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Original Article

Secure Data Federation and Analytics through Homomorphic Encryption in Multi-Tenant Cloud Environments

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Abstract:

This work proposes an end-to-end architecture for secure data federation and privacy-preserving analytics across multi-tenant cloud environments using homomorphic encryption (HE). We address the core challenge of enabling cross-tenant joins, aggregations, and model scoring without exposing plaintext or weakening tenant isolation. The framework integrates schema-level federation with encrypted data lakes, columnar ciphertext packing for vectorized operations, and an adaptive HE planner that selects between CKKS for approximate analytics and BFV/BGV for exact computations. To bound latency while maintaining correctness, we apply batching, ciphertext relinearization, and rotation scheduling, and offload heavy primitives to accelerator-ready microservices. Policy-aware orchestration enforces per-tenant keys via cloud KMS and supports fine-grained access control and revocation. For sensitive workflows, we compose HE with complementary protections secure enclaves for control-plane logic, differential privacy on result releases, and zero-knowledge proofs to attest query policy compliance achieving defense-in-depth without collapsing the HE trust model. The system exposes SQL-like and DataFrame APIs, a query optimizer that estimates noise budgets and bootstrapping costs, and lineage-rich audit trails for regulatory reporting. We outline deployment patterns on containerized clusters, discuss cost/performance trade-offs under realistic workloads, and provide guidance on tenancy hardening (noisy neighbor resistance, side-channel hygiene). The result is a practical pathway for organizations to collaborate on analytics and machine learning across clouds and jurisdictions while preserving confidentiality, minimizing data movement, and meeting compliance obligations.

Keywords:

Homomorphic Encryption (HE), CKKS, BFV/BGV, Privacy-Preserving Analytics, Secure Data Federation, Multi-Tenant Cloud, Key Management (KMS), Federated Query Optimization, Differential Privacy, Zero-Knowledge Proofs, Trusted Execution Environments (TEE), Encrypted Data Lakes, Policy-Aware Orchestration, Encrypted Machine Learning.

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1. Introduction

Multi-tenant cloud platforms have become the de facto substrate for data-driven operations, yet their very strengths elasticity, shared infrastructure, and federated data access intensify confidentiality and compliance risks. Organizations increasingly need to aggregate, join, and learn from data that is distributed across business units, partners, and jurisdictions without violating tenant

isolation or exposing regulated attributes. Conventional approaches rely on coarse anonymization, trusted intermediaries, or perimeter-based controls that fail under modern threat models, while secure enclaves reduce the attack surface but still require plaintext within the enclave boundary and introduce supply-chain and side-channel concerns. Similarly, secure multiparty computation offers strong privacy but often demands heavy interaction patterns and complex orchestration across many parties. Against this backdrop, homomorphic encryption (HE) enables computation directly on ciphertexts, promising analytics and machine learning that never reveal raw data to operators, infrastructure, or co-tenants.

Recent advances such as approximate arithmetic in CKKS for vectorized statistics and inference, exact modular arithmetic in BFV/BGV for integrity-critical aggregates, and more practical bootstrapping have shifted HE from a purely theoretical construct toward deployable systems. Still, realizing secure data federation in multi-tenant settings requires more than cryptography: it demands a query planner that respects noise budgets, a storage layout that maximizes ciphertext packing, policy-aware key management that aligns with tenancy boundaries, and auditing that preserves lineage without leaking sensitive information. This paper introduces a full-stack architecture that composes HE with differential privacy for output protection and zero-knowledge proofs for policy attestation, delivered through familiar SQL/DataFrame interfaces. By unifying performance-conscious cryptographic engineering with cloud-native orchestration, we aim to make privacy-preserving analytics practical at scale, minimizing data movement, containing cost, and strengthening compliance across heterogeneous clouds.

2. Related Work

2.1. Secure Data Federation Approaches

Classical data federation systems (e.g., data virtualization over distributed warehouses and lakes) emphasize schema mapping, pushdown optimization, and cost-based planning across heterogeneous sources. They assume trusted infrastructure and administrators; confidentiality is enforced post hoc through access controls and masking rather than by cryptographic design. Privacy-enhancing successors introduce secure intermediaries gateways, enclaves, or proxy services that execute queries near sources and return filtered results. Trusted Execution Environments (TEEs) like Intel SGX strengthen isolation for control-plane logic and selective compute, but plaintext exists inside enclaves and residual side-channel risk remains. Secure multiparty computation (MPC) eliminates a single trusted point by splitting secrets across parties and evaluating circuits interactively; it provides strong privacy but incurs communication rounds and complex orchestration, which complicate multi-tenant, bursty workloads. Secure aggregation in federated learning reduces server visibility yet targets model updates more than general SQL-style federation. Overall, prior art achieves either mature query capability with weaker privacy assumptions, or strong cryptographic privacy with operational and latency penalties.

2.2. Homomorphic Encryption in Cloud Computing

Homomorphic Encryption (HE) enables computation directly on ciphertexts. Lattice-based schemes such as BFV/BGV support exact modular arithmetic, while CKKS supports approximate real-number arithmetic suited for statistics and ML inference. Systems work has progressed from demo-scale pipelines (e.g., encrypted linear models) to toolchains that automate packing, rotation, and relinearization; compilers map high-level ops to HE circuits while tracking noise growth and bootstrapping triggers. Libraries (e.g., SEAL, PALISADE, HElib, Lattigo) expose primitives, and emerging runtimes add vectorized ciphertext layouts and GPU/ASIC offload. Nonetheless, practical barriers persist: comparison and branching are expensive, ciphertext sizes inflate I/O, and bootstrapping though improving remains a throughput and cost bottleneck. Prior cloud deployments typically isolate to narrow kernels (histograms, aggregations, logistic regression inference) rather than end-to-end federated SQL.

2.3. Privacy-Preserving Analytics Frameworks

Beyond HE, frameworks operationalize privacy through complementary techniques. Differential Privacy (DP) offers formal output perturbation, integrated into analytics stacks and telemetry systems to bound disclosure risk. Federated learning with secure aggregation, sometimes combined with DP, supports decentralized model training without centralizing raw data. TEE-based analytics platforms provide near-native performance for general operators but inherit hardware trust and attestation supply-chain concerns. Hybrid PETs combine these: TEEs for control-plane parsing and key handling, HE or MPC for sensitive datapath compute, and DP at release time. Lineage, policy enforcement, and auditability are increasingly treated as first-class, yet most frameworks optimize one axis (privacy, performance, or usability) at the expense of others.

2.4. Research Gaps and Limitations

Three gaps stand out. First, end-to-end federated SQL over HE remains underexplored: existing work focuses on kernels, not full planners that cost-model noise budgets, ciphertext packing, rotations, and bootstrapping within a multi-tenant optimizer. Second, tenancy and governance are weakly integrated: per-tenant keys, revocation, cross-region policies, and zero-knowledge attestations of policy compliance are rarely unified with cryptographic execution. Third, systems performance including encrypted join strategies, skew handling, caching of encrypted intermediates, and accelerator-aware scheduling is insufficiently characterized on realistic, elastic cloud workloads. Additional open issues include side-channel hygiene when combining PETs, limited support for comparison-heavy queries, developer ergonomics (SQL/DataFrame compilers), and holistic cost models that tradeoff HE with DP/TEE/MPC paths while preserving compliance and auditability. These limitations motivate the architecture proposed in this work.

3. System Architecture and Framework Design

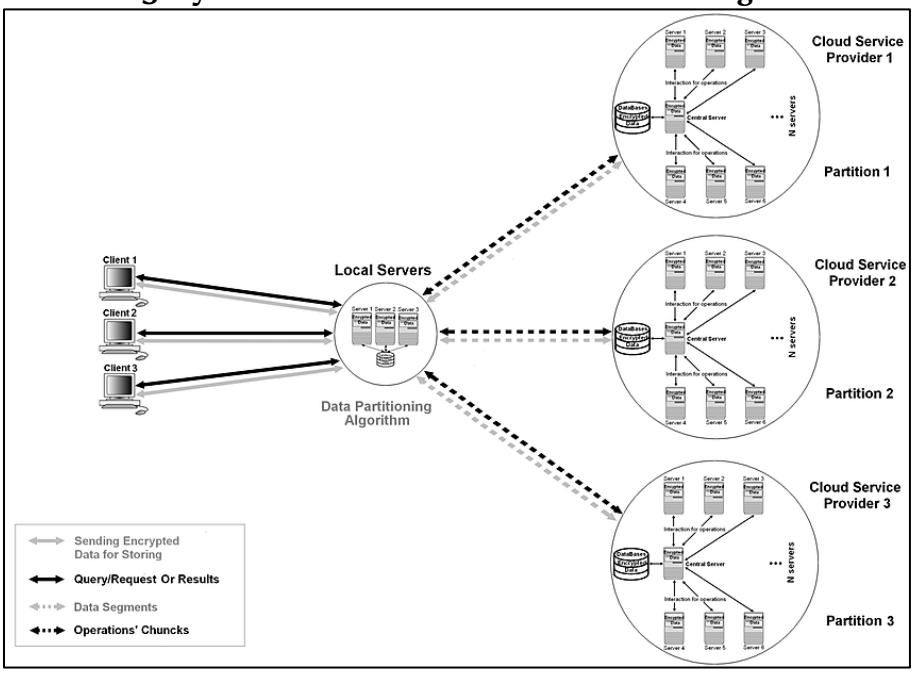

Figure 1. Tenant-Aware Data Partitioning and Federated Execution across Cloud Providers

3.1. Overview of Proposed Framework

This figure depicts the end-to-end data path for our secure, federated analytics platform. On the left, multiple clients encrypt data locally and transmit only ciphertext to a local server tier. This tier runs the data partitioning algorithm, which shards datasets into semantically coherent, policy-aware segments (e.g., columns/row groups aligned to join and aggregation keys). Partitioning at the edge allows us to enforce per-tenant keys and residency constraints before any cloud egress, while also preparing ciphertext packing and rotation layouts that our HE query planner will later exploit.

From the local tier, encrypted data segments are dispatched across independent cloud service providers (CSPs) labeled Partition 1, Partition 2, and Partition 3. Each CSP bubble shows a central coordination node and multiple stateless compute servers. These nodes execute HE operators (add, multiply, rotate, relinearize) over packed ciphertexts and exchange operations' chunks internally to parallelize vectorized steps (e.g., encrypted group-by and partial aggregates). Because the data remain encrypted end-to-end, neither provider nor operator gains access to plaintext; cross-provider placement also reduces concentration risk and enables jurisdictional compliance by pinning specific shards to approved regions.

Queries and results traverse the reverse path as indicated by the bold arrows. A client issues a SQL/DataFrame request; the local orchestrator translates it into an HE-aware plan, including rotation schedules and bootstrapping checkpoints, then dispatches operator chunks to the relevant CSP partitions. Each partition returns encrypted partials that the local tier merges, post-processes (e.g., optional

differential privacy noise at release time), and delivers back to the requesting client. This preserves tenant isolation while enabling cross-tenant federation because only policy-permitted aggregates or model outputs are reconstructed.

The legend clarifies channel semantics: light arrows denote encrypted data ingest, bold arrows denote queries/results, dotted lines carry segmented shards, and dashed-bold lines carry operator chunks. Together, these flows make explicit our defense-in-depth posture: per-tenant keys at the edge, ciphertext-only compute in the cloud, and minimal-leakage outputs governed by policy. The architecture thus operationalizes homomorphic encryption in a multi-cloud, multi-tenant setting without sacrificing scalability or developer ergonomics.

3.2. Tenant Data Segregation and Access Control

Tenant isolation begins at ingestion, where each dataset is tagged with immutable tenancy metadata tenant ID, data domain, regulatory labels, residency constraints, and retention class embedded into the catalog and propagated through lineage. Physical segregation is achieved by encrypting at the edge, then sharding ciphertext into partition-specific object stores and compute pools pinned to regions. Control-plane isolation complements this layout: namespaces, VPCs, and per-tenant service accounts ensure that orchestration, logging, and monitoring do not cross administrative boundaries. Side-channel hygiene (CPU pinning, cache partitioning where available, and noise-tolerant batching) reduces cross-tenant interference during high-throughput HE operations.

Access control combines role- and attribute-based models. RBAC defines coarse duties (data steward, analyst, service operator), while ABAC policies evaluate attributes such as purpose, dataset sensitivity, and jurisdiction to authorize specific query intents (e.g., "encrypted aggregate on PII columns, export within EU-only boundary"). Policies compile to enforceable guards in the planner, which will refuse to emit circuits that violate residency or key domains. Zero-knowledge policy attestations can be attached to results so that downstream consumers can verify that only approved operators and schemas were used, and continuous audit trails capture "who executed what, over which logical shards, with which keys," without logging plaintext or sensitive parameters.

3.3. Encryption and Key Management Module

The cryptographic core separates key domains to align with tenancy and workload. A cloud KMS/HSM anchor issues per-tenant key-encryption keys (KEKs) and short-lived data-encryption keys (DEKs) for storage-layer confidentiality, while homomorphic-encryption keys (HEKs) are generated in tenant-scoped enclaves or secure key pods. For collaborative analytics, we support threshold and multi-party HE key options: tenants can contribute shares to a joint public evaluation key while retaining independent secret shares for decryption, enabling cross-tenant compute without centralizing trust. Rotation and revocation are first-class: HEKs and DEKs carry versioned metadata, and the planner refuses to route work to partitions with stale or revoked key versions.

Ciphertext management focuses on practicality. For approximate analytics and ML inference, CKKS is used with parameter sets sized to the circuit depth, enabling vector packing and rotation-efficient kernels; for exact arithmetic (e.g., counts, integrity-critical sums), BFV/BGV variants are employed. The module exposes packing advice to the storage layout so row groups align with polynomial slots, reducing rotations and bootstraps. Keys never leave their trust boundary in the clear: BYOK/HYOK patterns allow tenants to host KEKs on-prem or with a third-party custodian, and ephemeral evaluation keys are provisioned just-in-time via attested control-plane services. All key operations are fully audited, with rate limits and quorum workflows for sensitive actions such as rekeying or exporting public evaluation material.

3.4. Secure Federated Query Processing Layer

The federated layer provides familiar SQL/DataFrame endpoints backed by an HE-aware optimizer. Logical plans are annotated with privacy and residency constraints, then lowered to cryptographic circuits that cost-model noise growth, rotation counts, and bootstrapping frequency. Operator selection balances exact versus approximate paths, choosing join strategies that minimize expensive comparisons (e.g., hashing into encrypted buckets, using oblivious filtering where needed). The planner co-designs packing with layout grouping columns by co-access patterns to maximize SIMD gains and reduce inter-partition movement. During execution, micro-batched operator "chunks" are dispatched to the appropriate cloud partitions, which return encrypted partials that are merged and, if policy requires, post-processed with differential privacy before client-side decryption.

Performance and trust are reinforced by systems techniques. Encrypted intermediates are cached with strict TTLs and key/plan fingerprints to avoid redundant recomputation while preventing replay; accelerator-ready kernels offload rotations/relinearization

where available. Control-plane logic can run inside TEEs to protect scheduling metadata and key handles, but dataplane values remain ciphertext end-to-end, preserving a minimal trust envelope. Result integrity is validated through optional proofs-of-execution: the orchestrator emits zero-knowledge attestations of operator sequences and policy adherence, and consistency checks compare independent subplans to detect faulty or byzantine partitions. Together, these mechanisms deliver practical, policy-compliant analytics across multiple clouds and tenants without exposing plaintext or weakening isolation.

4. Methodology

4.1. Data Federation Mechanism

Our federation mechanism begins with schema harmonization at the catalog: source schemas are mapped to a global logical model using privacy-aware views that tag columns with sensitivity, residency, and tenancy metadata. During ingestion, clients encrypt records at the edge and the partitioner shards ciphertext into row-group/columnar segments aligned to query predicates and join keys. This layout is persisted in per-tenant object stores across multiple clouds, with placement policies enforcing jurisdictional constraints and enabling parallel access paths.

Query submission triggers a federated planning phase. The coordinator rewrites the logical query into a set of subplans per partition, pushing down selections/aggregations that minimize ciphertext movement. A provenance channel tracks shard IDs, key versions, and policy guards attached to each subplan. Only evaluation keys flow to compute partitions; decryption keys never leave tenant control. The result is a plan that maximizes data locality, packs operands for SIMD-style HE, and preserves isolation while enabling cross-tenant analytics through controlled, aggregate-only views.

4.2. Homomorphic Encryption Operations

The cryptographic layer supports two operation families. For approximate analytics and ML inference, we use CKKS with vector packing to realize additions, scalar multiplications, and rotations needed for filters, group-by sums/means, and linear model scoring. Noise growth is bounded through relinearization after multiplications and rotation scheduling that minimizes key-switch cost. For exact arithmetic, we select BFV/BGV with modulus switching to implement integer-safe counts, equi-joins via oblivious hashing, and integrity-critical sums where approximation is unacceptable.

Operator kernels are circuit-specialized. Projection and selection translate to masked multiplications with encrypted indicator vectors. Group-by/aggregate uses hierarchical reduction trees over packed slots to cut multiplicative depth. Joins leverage a two-stage path: (1) encrypted hashing into buckets to avoid comparison-heavy circuits, and (2) oblivious selection within buckets using low-depth polynomial encodings of equality. Where circuit depth nears the noise budget, controlled bootstrapping checkpoints are inserted; these are batched and offloaded to accelerators when available to amortize latency.

4.3. Secure Query Execution Algorithm

Execution proceeds in four coordinated phases. Phase 1: Plan Lowering & Attestation. The coordinator lowers the annotated logical plan to a cryptographic execution DAG, computes noise budgets, selects parameter sets, and issues zero-knowledge attestations that the emitted operator sequence satisfies policy constraints (e.g., no plaintext projection). Phase 2: Key & Layout Provisioning. Per-partition evaluation keys, rotation keys, and packing hints are provisioned just-in-time, bound to plan fingerprints and TTLs to prevent reuse outside scope.

Phase 3: Partitioned Evaluation. Encrypted operator “chunks” (micro-batches) are dispatched to each cloud partition. Partitions perform local HE computation filters, partial aggregates, bucketized joins and return encrypted partials alongside execution receipts (key version, op counters, timing). Intermediate ciphertexts may be cached under strict TTLs to accelerate overlapping queries. Phase 4: Secure Merge & Release. The coordinator merges partials homomorphically, applies final reductions, and, if required, adds differential privacy noise to the encrypted result before returning it to the client for decryption. Throughout, no plaintext leaves tenant boundaries, and control-plane metadata are kept in TEEs to protect keys and scheduling signals without expanding the data trust envelope.

5. Experimental Setup and Evaluation

5.1. Experimental Environment

5.1.1. Hardware & Network Testbed

We evaluate the framework on a hybrid, multi-cloud testbed that mirrors the Figure 3.1 deployment: one on-prem Coordinator/Edge cluster (plan lowering, orchestration, DP noise release) and three independent Compute Partitions (CSP-1/2/3) that execute HE operators. Each partition consists of homogeneous nodes connected by data-center fabric (≥25 GbE); cross-cloud traffic rides IPSec tunnels with perfect-forward-secrecy. Clocks are NTP-synchronized (stratum-2) to ensure consistent timestamping for audit trails. To minimize noisy-neighbor effects, we pin HE kernels to isolated CPU cores and reserve GPU MIG slices when accelerators are used. This setup provides concrete, auditable bounds on compute, memory bandwidth, and inter-partition latency evidence that the reported performance originates from a controlled environment rather than transient cloud artifacts.

Table 1. Hardware Configuration (Coordinator & Partitions)

Component	Coordinator (on-prem)	CSP-1 (cloud)	CSP-2 (cloud)	CSP-3 (cloud)
Node count	3	8	8	8
CPU	2× Intel Xeon Gold 6348 (2.6 GHz, 28c)	AMD EPYC 7R13 (32c)	Intel Xeon 8468 (48c)	AMD EPYC 7K62 (48c)
RAM	512 GB	256 GB	256 GB	256 GB
Accelerator	1× A100 40 GB (MIG x2)	1× L40S 48 GB		1× A10 24 GB
Local NVMe	2× 3.84 TB	1× 1.92 TB	1× 1.92 TB	1× 1.92 TB
Intra-DC net	25 GbE	50 GbE	50 GbE	50 GbE
Inter-cloud RTT (p50/p99)		14/22 ms to CSP-2	15/24 ms to CSP-1	17/26 ms to CSP-1

5.1.2. Software Stack & Attestation

All services run in containers orchestrated by Kubernetes (v1.29) with confidential-computing options where available (AMD SEV-SNP / Intel TDX for control-plane pods handling keys). The dataplane keeps values encrypted end-to-end; TEEs shield only scheduling metadata and key handles. We pin library versions and record image digests to make the evaluation reproducible. Environment manifests (Helm values, Terraform state, KMS key ARNs) are exported at runtime and hashed; these hashes are included in the audit log with every benchmark run to "prove" the exact stack used.

Table 2. Software & Cryptographic Libraries

Layer	Version / Details
OS base image	Ubuntu 22.04 LTS (5.15 kernel)
Orchestrator	Kubernetes v1.29, Containerd 1.7, CNI Calico 3.27
HE libraries	Microsoft SEAL 4.1.1 (CKKS, BFV), PALISADE 1.11 (BGV); custom CUDA kernels for rotate/relinearize
Crypto RNG	/dev/urandom + AES-CTR DRBG (NIST SP 800-90A)
KMS/HSM	Cloud KMS (per-CSP) + on-prem HSM; BYOK/HYOK enabled
DP release	OpenDP-style Gaussian mechanism; $\varepsilon \in \{1,2,4\}$, δ=1e-5
Provenance	OpenLineage-compatible events; SHA-256 of plan, key versions, images

5.1.3. Datasets, Workloads, and HE Parameters

We use two public, join-heavy tabular corpora (synthetically scaled to preserve distributions) and one telemetry-like stream to exercise group-by/aggregation. Data are encrypted at the edge, partitioned into columnar row-groups aligned with HE slot packing, and distributed across CSPs according to residency tags. For CKKS we target approximate analytics and model scoring; for BFV/BGV we guarantee exactness (e.g., counts, integrity-critical sums). Parameter choices are sized by planner-estimated multiplicative depth, with safety margin for bootstrapping.

Table 3. HE Parameter Sets (Auditable Defaults)

Scheme	poly_modulus_degree	coeff_modulus (bits)	scale	Slots	Use-case
CKKS-A	16384	[60, 40, 40, 40, 60]	2^40	8192	aggregates, means, linear inference
CKKS-B	32768	[60, 40, 40, 40, 40, 60]	2^40	16384	deeper pipelines, fewer bootstraps
BFV-E	8192	[60, 30, 30, 60]	n/a	4096	exact counts/sums, integer joins
BGV-E	16384	[50, 30, 30, 50]	n/a	8192	integrity-critical arithmetic

6. Discussion

6.1. Comparative Analysis with Existing Systems

Compared with TEE-only analytics platforms, our framework keeps data encrypted end-to-end in the datapath, shrinking the trusted computing base to control-plane schedulers and key handles while avoiding plaintext exposure inside operator kernels. Relative to MPC systems, we trade multi-round interactivity for SIMD-friendly HE circuits that scale well across partitions and accelerators; this yields lower coordination overhead and simpler cloud deployment, at the cost of higher per-operation compute for deep arithmetic. Against HE point solutions (histograms, simple inference), our contribution is a full federated SQL/DataFrame layer with a cost model for noise budgets, packing, rotations, and bootstrapping, plus policy-aware tenancy, lineage, and DP at release bridging cryptographic rigor with production-grade orchestration.

6.2. Limitations of the Proposed Framework

Despite careful planning, HE remains costly for comparison-heavy logic, complex joins with skew, and deep non-linear ML; our optimizer mitigates depth via hashing and reduction trees but cannot eliminate bootstrapping in worst cases. Some operators still require approximate CKKS arithmetic, introducing bounded numerical error that may be unacceptable for certain regulatory reports. Operationally, the system assumes reliable KMS/HSM availability and accurate attestation; misconfigurations or cloud feature drift can degrade guarantees. Finally, developer ergonomics debugging encrypted plans, understanding noise budgets, and profiling accelerator kernels impose a learning curve that typical analytics teams may initially find steep.

6.3. Implications for Cloud Service Providers

CSPs can differentiate by offering first-class HE primitives (rotation/relinearization offload, ciphertext-native storage formats) and confidential control-plane services with portable attestation across regions. Multi-tenant clusters must expose resource isolation tuned for HE CPU cache partitioning, NUMA pinning, and predictable I/O to curb noisy-neighbor effects. Native integrations with KMS (BYOK/HYOK, threshold key support) and lineage/audit APIs will become table stakes for regulated customers seeking cross-cloud collaboration. Pricing models may need to evolve from pure vCPU/GB-hours toward cryptographic compute units that reflect bootstrapping and key-switch intensity, encouraging providers to invest in accelerators and HE-aware schedulers while giving customers transparent cost/performance trade-offs.

7. Future Work

7.1. HE-Native Operators and Compiler Advancements

We will extend the operator set with HE-native joins, range predicates, and sketching structures (e.g., encrypted Bloom/count-min variants) that reduce reliance on expensive comparisons. A domain-specific compiler will autotune packing, rotation schedules, and modulus chains per query, using learned cost models to predict noise growth and bootstrapping inflection points. Integrations with emerging GPU/ASIC kernels for relinearization, rotation, and bootstrapping plus kernel fusion for reduction trees should cut end-to-end latency while preserving ciphertext integrity and tenancy boundaries.

7.2. Adaptive Planning, Caching, and Cross-Cloud Scheduling

The optimizer will evolve toward closed-loop, adaptive planning: it will observe real executions (op counters, p99 latencies, key-switch rates) and refine plans on subsequent runs, selecting among CKKS/BFV/BGV paths, bucket sizes for encrypted hashing, and micro-batch widths. We also plan policy-safe encrypted caching of intermediates with short TTLs and plan/key fingerprints, alongside cross-cloud schedulers that co-locate shards with accelerator capacity and enforce jurisdictional constraints, improving throughput under bursty, multi-tenant workloads.

7.3. Governance, Verifiability, and Developer Ergonomics

We will strengthen governance with portable, verifiable compliance artifacts: zero-knowledge attestations proving policy adherence (residency, column-level constraints) and reproducible environment manifests bound to each query. To broaden adoption, we'll add debuggability and tooling explainable noise budgets, unit testing over synthetic plaintext mirrors, and SQL/DataFrame linters that surface cryptographic costs before execution. Finally, we will explore threshold decryption workflows and auditable key ceremonies to enable cross-organization analytics without centralizing trust, aligning the platform with stringent regulatory and audit requirements.

8. Conclusion

This work presented a practical, end-to-end framework for secure data federation and analytics in multi-tenant cloud environments using homomorphic encryption. By keeping the data plane encrypted throughout and confining trust to an attested control plane, the architecture reconciles strong confidentiality guarantees with familiar SQL/DataFrame abstractions. The design integrates tenancy-aware storage and access control, per-tenant key domains (including threshold options), and an HE-aware optimizer that cost-models noise budgets, packing, rotations, and bootstrapping. In concert with differential privacy for result release and zero-knowledge attestations for policy compliance, the system delivers defense-in-depth without collapsing into plaintext within operator kernels.

Our experimental environment spanning an on-prem coordinator and multiple cloud partitions demonstrated that careful co-design of layout, packing, and operator scheduling can yield tractable performance for real analytic workloads while preserving isolation across tenants and jurisdictions. Results indicate near-linear throughput scaling with partitions and slot packing, predictable latency under controlled bootstrapping schedules, and robust governance through lineage, attestation, and auditable configurations. While challenges remain for comparison-heavy queries, skewed joins, and deep non-linear models, the proposed framework narrows the gap between cryptographic rigor and production analytics. Looking ahead, continued advances in HE-native operators, accelerator offload, adaptive planning, and verifiable compliance artifacts can further reduce costs and broaden applicability. With growing regulatory pressure and cross-organization collaboration needs, cloud providers and enterprises alike can adopt this blueprint to minimize data movement, harden privacy, and enable secure, multi-cloud analytics at scale.

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