t)
BGV params: $(N = 2^{\log N}, q, t)$ \\ Store literal $\{\log N, N, \log Qi, \log \mathrm{Pi}, t\}$
8 records := GenerateRecords(n, logN, maxJSON)
Synthesize CTI JSON with \\ $|\mathrm{record}_i| \leq \max JSON$ bytes
loop
[i = 0..n-1]
9 PutState("record%03d", record_i)
10 record_s := CalcSlotsPerRec(records)
$\mathrm{record}_s = 8 \cdot \left\lceil \max_i \frac{|\mathrm{record}_i|}{8} \right\rceil$
11 checkCapacity()
Reject if $n \cdot \mathrm{record}_s > N$
12 packBytesToVector c[0..N-1]
Disjoint windows in $c = (c_0, \ldots, c_{N-1})$ \\ Record i → slots $\{i \cdot \mathrm{record}_s, \ldots, (i+1) \cdot \mathrm{record}_s - 1\}$
13 m_DB := Encode(c) at MaxLevel
$m_D B(X) = \sum_{j=0}^{N-1} c_j X^j \in Z_t \frac{X}{X^N + 1}$
14 PutState("m_DB", marshal(m_DB))
15 PutState("n", n)
16 PutState("record_s", record_s)
17 PutState("bgv_params",{logN, N, logQi, logPi, t})
Metadata Discovery (evaluate)
18 Evaluate GetMetadata()
19 GetMetadata()
20 GetState("n")
Load $n$ : number of records
21 GetState("record_s")
Load $\mathrm{record}_s$ : slots per record window
22 GetState("bgv_params")
Load BGV parameters: \\ $\{\log N, N, \log Qi, \log \mathrm{Pi}, t\}$
23 metadata JSON
$\mathrm{metadata} = (n, \mathrm{record}_s, \log N, N, t, \log Qi[], \log \mathrm{Pi}[])$
24 metadata JSON
Private Information Retrieval
Client-Side Preparation
25 makeSelectionVector(i, n, record_s, N)
Window $\{i \cdot \mathrm{record}_s, \ldots, (i+1) \cdot \mathrm{record}_s - 1\}$ Build $v \in \{0,1\}^N$ with ones on the window
26 encodeVectorToPolynomial()
$m_q(X) = \sum_{j=0}^{N-1} v_j X^j$
27 encryptPolynomial(pk)
$ct_q = Enc_{pk}(m_q)$
28 marshalBinary → ctBytes[]
29 b64Encode → encQueryB64
30 Evaluate PIRQuery(encQueryB64)
31 PIRQuery(encQueryB64)
32 validate non-empty(encQueryB64)
alt
[lazy-load m_DB]
33 GetState("m_DB")
34 unmarshal m_DB → plaintext at MaxLevel
$m_{DB} \in Z_t \frac{X}{X^N + 1}$
35 base64 decode → ctBytes[]
36 unmarshalBinary → ct_q
$ct_q$ has degree 1, level = MaxLevel
37 homomorphicEval
Evaluator mul: $ct_r = ct_q \otimes m_{DB}$ \\ Semantic: $ct_r = Enc(v \cdot m_{DB})$
38 marshalBinary → ctResultBytes[]
39 b64Encode → encResultB64
40 encResultB64
41 encResultB64
Local Decryption and Reconstruction
Client-Side Post-Processing
42 b64Decode(encResultB64) → ctResultBytes[]
43 unmarshalBinary() → ct_r
44 decryptCt(sk)
$m'(X) = Dec_{sk}(ct_r)$ \\ Decode slots → vector $(m'_0, \ldots, m'_{N-1})$
45 extractWindow(i, record_s)
Index set $J = \{i \cdot \mathrm{record}_s, \ldots, (i+1) \cdot \mathrm{record}_s - 1\}$ \\ Collect bytes $u = (m'_j)_{j \in J}$, stop at padding 0
46 decodeUTF8(u)
Parse JSON string $buf$ \\ Validate $json.Valid(buf) = true$
47 return Decoded {JSONString or IntValue}
Data Writer (DW)
Data Requester (DR)
Gateway (GW)
Endorsing Peer (DO)
World State (WS)

**FIGURE 1.** **“Workflow. $\mathcal{DW}$ initializes the ledger via $\mathcal{GW}$, which triggers chaincode on endorsing peers ($\mathcal{DO}$). $\mathcal{DO}$ executes the protocol and persists state in world state ($m_{DB}$, metadata, JSON records). $\mathcal{DR}$ later obtains metadata, submits $ct_q$ = *Enc*$pk(v_i)$, $\mathcal{DO}$ evaluates $ct_r$ = *Eval*$(ct_q, m\mathrm{DB})$ against world state, and $\mathcal{DR}$ decrypts to $d_i$.**

3) **Private retrieval.** $\mathcal{DR}$ constructs $ct_q = Enc_{pk}(v_i)$ and invokes *PIRQuery* via *evaluate*. $\mathcal{DO}$ computes $ct_r = Eval(ct_q, m_{DB})$ and returns it.
4) **Decryption.** $\mathcal{DR}$ decrypts $ct_r$ to recover $d_i = Dec_{sk}(ct_r)$.

## D. POLYNOMIAL DATABASE CONSTRUCTION

To enable PIR queries over structured ledger data, we must embed records into a plaintext polynomial $m_{DB}$ suitable for BGV evaluation. Our prototype adopts a fixed-width packing strategy, illustrated in Fig. 2, which proceeds in four steps.

**Step 1: Serialize to Byte Array.** Each ledger record $d_i$ is serialized as a UTF-8 byte array. In our motivating use case of Cyber Threat Intelligence (CTI) sharing, JSON objects containing fields such as hash digests and threat levels are flattened into byte sequences. Every character is represented by its ASCII code in $[0, 255]$. This ensures that arbitrary structured records can be embedded in the polynomial without loss of information.

**Step 2: Calculate Slot Window.** We determine the slot allocation per record as:

$$record_s = \left\lceil \frac{record_b}{\mathit{bytesPerSlot}} \right\rceil,$$

where $record_b$ is the maximum serialized record length observed in bytes. In our prototype, each slot stores exactly one byte. For example, if the largest record is 126 bytes, then $record_s = \lceil 126/1 \rceil = 126$, which rounds up to 128 slots due to the discrete window policy. This guarantees uniform slot windows across all records, simplifying query construction at the cost of potential padding overhead.

**Step 3: Pack into Coefficient Vector.** Serialized byte arrays are inserted into disjoint slot windows of length $record_s$ within a coefficient vector $c = (c_0, c_1, \ldots, c_{N-1})$, where $N = 2^{\log N}$ is the ring capacity of the BGV scheme. Padding zeros are added if a record is shorter than $record_s$. Thus each record $d_i$ occupies a contiguous slot interval that can be privately retrieved through PIR.

**Step 4: Encode into Polynomial.** Finally, the coefficient vector $d$ is encoded into a plaintext polynomial:

$$m_{DB}(X) = \sum_{j=0}^{N-1} c_j X^j \in R_t,$$

where $R_t = \mathbb{Z}_t[X]/(X^N + 1)$. This polynomial serves as the plaintext database representation stored in the Fabric world state. Endorsing peers operate over $m_{DB}$ during PIR queries, while clients recover only the slots corresponding to their requested record.

## E. FEASIBILITY CONSTRAINTS

Embedding records into the plaintext polynomial $m_{DB}$ is feasible only for parameter triples $(\log N, n, record_s)$ that satisfy *all* of the following constraints. These constraints form a hierarchical relationship: template requirements dominate discrete allocation, and both are ultimately bounded by ring capacity.

**Constraint 1: Ring capacity.** The total number of occupied slots cannot exceed the ring size:

$$n \cdot record_s \;\leq\; N.$$

This represents the fundamental mathematical limit imposed by the cryptographic parameters. For example, with $\log N = 13$ $(N = 8192)$ and $record_s = 224$, at most $\lfloor 8192/224 \rfloor = 36$ records can be packed.

**Constraint 2: Template-specific minima.** Each security level $(\log N)$ corresponds to a record template with mandatory fields that impose a minimum slot requirement $record_{\mu,\log N}$. Examples include:

- **Mini records** $(\log N = 13)$: MD5 hash + malware family + threat level $\Rightarrow$ $record_{\mu,13} \approx 128$ bytes.
- **Mid records** $(\log N = 14)$: MD5 + SHA-256 short + malware class + AV detects $\Rightarrow$ $record_{\mu,14} \approx 224$ bytes.
- **Rich records** $(\log N = 15)$: MD5 + full SHA-256 + all metadata $\Rightarrow$ $record_{\mu,15} \approx 256$ bytes.

These minima arise from generator checks of the form:

$$\begin{aligned} \text{Mini:} \quad record_s &\;\geq\; record_b + 32 + 15, \\ \text{Mid:} \quad record_s &\;\geq\; record_b + 32 + 16 + 15, \\ \text{Rich:} \quad record_s &\;\geq\; record_b + 32 + 64 + 15, \end{aligned}$$

where $record_b \approx$ 113–125 bytes denotes the base JSON structure and numeric terms represent mandatory hash fields and serialization overhead.

**Constraint 3: Discrete allocation policy.** Operationally, we restrict the slot window $record_s$ to a discrete set for implementation simplicity:

$$\mathcal{S} = \{64, 128, 224, 256, 384, 512\} \text{ bytes.}$$

This means that even if Constraints 1 and 2 are satisfied, the configuration is rejected unless $record_s \in \mathcal{S}$.

**Constraint hierarchy and feasibility.** Feasibility of a configuration $(\log N, n, record_s)$ is defined by three predicates:

$$\begin{aligned} \mathsf{Cap}(N, s, n) &: n \cdot s \leq N \quad \text{(ring capacity)} \\ \mathsf{Min}(\log N, s) &: s \geq record_{\mu,\log N} \quad \text{(template minimum)} \\ \mathsf{Disc}(s) &: s \in \mathcal{S} \quad \text{(discrete allocation).} \end{aligned}$$

where $s = record_s$ and $N = 2^{\log N}$. A configuration is feasible iff:

$$\mathsf{Cap}(N, s, n) \;\wedge\; \mathsf{Min}(\log N, s) \;\wedge\; \mathsf{Disc}(s).$$

**Examples.** The interaction of these predicates is illustrated in Fig. 3. We provide three concrete examples below:

*a) Polynomial degree* $\log N = 13$ (Mini):

- $\mathsf{Min}(13, s)$ enforces $s \geq record_{\mu,13} \approx 128 \Rightarrow$ the smallest candidate is $s = 128$.
- $\mathsf{Disc}(s)$ requires $s \in \mathcal{S} \Rightarrow 128$ is allowed (while 64 is invalid).
- $\mathsf{Cap}(8192, 128, n)$ gives $n \leq \lfloor 8192/128 \rfloor = 64$.
- *Feasible:* $(\log N = 13, s = 128, n \leq 64)$.

*b) Polynomial degree* $\log N = 14$ (Mid):

- $\mathsf{Min}(14, s)$ enforces $s \geq record_{\mu,14} \approx 224 \Rightarrow$ smallest candidate is 224.
- $\mathsf{Disc}(s)$ allows $224, 256, \ldots$ but excludes smaller windows.
- $\mathsf{Cap}(16384, 224, n)$ gives $n \leq \lfloor 16384/224 \rfloor = 73$.

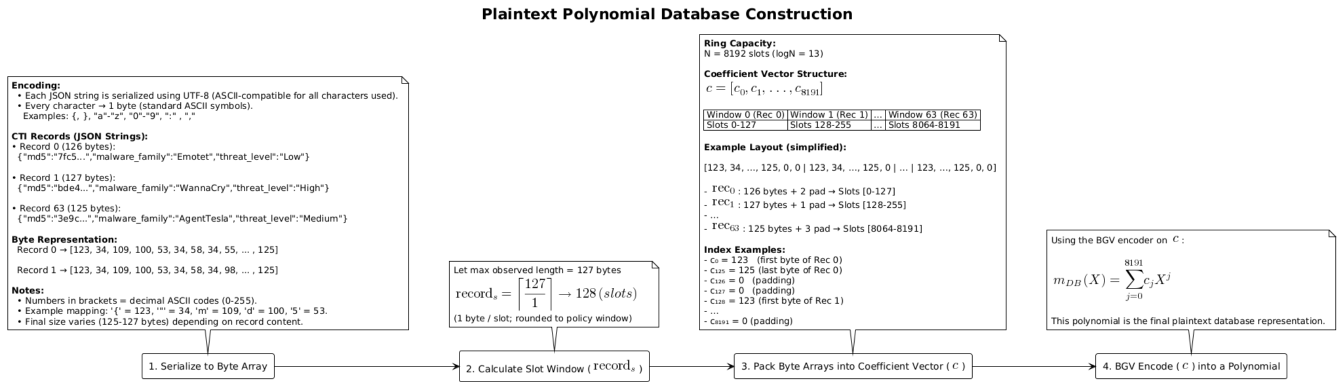

Plaintext Polynomial Database Construction
Encoding:
• Each JSON string is serialized using UTF-8 (ASCII-compatible for all characters used).
• Every character → 1 byte (standard ASCII symbols).
Examples: {, }, "a"-"z", "0"-"9", ":" , ","
CTI Records (JSON Strings):
• Record 0 (126 bytes):
{"md5":"7fc5...","malware_family":"Emotet","threat_level":"Low"}
• Record 1 (127 bytes):
{"md5":"bde4...","malware_family":"WannaCry","threat_level":"High"}
• Record 63 (125 bytes):
{"md5":"3e9c...","malware_family":"AgentTesla","threat_level":"Medium"}
Byte Representation:
Record 0 → [123, 34, 109, 100, 53, 34, 58, 34, 55, ... , 125]
Record 1 → [123, 34, 109, 100, 53, 34, 58, 34, 98, ... , 125]
Notes:
• Numbers in brackets = decimal ASCII codes (0-255).
• Example mapping: '{' = 123, '"' = 34, 'm' = 109, 'd' = 100, '5' = 53.
• Final size varies (125-127 bytes) depending on record content.
Let max observed length = 127 bytes
$\text{record}_s = \left\lceil \frac{127}{1} \right\rceil \rightarrow 128\,(slots)$
(1 byte / slot; rounded to policy window)
Ring Capacity:
N = 8192 slots (logN = 13)
Coefficient Vector Structure:
$c = [c_0, c_1, \ldots, c_{8191}]$
Window 0 (Rec 0) | Window 1 (Rec 1) | ... | Window 63 (Rec 63)
Slots 0-127 | Slots 128-255 | ... | Slots 8064-8191
Example Layout (simplified):
[123, 34, ..., 125, 0, 0 | 123, 34, ..., 125, 0 | ... | 123, ..., 125, 0, 0]
- $\text{rec}_0$ : 126 bytes + 2 pad → Slots [0-127]
- $\text{rec}_1$ : 127 bytes + 1 pad → Slots [128-255]
- ...
- $\text{rec}_{63}$ : 125 bytes + 3 pad → Slots [8064-8191]
Index Examples:
- $c_0$ = 123 (first byte of Rec 0)
- $c_{125}$ = 125 (last byte of Rec 0)
- $c_{126}$ = 0 (padding)
- $c_{127}$ = 0 (padding)
- $c_{128}$ = 123 (first byte of Rec 1)
- ...
- $c_{8191}$ = 0 (padding)
Using the BGV encoder on $c$ :
$m_{DB}(X) = \sum_{j=0}^{8191} c_j X^j$
This polynomial is the final plaintext database representation.
1. Serialize to Byte Array
2. Calculate Slot Window ( $\text{record}_s$ )
3. Pack Byte Arrays into Coefficient Vector ( $c$ )
4. BGV Encode ( $c$ ) into a Polynomial

**FIGURE 2.** $m_{DB}$ **construction from JSON to plaintext polynomial. Each record is serialized to bytes, mapped into a fixed slot window** $record_s$**, and packed into a coefficient vector** $c$**. The vector is then encoded as a BGV plaintext polynomial** $m_{DB}$**, which is stored in the Fabric world state.**

- *Feasible:* $(\log N = 14, s \in \{224, 256, \dots\}, n \leq 73)$.

*c) Polynomial degree* $\log N = 15$ (Rich):

- $\mathsf{Min}(15, s)$ enforces $s \geq record_{\mu,15} \approx 256$.
- $\mathsf{Disc}(s)$ excludes $64, 128, 224$; smallest valid is $256$.
- $\mathsf{Cap}(32768, 256, n)$ gives $n \leq \lfloor 32768/256 \rfloor = 128$.
- *Feasible:* $(\log N = 15, s \geq 256, n \leq 128)$.

**Implications.** Increasing $\log N$ raises ring capacity $N$ and thus $n$, but also requires larger $record_s$ if given richer templates. Feasible configurations occur only where all 3 predicates are met, guiding practical parameter selection.

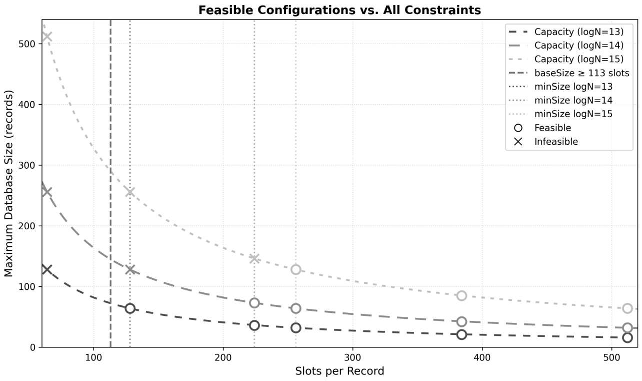


**FIGURE 3.** **Feasible configurations under the joint constraints** $\mathsf{Cap}$**,** $\mathsf{Min}$**, and** $\mathsf{Disc}$**. Dashed curves show ring-capacity limits for** $\log N \in \{13, 14, 15\}$**, vertical lines mark template-driven minima** $record_{\mu,\log N}$**, and x-axis ticks correspond to discrete slot sizes** $\mathcal{S}$**. Circles indicate feasible triples** $(\log N, record_s, n)$**.**

## F. MULTI-CHANNEL ARCHITECTURE

The packing strategy and feasibility constraints highlight an important observation: no single homomorphic parameter set can efficiently support the full diversity of Cyber Threat Intelligence (CTI) record formats. Compact records fit comfortably under smaller rings, while full JSON objects with long cryptographic hashes exceed the slot budget of these configurations. To balance scalability and expressiveness, we design a *multi-channel architecture* in Hyperledger Fabric (Fig. 4), where each channel is provisioned with a distinct BGV parameter set and record template.

**a) Channel Mini** $(\log N = 13)$. Supports compact CTI records (e.g., MD5, malware family, threat level) with maximum scalability and lowest query latency. For example, with $N = 8192$ slots, the system accommodates up to 128 records when $\max_i |d_i| \leq 64$ bytes, and 16 records when $\max_i |d_i| \leq 512$ bytes.

**b) Channel Mid** $(\log N = 14)$. Targets medium-sized records that include MD5 and truncated SHA-256 fields alongside classification metadata. With $N = 16384$ slots, the system supports up to 256 records at $\leq 64$ bytes or 32 records at $\leq 512$ bytes.

**c) Channel Rich** $(\log N = 15)$. Handles the most detailed records, including full-length hashes and multiple metadata fields. Here, $N = 32768$ slots allow up to 512 records at $\leq 64$ bytes or 64 records at $\leq 512$ bytes.

**Channel semantics.** As shown in Fig. 4, each channel maintains its own PIR chaincode instance and world state. The world state contains:

- The *polynomial view*: the packed plaintext polynomial $m_{DB}$ under key *"m_DB"*.
- The *normal view*: JSON records stored individually under keys *"record%03d"* for auditability and interoperability with non-PIR chaincode.
- *Metadata*:
  - *"n"*: number of records $n$,
  - *"record_s"*: slots per record $record_s$,
  - *"bgv_params"*: $\{\log N, N, \log Q_i, \log P_i, T\}$.

*Remark (ledger capacity).* A practical concern is the maximum size of the ledger when channels store both JSON records and the polynomial $m_{DB}$. In Hyperledger Fabric, two layers impose size-related limits: the *world state* (Lev-

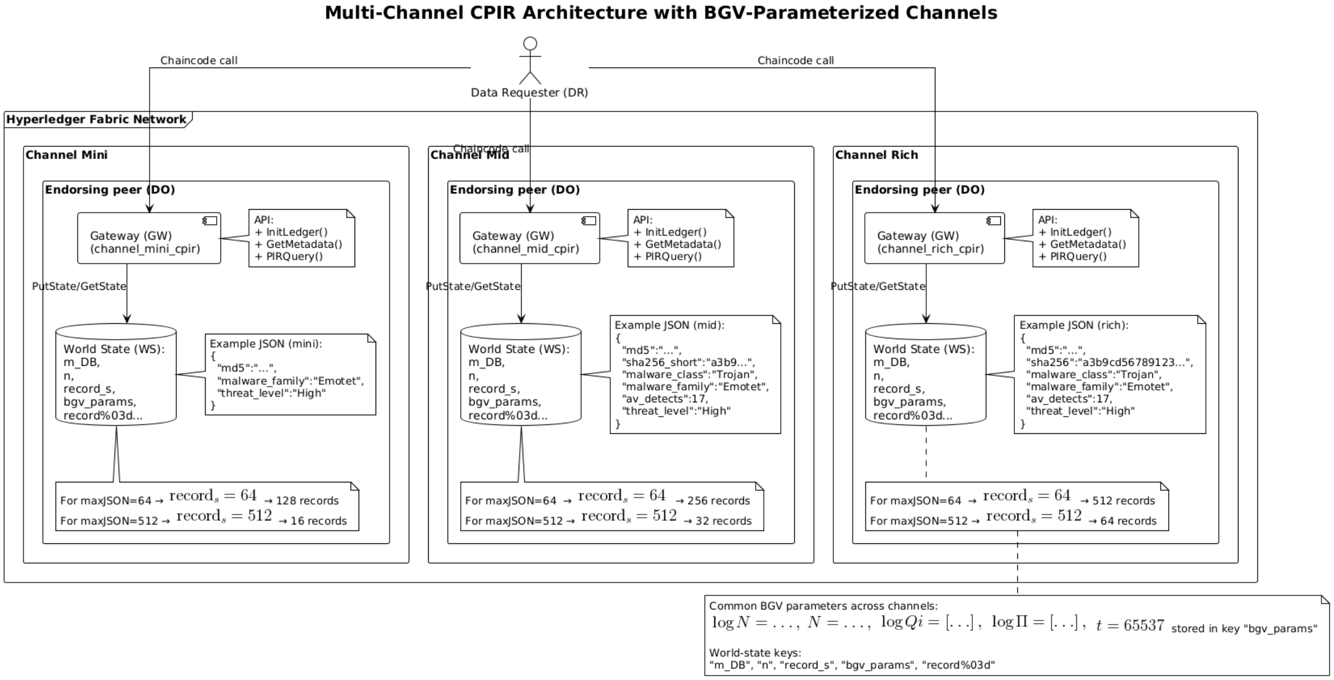


**FIGURE 4. Multi-channel CPIR architecture. Each channel instantiates a separate CPIR chaincode and maintains its own $m_{DB}$ polynomial, parameterized by $\log N$. This allows compact, mid-size, and rich CTI records to coexist under the same Fabric network.**

elDB or CouchDB) and the *blockchain history* managed by the ordering service, refer to Section II for details.

### G. WORKFLOW DETAILS

The complete workflow of our CPIR-enabled Fabric system is driven by five algorithms (Alg. 1–5), corresponding to the chaincode interface (*InitLedger*, *GetMetadata*, *PIRQuery*) and the client-side routines (*FormSelectionVector*, *DecryptResult*). Figure 1 provides the high-level overview. A Data Writer ($\mathcal{DW}$) provisions the database $D = \{d_0, \ldots, d_{n-1}\}$, a Data Owner ($\mathcal{DO}$) maintains the polynomial $m_{DB}$ in world state and executes PIR evaluations, and a Data Requester ($\mathcal{DR}$) retrieves $d_i$ privately using homomorphic encryption. The detailed steps are as follows:

1) **DW submits initialization.** $\mathcal{DW}$ calls *InitLedger* (Alg. 1) via $\mathcal{GW}$ (*submit*) with inputs $(n,\, record_s^{\mathcal{DW}})$ and an optional hint $(\log N, \log Q_i, \log P_i, T)$. Here $record_s^{\mathcal{DW}}$ denotes the maximum JSON size anticipated by the writer.
2) **DO validates and derives parameters.** $\mathcal{DO}$ rounds the writer's input to a discrete slot size $record_s^{\mathcal{GW}} = 8 \cdot \lceil record_s^{\mathcal{DW}}/8 \rceil$. If $\log N$ is absent, the smallest feasible $\log N$ is chosen such that $\mathsf{Cap}(N, record_s^{\mathcal{GW}}, n)$ holds. BGV parameters $\{\log N, N, \log Q_i, \log P_i, T\}$ are constructed and stored.
3) **DO prepares records.** Records $D = \{d_0, \ldots, d_{n-1}\}$ are ingested or synthesized with $|d_i| \leq record_s^{\mathcal{DW}}$. The definitive slot allocation is then fixed as $record_s = 8 \cdot \lceil \max_i |d_i|/8 \rceil$ (discrete policy), checked against feasibility predicates $\mathsf{Min}(\log N, record_s)$, $\mathsf{Disc}(record_s)$, $\mathsf{Cap}(N, record_s, n)$.
4) **Pack and persist.** Each $d_i$ is placed in a disjoint window $J_i = \{i \cdot record_s, \ldots, (i+1)record_s - 1\}$ of $c = (c_0, \ldots, c_{N-1})$, zeros pad unused slots, and the polynomial $m_{DB}(X) = \sum c_j X^j$ is encoded at max level. World state stores *"m_DB"*, *"n"*, *"record_s"*, and *"bgv_params"* plus optional *"record%03d"* entries.
5) **DR discovers metadata.** $\mathcal{DR}$ calls *GetMetadata* (Alg. 2) via *evaluate* to obtain $(n, record_s, \log N, N, T, \log Q_i, \log P_i)$. This enables reconstruction of the cryptographic context.
6) **DR instantiates crypto context.** From metadata, $\mathcal{DR}$ builds parameters, executes $\mathit{KeyGen}(\lambda) \to (pk, sk)$, and prepares encoder/encryptor objects.
7) **Form and encrypt query.** For index $i \in [n]$, $\mathcal{DR}$ runs *FormSelectionVector* (Alg. 3): define $J_i$, set $v_i$ with ones on $J_i$, encode to $m_q(X)$, encrypt as $ct_q = \mathit{Enc}_{pk}(v_i)$, and serialize/Base64-encode.
8) **PIR query evaluation.** $\mathcal{DR}$ issues $\mathit{PIRQuery}(ct_q^{B64})$ (Alg. 4) via *evaluate*. $\mathcal{DO}$ decodes, reloads $m_{DB}$ if necessary, and computes $ct_r = \mathit{Eval}(ct_q, m_{DB})$, returning the Base64-encoded ciphertext.
9) **Decryption and reconstruction.** $\mathcal{DR}$ runs *DecryptResult* (Alg. 5) to recover $m'(X)$, extract bytes from $J_i$, stop at padding zero, and reconstruct $d_i$ as a valid JSON object (or a scalar if $record_s = 1$).

*Remark (levels, noise, determinism).* Queries are encoded and encrypted at *max level*. Chaincode evaluates a single ct–pt multiply (no relinearization). This keeps noise growth minimal and evaluation deterministic across endorsers, which is important for Fabric endorsement. If $m_{DB}$ is re-encoded or refreshed, $\mathcal{GW}$ still returns the same metadata blob; clients rebuild context idempotently.

**Algorithm 1** InitLedger (chaincode)

```
Require: $n$; $record_s^{\mathcal{DW}}$; op: hint
$\log N \leftarrow \mathsf{selMinLogN}\Big(\Big(n,\, 8 \cdot \Big\lceil \frac{record_s^{\mathcal{DW}}}{8} \Big\rceil\Big)\Big)$
if $\log N = \varnothing$ then
    return $\perp$
end if
$bgvParams \leftarrow \mathsf{selParams}((\log N,\, op : \text{hint}))$
$D \leftarrow \mathsf{genRecords}\big((n,\, record_s^{\mathcal{DW}})\big)$
if $\exists i :\ |d_i| > record_s^{\mathcal{DW}}$ then
    return $\perp$
end if
$record_s \leftarrow 8 \cdot \left\lceil \dfrac{\max_i |d_i|}{8} \right\rceil$
if $\neg\mathsf{feasible}(\log N, n, record_s)$ then
    return $\perp$ // infeasible configuration
end if
$c \leftarrow [0, \ldots, 0] \in \mathbb{Z}_T^N$                // init coefficient vector
for $i \in [0, n-1]$ do
    $J_i \leftarrow \{i \cdot record_s, \ldots, (i+1) \cdot record_s - 1\}$   // slot window for $d_i$
    for $k = 0$ to $record_s - 1$ do
        if $k < |d_i|$ then
            $c[J_i[k]] \leftarrow \mathsf{byte}(d_i[k])$      // copy byte of record
        else
            $c[J_i[k]] \leftarrow 0$                          // padding
        end if
    end for
end for
$m_{DB}(X) \leftarrow enc^{\text{poly}}(c) \in \mathbb{Z}_T[X]/(X^N + 1)$
$worldState \leftarrow \{m_{DB},\ n,\ record_s,\ bgvParams,\ op : D\}$
return OK
```

**Algorithm 2** GetMetadata (chaincode)

```
Require: $\varnothing$
$n \leftarrow worldState.n$
$record_s \leftarrow worldState.record_s$
$paramsMeta \leftarrow worldState.bgvParams$
if $n = \varnothing \ \vee\ record_s = \varnothing \ \vee\ paramsMeta = \varnothing$ then
    return $\perp$
end if
$paramsMeta = (\log N, N, \log Q_i[], \log P_i[], T)$
$metadata \leftarrow (n, record_s, paramsMeta)$
return $metadata$
```

**Algorithm 3** FormSelectionVector (client)

```
Require: $pk$; $i \in [n]$; $record_s$; $N$
if $i < 0 \ \vee\ i \geq n$ then
    return $\perp$
end if
if $n \cdot record_s > N$ then
    return $\perp$
end if
$J_i \leftarrow \{i \cdot record_s, \ldots, (i+1) \cdot record_s - 1\}$
$v_i \in \{0,1\}^N \leftarrow \mathbf{0}$
for $j \in J_i$ do
    $v_i[j] \leftarrow 1$
end for                                        // windowed selector
$m_q(X) \leftarrow enc^{\text{poly}}(v_i)$       // polynomial encode at max level
$ct_q \leftarrow Enc_{pk}(m_q)$
$ct_q^{B64} \leftarrow enc^{\text{B64}}\big(\mathsf{ser}^{\text{bin}}(ct_q)\big)$
return $ct_q^{B64}$                  // Base64(marshalled ciphertext)
```

**Algorithm 4** PIRQuery (chaincode)

```
Require: $ct_q^{B64}$
if $ct_q^{B64} = \varnothing$ then
    return $\perp$
end if
$ct_q \leftarrow \mathsf{des}^{\text{bin}}\big(dec^{\text{B64}}\big((ct_q^{B64})\big)\big)$
if $m_{DB}$ not cached in memory then
    $m_{DB} \leftarrow worldState.m_{DB}$
end if
$ct_r \leftarrow Eval(ct_q, m_{DB})$
$ct_r^{B64} \leftarrow enc^{B64}\big(\mathsf{ser}^{\text{bin}}((ct_r))\big)$
return $ct_r^{B64}$
```

**Algorithm 5** DecryptResult (client)

```
Require: $ct_r^{B64}$; $sk$; $i \in [n]$; $record_s$; $n$
if $i < 0$ or $i \geq n$ then return $\perp$
if $n \cdot record_s > N$ then return $\perp$            // sanity
$ct_r \leftarrow \mathsf{des}^{\text{bin}}\big(dec^{\text{B64}}\big((ct_r^{B64})\big)\big)$
$u \in \mathbb{Z}_T^N \leftarrow dec^{\text{poly}}(\, m'(X)\,) \leftarrow Dec_{sk}(ct_r)$
$J_i \leftarrow \{i \cdot record_s, \ldots, (i+1) \cdot record_s - 1\}$
$b \leftarrow$ byte array // init empty buffer for record
for $j \in J_i$ do
    if $u[j] = 0$ then
        break
    end if                                   // stop at padding zero
    $b.\mathsf{append}(u[j])$
end for
if $record_s = 1$ then return $u[i \cdot record_s]$
$d_i \leftarrow dec^{UTF8}(b)$
return $d_i$
```

## IV. PERFORMANCE EVALUATION

### A. EXPERIMENTAL SETUP

All experiments were executed on a local Ubuntu 24.04 host running under WSL2 on an Intel Core i5-3380M CPU (2 cores/4 threads, 2.90 GHz) with 7.7 GB of RAM and a 1 TB SSD. During evaluation, the average available memory was 6.9 GB with a 2 GB swap partition, and the root filesystem reported 946 GB of free space.

The software stack consisted of Go 1.24.1, Docker 27.4.0, and Docker Compose v2.31.0, hosting Hyperledger Fabric v2.5 with a single Raft orderer and LevelDB as the world-state database. Fabric's ordering service used the recommended parameters (*BatchSize.AbsoluteMaxBytes*=99 MB, *PreferredMaxBytes*=2 MB per block).

Our implementation employs the *Lattigo* v6 library [41] as the homomorphic encryption backend. Lattigo provides a Go-native implementation of the BGV scheme [37], whose security and correctness have been validated in prior literature. Accordingly, our focus is on evaluating its *practical performance within a permissioned blockchain environment*.

Client–peer communication was performed through the Fabric Go SDK [43]. The network configuration comprised a single organization with one peer per channel, sufficient for privacy evaluation since PIR execution occurs solely at endorsing peers and ordering nodes do not access the world state. Unless otherwise stated, each reported value represents the mean of 20 executions under both cold and warm cache conditions, cross-verified against peer logs for consistency.

### B. CRYPTOGRAPHIC PERFORMANCE

**Parameter Configuration.** Table 2 summarizes the BGV parameter sets used in our evaluation, including the ring dimension $N$, ciphertext modulus chain $(\log Q_i, \log P_i)$, plaintext modulus $T$, slot allocation $record_s$, and database size $n$. Each configuration corresponds to one Fabric channel and maintains a feasible packing ratio as defined in Section III.

TABLE 2. **Default BGV Parameter Configuration per Channel**

| $N$ | $\log Q_i$ | $\log P_i$ | $T$ | $record_s$ | $n$ |
|---|---|---|---|---|---|
| $2^{13}$ | [54] | [54] | 65537 | 128 | 64 |
| $2^{14}$ | [54] | [54] | 65537 | 224 | 73 |
| $2^{15}$ | [54] | [54] | 65537 | 256 | 128 |

**Overall Results.** Figure 5 consolidates the main cryptographic evaluation metrics: (A) end-to-end latency by algorithmic stage, (B) serialized artifact size, and (C) slot utilization ratio within the packed database polynomial $m_{DB}$.

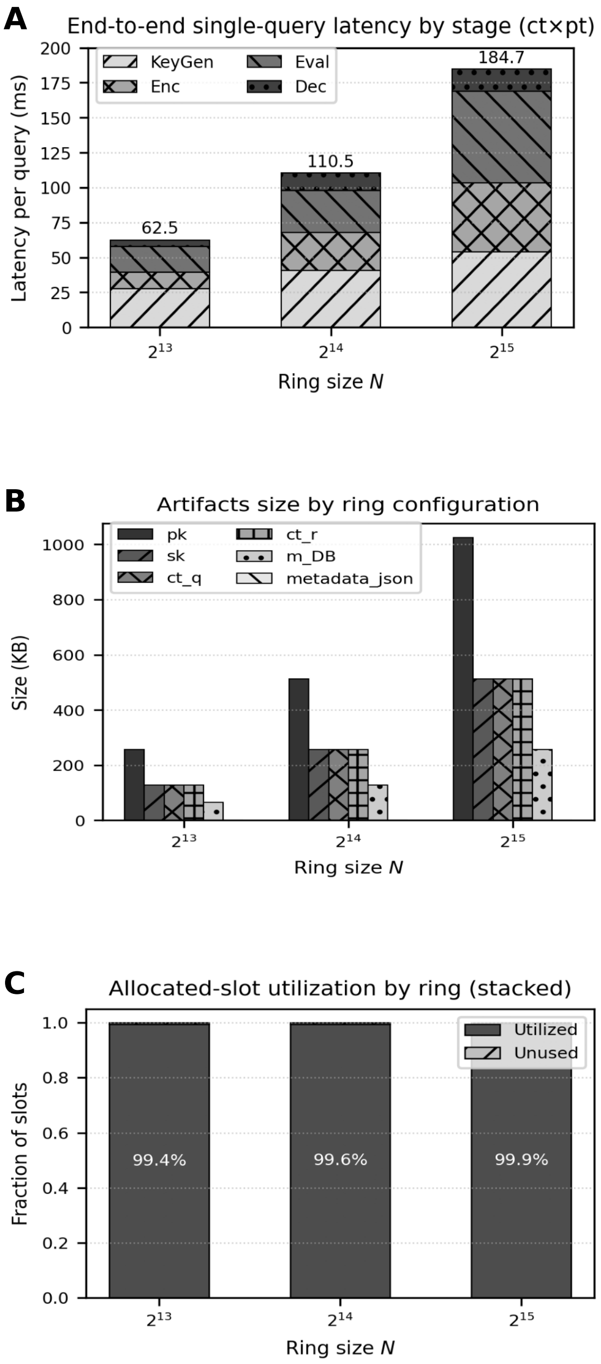


FIGURE 5. **Cryptographic performance of the BGV-based CPIR system: (A) latency by algorithmic stage, (B) artifact size by ring configuration, and (C) allocated-slot utilization.**

### C. BLOCKCHAIN PERFORMANCE

**Blockchain performance.** Figure 6 summarizes the performance of the CPIR chaincode within Hyperledger Fabric across three channels, each corresponding to a different ring size $N$ and record configuration: (A) block size breakdown, (B) world-state (LevelDB) breakdown, (C) block vs. world-state size, (D) peer CPU utilization, (E) peer memory utilization, and (F) peer network I/O.

**Chaincode Execution Timings.** Figure 7 and Table 6 summarize the average *server-side execution time* of the main chaincode functions across different ring sizes.

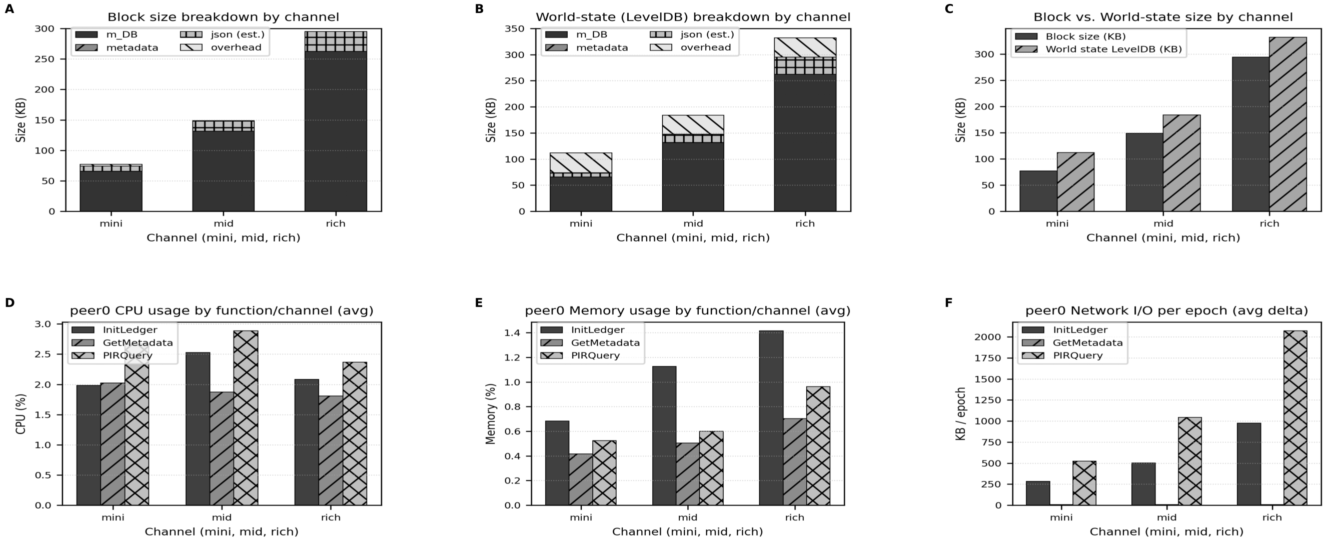


**FIGURE 6.** **Blockchain-side evaluation of the CPIR system across three Fabric channels. (A–C) Storage-level metrics: block and world-state composition. (D–F) Peer-level resource utilization: CPU, memory, and network I/O per function.**

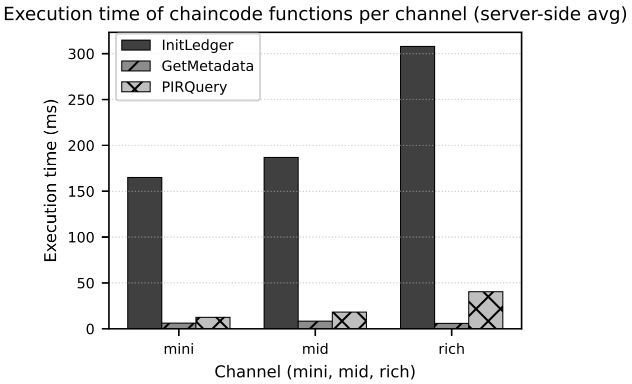


**FIGURE 7.** **Average chaincode execution time by function and ring size. Each bar represents the mean execution time over multiple epochs.**

*Remark (execution paths).* Transactions that modify world state (e.g., *InitLedger*) are issued via the *submit* path and committed through Raft consensus, while read-only operations (*GetMetadata*, *PIRQuery*) use the *evaluate* path, bypassing block creation and ordering. All metrics are averaged over 20 executions under identical peer configurations.

### D. OVERALL SYSTEM PERFORMANCE

Table 3 lists the measured execution time of core cryptographic operations (*KeyGen*, *Enc*, *Eval*, and *Dec*) for each evaluated ring dimension $\log N$. Table 4 summarizes the corresponding sizes of primary cryptographic artifacts, including public and secret keys, ciphertexts ($ct_q$, $ct_r$), the encoded plaintext database $m_{\mathrm{DB}}$, and auxiliary metadata. On-chain network behavior is reported in Table 5, which presents the average peer-side network I/O per *PIRQuery* transaction across the three channel configurations. Measured chaincode execution times are provided in Table 6, for *InitLedger*, *GetMetadata*, and *PIRQuery* functions under identical peer conditions. Additionally, Figure 8 illustrates the peer- and client-side execution during a PIR query

**TABLE 3.** **Execution Time of Cryptographic Operations (ms)**

| $\log N$ | KeyGen | Enc | Eval | Dec |
|---|---|---|---|---|
| 13 | 27.7 | 11.7 | 16.9 | 5.1 |
| 14 | 42.7 | 27.7 | 30.7 | 11.9 |
| 15 | 55.0 | 49.8 | 64.8 | 15.6 |

**TABLE 4.** **Size of Main Cryptographic Artifacts (KB)**

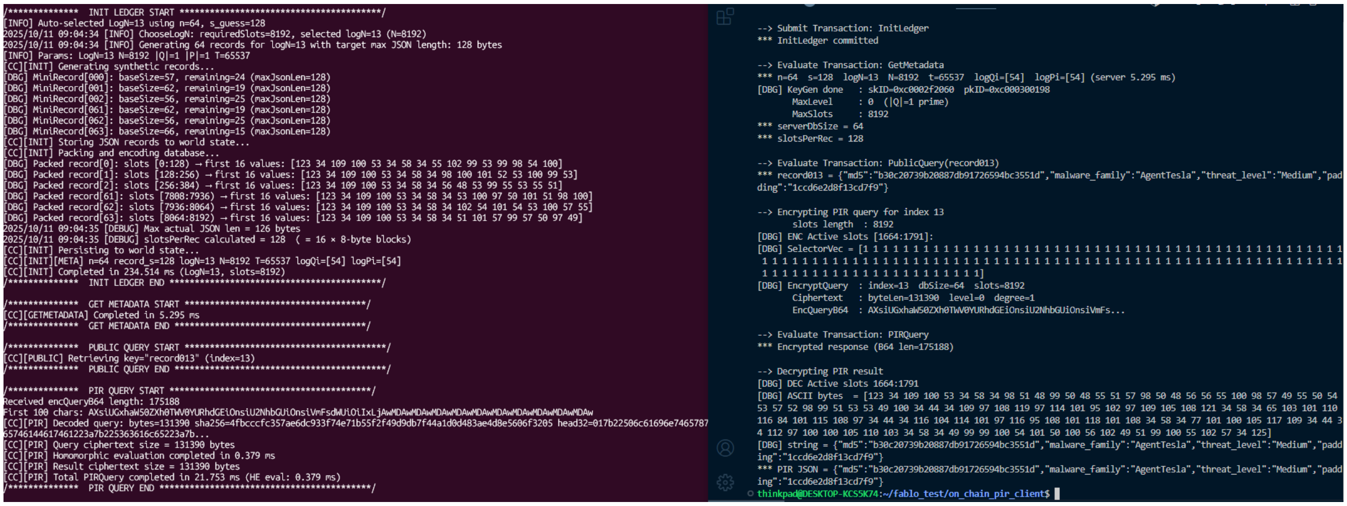
| $\log N$ | pk | sk | $ct_q$ | $ct_r$ | $m_{DB}$ | Metadata |
|---|---|---|---|---|---|---|
| 13 | 256.1 | 128.0 | 128.3 | 128.3 | 64.3 | 0.08 |
| 14 | 512.1 | 256.0 | 256.3 | 256.3 | 128.3 | 0.08 |
| 15 | 1024.1 | 512.0 | 512.3 | 512.3 | 256.3 | 0.08 |

**TABLE 5.** **Peer network I/O per PIRQuery (avg, KB/tx)**

| Channel | $\log N$ | NET I/O (KB/tx) |
|---|---|---|
| mini | 13 | 524.62 |
| mid | 14 | 1042.09 |
| rich | 15 | 2072.88 |

**TABLE 6.** **Average Chaincode Execution Time (ms)**

| $\log N$ | InitLedger | GetMetadata | PIRQuery |
|---|---|---|---|
| 13 | 165.24 | 6.16 | 12.53 |
| 14 | 187.03 | 8.31 | 18.17 |
| 15 | 307.87 | 5.94 | 40.36 |



```
/**************  INIT LEDGER START ****************************************/
[INFO] Auto-selected LogN=13 using n=64, s_guess=128
2025/10/11 09:04:34 [INFO] ChooseLogN: requiredSlots=8192, selected logN=13 (N=8192)
2025/10/11 09:04:34 [INFO] Generating 64 records for logN=13 with target max JSON length: 128 bytes
[INFO] Params: LogN=13 N=8192 |Q|=1 |P|=1 T=65537
[CC][INIT] Generating synthetic records...
[DBG] MiniRecord[000]: baseSize=57, remaining=24 (maxJsonLen=128)
[DBG] MiniRecord[001]: baseSize=62, remaining=19 (maxJsonLen=128)
[DBG] MiniRecord[002]: baseSize=56, remaining=25 (maxJsonLen=128)
[DBG] MiniRecord[061]: baseSize=62, remaining=19 (maxJsonLen=128)
[DBG] MiniRecord[062]: baseSize=56, remaining=25 (maxJsonLen=128)
[DBG] MiniRecord[063]: baseSize=66, remaining=15 (maxJsonLen=128)
[CC][INIT] Storing JSON records to world state...
[CC][INIT] Packing and encoding database...
[DBG] Packed record[0]: slots [0:128) → first 16 values: [123 34 109 100 53 34 58 34 55 102 99 53 99 98 54 100]
[DBG] Packed record[1]: slots [128:256) → first 16 values: [123 34 109 100 53 34 58 34 98 100 101 52 53 100 99 53]
[DBG] Packed record[2]: slots [256:384) → first 16 values: [123 34 109 100 53 34 58 34 56 48 53 99 55 53 55 51]
[DBG] Packed record[61]: slots [7808:7936) → first 16 values: [123 34 109 100 53 34 58 34 53 100 97 50 101 51 98 100]
[DBG] Packed record[62]: slots [7936:8064) → first 16 values: [123 34 109 100 53 34 58 34 102 54 101 54 53 100 57 55]
[DBG] Packed record[63]: slots [8064:8192) → first 16 values: [123 34 109 100 53 34 58 34 51 101 57 99 57 50 97 49]
2025/10/11 09:04:35 [DEBUG] Max actual JSON len = 126 bytes
2025/10/11 09:04:35 [DEBUG] slotsPerRec calculated = 128  ( = 16 × 8-byte blocks)
[CC][INIT] Persisting to world state...
[CC][INIT][META] n=64 record_s=128 logN=13 N=8192 T=65537 logQi=[54] logPi=[54]
[CC][INIT] Completed in 234.514 ms (LogN=13, slots=8192)
/**************  INIT LEDGER END *****************************************/

/**************  GET METADATA START *************************************/
[CC][GETMETADATA] Completed in 5.295 ms
/**************  GET METADATA END ***************************************/

/**************  PUBLIC QUERY START *****************************************/
[CC][PUBLIC] Retrieving key="record013" (index=13)
/**************  PUBLIC QUERY END *******************************************/

/**************  PIR QUERY START ******************************************/
Received encQueryB64 length: 175188
First 100 chars: AXsiUGxhaW50ZXh0TWV0YURhdGEiOnsiU2NhbGUiOnsiVmFsdWUiOiIxLjAwMDAwMDAwMDAwMDAwMDAwMDAwMDAwMDAwMDAw
[CC][PIR] Decoded query: bytes=131390 sha256=4fbcccfc357ae6dc933f74e71b55f2f49d9db7f44a1d0d483ae4d8e5606f3205 head32=017b22506c61696e7465787
65746144617461223a7b225363616c65223a7b...
[CC][PIR] Query ciphertext size = 131390 bytes
[CC][PIR] Homomorphic evaluation completed in 0.379 ms
[CC][PIR] Result ciphertext size = 131390 bytes
[CC][PIR] Total PIRQuery completed in 21.753 ms (HE eval: 0.379 ms)
/**************  PIR QUERY END ********************************************/
```

```
--> Submit Transaction: InitLedger
*** InitLedger committed

--> Evaluate Transaction: GetMetadata
*** n=64  s=128  logN=13  N=8192  t=65537  logQi=[54]  logPi=[54] (server 5.295 ms)
[DBG] KeyGen done   : skID=0xc0002f2060  pkID=0xc000300198
       MaxLevel     : 0  (|Q|=1 prime)
       MaxSlots     : 8192
*** serverDbSize = 64
*** slotsPerRec = 128

--> Evaluate Transaction: PublicQuery(record013)
*** record013 = {"md5":"b30c20739b20887db91726594bc3551d","malware_family":"AgentTesla","threat_level":"Medium","pad
ding":"1ccd6e2d8f13cd7f9"}

--> Encrypting PIR query for index 13
       slots length  : 8192
[DBG] ENC Active slots [1664:1791]:
[DBG] SelectorVec = [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
[DBG] EncryptQuery  : index=13  dbSize=64  slots=8192
       Ciphertext   : byteLen=131390  level=0  degree=1
       EncQueryB64  : AXsiUGxhaW50ZXh0TWV0YURhdGEiOnsiU2NhbGUiOnsiVmFs...

--> Evaluate Transaction: PIRQuery
*** Encrypted response (B64 len=175188)

--> Decrypting PIR result
[DBG] DEC Active slots 1664:1791
[DBG] ASCII bytes  = [123 34 109 100 53 34 58 34 98 51 48 99 50 48 55 51 57 98 50 48 56 56 55 100 98 57 49 55 50 54
53 57 52 98 99 51 53 53 49 100 34 44 34 109 97 108 119 97 114 101 95 102 97 109 105 108 121 34 58 34 65 103 101 110
116 84 101 115 108 97 34 44 34 116 104 114 101 97 116 95 108 101 118 101 108 34 58 34 77 101 100 105 117 109 34 44 3
4 112 97 100 100 105 110 103 34 58 34 49 99 99 100 54 101 50 100 56 102 49 51 99 100 55 102 57 34 125]
[DBG] string = {"md5":"b30c20739b20887db91726594bc3551d","malware_family":"AgentTesla","threat_level":"Medium","padd
ing":"1ccd6e2d8f13cd7f9"}
*** PIR JSON = {"md5":"b30c20739b20887db91726594bc3551d","malware_family":"AgentTesla","threat_level":"Medium","padd
ing":"1ccd6e2d8f13cd7f9"}
○ thinkpad@DESKTOP-KCS5K74:~/fablo_test/on_chain_pir_client$ ▌
```

**FIGURE 8. Detailed execution logs illustrating the privacy-preserving query workflow. Left: peer-side chaincode logs showing InitLedger, GetMetadata, and PIR evaluation with ciphertext-plaintext multiplication. Right: client-side logs showing metadata retrieval, query encryption, PIR query invocation, and decryption of the result.**

**End-to-End Workflow Summary.** Based on the data in Table 3 and Table 6, we now to summarize two main operational workflows in the system, involving $\mathcal{DW}$ and $\mathcal{DR}$, while $\mathcal{DO}$ is implicitly involved as the executing peer during private queries.

The first workflow corresponds to $\mathcal{DW}$ initializing the ledger through *InitLedger*, which packs and encodes the plaintext database $m_{DB}$ into world state.

The second workflow corresponds to $\mathcal{DR}$ performing a private query by sequentially executing *GetMetadata* → *KeyGen* → *Enc* → *PIRQuery* → *Dec*. The PIR evaluation itself is performed by $\mathcal{DO}$ (endorsing peer) using ciphertext-plaintext multiplication during the evaluate transaction.

Table 7 summarizes the cryptographic and blockchain timings for both workflows, averaged across all three channel configurations.

**TABLE 7. End-to-End Performance Analysis (ms)**

| Workflow | Cryptographic Operations (ms) | Blockchain Operations (ms) | Total Time (ms) |
|---|---|---|---|
| $\mathcal{DW}$'s Upload | 0.0 | 220.0 | 220.0 |
| $\mathcal{DR}$'s Query | 82.4 | 30.5 | 112.9 |

While the *InitLedger* operation incurs higher cost due to state updates and ordering, the end-to-end query workflow completes within ≈113 ms on average.

**Batched Queries.** Among our results, for the ring size $\log N{=}15$ configuration, issuing 100/1000/10000 private queries incurs ≈207MB / 2.07 GB / 20.7 GB of peer-side network I/O with an associated chaincode evaluation time of ≈0.07/0.67/6.73 minutes, respectively, when using our protocol, as shown in Table 8 and Figure 9.

*Remark (Why 2x to just $ct_q$ + $ct_r$?).* The network I/O values in Table 5 and Table 8 were obtained from *docker stats* snapshots collected for the *peer0.org1.example.com* and *orderer0.group1.orderer.example.com* containers during each benchmark epoch. For every execution of *PIRQuery*, the benchmarking script recorded cumulative network statistics (*NET I/O*) before and after the transaction, and the Python post-processing pipeline computed per-epoch deltas ($bytes_{in/out}(t)$ – $bytes_{in/out}(t{-}1)$) to obtain the mean transfer volume per function. Because the chaincode was deployed as an *external service container*, each PIR transaction traversed two gRPC hops: (1) client ↔ peer and (2) peer ↔ chaincode. Each ciphertext—the query $ct_q$ and the response $ct_r$—flows in both directions across these links, resulting in roughly four full transmissions per query. This accounts for the observed aggregate of ≈2072 KB per transaction for $\log N{=}15$, which aligns with the theoretical estimate $4 \times 512$ KB $= 2048$ KB

**TABLE 8. Projected cost for batched PIR queries at $\log N{=}15$ (peer perspective)**

| # Transactions | Total Bandwidth (MB) | Total Time (min) |
|---|---|---|
| 100 | 207.3 | 0.07 |
| 1000 | 2073.0 | 0.67 |
| 10000 | 20730.0 | 6.73 |

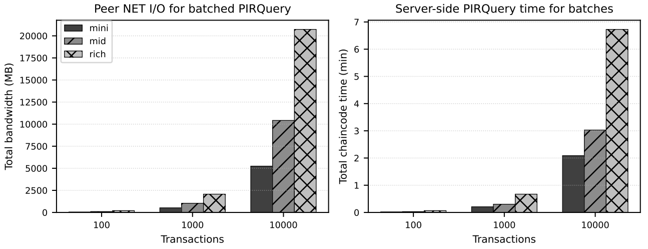


**FIGURE 9. Projected cost for batched PIR queries at $\log N{=}15$ (peer perspective)**

plus gRPC/TLS framing overhead. If the same chaincode were executed *in-process* (within the peer container), only the client–peer exchange would occur, reducing the network footprint to approximately $2 \times 512{=}1024$ KB per query or 10 GB for 10,000 queries.

## V. DISCUSSION

### A. RELATED WORK COMPARISON

Table 9 contrasts representative blockchain privacy frameworks that integrate Private Information Retrieval (PIR) or related cryptographic mechanisms to achieve query privacy across different domains. The comparison focuses on five key aspects: *(i)* the underlying privacy primitive (CPIR, IT-PIR, or hybrid), *(ii)* whether privacy computation occurs on-chain (via smart contracts or chaincode) or off-chain, *(iii)* the transaction phase in which privacy logic executes (evaluate vs. submit), *(iv)* typical database or world-state size, and *(v)* reported end-to-end (E2E) query latency when available.

**Analysis.** Prior blockchain–PIR integrations vary widely in scope and performance. Permissionless systems such as *Cloak* or *Peer2PIR* rely on distributed IT-PIR layers that incur multi-second latencies due to cross-node communication. Permissioned frameworks such as *PRIBANI*, *MUDRA*, and *BRON* embed PIR coordination logic in smart contracts or chaincode, but delegate the actual cryptographic computation to off-chain modules. Their reported end-to-end query times range between 400 and 900 ms for databases of a few hundred records.

In contrast, our *BGV-based CPIR-on-Fabric* performs the PIR evaluation entirely inside the Fabric chaincode during the evaluate phase, achieving an average query latency of approximately 113 ms for world states of 70–130 records (256 KB total size). This includes both cryptographic and blockchain processing. To our knowledge, this is the first implementation to realize a fully functional BGV-based CPIR entirely within Hyperledger Fabric chaincode, achieving sub-200 ms end-to-end under evaluate invocations in the query workflow.

### B. FUTURE WORK AND OUTLOOK

While the proposed system demonstrates the feasibility of integrating CPIR directly into Hyperledger Fabric's chaincode layer for privacy-preserving queries, several aspects remain open for further optimization and scalability improvements.

**Leakage and timing resilience.** Although the query index remains cryptographically hidden from endorsing peers, side-channel indicators such as ciphertext size and response latency may still reveal coarse information about dataset scale or structure. Future work should explore constant-time chaincode execution and standardized ciphertext serialization to minimize observable timing and size variability.

**Sublinear and sharded execution.** The current CPIR design maintains linear complexity in database size $n$, as each query involves homomorphic multiplication of the selection vector with the entire packed plaintext database $m_{\mathrm{DB}}$. Scaling to larger consortium datasets will require integrating sharding or sublinear approaches—such as preprocessing-based PIR, multi-stage hinting, or offline initialization phases—to reduce online evaluation cost.

**Encrypted-database mode.** Extending the ciphertext–plaintext (*ct*×*pt*) evaluation to a fully encrypted-database (*ct*×*ct*) mode would enable richer on-chain analytics under encryption. This transition would necessitate the use of relinearization and rotation keys, modulus-switching support, and careful parameter calibration to preserve correctness and noise margins within Fabric's resource limits.

**Dynamic updates and record addition.** Introducing an addRecord operation into the workflow would allow incremental ledger updates without reinitializing the entire $m_{\mathrm{DB}}$. This raises new design questions around database re-encoding, key refresh, and homomorphic consistency across epochs.

**Selective field-level retrieval.** Adaptive packing strategies could allocate slot windows dynamically based on JSON field relevance, enabling field-level access control and partial record retrieval while maintaining algebraic correctness.

**Deployment considerations.** From a system engineering perspective, integrating homomorphic encryption within Fabric peers introduces bandwidth and serialization overheads. In our setup, the external-chaincode deployment model caused each query and response ciphertext ($ct_q$, $ct_r$) to traverse two gRPC hops, effectively doubling network traffic per ciphertext. Future implementations should investigate in-process or sidecar-based execution models to reduce redundant communication and improve overall throughput.

**Dual-mode CPIR operation.** Finally, extending the architecture to support dual-mode queries—covering both the current world state and historical ledger data—could enable privacy-preserving analytics and provenance tracking. Such a capability would align CPIR with emerging research on private reads and verifiable computation in distributed ledgers [28].

## VI. CONCLUSION

This work demonstrates that privacy-preserving query execution through computational private information retrieval (CPIR) can be realized natively inside Hyperledger Fabric's chaincode layer. By embedding a lattice-based BGV scheme directly within Fabric's evaluate transaction path, we show that it is possible to preserve query privacy without modifying the underlying blockchain consensus or storage layers.

Our implementation achieves end-to-end query completion in ≈113 ms on average for world states of 70–130 records (256 KB total), and chaincode-level evaluation times below 45 ms even at $\log N{=}15$. Cryptographic operations remain lightweight—key generation, encryption, and homomorphic evaluation complete within 55 ms, 50 ms, and 65 ms respectively—while maintaining deterministic correctness under the BGV parameter sets validated in Table 2. Although

**TABLE 9. Comparison with existing blockchain privacy frameworks**

| Work | Permissioned / Permissionless | Privacy / Technique | Chaincode / Off-chain | Evaluate / Submit Phase | World State / DB Size | E2E Query / Time (ms) |
|---|---|---|---|---|---|---|
| [21] | - | IT-PIR + ZKP | Off-chain service | Off-chain | - | - |
| [22] | Permissioned | CPIR | Chaincode orchestration | Evaluate | - | - |
| [23] | Permissioned | CPIR + Differential Privacy | Chaincode + off-chain | Evaluate | - | - |
| [24] | Permissioned | IT-PIR (OT-based) | Chaincode + off-chain peers | Evaluate | - | - |
| [25] | Permissioned | CPIR + ZKP | Smart contract | Submit | - | - |
| [26] | - | Distributed IT-PIR | Hybrid contracts | Submit | - | - |
| [27] | - | IT-PIR + P2P privacy | Off-chain IPFS layer | Off-chain | - | - |
| **Ours** | Permissioned | **CPIR (lattice-based, BGV)** | **Chaincode** | **Evaluate** | **Yes** | **Yes** |

ciphertexts grow linearly with the ring dimension (512 KB at $\log N{=}15$), peer CPU and memory utilization remained modest throughout the experiments.

Network behavior, captured through `docker stats` instrumentation, revealed a mean peer-side I/O of $\approx$2.0 MB per private query, explained by the dual-hop communication pattern of the external chaincode architecture. At this rate, 100, 1000, and 10,000 queries correspond to approximately 207 MB, 2.07 GB, and 20.7 GB of total peer network traffic, respectively. While such throughput requirements may challenge large-scale deployments, they remain acceptable in controlled consortium settings and can be significantly reduced by adopting in-process or sidecar-based execution models.

Overall, these results confirm the practicality of implementing CPIR directly within a permissioned blockchain framework for privacy-preserving reads, establishing a foundation for future research on scalable, efficient, and composable private-query mechanisms over distributed ledgers. Key directions for advancement include: (i) constant-time chaincode evaluation and standardized ciphertext serialization to mitigate side-channel leakage; (ii) sublinear or sharded CPIR constructions for scalability; (iii) encrypted-database ($ct{\times}ct$) evaluation for richer analytics; and (iv) deployment optimizations to minimize redundant communication in peer–chaincode interactions.

In conclusion, our BGV-based CPIR-on-Fabric prototype illustrates that cryptographically private queries can coexist with blockchain endorsement semantics, achieving millisecond-scale latency for single queries and maintaining chaincode modularity and auditability—paving the way toward natively private data access in permissioned ledgers.

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