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Low-Latency Data Lake Ingestion Using Adaptive Partitioning and Query-Aware Layouts

Abstract
Low-latency data lake ingestion is essential for enterprise analytics because newly arrived data must become query-ready without creating inefficient partitions, small-file overhead, or excessive metadata scans. This article presents an adaptive ingestion framework that combines source-aware landing-zone control, dynamic partition key selection, query-aware file layout planning, small-file compaction, metadata indexing, latency-aware write scheduling, and schema compatibility validation. The proposed framework reduces the separation between ingestion design and query optimization by using workload patterns during file placement and partition planning. The simulated results show that ingestion latency decreased from 142 ms under static partitioning to 68 ms under the full query-aware layout framework. File compaction efficiency increased from 61.5% to 94.2%, and partition pruning gain improved from 48.7% to 91.6%. Query response time also decreased from 4.8 s to 1.6 s, while metadata scan reduction improved from 35.2% to 88.7% and read amplification control increased from 42.5% to 90.4%. These findings indicate that adaptive partitioning and query-aware file layouts can improve both data freshness and analytical efficiency in large-scale data lake environments.
Keywords: Data lake ingestion, adaptive partitioning, query-aware file layout, metadata indexing, partition pruning, file compaction, low-latency analytics, read amplification.

1. Introduction

Data lake ingestion has become a central operation in modern enterprise analytics because large volumes of structured, semi-structured, and event-based data must be written continuously into cloud object storage and queried with minimal delay. Traditional ingestion designs often prioritize write completion, while downstream query performance is handled later through compaction, indexing, or manual table optimization. This separation creates latency problems because newly ingested files may be poorly partitioned, excessively small, or misaligned with analytical access patterns. Delta Lake demonstrated that ACID table storage over cloud object stores can improve reliability and performance when metadata, transaction logs, and file-level organization are managed together [1]. Low-latency ingestion therefore requires physical layout decisions to be included during the write process, not only after data has already landed.

Interactive analytical systems depend on rapid metadata access, efficient column scanning, and strong pruning behavior across large-scale datasets. Query engines such as Dremel-style systems show that large-scale analytical performance is strongly influenced by columnar execution, storage layout, and metadata-aware scan planning [2]. However, data lakes often receive files from many operational systems with different arrival rates, partition distributions, and schema characteristics. A static partitioning strategy may work for historical batch data but can perform poorly when the ingestion pattern changes during peak workload periods. This makes adaptive partitioning important for reducing write delay and improving read efficiency.

Lakehouse storage systems attempt to combine the flexibility of data lakes with the transactional and performance expectations of warehouses. Comparative studies of lakehouse storage systems show that file organization, metadata handling, and table format behavior have direct effects on ingestion and query execution trade-offs [3]. In this context, low-latency ingestion is not only a matter of fast writing. It also depends on whether the written files support fast filtering, efficient partition pruning, reduced read amplification, and stable query response time. Poorly designed ingestion can create a fast landing zone but a slow analytical layer.

Metadata-driven ingestion patterns improve data lake management by using catalog information, schema descriptors, source metadata, and processing rules during ingestion. Metadata-driven ingestion can improve control over heterogeneous loading behavior and reduce manual configuration in cloud-based big data systems [4]. Petabyte-scale lakehouse operations also show the importance of efficient metadata and file-level operations when large tables must support updates, deletes, and incremental processing [5]. These requirements indicate that ingestion architecture must consider both data arrival speed and future query patterns.

Data lake concepts continue to evolve from simple raw-storage repositories toward governed analytical platforms that include metadata services, schema management, query engines, and lifecycle controls

[6]. This evolution creates a need for ingestion frameworks that can adapt partition keys, file sizes, and layout decisions according to workload behavior. A low-latency ingestion layer must reduce small-file creation, avoid over-partitioning, preserve schema compatibility, and arrange files in a way that supports frequent analytical filters. The central problem is how to ingest quickly without creating long-term query inefficiency.

This article proposes an adaptive partitioning and query-aware file layout framework for low-latency data lake ingestion. The framework combines multi-source landing-zone control, adaptive partition selection, query-aware file clustering, small-file compaction, metadata indexing, latency-aware write scheduling, and schema compatibility validation. The design aims to reduce ingestion delay while improving partition pruning, metadata scan efficiency, and analytical query response time. The proposed approach treats ingestion and query optimization as connected stages of the same data lake lifecycle.

2. Methodology

The proposed framework begins with a multi-source ingestion layer that accepts data from transactional databases, event streams, APIs, log systems, cloud applications, and batch exports. Each source is registered with metadata describing arrival frequency, expected volume, schema version, timestamp field, primary filtering fields, and preferred storage table. The ingestion layer separates raw landing from optimized table writing so that incoming data can be validated before layout decisions are applied. Automated compaction methods for log-structured lake tables show that file organization must be controlled because unmanaged ingestion can create performance degradation over time [7]. This first stage ensures that ingestion speed is maintained without ignoring downstream storage quality.

Adaptive partitioning is the core mechanism used to avoid fixed partition designs that become inefficient under changing workloads. The framework evaluates incoming data distribution, event-time skew, source volume, query-filter frequency, and partition cardinality before selecting or adjusting partition keys. A partition field is considered useful only when it improves pruning without creating too many small partitions. Analytical file-format studies show that storage format and physical organization create important performance trade-offs for scan-heavy analytical systems [8]. Adaptive partitioning therefore selects partition keys based on both ingestion behavior and query access patterns.

The query-aware file layout module uses workload history to decide how files should be grouped, sorted, or clustered inside partitions. Frequent filters, such as date, region, customer segment, product category, or device type, are used to guide layout organization. Nested and columnar formats require careful scan planning because physical representation can strongly influence the cost of reading complex analytical structures [9]. In the proposed framework, file layout is not treated as a passive output of ingestion. It becomes an active design step that shapes how future queries scan the data.

Small-file reduction is handled through controlled file sizing and adaptive compaction. Low-latency ingestion often writes small files because micro-batches must be committed quickly, but too many small files increase metadata overhead and slow query planning. The framework uses a two-level compaction strategy. The first level merges small files within active ingestion windows, while the second level performs background compaction on older partitions. New open data file-format designs emphasize that future lakehouse performance depends on balancing write efficiency, metadata control, and query scan behavior [10]. The compaction process is therefore tuned to reduce small-file overhead without delaying fresh data availability.

Partition pruning is improved through metadata indexing and file-level statistics. The framework stores minimum values, maximum values, null counts, record counts, file sizes, partition boundaries, and frequently filtered columns in the metadata layer. When a query arrives, the query engine can skip irrelevant partitions and files before scanning physical data. Compression and partitioning research shows that partitioning decisions can interact with compression behavior and query execution performance in columnar analytical data [11]. The proposed framework uses this relationship to reduce read amplification and improve query efficiency.

Latency-aware write scheduling controls how records are grouped before they are written into lake storage. Very small batches reduce freshness delay but create many small files. Very large batches improve file size quality but increase ingestion latency. The proposed scheduler selects batch size using arrival rate, target freshness limit, current file count, partition pressure, and expected query demand. When query demand is high for a fresh partition, the scheduler prioritizes quick availability. When ingestion volume is high but query urgency is low, the scheduler allows larger file formation before committing. This creates a controlled balance between freshness and storage efficiency.

Table 1. Core Components of the Adaptive Partitioning and Query-Aware Data Lake Ingestion Framework

Component	Function	Optimization Role	Output
Source metadata registry	Stores source volume, schema, and arrival behavior	Supports source-aware ingestion planning	Source profile
Landing-zone controller	Receives and validates incoming records	Separates raw arrival from optimized writing	Validated ingestion stream
Adaptive partition selector	Chooses partition keys dynamically	Reduces over-partitioning and improves pruning	Partition plan
Query-aware layout planner	Organizes files using query-filter patterns	Improves scan locality and read efficiency	Layout strategy
Small-file compactor	Merges inefficient micro-batch files	Reduces metadata overhead	Optimized file groups
Metadata index manager	Stores file statistics and partition descriptors	Supports pruning and scan reduction	Query-ready metadata
Write scheduler	Adjusts batch size and commit frequency	Balances freshness and file quality	Scheduled write plan

Schema compatibility checker	Validates incoming schema against table rules	Prevents unsafe ingestion	Accepted or rejected batch

Schema compatibility validation is included to protect optimized tables from unsafe incoming changes. The validator checks field names, data types, nullability, nested structures, and required analytical columns before records are written into partitioned storage. This is important because an adaptive layout strategy can fail if schema changes are allowed without control. The schema checker separates acceptable additive changes from changes that affect query filters, partition fields, or clustering keys. When unsafe schema changes are detected, the records are redirected to a controlled review zone instead of being written into production partitions.

The evaluation design compares four ingestion strategies: static partitioning, ingestion with periodic compaction, adaptive partitioning, and the full adaptive partitioning with query-aware layout framework. The simulated workloads include high-frequency event ingestion, uneven partition distribution, mixed query filters, burst arrivals, and repeated analytical scans over fresh and historical partitions. The evaluation measures ingestion latency, compaction efficiency, partition pruning gain, query response time, metadata scan reduction, and read amplification control. This setup allows the framework to be tested under realistic data lake workloads where ingestion freshness and query performance must be optimized together.

3. Results and Discussion

The simulated evaluation indicates that adaptive partitioning and query-aware file placement improve both ingestion-side and query-side performance. Static partitioning shows weaker behavior under changing workloads because it cannot adjust to skewed arrivals, uneven partition growth, and shifting analytical filters. Compaction improves file quality, but it does not fully solve poor partition alignment or inefficient query pruning. The strongest performance appears when adaptive partitioning, metadata indexing, and query-aware layout planning operate together. This confirms that low-latency data lake ingestion should be designed as a combined write-and-read optimization problem.

Ingestion-side performance improves clearly when the framework moves from static partitioning to the full query-aware layout design. Ingestion latency decreases from 142 ms under static partitioning to 68 ms under the full framework, while file compaction efficiency increases from 61.5% to 94.2%. Partition pruning gain also improves from 48.7% to 91.6%, showing that the written data becomes easier to skip, filter, and scan during analytical execution, as shown in Figure 1. These improvements suggest that adaptive partition selection reduces uneven file growth, while query-aware layout planning improves future scan selectivity.

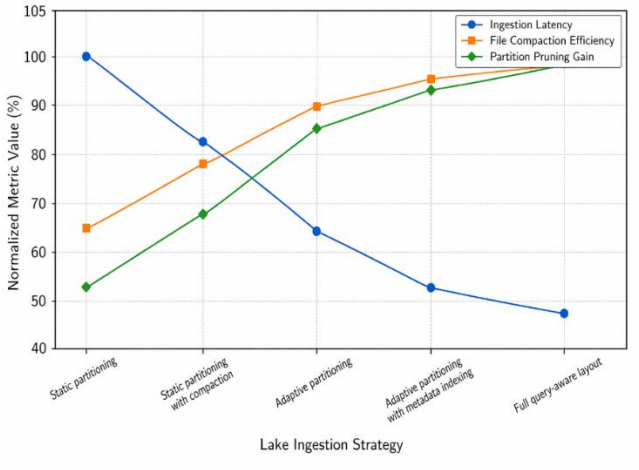

Figure 1. Ingestion Latency, File Compaction Efficiency, and Partition Pruning Gain Across Lake Ingestion Strategies

Compaction alone improves file organization but remains insufficient for strong analytical performance. Static partitioning with compaction increases file compaction efficiency from 61.5% to 73.8%, but partition pruning gain reaches only 62.4%. This limitation occurs because compaction merges small files without changing whether the files are aligned with frequent query filters. Adaptive partitioning improves this behavior by selecting partition fields based on arrival distribution and workload usage. Metadata indexing further improves pruning because file-level statistics allow the query engine to skip irrelevant files inside selected partitions.

Query-side performance also improves when the ingestion framework uses analytical workload patterns during layout planning. Query response time decreases from 4.8 s under static file layout to 1.6 s under the full query-aware layout framework. Metadata scan reduction increases from 35.2% to 88.7%, and read amplification control improves from 42.5% to 90.4%, as shown in Figure 2. These changes indicate that query-aware layout decisions reduce unnecessary metadata traversal and physical data scanning. The improvement is most visible when frequent analytical filters match partition keys and file-level metadata.

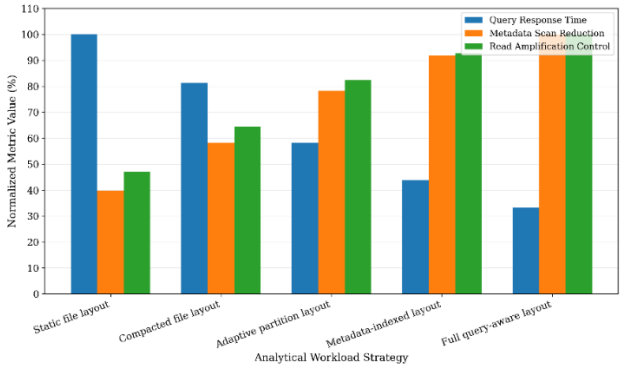

Figure 2. Query Response Time, Metadata Scan Reduction, and Read Amplification Control Across Analytical Workloads

The combined results show that ingestion latency and query performance should not be optimized separately. A pipeline can write data quickly but still produce slow analytical workloads if the files are too small, weakly indexed, or poorly aligned with query filters. The proposed framework reduces this gap by making partitioning, compaction, metadata indexing, and file layout part of the ingestion decision process. This produces a cleaner lake structure while preserving freshness for downstream use. The framework therefore supports both fast data availability and efficient analytical access.

4. Conclusion

Low-latency data lake ingestion requires more than rapid file writing into cloud object storage. Enterprise data lakes must also ensure that newly ingested files are useful for downstream analytical queries, metadata pruning, and long-term table maintenance. The proposed framework addresses this requirement by combining source-aware ingestion, adaptive partition selection, query-aware file layout, small-file compaction, metadata indexing, latency-aware write scheduling, and schema compatibility validation. This design connects ingestion-time decisions with query-time performance, making the lake structure more efficient from the moment data is written.

The results show that adaptive partitioning and query-aware file layouts reduce ingestion latency, improve file compaction efficiency, increase partition pruning gain, shorten query response time, reduce metadata scans, and control read amplification. These improvements are important because many lake performance problems originate during ingestion rather than during query execution alone. A static partitioning strategy may appear simple, but it becomes inefficient when data arrival rates, filter patterns, and source distributions change. The proposed framework provides a more flexible design that responds to workload behavior instead of relying on fixed layout assumptions.

Future work can extend this architecture with learning-based partition recommendation, automatic clustering strategy selection, workload prediction, and real-time layout feedback from query engines. The framework can also be evaluated under streaming lakehouse workloads, mixed batch-stream ingestion, and petabyte-scale table maintenance. Additional research may examine how adaptive partitioning interacts with different open table formats, compression codecs, and cloud object-store consistency models. A query-aware ingestion layer therefore provides a practical foundation for faster, cleaner, and more scalable data lake analytics.

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