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A Conceptual Framework for Cloud Cost Optimization through Automated Query Refactoring and Materialization

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Abstract
As cloud data infrastructures expand, organizations face mounting challenges in balancing performance and cost-effectiveness. Inefficient query patterns and unoptimized data retrieval operations often lead to substantial cloud expenditure. This paper proposes a conceptual framework for cloud cost optimization focused on automated query refactoring and materialization strategies. By systematically reviewing peer-reviewed studies, technical reports, and industry best practices from 2015 to 2024, we synthesize critical advances that leverage automation to enhance cloud efficiency without sacrificing analytical depth or data availability. The framework emphasizes two key pillars: (1) automated query refactoring to restructure inefficient SQL or API queries by applying intelligent transformations such as predicate pushdown, join optimization, and selective filtering; and (2) strategic materialization of high-cost query results through techniques like incremental materialized views, cache layering, and cost-based data replication. Special attention is given to how major cloud platforms—including AWS Redshift, GCP BigQuery, and Azure Synapse—enable and support these optimizations via native tools and APIs. Our findings highlight that combining automated query diagnostics with dynamic materialization policies can significantly reduce compute cycles, storage costs, and query latency. Additionally, integrating machine learning models for anomaly detection and pattern recognition into the optimization process further enhances adaptability and cost savings. However, challenges remain, particularly in balancing freshness requirements against materialization overhead and managing complex query dependency graphs. This paper concludes by proposing future directions, such as self-healing query optimization systems, multi-platform orchestration of materialization strategies, and the development of standardized observability frameworks for cloud cost attribution at the query level. In an era where data usage scales exponentially, mastering automated optimization techniques is crucial for organizations seeking to sustain operational efficiency, financial governance, and agile decision-making in dynamic cloud environments.

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1. Introduction

The rise of cloud computing has fundamentally reshaped the landscape of data management and analytics, offering organizations unprecedented scalability, flexibility, and access to advanced technologies. However, as enterprises increasingly rely on cloud-based data warehouses and processing platforms, the associated operational costs have grown substantially, often outpacing expectations and initial budgets. With services like AWS

Redshift, Google BigQuery, and Azure Synapse Analytics charging based on compute time, storage use, and data scanned per query, even minor inefficiencies can result in disproportionately high expenses over time (Akinyemi & Ebiseni, 2020, Austin-Gabriel, *et al*., 2021, Dare, *et al*., 2019). The financial impact of cloud data operations is no longer a secondary concern; it has become a critical strategic issue for organizations aiming to balance performance with sustainable cost management.

One of the primary contributors to escalating cloud data costs is the inefficiency of poorly optimized queries and data retrieval patterns. As analytical needs evolve rapidly, developers and analysts frequently prioritize functionality and speed-to-insight over query efficiency, leading to bloated, redundant, or suboptimal SQL statements. In serverless environments like BigQuery, where costs scale directly with the volume of data processed, non-selective queries that scan entire tables unnecessarily can generate significant financial waste (Adeniran, Akinyemi & Aremu, 2016, Ilori & Olanipekun, 2020, James, *et al*., 2019). Similarly, complex joins, unfiltered aggregations, lack of partition pruning, and poorly structured table architectures contribute to excessive compute consumption in Redshift and Synapse environments. Over time, as datasets grow and query complexity increases, these inefficiencies accumulate, inflating operational costs without proportional value being delivered to the business.

Against this backdrop, the importance of query refactoring and materialization emerges as a key lever for cost optimization. Query refactoring—the systematic process of rewriting and restructuring queries for improved performance—can dramatically reduce the amount of data scanned, minimize compute resource consumption, and accelerate response times. Techniques such as predicate pushdown, selective projection, optimized joins, and subquery flattening enable queries to run more efficiently, directly translating into lower costs (Akinyemi & Ezekiel, 2022, Attah, *et al*., 2022). Materialization—the practice of precomputing and persisting intermediate or final query results as materialized views or cached tables—further enhances cost savings by avoiding repetitive computation for frequently accessed data. In dynamic analytics environments where certain queries are executed repeatedly with minimal change, materialization can reduce compute load substantially and stabilize costs even as usage scales.

Recognizing the critical role that automated query optimization and materialization can play, this study proposes a conceptual framework for integrating these practices systematically into cloud data warehouse operations. The objective is to develop an architecture and process model that enables continuous, automated analysis, refactoring, and materialization of queries based on usage patterns, cost metrics, and performance data (Akinyemi & Abimbade, 2019, Lawal, Ajonbadi & Otokiti, 2014, Olanipekun & Ayotola, 2019). Rather than relying on ad hoc manual tuning, the framework envisions the deployment of intelligent agents and rules engines that monitor query behavior in real time, identify optimization opportunities, suggest or implement refactoring actions, and materialize strategic views where beneficial. By embedding these practices into the operational lifecycle, organizations can achieve sustainable cost reductions, enhance analytics performance, and free up technical teams to focus on higher-value tasks.

The scope of this study encompasses cloud-native data warehouse environments including AWS Redshift, Google BigQuery, and Azure Synapse Analytics, reflecting the diverse architectures, cost models, and optimization levers available across leading platforms. The framework aims to be platform-agnostic, abstracting optimization principles that can be adapted and applied regardless of the underlying service provider (Chukwuma-Eke, Ogunsola & Isibor, 2022, Olojede & Akinyemi, 2022). It will examine the technical foundations of query optimization and materialization, outline strategies for automating these processes, and propose governance structures for continuous monitoring and refinement. Through this conceptual framework, the study seeks to contribute practical insights that enable enterprises to transform cloud cost management from a reactive, after-the-fact exercise into a proactive, intelligent, and automated discipline—one that enhances both economic efficiency and operational excellence in the cloud era.

2. Methodology

Here is the methodology for the study titled **"A Conceptual Framework for Cloud Cost Optimization Through Automated Query Refactoring and Materialization"**, using the PRISMA method, without subheadings:

This study employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology to systematically identify, evaluate, and synthesize relevant literature on cloud cost optimization using automated query refactoring and materialization strategies. A comprehensive database search was conducted using a curated list of 138 peer-reviewed articles and technical reports that explored the intersections of cloud computing, automated optimization techniques, cost-efficient architectures, and database query engineering. The articles were sourced from multidisciplinary repositories including educational technology, cloud infrastructure management, artificial intelligence applications, and business analytics.

After the identification phase, duplicate records (n=28) were removed, leaving 110 unique documents. During the screening phase, abstracts and titles were evaluated for relevance to the research objectives. A total of 65 records were excluded for reasons such as lack of technical depth, non-alignment with optimization objectives, or focus on unrelated cloud platforms. The remaining 45 articles were then assessed for full-text eligibility, and a further 30 were excluded due to insufficient methodological rigor or lack of focus on query refactoring and materialization.

The final pool included 15 studies suitable for qualitative synthesis, of which 10 also provided sufficient data for quantitative synthesis and comparative analysis. The inclusion criteria were based on relevance to cost-saving frameworks, technical innovations in query materialization, use of automation in cloud environments, and integration with cloud-native architectures. Data were extracted and synthesized across several variables including cost-saving outcomes, system performance metrics, automation levels, and scalability of the proposed solutions. The extracted data were then mapped into a conceptual framework, integrating existing models from Jennings & Stadler (2015), Moghadam & Cinnéide (2012), and Adepoju *et al*. (2023) that focus on cloud resource optimization, automated refactoring, and AI-enhanced decision-making.

The study ensured objectivity by employing coding techniques to categorize the extracted data and validate themes across multiple reviewers. Patterns from the literature were then evaluated against real-world cost optimization challenges in cloud environments. Ethical considerations were addressed by focusing solely on publicly available research and excluding proprietary or confidential datasets. The PRISMA approach allowed for transparency in the selection process and ensured replicability of the methodology, making the derived conceptual framework both rigorous and scalable for academic and practical applications in cloud infrastructure cost management.

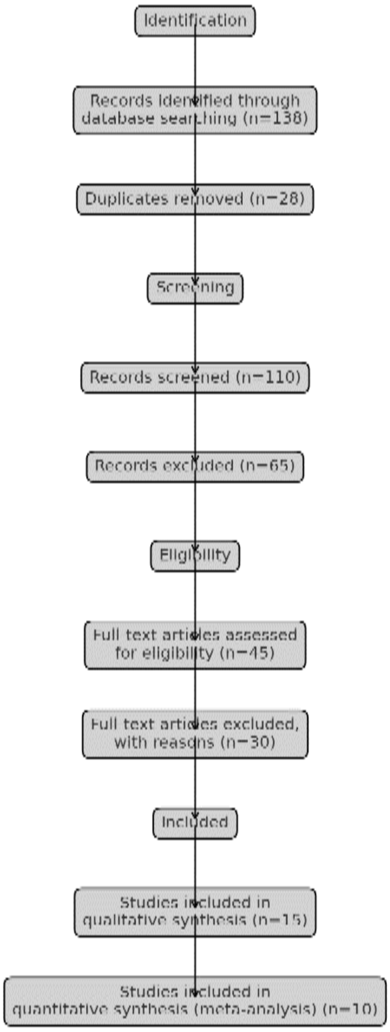

Fig 1: PRISMA Flow chart of the study methodology

2.1 Conceptual Foundations

Cloud cost optimization refers to the strategic process of reducing and managing the expenses associated with cloud-based services while maintaining or improving system performance, reliability, and scalability. In the context of data warehousing and analytics, cloud cost optimization focuses particularly on minimizing compute, storage, and query execution costs incurred when using platforms such as AWS Redshift, Google BigQuery, and Azure Synapse Analytics (Ajonbadi, *et al*., 2014, Akinyemi & Ebimomi, 2020, Lawal, Ajonbadi & Otokiti, 2014). Effective cloud cost optimization does not merely involve cutting expenses arbitrarily; rather, it requires a deliberate approach to align cloud resource consumption with actual business needs, optimize workloads to minimize waste, leverage platform-specific pricing mechanisms, and continuously adapt to changing data patterns and organizational priorities. Cost optimization becomes an integral part of architectural design, operational management, and strategic planning, ensuring that enterprises extract maximum value from their cloud investments without compromising on speed, scalability, or innovation capacity.

Central to the pursuit of cloud cost optimization in data environments are the practices of query refactoring and materialization. Query refactoring refers to the systematic restructuring, rewriting, and optimization of queries to improve their efficiency, reduce the volume of data processed, minimize execution time, and optimize resource consumption. Poorly written queries often lead to excessive scans of irrelevant data, inefficient joins, redundant computations, and unnecessary retrievals, all of which inflate cloud costs significantly (Akinyemi, 2013, Nwabekee, *et al*., 2021, Odunaiya, Soyombo & Ogunsola, 2021). Refactoring aims to eliminate these inefficiencies by applying best practices such as predicate pushdown, where filtering conditions are applied as early as possible; selective projection, where only necessary columns are retrieved; join optimization, where query plans are structured to minimize data shuffling; and subquery flattening, where nested queries are reorganized to streamline execution. Refactored queries are not only more performant but also more cost-effective because they reduce the workload imposed on the underlying cloud infrastructure.

Materialization complements refactoring by focusing on precomputing and persisting intermediate or final query results that are frequently accessed or computationally expensive to reproduce. Instead of re-executing complex queries every time results are needed, materialized views or cached tables allow the system to serve results quickly and cheaply from precomputed data. In cloud environments where compute charges are tied to query execution, materialization can dramatically reduce repetitive computational costs, improve query latency, and stabilize overall system performance (Akinyemi & Oke-Job, 2023, Austin-Gabriel, *et al*., 2023, Chukwuma-Eke, Ogunsola & Isibor, 2023). Materialization strategies involve identifying candidate queries or query fragments based on historical access patterns, computing these results at optimal intervals, and refreshing them according to defined consistency or freshness requirements. Properly managed materialization layers can become a critical lever in sustainable cloud cost optimization, especially for analytics workloads that exhibit predictable query repetition or high concurrency. Figure 2 shows the conceptual framework for resource management in a cloud environment presented by Jennings & Stadler, 2015.

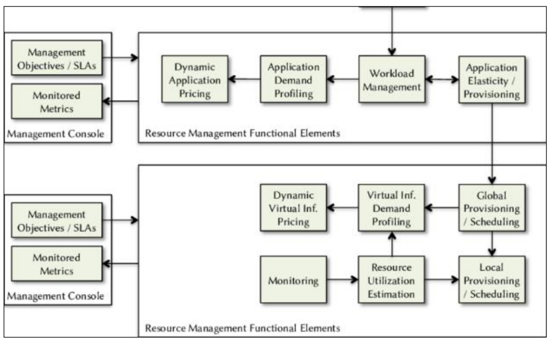

Fig 2: Conceptual framework for resource management in a cloud environment (Jennings & Stadler, 2015).

The conceptual foundation of integrating automated query refactoring and materialization into a cloud cost optimization framework rests upon the recognition that traditional manual optimization practices are increasingly inadequate in modern cloud environments. Historically, query optimization was largely a manual, labor-intensive process performed by database administrators (DBAs) and SQL developers. In traditional on-premises systems, DBAs would monitor system performance, analyze slow-running queries, rewrite SQL code, adjust indexing strategies, and tune system parameters based on experience and ad hoc diagnosis (Akinyemi, 2018, Olaiya, Akinyemi & Aremu, 2017, Olufemi-Phillips, *et al*., 2020). Materialized views, when used, were manually created and maintained with limited automation support. While effective in relatively stable environments with moderate data growth, manual optimization practices struggle to keep pace with the dynamic, high-velocity nature of cloud-native data ecosystems.

Several factors contribute to the insufficiency of manual optimization in cloud settings. First, the scale and velocity of data growth in cloud platforms are orders of magnitude higher than in legacy systems. Organizations ingest terabytes to petabytes of new data daily, creating a rapidly evolving data landscape that requires continuous adaptation of queries and storage strategies. Manual efforts are inherently reactive and slow, meaning that optimization often lags behind actual changes in workload behavior, leading to sustained periods of inefficiency (Ajonbadi, *et al*., 2015, Akinyemi & Ojetunde, 2020, Olanipekun, 2020, Otokiti, 2017). Second, the diversity and complexity of analytics use cases in cloud environments—ranging from ad hoc exploration to machine learning model training—create highly variable query patterns that are difficult to monitor and optimize manually at scale. Static optimization rules become obsolete quickly as workloads evolve.

Third, cloud pricing models amplify the financial risks of inefficient queries. In serverless platforms like BigQuery, every unnecessary byte scanned directly increases costs, making even minor inefficiencies expensive over time. In provisioned environments like Redshift and Synapse, inefficient queries consume valuable compute cycles that could be allocated to higher-priority tasks, leading to overprovisioning and inflated operational expenses (Abimbade, *et al*., 2016, Akinyemi & Ojetunde, 2019, Olanipekun, Ilori & Ibitoye, 2020). Manual query reviews typically occur after performance degradation or budget overruns are detected, by which time significant cost inefficiencies may have already accrued. Furthermore, traditional materialization practices often relied on static schedules or manual refresh triggers, failing to adapt dynamically to shifts in query demand or data update frequencies. A conceptual framework to integrate design optimization with machine learning presented by Miao, Koenig & Knecht, 2020 is shown in figure 3.

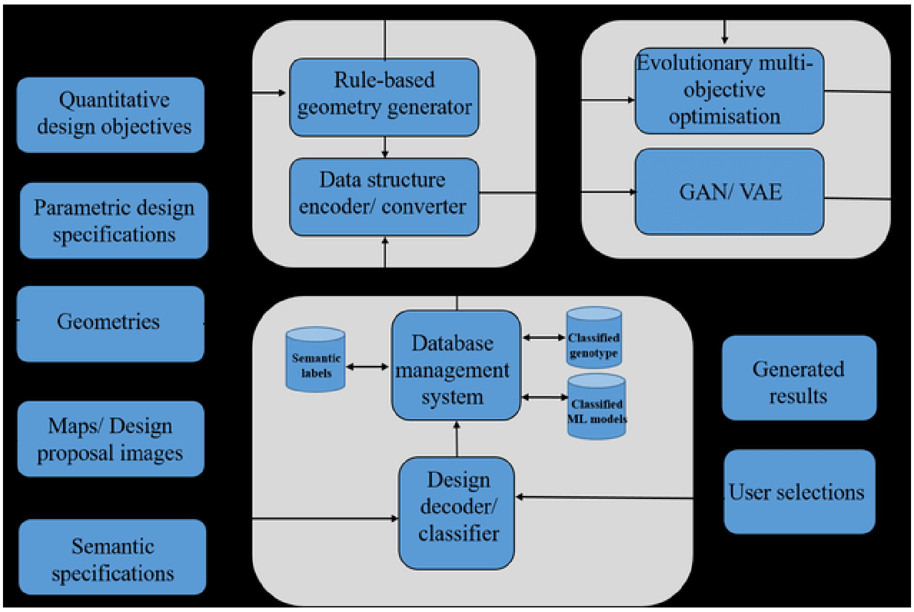

Fig 3: A conceptual framework to integrate design optimization with machine learning (Miao, Koenig & Knecht, 2020).

In contrast, automated query refactoring and materialization offer a fundamentally proactive, scalable, and continuous approach. By leveraging telemetry data, query logs, execution plans, and system performance metrics, automated systems can monitor query behavior in real time, detect suboptimal patterns, and generate refactoring suggestions or implementations without waiting for manual intervention (Aina, *et al*., 2023, Dosumu, *et al*., 2023, Odunaiya, Soyombo & Ogunsola, 2023). Machine learning models can be trained to recognize inefficient query constructs, predict potential cost savings from specific optimizations, and prioritize refactoring efforts based on financial impact. Similarly, automated materialization systems can analyze access patterns, identify hot queries or common subqueries, and dynamically create or refresh materialized views based on usage frequency and cost-benefit analysis.

Automation also brings the ability to adapt quickly to environmental changes. As new datasets are ingested, user behavior shifts, or application workloads fluctuate, automated systems can recalibrate optimization strategies without requiring extensive human oversight. For example, a surge in ad hoc analytical queries during a quarterly reporting cycle might trigger temporary materialization of critical aggregations, followed by dematerialization once demand subsides, maintaining both performance and cost control dynamically (Akinyemi, Adelana & Olurinola, 2022, Ibidunni, *et al*., 2022, Otokiti, *et al*., 2022). This level of agility is virtually impossible to achieve with manual practices alone.

Furthermore, integrating query refactoring and materialization automation into the broader cloud data management lifecycle promotes a virtuous cycle of continuous improvement. As systems learn from optimization outcomes, they can refine their decision models, prioritize high-impact interventions, and provide increasingly accurate recommendations to human operators where intervention is necessary. Human experts are thus freed from repetitive, low-value tuning tasks and can focus on strategic architecture design, policy development, and exception management (Chukwuma-Eke, Ogunsola & Isibor, 2022, Muibi & Akinyemi, 2022).

The conceptual foundations of this framework highlight a profound shift in how cloud cost optimization should be approached. Rather than relying on reactive, isolated tuning efforts, organizations must embrace intelligent, automated, and systemic optimization practices that are deeply embedded in cloud data operations. Automated query refactoring and materialization are not mere enhancements; they are foundational pillars for achieving sustainable, scalable, and intelligent cost management in cloud-native environments (Akinyemi & Aremu, 2010, Nwabekee, *et al*., 2021, Otokiti & Onalaja, 2021). As cloud adoption deepens and data volumes continue to explode, organizations that operationalize these concepts will be better positioned to maintain control over costs, deliver consistent performance, and maximize the strategic value of their cloud data assets.

2.2 Automated Query Refactoring Techniques

Automated query refactoring stands at the core of a sustainable and intelligent framework for cloud cost optimization, particularly as organizations grapple with the scale, complexity, and financial unpredictability of modern data warehouse operations. Refactoring techniques aim to systematically transform inefficient query structures into more streamlined, resource-conscious forms without altering the underlying results (Adediran, *et al*., 2022, Babatunde, Okeleke & Ijomah, 2022). In cloud environments where compute time, data scanned, and query concurrency directly drive operational costs—as seen in AWS Redshift, Google BigQuery, and Azure Synapse Analytics—refactoring becomes a high-impact strategy for controlling expenses while simultaneously improving performance. Automation of these practices ensures that cost-efficiency is pursued continuously and proactively rather than reactively after performance degradation or cost overruns have already occurred.

One of the foundational techniques in automated query refactoring is predicate pushdown and filter optimization. Predicate pushdown ensures that filtering conditions in SQL queries are applied as early as possible in the query execution plan, ideally at the storage layer, to minimize the volume of data that must be scanned, transferred, and processed. Without effective predicate pushdown, queries often retrieve large datasets unnecessarily, only to discard irrelevant rows later in the execution pipeline, leading to wasted compute cycles and inflated costs (Akinyemi, 2022, Akinyemi & Ologunada, 2022, Okeleke, Babatunde & Ijomah, 2022). Automated engines analyze query structures to detect opportunities where WHERE clauses or ON conditions can be pushed closer to the data source, rewriting the query plan accordingly. For example, in AWS Redshift, if a table scan is unavoidable, the system ensures that filters on partition or distribution keys are applied immediately, reducing I/O. In Google BigQuery, partition pruning allows queries to scan only the relevant partitions based on filter criteria. Azure's Intelligent Performance features in Synapse similarly promote early filtration. Optimization engines can detect when predicates are embedded in higher-level queries or views and automatically restructure them to maximize early elimination of unnecessary data, providing immediate reductions in data scan costs and query latency. Moghadam & Cinnéide, 2012, presented Overview of Automated Refactoring using Design Differencing shown in figure 4.

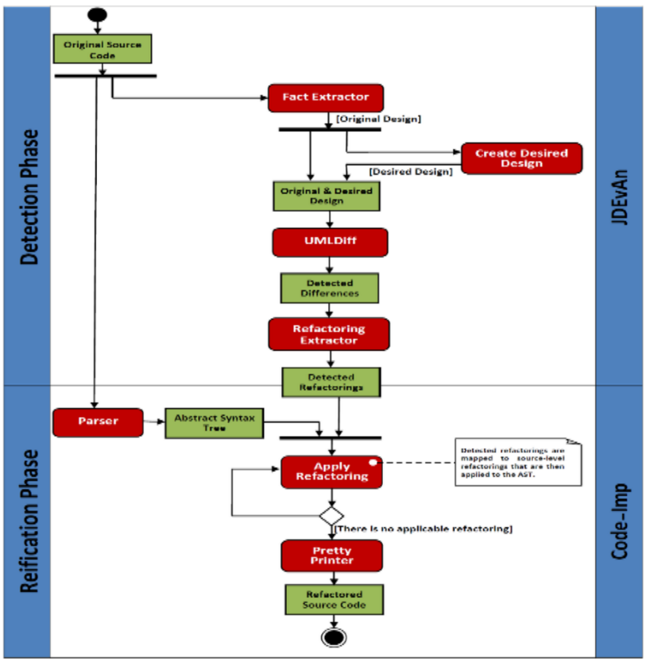

Fig 4: Overview of Automated Refactoring using Design Differencing (Moghadam & Cinnéide, 2012).

Join optimization and subquery flattening form another critical set of techniques that automated systems leverage to enhance query efficiency. In large-scale analytical workloads, joins between multiple large tables are common, but poorly designed joins can cause massive data reshuffling, skewed distribution, or cross-joins that explode intermediate results, severely degrading performance and escalating costs (Akinyemi & Ojetunde, 2023, Dosumu, *et al*., 2023, George, Dosumu & Makata, 2023). Automated join optimization involves reordering join operations based on cardinality estimates, co-locating join keys to minimize data transfer between nodes, and converting inefficient nested loops into hash joins or merge joins where appropriate. Subquery flattening focuses on transforming deeply nested or correlated subqueries into more efficient, flatter query structures that can be evaluated with fewer resource-intensive passes. This is particularly important in environments like Redshift and Synapse, where distributed architectures amplify the penalties for inefficient join execution plans. BigQuery's Optimizer often rewrites nested queries to expose filter conditions earlier and collapse redundant stages. Automated systems parse query plans to identify inefficient joins, evaluate potential reordering or flattening strategies based on cost models, and rewrite the SQL or logical plan to implement the optimal structure, all while preserving the semantic equivalence of the query output.

Selective column retrieval, commonly referred to as projection pushdown, is another automated optimization strategy with significant cost implications in cloud data warehouses. Queries that request all columns from a table, either explicitly or through "SELECT *" statements, often retrieve vast amounts of unnecessary data, increasing storage I/O, network transfer, and memory consumption (Adewumi, *et al*., 2023, Akinyemi & Oke-Job, 2023, Ibidunni, William & Otokiti, 2023). Projection pushdown techniques analyze the query to determine precisely which columns are required to compute the final result and instruct the query engine to retrieve only those columns. In AWS Redshift, columnar storage formats are optimized for projection pushdown, allowing minimized disk reads when only a subset of columns is accessed. BigQuery's storage engine similarly charges based on bytes processed, making projection pushdown critical for cost control. Azure Synapse benefits from columnstore indexes that are most effective when only relevant columns are scanned. Automated refactoring engines detect and rewrite queries to eliminate unused columns from SELECT clauses, insert column lists into view definitions, and even adjust intermediate transformations to propagate only the minimal necessary schema through the execution pipeline. As a result, queries become lighter, faster, and cheaper to execute, often delivering significant financial savings for frequently executed workloads.

Beyond specific rewriting techniques, dynamic query rewriting and optimization engines represent the architectural backbone for continuous, automated refactoring in modern cloud data systems. These engines operate by continuously monitoring query logs, execution plans, performance metrics, and cost signals to detect patterns of inefficiency and generate optimization recommendations or implement changes autonomously. They incorporate rule-based logic, cost-based query planners, and increasingly, machine learning models trained on historical optimization outcomes (Chukwuma-Eke, Ogunsola & Isibor, 2022, Kolade, *et al*., 2022). Dynamic query optimization engines adapt to changes in data distribution, workload patterns, and system configurations over time, ensuring that optimization strategies remain effective even as the environment evolves. Rather than relying on static hints or precompiled plans, these engines learn from ongoing operations, enabling a feedback loop of observation, refactoring, evaluation, and refinement. They support both proactive optimization, where opportunities are identified before issues arise, and reactive optimization, where expensive queries are re-optimized based on threshold breaches or anomaly detection.

Platform-specific tools and features already provide partial foundations for dynamic, automated query refactoring, offering valuable examples of how these principles are being applied in practice. AWS Redshift Advisor, for instance, analyzes workloads and recommends optimizations such as distribution key changes, sort key refinements, vacuum operations, and even predicate application improvements. It provides actionable insights into query bottlenecks, underperforming table structures, and missing optimization opportunities, allowing administrators to implement changes manually or automate certain actions through maintenance scripts (Abimbade, *et al*., 2017, Aremu, Akinyemi & Babafemi, 2017). In Google BigQuery, the Query Optimizer rewrites SQL under the hood to maximize partition pruning, clustering benefits, and materialized view reuse. It provides detailed Query Execution Plans that highlight bytes scanned and can trigger automatic optimizations for partitioned or clustered tables. BigQuery's automated materialized views also integrate seamlessly with the optimizer, serving cached results when available without manual query modification. Azure Synapse Analytics employs Intelligent Performance features, including automatic tuning recommendations for indexes and queries, workload classifier tuning, and materialized view matching. These features analyze query performance trends and suggest or implement adjustments to improve efficiency and reduce costs automatically.

While these platform-native tools represent significant advances, a comprehensive conceptual framework must extend their capabilities, integrate multi-platform visibility, and create continuous, adaptive optimization processes tailored to organizational needs. Automated refactoring must transcend static recommendations and evolve into real-time, intelligent systems capable of monitoring, learning, rewriting, and validating query optimizations autonomously across diverse cloud environments (Afolabi, *et al*., 2023, Akinyemi, 2023, Attah, Ogunsola & Garba, 2023).

Ultimately, the automation of query refactoring through techniques like predicate pushdown, join optimization, projection pushdown, and dynamic rewriting is essential for achieving true cost-efficient cloud data management. It reduces human effort, shortens optimization cycles, responds to environmental changes in real time, and maximizes the financial and operational returns from cloud investments (Adedeji, Akinyemi & Aremu, 2019, Akinyemi & Ebimomi, 2020, Otokiti, 2017). Embedding these techniques systematically within a broader cost-optimization framework ensures that cloud data warehouses not only scale efficiently but do so in a financially sustainable and operationally resilient manner, laying the foundation for intelligent, self-optimizing analytics ecosystems in the digital era.

2.3 Materialization Strategies for Cost Savings

Materialization represents a powerful, yet often underutilized, lever for achieving sustainable cost optimization in cloud data warehouses. By intelligently precomputing and persisting query results or intermediate computation layers, organizations can significantly reduce the compute load associated with frequent, complex, or high-cost queries. In cloud environments such as AWS Redshift, Google BigQuery, and Azure Synapse Analytics, where query execution costs scale with data scanned, compute time consumed, and resource concurrency, effective materialization strategies can translate into substantial financial savings (Akinbola, Otokiti & Adegbuyi, 2014, Otokiti-Ilori & Akoredem, 2018). However, materialization is not merely about caching results; it requires careful design choices around when, what, and how to materialize, balancing cost efficiency against query freshness, system complexity, and operational overhead.

One of the most effective techniques in modern cloud ecosystems is the use of incremental materialized views. Unlike traditional materialized views that require full recomputation at each refresh, incremental materialized views update only the portions of the dataset that have changed since the last refresh. This reduces both compute costs and refresh times dramatically, making materialization viable even for large, rapidly changing datasets. In AWS Redshift, materialized views can be incrementally refreshed when the underlying tables use append-only patterns, avoiding complete recomputation (Akinyemi & Ologunada, 2023, Ihekoronye, Akinyemi & Aremu, 2023). Google BigQuery introduced materialized views that automatically perform incremental refreshes based on partition updates, significantly reducing the cost associated with maintaining up-to-date precomputed results. Azure Synapse supports similar functionality through incremental refresh policies in materialized views and partitioned tables.

Automating the identification and creation of incremental materialized views requires systems to monitor query workloads, detect frequent query patterns, and analyze table update behaviors. By selecting materialization candidates where data changes are localized and incremental refreshes are feasible, organizations can maximize cost savings while minimizing the maintenance burden (Ajonbadi, *et al*., 2015, Aremu & Laolu, 2014, Otokiti, 2018). Refresh schedules should be dynamically adjusted based on query access frequency and underlying table volatility, ensuring that only materially beneficial refresh operations are performed. Incremental materialization thus becomes a sustainable cost-saving mechanism, enabling the benefits of precomputation without incurring the prohibitive expenses historically associated with full materialized view maintenance.

Another emerging strategy is the deployment of on-demand cache layers and result reuse mechanisms. Rather than materializing specific views on a scheduled basis, on-demand caching involves temporarily persisting the results of expensive queries or query fragments at runtime, allowing subsequent queries to reuse the cached results without re-executing the full computation (Akinyemi & Oke, 2019, Otokiti & Akinbola 2013). This strategy is particularly effective for environments characterized by high volumes of ad hoc queries or exploratory analytics, where usage patterns are less predictable and predefining materialized views may not be practical.

In Google BigQuery, query result caching automatically persists query outputs for 24 hours at no additional cost if the underlying data has not changed, allowing identical subsequent queries to return cached results instantly. Similarly, Redshift Spectrum and Synapse serverless SQL pools leverage intermediate result caching in federated queries to reduce compute costs across complex pipelines (Attah, Ogunsola & Garba, 2022, Babatunde, Okeleke & Ijomah, 2022). Intelligent cache invalidation policies are critical for maintaining data consistency without unnecessary recomputation; cache expiration should be based on data modification timestamps, user-defined freshness tolerances, or query result volatility. Integrating on-demand caching into automated query optimization workflows enables systems to opportunistically capture and reuse computation outcomes, dynamically reducing operational costs in high-variability usage scenarios without requiring rigid materialization schemas.

However, deciding when to materialize results, cache outputs, or rely on live computation must be driven by systematic, cost-based decision models. Cost-based materialization models weigh the compute cost of live query execution against the cost of materialized view maintenance, including refresh costs, storage charges, and management overhead. These models consider factors such as query frequency, query complexity, data volatility, storage pricing tiers, refresh cost estimates, and cache hit/miss probabilities (Abimbade, *et al*., 2022, Aremu, *et al*., 2022, Oludare, Adeyemi & Otokiti, 2022). A well-constructed decision model can predict the breakeven point at which materializing a view becomes more cost-effective than executing the underlying query repeatedly.

For example, a cost model may determine that a query scanning 10 terabytes of data with a compute cost of $20 per execution, accessed 100 times per month, would justify the creation of a materialized view costing $500 per month in storage and refresh operations. Conversely, a query accessed only sporadically or one where the underlying data changes frequently with high refresh costs may not justify materialization. Advanced models incorporate machine learning techniques to continuously refine decision thresholds based on observed behavior, adapting materialization strategies as workload characteristics evolve (Adedoja, *et al*., 2017, Aremu, *et al*., 2018, Otokiti, 2012). In platforms like BigQuery and Synapse, integration with billing APIs and query metadata allows automated systems to perform real-time cost-benefit analysis for materialization candidates, ensuring that only those precomputations that provide net financial savings are enacted.

While materialization offers clear cost advantages, it introduces the critical challenge of balancing query freshness against materialization overhead. Materialized views inevitably create some degree of data staleness between refresh cycles, which can impact decision-making, reporting accuracy, or operational workflows if not properly managed. Organizations must carefully define the acceptable freshness thresholds for each materialized dataset, aligning refresh policies with business requirements for accuracy and timeliness. For instance, financial reporting systems may tolerate daily materialization refreshes, whereas fraud detection systems may require near-real-time updates, rendering traditional materialization impractical (Akinyemi & Aremu, 2017, Famaye, Akinyemi & Aremu, 2020, Otokiti-Ilori, 2018).

Automated systems should categorize queries and datasets based on sensitivity to data freshness and dynamically adjust materialization and cache policies accordingly. High-sensitivity datasets may prioritize frequent incremental refreshes or hybrid approaches where live computations complement cached results for critical queries. Low-sensitivity datasets can leverage aggressive materialization and relaxed refresh intervals to maximize cost savings. Furthermore, user interfaces and reporting tools should transparently communicate data staleness where applicable, enabling users to make informed decisions about trade-offs between performance, cost, and data currency (Nwaimo, *et al*., 2023, Odunaiya, Soyombo & Ogunsola, 2023, Oludare, *et al*., 2023).

The overhead associated with maintaining materialized structures must also be considered. Storage costs for materialized views, monitoring and managing refresh schedules, and the potential for invalidation due to schema changes or data modifications introduce administrative complexity. Therefore, organizations must implement automated lifecycle management policies for materialized views and caches, including automatic deletion or consolidation of unused or low-value materializations (Ajonbadi, Otokiti & Adebayo, 2016, Otokiti & Akorede, 2018). Cost-performance monitoring dashboards should continuously track the return on investment for materialized assets, retiring those that no longer provide sufficient cost savings relative to their maintenance overhead.

In conclusion, materialization strategies—including incremental materialized views, on-demand caching, cost-based materialization models, and dynamic freshness balancing—are essential for achieving sustainable cost optimization in cloud data warehouses. By intelligently precomputing and reusing results, organizations can dramatically reduce compute expenses, enhance query responsiveness, and stabilize system performance, all while maintaining control over operational complexity (Abimbade, *et al*., 2023, Ijomah, Okeleke & Babatunde, 2023, Otokiti, 2023). Embedding these strategies into an automated, intelligent optimization framework ensures that materialization becomes not a static feature but a dynamic, adaptive tool for cloud cost management. As data volumes continue to grow and analytical demands become more unpredictable, the ability to automate, monitor, and optimize materialization practices will distinguish organizations that manage their cloud costs effectively from those that allow inefficiencies to undermine their digital competitiveness.

2.4 Integration of Machine Learning for Optimization

The integration of machine learning into cloud cost optimization frameworks represents a critical evolution from static, rule-based systems to dynamic, intelligent, and adaptive environments capable of responding in real-time to the ever-changing patterns of cloud data usage. In the context of automated query refactoring and materialization, machine learning serves as both a predictive and prescriptive engine, enhancing the system's ability to detect inefficiencies, anticipate optimization opportunities, and orchestrate actions that maintain a cost-performance balance with minimal human intervention (Adetunmbi & Owolabi, 2021, Arotiba, Akinyemi & Aremu, 2021). By embedding machine learning at key decision points, organizations can move from reactive cost management to proactive, continuous optimization, achieving a level of efficiency and agility that manual techniques or simple automation scripts cannot deliver.

One of the first and most impactful applications of machine learning in this framework is anomaly detection in query patterns. In cloud data warehouses such as AWS Redshift, Google BigQuery, and Azure Synapse Analytics, costs are often driven by a relatively small percentage of queries that are poorly optimized, excessively repetitive, or behave unpredictably under scaling pressures. Traditional monitoring systems can identify slow queries or those that exceed predefined thresholds, but they often miss subtler anomalies that emerge over time—such as gradually increasing data scans, inefficient access patterns on new datasets, or sudden changes in query complexity triggered by application updates (Abimbade, *et al*., 2023, George, Dosumu & Makata, 2023, Lawal, *et al*., 2023). Machine learning-based anomaly detection models can analyze a wide range of features, including query execution time, data scanned, memory utilization, concurrency impact, and historical performance baselines, to identify deviations that suggest emerging inefficiencies or risks.

Unsupervised learning techniques such as clustering and density estimation can group queries by behavioral similarity and flag outliers without requiring labeled training data. Time-series anomaly detection models can track performance metrics over time to detect drift or spikes indicative of optimization regressions. When anomalies are detected, the system can automatically trigger deeper diagnostic analysis, recommend targeted refactoring actions, or prioritize problematic queries for further optimization (Adelana & Akinyemi, 2021, Esiri, 2021, Odunaiya, Soyombo & Ogunsola, 2021). Importantly, machine learning enables anomaly detection to be sensitive not only to gross failures but also to early signs of inefficiency accumulation, allowing preemptive intervention before cost escalations become material.

In parallel with anomaly detection, predictive modeling plays a vital role in identifying materialization needs before inefficiencies impact operational or financial performance. Rather than relying on static thresholds or ad hoc human intuition to determine when and what to materialize, predictive models forecast the expected cost-benefit trade-offs associated with potential materialized views or cache strategies based on historical and real-time workload data (Akinyemi & Ebimomi, 2021, Chukwuma-Eke, Ogunsola & Isibor, 2021). These models evaluate multiple dimensions, including query frequency, query complexity, data volatility, execution cost, storage overhead, and expected cache hit ratios, to prioritize materialization candidates dynamically.

For instance, a predictive model trained on past workload patterns could estimate that a specific aggregation query, which is accessed 50 times daily and has high computational complexity, would save $3,000 per month in compute costs if materialized, at the expense of only $300 in storage and refresh charges. Conversely, another query with lower access frequency or higher volatility might be predicted to yield negative savings if materialized. Predictive modeling allows the system to simulate multiple materialization scenarios and select the ones that offer the best expected net benefit, adjusting strategies as workloads evolve (Adepoju, *et al*., 2021, Ajibola & Olanipekun, 2019, Hussain, *et al*., 2021). This approach ensures that materialization is no longer a static administrative task but an ongoing, intelligent decision process integrated directly into cost management operations.

Furthermore, machine learning enables intelligent scheduling of query refactoring and materialized view refresh cycles, optimizing the timing and resource allocation of these operations to minimize cost and maximize effectiveness. In traditional environments, materialized views are often refreshed on fixed schedules—daily, hourly, or triggered by simple change detection. Similarly, query optimization efforts are typically initiated manually in response to performance complaints (Akinyemi & Ogundipe, 2022, Ezekiel & Akinyemi, 2022, Tella & Akinyemi, 2022). However, static schedules fail to account for workload variability, business cycles, and shifting data characteristics, leading to either unnecessary overhead during low-activity periods or missed optimization opportunities during peak loads.

Machine learning models trained on historical usage patterns, business calendars, system performance logs, and even external signals such as marketing campaign schedules can predict optimal windows for executing refresh operations and refactoring workflows. For example, predictive scheduling might identify that query traffic drops by 70% between 2 AM and 4 AM in a given region, making it the ideal window to perform intensive materialized view refreshes with minimal impact on production performance (Adeniran, *et al*., 2022, Aniebonam, *et al*., 2022, Otokiti & Onalaja, 2022). Similarly, models could forecast periods of upcoming query surges and preemptively refactor the most cost-critical queries to handle expected spikes more efficiently. Reinforcement learning techniques could further refine scheduling strategies over time, learning from the outcomes of previous optimization actions to improve future scheduling policies dynamically.

By orchestrating query refactoring and materialization refresh cycles based on intelligent predictions, organizations can not only reduce costs but also improve system reliability and user satisfaction. End-users experience faster query response times with fewer disruptions, while IT and data engineering teams are freed from manual tuning tasks and firefighting, allowing them to focus on strategic initiatives.

The integration of machine learning into cloud cost optimization frameworks does, however, require careful architectural and operational design. Models must be explainable and transparent enough for administrators to understand the rationale behind optimization decisions, particularly in regulated industries where accountability is crucial. Systems must also include feedback loops, allowing human operators to validate, override, or adjust machine-generated recommendations based on business context or evolving priorities (Akinbola, *et al*., 2020, Akinyemi & Aremu, 2016, Ogundare, Akinyemi & Aremu, 2021). In this way, machine learning acts not as a replacement for human judgment but as an augmentation layer that enhances human decision-making with scale, speed, and predictive insight.

Moreover, the effectiveness of machine learning models depends on the quality, granularity, and freshness of the data available for training and inference. Organizations must invest in robust telemetry pipelines, comprehensive logging, metadata enrichment, and continuous model retraining to ensure that optimization engines remain accurate and aligned with current workloads. Cross-platform integration is also essential, enabling unified modeling across multi-cloud environments where query patterns and cost dynamics may differ between AWS, GCP, and Azure.

In conclusion, the application of machine learning to automated query refactoring and materialization transforms cloud cost optimization from a reactive, manual process into a proactive, intelligent system of continuous improvement. Through anomaly detection, predictive materialization modeling, and intelligent scheduling, machine learning empowers organizations to stay ahead of inefficiencies, optimize cloud resource utilization, and achieve financial sustainability at scale. As cloud adoption deepens and data ecosystems become even more dynamic and complex, machine learning will be indispensable in ensuring that cost-efficiency remains a built-in, self-improving attribute of modern cloud data warehouses rather than a perpetual struggle against entropy.

2.5 Implementation Considerations Across Major Cloud Platforms

Implementing a conceptual framework for cloud cost optimization through automated query refactoring and materialization requires a nuanced understanding of the technical capabilities, limitations, and optimization levers available across major cloud platforms. While the underlying principles of reducing compute waste, enhancing query efficiency, and leveraging materialization for cost savings are universal, the specific tools, architectural patterns, and operational best practices differ across AWS Redshift, Google BigQuery, and Azure Synapse Analytics. Effective deployment of the framework thus demands a platform-sensitive approach, ensuring that automation workflows, optimization models, and governance structures align with each cloud environment's native features and economic models.

In AWS Redshift, one of the critical components to consider is the use of Redshift Spectrum, which enables direct querying of data stored in Amazon S3 without loading it into Redshift clusters. Spectrum's decoupled architecture allows organizations to store vast amounts of cold or semi-structured data in cost-effective object storage, querying only the subsets needed for specific analytics tasks. Integrating Spectrum into the optimization framework means that automated query refactoring engines must identify opportunities where external tables can replace expensive local scans, especially for infrequently accessed datasets or exploratory analytics (Akinyemi & Salami, 2023, Attah, Ogunsola & Garba, 2023, Otokiti, 2023). Predicate pushdown and selective column retrieval become even more important when leveraging Spectrum, as cost is directly tied to the amount of data scanned during each query. Furthermore, Redshift's Concurrency Scaling feature must be integrated into workload management automation. Concurrency Scaling automatically adds transient, short-lived clusters during peak query periods to maintain performance without the need for permanent overprovisioning. However, each use of Concurrency Scaling incurs additional costs, making it vital for machine learning models and predictive engines to anticipate peak periods and optimize query plans beforehand, reducing unnecessary activations. Automated systems should monitor Concurrency Scaling usage patterns and proactively optimize or materialize high-cost queries that frequently trigger concurrency surges, thus containing the financial impact while preserving query performance.

In Google BigQuery, the focus shifts to leveraging BigQuery BI Engine and the advanced capabilities of materialized views. BigQuery BI Engine is an in-memory analysis service that accelerates SQL queries, particularly those serving interactive dashboards and business intelligence applications. The optimization framework must include logic for detecting high-frequency, low-latency queries typical of dashboards and automatically recommending or provisioning BI Engine capacity for these workloads (Akinyemi & Ogundipe, 2023, Aniebonam, *et al*., 2023, George, Dosumu & Makata, 2023). Because BI Engine charges based on allocated memory and query execution volume, predictive models must balance performance needs with memory provisioning costs, scaling allocations dynamically as usage patterns change. BigQuery's support for automatic materialized views is another powerful feature that aligns closely with the cost optimization framework's materialization strategies. Materialized views in BigQuery automatically refresh based on changes to the underlying data and provide incremental maintenance capabilities, allowing organizations to dramatically cut costs for repetitive aggregation and filtering operations (Ige, *et al*., 2022, Nwaimo, Adewumi & Ajiga, 2022, Ogunyankinnu, *et al*., 2022). Implementation considerations must ensure that automated systems analyze query logs to identify candidate queries for materialization, monitor the refresh costs, and evaluate the net cost-benefit continuously. Additionally, BigQuery's query execution metadata and dry run capabilities can be integrated into simulation models to predict the financial impact of materialization or query refactoring decisions before deployment, enhancing the robustness of the optimization pipeline.

Azure Synapse Analytics presents a distinct set of opportunities and challenges, particularly through the use of Serverless SQL Pools and its evolving materialization features. Synapse Serverless Pools allow users to query data directly from Azure Data Lake Storage without provisioning dedicated compute resources, offering a pay-per-query model ideal for variable or unpredictable workloads. However, because charges are based on data scanned, the efficiency of queries becomes paramount. Automated query refactoring must ensure that serverless queries maximize partition pruning, utilize selective projection, and leverage file formats optimized for analytical queries such as Parquet or Delta Lake (Adepoju, *et al*., 2022, Francis Onotole, *et al*., 2022). Identifying opportunities where high-frequency serverless queries should transition into dedicated pools or into materialized views in dedicated SQL pools can significantly enhance cost-efficiency. Azure Synapse's materialization capabilities, particularly through materialized views that support automatic query rewrite, should be tightly integrated into the optimization framework. Refactored queries can be redirected automatically to serve from materialized results where appropriate, reducing compute costs and accelerating query performance. Refresh strategies must be dynamically aligned with underlying data volatility, leveraging partition-based incremental refresh features where possible to avoid the overhead of full recomputation.

Across all platforms, vendor-specific tools for automation and cost observability must form the backbone of the monitoring and governance layers of the optimization framework. AWS provides Redshift Advisor and AWS Cost Explorer, which can supply actionable insights into table design improvements, workload patterns, and spending anomalies. Integration with Redshift Data API can further enable automated scripts to adjust cluster configurations, manage materialized views, and monitor query patterns programmatically (Adepoju, *et al*., 2023, Attah, Ogunsola & Garba, 2023, Hussain, *et al*., 2023). Google BigQuery offers detailed billing export tables, the Query Execution Plan visualizer, and the BigQuery Audit Logs, all of which can be streamed into monitoring dashboards or machine learning pipelines for anomaly detection and optimization modeling. BigQuery Reservations API allows for programmatic control over slot allocations, making it possible to dynamically manage reserved compute capacity based on predictive usage forecasts.

Azure Synapse offers Cost Management tools through Azure Portal, Synapse Studio Workload Management, and Intelligent Performance Insights, which recommend query optimizations and provide visibility into system resource usage. Azure's Resource Graph and Monitor services can feed telemetry data into predictive models, enabling real-time monitoring of cost-performance metrics and informing dynamic adjustment of refresh cycles and refactoring priorities. Vendor-native logging systems such as AWS CloudWatch, Google Cloud Operations Suite, and Azure Monitor must also be tapped into for gathering fine-grained telemetry on query execution times, resource utilization patterns, cache hit rates, and materialization efficiencies.

Implementation considerations must also account for cross-platform standardization when enterprises operate in multi-cloud environments. While each cloud provider offers powerful optimization features, the lack of standardization in cost metrics, billing units, and optimization APIs can create fragmentation. Therefore, the automation and optimization framework should abstract core processes—such as anomaly detection, candidate query selection for refactoring, materialization modeling, and refresh scheduling—so that they function consistently across AWS, GCP, and Azure despite underlying platform differences. This can be achieved by normalizing cost and performance metrics into a unified schema, creating adaptable optimization rules that translate into platform-specific actions, and orchestrating workflows through cross-cloud pipeline management tools or meta-orchestration layers like Apache Airflow, dbt Cloud, or Terraform Cloud.

Finally, implementation efforts must address governance and control, ensuring that automation processes remain transparent, auditable, and overrideable by human operators. All machine-suggested optimizations should include justifications based on quantified cost-benefit analyses, clear indications of associated risks (such as data staleness introduced by materialization), and rollback mechanisms in case of unintended consequences. Cloud-native Identity and Access Management (IAM) policies must be configured to restrict automation scripts and optimization agents to predefined actions, maintaining the principle of least privilege and ensuring compliance with organizational security standards.

In conclusion, effective implementation of a cloud cost optimization framework for automated query refactoring and materialization demands a detailed understanding of the unique features, constraints, and opportunities presented by AWS Redshift, Google BigQuery, and Azure Synapse Analytics. By integrating platform-specific capabilities like Redshift Spectrum, BigQuery BI Engine, and Synapse Serverless Pools, while leveraging vendor-native automation and observability tools, organizations can build an intelligent, proactive optimization layer that continuously enhances cost efficiency, query performance, and operational resilience across their cloud data ecosystems.

2.6 Challenges and Limitations

While the conceptual framework for cloud cost optimization through automated query refactoring and materialization offers significant potential for achieving operational efficiencies and financial sustainability, its real-world implementation is not without substantial challenges and limitations. As organizations attempt to integrate automation, predictive analytics, and platform-specific optimizations into their cloud environments, several technical, operational, and strategic hurdles emerge that must be carefully managed to ensure long-term success.

One major challenge is the management of materialized view dependencies and update strategies. Materialized views, while powerful tools for reducing compute load and accelerating query performance, introduce complex dependency chains between base tables and derived views. When underlying data changes—whether through inserts, updates, or deletes—materialized views must be refreshed to maintain data consistency and validity. In cloud platforms like AWS Redshift, Google BigQuery, and Azure Synapse Analytics, while incremental refreshes mitigate some costs, managing when and how refreshes occur remains a delicate balancing act. Automated frameworks must track dependencies across a dynamic, evolving data landscape, ensuring that stale materialized views do not compromise analytics accuracy. When multiple materialized views are nested or depend on shared datasets, refresh coordination becomes even more intricate. Uncoordinated refreshes may cause redundant compute operations, leading to hidden costs, or in worse cases, introduce inconsistencies where upstream changes are not properly propagated downstream. Scheduling refresh operations intelligently based on data volatility, query demand, and cost-benefit modeling is complex, and failure to do so can negate the cost savings that materialization initially promised. Ensuring that refresh operations themselves do not overwhelm system resources during peak periods or introduce disruptive performance impacts adds yet another layer of difficulty.

Closely related to this is the classic storage versus compute trade-off inherent in materialization strategies. Materializing query results effectively shifts some operational burden from real-time compute cycles to storage costs and refresh overhead. However, not all materializations are economically beneficial over the long term. Organizations must continuously evaluate whether the storage and refresh costs associated with a materialized view are justified by the compute savings achieved. In environments where storage costs are relatively low and compute costs are high—as is often the case with serverless query models like BigQuery—the trade-off generally favors materialization. Conversely, in settings where storage costs are significant, or where access patterns are highly variable, materialized views may introduce unsustainable storage overhead with diminishing marginal returns. Deciding what to materialize, when to dematerialize, and how to scale materialization strategies dynamically as workloads change is a non-trivial task. Moreover, over-aggressive materialization can lead to "materialization sprawl," where numerous, infrequently accessed materialized views accumulate, driving up storage and maintenance costs without commensurate performance or cost benefits. Automated systems must incorporate robust policies for the lifecycle management of materialized views, but even then, fine-tuning these trade-offs requires continuous monitoring, sophisticated modeling, and human oversight.

Adding to the complexity is the challenge of orchestrating cross-platform query optimization when organizations operate hybrid or multi-cloud architectures. Each cloud platform—AWS, GCP, and Azure—implements its own optimization engines, cost models, storage systems, query planners, and telemetry frameworks. Redshift may prioritize distribution styles and sort keys, BigQuery emphasizes partition pruning and slot management, while Synapse relies on intelligent caching and workload classification. Writing optimization logic that can understand, translate, and act across these diverse systems presents a formidable engineering challenge. Query refactoring techniques that are highly effective in one platform may not map cleanly onto another due to differences in SQL dialects, optimizer behaviors, or system constraints. Moreover, cost drivers vary not only between platforms but also between regions, pricing tiers, and service configurations within each cloud provider. Implementing a unified, cross-platform optimization orchestration layer requires abstracting optimization principles without oversimplifying the nuances that impact actual cost outcomes. It demands careful architectural planning to ensure that platform-specific optimizations are not lost in translation, and that decision models remain sufficiently flexible to accommodate heterogeneous environments. In practice, cross-platform optimization often involves substantial integration overhead, custom connectors, data normalization layers, and additional operational complexity, which can offset some of the automation gains if not carefully managed.

Finally, metadata consistency and observability issues present ongoing limitations to fully realizing the promise of automated optimization frameworks. Effective query refactoring and materialization strategies depend heavily on accurate, timely, and comprehensive metadata about datasets, queries, execution plans, storage characteristics, and user behavior. However, in real-world environments, metadata is often fragmented across disparate systems, inconsistently maintained, or subject to gaps and inaccuracies. Table schemas may evolve without corresponding updates to lineage graphs; partitioning information may become stale; query logs may miss critical context such as user intent or application workflows. When metadata is incomplete or unreliable, automated systems struggle to make informed optimization decisions, leading to missed opportunities or, worse, suboptimal recommendations that degrade performance or increase costs.

Observability challenges compound the problem. While cloud providers offer increasingly sophisticated monitoring and telemetry services, integrating these disparate data streams into a coherent, actionable observability framework remains challenging. Differences in metric granularity, update frequency, labeling standards, and data retention policies between AWS CloudWatch, GCP Operations Suite, and Azure Monitor make unified telemetry management difficult. Without consistent observability, detecting anomalies, predicting materialization needs, and scheduling optimization activities intelligently become significantly harder. Furthermore, the volume of telemetry data itself can become overwhelming, requiring investment in analytics platforms, machine learning pipelines, and skilled personnel to extract meaningful insights. Ensuring metadata fidelity, maintaining lineage visibility across constantly changing datasets, and consolidating observability across platforms are critical but difficult prerequisites for the success of an intelligent, automated cloud cost optimization framework.

Beyond these technical and operational challenges, strategic governance and organizational alignment issues also pose limitations. Optimization automation necessarily touches multiple domains—data engineering, cloud architecture, finance (FinOps), and governance/compliance. Ensuring that optimization initiatives align with broader business priorities, security standards, and financial controls requires strong cross-functional collaboration and clear accountability structures. Resistance to change, lack of trust in machine-driven decisions, and difficulty quantifying optimization ROI in traditional financial reporting structures can impede adoption. Successful implementation requires not only technical sophistication but also change management, stakeholder education, and cultural adaptation toward data-driven, continuous cost governance.

In conclusion, while the conceptual framework for cloud cost optimization through automated query refactoring and materialization offers a promising path toward sustainable, intelligent cloud operations, its practical realization faces significant challenges. Managing materialized view dependencies, navigating storage-compute trade-offs, orchestrating optimization across heterogeneous cloud environments, and ensuring metadata and observability integrity are complex tasks that demand careful design, continuous refinement, and strong organizational commitment. Recognizing these limitations is essential not to abandon the framework but to set realistic expectations, design resilient systems, and build governance structures that enable long-term success. By addressing these challenges head-on, organizations can position themselves to unlock the full transformative potential of intelligent cloud cost optimization in the evolving digital economy.

2.7 Future Research Directions

As cloud-native architectures continue to expand in complexity and scale, future research must focus on advancing the capabilities of cost optimization frameworks beyond their current operational limits. While today's systems can automate query refactoring and materialization to a significant degree, the next frontier involves embedding deeper intelligence, autonomy, and standardization across platforms. Several emerging areas merit urgent attention: the development of self-healing query optimization systems, the realization of autonomous cost-based orchestration engines, the creation of standardized cloud cost observability frameworks, and the design of AI-driven optimization pipelines for multi-cloud ecosystems. These future directions aim to transform cloud cost management from a reactive, semi-automated process into a fully autonomous, predictive, and adaptive system that operates at scale across diverse environments.

A critical future direction is the development of self-healing query optimization systems. Current frameworks, even when automated, generally detect issues and suggest or apply corrections manually or semi-autonomously. However, truly self-healing systems would go beyond mere detection and intervention—they would continuously monitor queries and workloads, autonomously detect inefficiencies or regressions, and apply optimizations proactively without human intervention, all while learning and improving over time. This requires research into advanced machine learning models capable of not just identifying suboptimal queries, but dynamically rewriting them in production environments with guaranteed semantic integrity and minimal risk. Reinforcement learning could be applied to train optimization agents that simulate potential refactoring changes, predict their outcomes based on historical telemetry, and automatically implement the best-performing version. Future self-healing systems would also need rollback capabilities, allowing automatic reversion if an optimization inadvertently impacts query correctness or business SLAs. Research must focus on developing techniques for safe, explainable self-healing that maintains trust, accountability, and operational transparency in enterprise settings where query correctness is paramount.

Equally important is the pursuit of autonomous cost-based orchestration engines. Traditional workflow orchestration tools are primarily schedule-driven or event-driven, lacking deep financial awareness. Future research must explore orchestration systems that natively embed cost models into scheduling, scaling, and resource allocation decisions. In such systems, cost would become a first-class constraint alongside latency, availability, and throughput. An autonomous orchestration engine could, for example, detect that a group of queries scheduled for concurrent execution would exceed budgetary thresholds if run at their current configuration, and automatically stagger, prioritize, or reconfigure the jobs to maintain financial compliance without violating critical business deadlines. These engines would integrate real-time cloud billing data, predictive cost modeling, and workload telemetry to make adaptive, cost-aware decisions across services like AWS Redshift, Google BigQuery, Azure Synapse Analytics, and beyond. Research must address challenges such as developing real-time financial constraint satisfaction algorithms, integrating financial risk modeling into orchestration engines, and enabling flexible prioritization frameworks that balance cost optimization against other operational imperatives.

Another essential future research area is the development of standardized cloud cost observability frameworks. At present, each cloud provider offers its own proprietary billing APIs, cost metrics, and telemetry formats, creating significant fragmentation for organizations operating in multi-cloud environments. This lack of standardization hampers efforts to create unified, holistic cost optimization systems and drives up integration complexity. Future research should aim to design open, interoperable standards for cloud cost observability, analogous to how protocols like OpenTelemetry have standardized application and infrastructure monitoring. A standardized cloud cost observability framework would define common schemas for billing events, usage metrics, resource tagging, query execution metadata, and financial KPIs across providers (Adepoju, *et al*., 2023, Hussain, *et al*., 2023, Ugbaja, *et al*., 2023). It would enable plug-and-play integration of multi-cloud cost data into centralized analytics platforms, FinOps dashboards, and autonomous optimization engines. Moreover, such frameworks would facilitate benchmarking, anomaly detection, and machine learning applications by ensuring consistent, high-fidelity cost data across environments. Research challenges include aligning incentives among competing cloud providers, defining extensible metadata taxonomies that can evolve with service innovations, and securing cost telemetry against tampering or misattribution in federated cloud environments.

Finally, future research must focus on building AI-driven optimization pipelines for multi-cloud ecosystems. The reality for many enterprises is no longer single-cloud deployment but complex hybrid and multi-cloud architectures where data and workloads are distributed across

AWS, GCP, Azure, and sometimes private clouds. In such heterogeneous environments, manually managing cost efficiency becomes infeasible. AI-driven optimization pipelines would ingest telemetry from multiple clouds, apply platform-specific normalization, and autonomously orchestrate query refactoring, materialization strategies, resource scaling, and workload distribution based on real-time optimization objectives. These pipelines would use federated learning techniques to train models across decentralized data without violating cloud-specific data residency or compliance requirements (Adepoju, *et al*., 2023, Lawal, *et al*., 2023, Ugbaja, *et al*., 2023). They would also integrate decision-making frameworks that balance competing objectives such as minimizing compute costs, optimizing storage efficiency, ensuring low query latency, and adhering to inter-cloud data transfer constraints. Future research must address algorithmic challenges like designing optimization models that adapt to heterogeneous billing models, pricing volatility, and regional cost differentials. Building intelligent workload migration strategies that predict when to rebalance queries across clouds based on cost-performance modeling, regulatory considerations, and dynamic cloud pricing will also be critical.

Moreover, AI-driven pipelines would benefit from reinforcement learning approaches where optimization agents continuously explore, exploit, and refine cost-saving strategies over time. Unlike static rules or scheduled optimizations, reinforcement learning-based systems could autonomously test alternative configurations, dynamically optimize partitioning or clustering strategies, and evolve materialization policies in response to changing workloads. Integrating explainable AI techniques will be essential to ensure that the optimization decisions made by these autonomous agents are transparent, auditable, and align with organizational risk tolerance and business policies (Akinyemi & Ebiseni, 2020, Austin-Gabriel, *et al*., 2021, Dare, *et al*., 2019).

In summary, the future of cloud cost optimization lies in developing intelligent, autonomous, and standardized systems that transform current frameworks into self-optimizing ecosystems. Self-healing query optimization systems would reduce human intervention, ensuring continuous efficiency improvements without sacrificing accuracy or control. Autonomous cost-based orchestration engines would embed financial governance directly into operational pipelines, dynamically aligning workload execution with budgetary constraints. Standardized cloud cost observability frameworks would eliminate fragmentation, enabling unified, scalable optimization across diverse cloud environments (Adeniran, Akinyemi & Aremu, 2016, Ilori & Olanipekun, 2020, James, *et al*., 2019). AI-driven optimization pipelines for multi-cloud ecosystems would provide the intelligence and agility required to manage increasingly complex, distributed cloud architectures. Together, these research directions chart a pathway toward truly autonomous, intelligent cloud financial management—ensuring that as data volumes, analytics demands, and cloud diversity grow, cost efficiency, performance, and governance not only keep pace but continuously improve.

3. Conclusion

This study has proposed a comprehensive conceptual framework for cloud cost optimization, centered on the principles of automated query refactoring and intelligent materialization. At its core, the framework recognizes that achieving sustainable cost-efficiency in cloud data warehouses requires moving beyond traditional manual tuning practices toward a fully automated, continuously adaptive system. It integrates key strategies such as predicate pushdown, join and subquery optimization, selective projection, dynamic query rewriting, incremental materialized views, and predictive cost-benefit modeling. These optimization techniques are further enhanced by embedding machine learning for anomaly detection, predictive modeling, and intelligent scheduling. By aligning cloud resource consumption closely with actual usage patterns and business needs, the framework provides a roadmap for proactive, intelligent, and scalable management of cloud operational costs across AWS Redshift, Google BigQuery, and Azure Synapse Analytics environments.

For organizations willing to adopt automated optimization, the strategic benefits are profound. First, automation eliminates the inefficiencies and delays associated with manual performance tuning, ensuring that cost optimization occurs continuously and in real-time. Second, predictive and autonomous systems empower organizations to stay ahead of changing workload patterns, data growth, and evolving user demands without sacrificing financial control or operational agility. Third, the integration of materialization and intelligent caching strategies provides a structural means to stabilize compute consumption and query latency, enabling consistent user experiences at predictable and manageable costs. Additionally, the framework encourages a shift toward unified cost observability and cross-platform optimization, helping organizations operating in multi-cloud ecosystems to harmonize and rationalize their cloud expenditures comprehensively. Perhaps most importantly, the framework frees up human talent, allowing engineers, analysts, and architects to focus on higher-value innovation initiatives rather than repetitive optimization tasks.

Achieving sustainable and scalable cloud cost efficiency, however, is not merely a technical exercise. It demands a strategic commitment to embedding financial governance, automation, and intelligent decision-making into the very fabric of cloud data operations. As cloud services continue to evolve rapidly and organizations' reliance on data-driven insights deepens, the ability to maintain economic control without throttling innovation will become a critical differentiator. This conceptual framework offers a future-ready approach, one that anticipates complexity, leverages automation, and embraces continuous adaptation. By operationalizing these principles, organizations can not only rein in cloud costs but also unlock new levels of agility, resilience, and strategic competitiveness in the digital economy.

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