World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(RESEARCH ARTICLE)

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DATA WAREHOUSE OPTIMIZATION TECHNIQUES: A SURVEY OF QUERY PROCESSING, STORAGE, AND PERFORMANCE ENHANCEMENT METHODS

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World Journal of Advanced Engineering Technology and Sciences, 2026, 20(02), 216–226

Publication history: Received on 01 July 2026; revised on 17 August 2026; accepted on 19 August 2026

Article DOI: https://doi.org/10.30574/wjaets.2026.20.2.0408

ABSTRACT

Data warehouses today are an essential part of existing Business Intelligence (BI) solutions, that collect data from multiple sources and enable analytical processing for strategic decision making. However, as enterprise data grows, and analytical queries become more complex, faster insights are demanded that present a new set of challenges with query execution and storage, scalability, and overall system performance. This survey aims to give an overview of the data warehouse optimization techniques with emphasis on three important areas: Query Processing Optimizations; Storage Optimizations, and Performance Improvement Techniques. Popular techniques like query transformation, access path selection, join optimizations, data partitioning, indexing, materialized views, memory and buffer management, workload management, resource allocation, parallel processing and load balancing are covered. Furthermore, a comparative study of recent research is given highlighting the research trends, strengths and limitations and gaps in the literature. The survey reveals several areas for improving the scalability, responsiveness, and reliability of modern data warehouse designs, including effective query execution techniques, optimized storage structures, and resource management strategies. The results provide practical recommendations for practitioners and researchers related to the best optimization strategies for analysis settings.

Keywords: Data Warehouse, Query Optimization, Storage Optimization, Performance Enhancement, Query Processing, Business Intelligence.

1 INTRODUCTION

Large volumes of data from operations and history can be now stored and integrated into a data warehouse for informed decision-making, a critical component of the modern business intelligence (BI) environments [1]. The demand for effective and efficient data warehousing has increased tremendously as enterprises continue to generate huge volumes of data from transactional systems, cloud platforms, enterprise applications and digital services [2]. Data warehouses consist of one or more data sources that are used to collect and store data, in accordance with the four key principles of subject-oriented, integrated, time-variant, and non-volatile. Data warehouses provide a unified and consistent view of organization's data to support analytical processing, reporting, forecasting and strategic planning across the business functions. These systems are crucial for organizations in a data-driven world, providing valuable insights that lead to

action, efficient operations, and monitoring of business performance and competitiveness [3]. Therefore, the performance of a data warehouse can have a great impact on the quality and timeliness of business decisions.

The problem of data warehouse systems maintaining performance and scalability as data grows and analytical demands grow is growing [4]. Today, decision support applications can include multi-dimensional analysis, multiple simultaneous users, and complex SQL queries, which are all demanding large amounts of storage and query processing [5]. Without optimization, organizations may experience reduced query performance, excessive storage consumption, resource waste, and increased costs. In distributed and cloud-based data warehouse systems, scalability and performance are key factors in delivering timely analytical results, exacerbating these challenges. Thus, optimization of data warehouses is a significant requirement to perform queries efficiently, store data optimally, reduce maintenance work, and achieve uniform performance of the system [6][7]. A host of techniques have been developed to solve these problems: indexing, partitioning, compression, materialized views, query rewriting, parallel query processing and workload optimization.

The current rapid evolution of data warehouse technology, combined with the demand for scalable analytical systems, requires a comprehensive evaluation of the current optimization techniques. This survey focuses on three key areas of data warehouse optimization: query processing, storage optimization, and techniques to improve performance. It offers a general overview of existing and new solutions, their pros and cons, and the ability to apply them in various data warehouse scenarios. Furthermore, the survey offers an introduction to the ongoing research challenges and issues that can serve as an orientation for future research and practice in the design of efficient data warehouse systems that are scalable and high performance.

1.1 Structure of the Paper

The following is the structure of the rest of the paper. The foundations of data warehousing are covered in Section II. Section III covers query processing optimization techniques and Section IV covers storage optimization techniques. The performance enhancement strategies to improve scalability and resource use are reviewed in Section V. A comparison of recent studies is provided in Section VI. Section VII concludes the study and offers proposed avenues for future research.

2 FOUNDATIONS OF DATA WAREHOUSING

Data warehouses are a way to improve data management by integrating data from various sources into a unified system, which is optimized for analysis. These strong solutions allow organisations to retain old data and translate it into useful insight [8]. Data warehouses support elaborate analytical processes and strategic decision-making by centralising data in an approach that prioritises accessibility, consistency, and interpretability.

The architecture of a data warehouse is the framework and parts of a data warehousing system that ensures the effective collection, storage, and management of massive amounts of data from diverse sources for the goal of analysis and reporting. Figure 1 shows the foundational role of a well-designed Data Warehouse architecture in supporting efficient data analysis and decision-making.

2.1 Components of Data Warehouse

The following is a high-level summary of the main levels and components of traditional data warehouse architectures:

2.1.1 Source Systems

Data that ends up in a data warehouse usually starts its journey from source systems, which can be anything from a variety of databases and apps to external data feeds. Data warehouse processing and analysis begins with these systems' generation of raw data.

2.1.2 Data Processing

Data is extracted from source systems and transformed into an appropriate format for analysis using the Extract, Transform, Load (ETL) process. In this stage, ETL technologies are essential to the correct and effective transfer of data.

2.1.3 Staging Area

The staging area is a kind of interim storage where raw data is kept until it is processed further. This process enables the validation, cleaning, and transformation of data prior to its loading into the data warehouse.

2.1.4 Data Warehouse Database

The data warehouse database is the central component of data warehouse architecture [9]. This kind of database is usually structured according to a dimensional model and contains tables such as fact tables and dimension tables, which are ideal for analytical queries. Snowflake, SQL Server, and Oracle are three examples of popular database technology.

2.1.5 Data Mart

Data marts are specialised parts of the larger data warehouse that are created to meet the needs of certain departments or business units. They enable easier and more directed analysis of data, which enhances query speed for certain queries.

2.1.6 Business Intelligence Layer

The Business Intelligence layer is on top of the data warehouse, providing end-user interfaces and tools to access and analyse data. BI tools such as Tableau, Power BI or Looker can be used to create dashboards, reports, and visualisations.

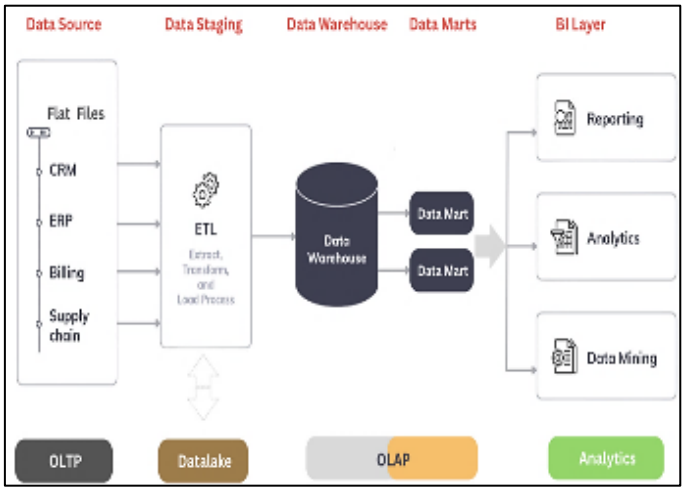

Figure 1: Data Warehouse Architecture

2.2 Need for Data Warehouse Optimization

As organizations continue to accumulate data, analytical queries become more complex and frequently include multiple joins, aggregations, and multidimensional operations. These workloads can cause inefficiency in query processing, excessive disk I/O, high memory usage, and overall slow query response times if not optimized properly. As a result, optimizing is now a critical need for keeping modern data warehouse systems performing, scalable, and reliable. The need for data optimization given in Table 1.

Optimizing data warehouse performance isn't just about query performance. Optimized solutions enable efficient usage of storage space, improve the use of resources, and provide scalability for parallel analytics workloads, while sustaining the consistent system performance.

Table 1: Key Reasons for Data Warehouse Optimization

Requirement	Description	Impact
Growing Data Volume	Continuous accumulation of enterprise data increases storage and processing requirements.	Improved scalability and storage efficiency
Complex Analytical Queries	OLAP queries involve multiple joins, aggregations, and filtering operations.	Reduced query execution time
High Disk I/O	Full-table scans increase data access latency.	Faster data retrieval through optimized storage
Resource Utilization	Inefficient CPU and memory usage affects overall performance.	Better utilization of computational resources

Concurrent User Access	Multiple users execute analytical queries simultaneously.	Higher throughput and consistent performance
Cloud Scalability	Dynamic workloads require elastic resource allocation.	Improved scalability and cost efficiency

These challenges are addressed properly by using appropriate optimisation techniques, which enhance the efficiency of the queries, resource usage, scalability, and system performance.

3 QUERY PROCESSING OPTIMIZATION TECHNIQUES

An optimization of the query is an important part of data warehouse systems, which needs to reduce the time of query execution and reduce the consumption of query resources while ensuring that data warehouse systems have high analysis performance [10]. The most effective strategy for execution is generated by database management systems using optimisation methods. Modern data warehouses primarily rely on cost-based optimization (CBO), which evaluates alternative execution plans using statistical metadata such as cardinality, data distribution, and index information.Table 2 summarizes the major strategies and their contributions to warehouse performance.

Table 2: Major Query Optimization Strategies In Data Warehouses

Optimization Category	Primary Objective	Representative Techniques	Performance Impact
Query Transformation	Rewrite SQL into equivalent but efficient forms	Predicate pushdown, projection pruning, subquery flattening	Reduces intermediate results
Access Path Optimization	Select efficient data retrieval method	Index scan, bitmap index, column pruning	Minimizes disk I/O
Join Optimization	Determine optimal join order and algorithm	Hash join, merge join, nested-loop join	Accelerates multi-table queries
Aggregation Optimization	Improve GROUP BY and OLAP operations	Partial aggregation, materialized aggregation	Faster analytical processing
Parallel Query Processing	Distribute computation across processors	MPP execution, distributed joins	Improves scalability
Adaptive Optimization	Modify execution plans dynamically	Runtime re-optimization, adaptive joins	Handles workload variations

3.1 Query Transformation

A cost-independent transformation is a rule-based static rewrite of a query that should result in a more efficient query while maintaining semantic equality [11]. The needed rules are distinguished by their broad applicability rather than their cost dependence; that is, they typically result in improved, more efficient query forms. Examples of such rewrites include view resolution, DISTINCT clause removal, and predicate push-downs. Several rewrites need the availability of certain data dependencies, such as key information, in order to generate semantically identical plans.

3.2 Access Path Optimization

After logical transformation, the optimizer determines the most efficient mechanism for accessing data. The selection of an appropriate access path significantly influences query latency, particularly in star-schema warehouses containing very large fact tables. Common access methods include sequential scans, B-tree indexes, bitmap indexes, and columnar storage scans. Bitmap indexes are especially effective for low-cardinality attributes frequently appearing in filtering predicates, whereas column-oriented storage minimizes unnecessary I/O by retrieving only referenced attributes. Consequently, access path optimization reduces storage access overhead and improves analytical query throughput.

3.3 Join Optimization

Join processing typically dominates the execution cost of warehouse queries because analytical workloads frequently integrate fact tables with multiple dimension tables. Hence, it is indispensable to determine both the join sequence and

the physical join algorithm [12]. The modern optimizers estimate the cardinality and cost of various join trees and choose join algorithms based on the data distribution and indexing characteristics, like Hash Join, Merge Join, or Nested Loop Join. Dependency-aware optimization is another improvement on join elimination by leveraging functional and inclusion dependency, uniqueness dependency and avoiding unnecessary relational operations.

3.4 Adaptive and Intelligent Query Optimization

The execution plans are constantly updated based on runtime observations rather than just pre-computed statistics which is called adaptive query optimization [13]. The machine learning models can learn heuristics about workloads from past executions and use them to improve cardinality estimation, cost prediction, and plan enumeration. Unlike the traditional cost-based optimizers, these intelligent optimizers can handle the high skew of data and the dynamic nature of data in high-volume environments like cloud-native or distributed data warehouses.

4 STORAGE OPTIMIZATION TECHNIQUES

The storage optimisation control elements are capacity, performance, and storage cost during the data lifecycle. It helps optimize the performance, scalability, and responsiveness of data warehouse systems, by minimizing data storage space and latency during access. The analytical workloads are characterized by large scale scans, aggregations and complex joins, hence optimized storage structures are necessary for providing high query performance.

4.1 Data Partitioning

Data partitioning breaks large warehouse tables into smaller logical partitions, so that the query processor can read only the partition it needs while executing a query. The technique helps to enhance the performance of the queries, streamline data management and enable parallel processing.

There are two different partitioning styles: horizontal and vertical [14]. Vertical Partitioning relates to the projection of the relations to produce smaller relations called vertical fragments. Vertical partitioning is appropriate for characteristics that are used in the fragmentation, because it can provide access to smaller sets of pieces, can be used to handle projection requests, and makes the pieces easier to retrieve.

Figure 2 and Figure 3 are examples of horizontal and vertical partitioning in a data warehouse, respectively. The horizontal partitioning example is when the records are split between different partitions, but the table structure remains the same. In the vertical partitioning example, attributes are divided into separate partitions using a common primary key

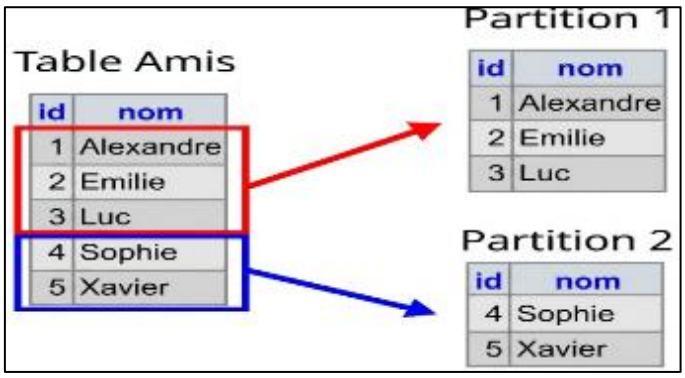

Figure 2: Horizontal Partitioning

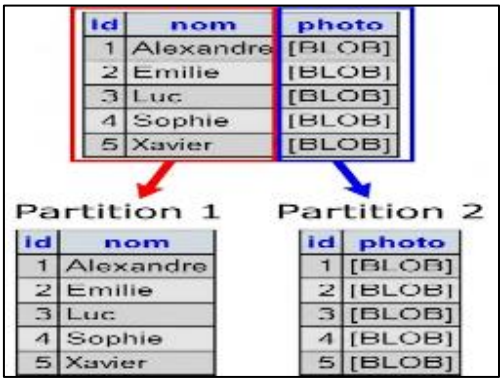

Figure 3: Vertical Partitioning

4.2 Indexing Technique

Efficient data retrieval is a fundamental requirement of modern storage systems, and indexing serves as a storage optimization technique to achieve this goal. It creates a separate, organized structure that stores references to the locations of records, allowing the required data to be found quickly without scanning the entire dataset. Thus, indexing approaches in may be categorised into three basic categories depending to the type of structure used:.

4.2.1 Hashing-Based Technique

This method is attractive in the context of multidimensional data indexing because it reduces a data item to a low-dimensional representation—a short code composed of a handful of bits. A hash-based indexing structure can be adopted in terms of space and time efficiency and is able to identify duplicate data in a large dataset [15].

4.2.2 Tree-Based Technique

In this method, the data is stored as a hierarchical structure, which can be searched, inserted and deleted efficiently. It uses nodes and branches (e.g., B-tree, B+ tree, R-tree) to quickly locate records by minimizing disk accesses. It is often used in databases and file systems for efficient query processing and data retrieval.

4.2.3 Bitmap-Based Technique

The bitmap index method is defined as follows: each tuple is associated with a set of attributes, each bit (0/1) is a value of one of the attributes. If the ith data element satisfies the property, the bit sequence will have a 1 at position i, and 0 otherwise. Bitmap index responds to complicated queries quickly and efficiently using logical operations like AND, OR, NOT, and XOR.

4.3 Materialized Views

The data warehouse stores auxiliary views, which are the basis for materialised views, as well as the base relations. By updating materialised views whenever base relations are modified, the consistency and integrity of materialised views are maintained. View maintenance is the process of upgrading materialised views, and it is always accompanied by a cost [16]. It is impossible to materialise all views in the data warehouse due to integrity, time, and disc space constraints. In order to address user enquiries, it is necessary to select an appropriate set of views for materialisation. The query response time for these queries should be reduced. The problem of selecting an appropriate set of viewpoints for materialisation is referred to as the view selection problem. In addition to using storage space, the definition of a materialised view involves a number of joins and sophisticated aggregate operators. A materialised view may speed up a query by doing costly computations in advance and then storing the results in a data warehouse as an auxiliary view.

4.3.1 Best practices for storage optimization

The strategic actions listed below assist organisations in optimising their storage.

- **Assess storage needs:** The first step is to identify the current storage utilization and identify the workloads that will best benefit from optimization, and where optimization will make the greatest impact, to improve performance or reduce cost.
- **Implement automated data management:** Automated data tiering and lifecycle rules can move data between storage types based on access patterns, without requiring manual operations, and ensure that data is stored in the most cost-effective location.

- **Carry out routine monitoring:** By keeping track of performance metrics and storage trends, organisations can prevent storage problems from disrupting their operations.
- **Test before deploying:** Test optimisation changes in non-production environment to ensure that changes affect application behavior and performance, and identify potential side effects before the changes are broadly deployed.
- **Meet business needs:** Optimize future data growth and economic performance management. Without overbuilding infrastructure, the best storage optimisation techniques complement business goals.

5 PERFORMANCE ENHANCEMENT METHODS

This section discusses performance enhancement methods that optimize computational resources, workload execution, and scalability through efficient memory management, parallel processing, load balancing, and cloud-based optimization strategies.

5.1 Memory and Buffer Management

An integral part of any transaction system, the buffer manager (BM) controls access to the database's non-volatile storage version and reads and writes pages to and from the buffer pool in 1/0s. The BM's fix primitive may be used to enquire about the database's buffer address for a certain logical page [17]. BM allots a buffer slot and reads the requested page if it is not in the buffer pool. The present contents of a page on non-volatile storage may not be relevant in some situations (e.g., during a B-tree page split, when the new page is allocated). If the page cannot be located in the buffer pool, the fix-new primitive may be used to request that the BM create a ji-ee slot and then provide the address of that slot. The page will subsequently be formatted as required by the fix-new invoker. A page that has been fixed in the buffer pool cannot be replaced until the data manipulative component issues the unfix primitive.

5.2 Workload management

Organizations may create resource governance frameworks that guarantee key workloads are given the proper priority while avoiding resource monopolization by certain users or queries thanks to workload management features. Workload Management (WLM) settings in Redshift specify query queues, resource allocations, and query routing rules, which are used to accomplish workload management [18]. Dedicated resources with high concurrency settings are advantageous for short-running dashboard queries, but other optimization strategies that priorities throughput over concurrency are needed for complicated analytical workloads. A customized configuration that is in line with the particular workload management of each platform is necessary due to the large variation in implementation methodologies between platforms.

5.3 Resource Allocation and Scaling Strategies

The ability to scale storage and computing resources independently according to workload demands is a key feature of cloud data warehouses that radically alter resource management. This approach uses a tree with a hierarchical structure to store the data, which allows for efficient search, insertion, and deletion operations. It utilizes nodes and branches (such as B-tree, B+ tree and R-tree) to help quickly find records with as little disk access as possible. This is frequently used in databases and file systems for fast queries and retrieval.

5.4 Parallelism and Load Balancing

Parallelism is one of the most significant techniques that can be used to enhance the performance of data warehouse systems by enabling multiple operations to be carried out simultaneously on different processors or nodes of a distributed computing system. Paralleling analytical workloads by breaking them into autonomous tasks shortens the response time for queries and increases system throughput. The most common intra-query parallelism methods are multiple operators that are applied to the same query running in parallel, and multiple queries running simultaneously are the primary methods of inter-query parallelism.

Load balancing is used in conjunction with parallel execution to allocate the work to the resources in an even distribution. Load balancing prevents congestion of nodes, avoids underutilization of resources, and guarantees consistent performance when the query load is high. Modern distributed data warehouses distribute tasks dynamically, according to availability of processors, the nature of the workload and resource usage, thus making them more scalable and ensuring balanced execution across clustered environments.

Figure 4 illustrates a SQL aggregate query that returns the sum of each region's sales. A parallel data warehouse [19], allows for the query to be run on several partitions or nodes and have partial results merged to increase query performance, resource usage, and execution speed.

```
SELECT Region,
    SUM(Sales_Amount) AS Total_Sales
FROM Sales_Fact
GROUP BY Region;
```

Figure 4: Example SQL Query for Parallel Aggregation

This aggregation query may be able to be executed in parallel by processing data partitions on multiple nodes in a distributed data warehouse. Partial aggregates are calculated at each node, and then merged together to form the final result, thus speeding up the execution of the queries.

6 LITERATURE REVIEW

This literature review highlights key areas such as AI optimization, distributed systems, query optimization, and performance improvement. Yet, there are only limited solutions which offer integrated solutions for query processing, storage optimization and adaptive performance management.

A. V. Chaudhari (2026) proposes an AI-powered optimization system that integrates query optimization based on machine learning, intelligent workload management, and forecasting resource provisioning into the cloud data warehouse systems. As per the outcomes, the scalability and operational performance of large scale cloud data warehouse is significantly enhanced by intelligent automation with AI techniques [20].

L. AlOud and O. Alharbi (2026) introduces covers distributed data warehouse (DDW) architectures in a SLR, with a focus on governance, security, scalability and real-time analytics issues. The study highlights on the current trend of multi-paradigm architectures that use multiple concepts to achieve a balance between security, autonomy, governance, and performance [21].

J. Nalla (2025) provides a systematic approach to understanding the basics of data modeling to the advanced concepts of query optimization for performance tuning in cloud data warehouse systems. Performance and cost-efficiency of cloud deployment can be greatly affected by many schema design choices, partitioning strategies, and indexing algorithms. The article will investigate platform-specific factors with universal best practices that data engineers and warehouse architects can use for finding and fixing performance bottlenecks [18].

M. K. S. Uddin and K. M. R. Hossan (2024) delves into the usage of data warehouse systems driven by AI to enhance the administration and use of large data. A game-changer in data warehousing is the use of AI, which improves the speed, accuracy, and scalability of data processing. This study consolidates the results of the literature to emphasise the primary advantages, including real-time analytics, automated data extraction, transformation, and loading (ETL) processes, and enhanced data quality through advanced purification and anomaly detection [22].

B. Milicevic and Z. Babovic (2024) tries to provide a comprehensive overview of methods that use DL models in the query execution engine at different levels. They classify these methods into three classes according to the ways these models are used: for optimising queries, for enhancing index structures and, by extension, data manipulation techniques, and for modifying query optimisers from the outside [23].

H. Tm, U. K, M. Shafiulla, and Dadapeer (2023) suggests a set of guidelines for the formatting of SQL queries that must be adhered to in order to optimise them. The method involves determining whether the query necessitates indexing on specific columns in the event that it incorporates filtration. Reducing query execution time, the suggested model

analyses SQL optimisation approaches in detail to improve database query speed, and it seeks to transform user SQL queries into optimised ones by removing unneeded data and columns [24].

Table 3 summarizes recent studies on data warehouse optimization, highlighting their research focus, major contributions, advantages, limitations, and future research directions to identify existing gaps.

Table 3: Comparative Analysis of Recent Studies on Data Warehouse Optimization Techniques

Authors	Focus	Contributions	Advantages	Limitations	Future Work
A. V. Chaudhari (2026)	AI-based optimization for cloud data warehouses	Proposed ML-based query optimization, workload prediction, and dynamic resource allocation.	Improves scalability, query performance, and resource utilization.	Limited to cloud environments; storage optimization not addressed.	Extend to hybrid/multi-cloud systems and storage-aware optimization.
L. AlOud & O. Alharbi (2026)	Distributed data warehouse architectures	Reviewed security, federated, lakehouse, and streaming architectures.	Provides comprehensive architectural insights.	Limited focus on query optimization and performance evaluation.	Integrate AI-driven optimization with distributed architectures.
J. Nalla (2025)	Cloud data warehouse performance tuning	Presented best practices for schema design, partitioning, indexing, and queries.	Enhances performance and cost efficiency.	No AI-based or adaptive optimization techniques.	Develop self-tuning and ML-based optimization methods.
M. K. S. Uddin & K. M. R. Hossan (2024)	AI-powered data warehousing	Reviewed AI for ETL automation, analytics, and data quality.	Improves automation, scalability, and data accuracy.	Limited coverage of query and storage optimization.	Integrate AI for end-to-end warehouse optimization.
B. Milicevic & Z. Babovic (2024)	Deep learning in query execution	Categorized deep learning for indexing, query optimization, and parameter tuning.	Highlights intelligent database optimization methods.	Limited real-world validation and storage optimization.	Develop unified deep learning-based optimization frameworks.
H. Tm, U. K, M. Shafiulla & Dadapeer (2023)	SQL query optimization	Proposed SQL formatting and indexing rules for faster execution.	Simple and effective for improving query performance.	Rule-based and not adaptive to dynamic workloads.	Apply AI for automatic query rewriting and indexing.

7 CONCLUSION AND FUTURE WORK

Optimizing large-scale analytical systems has become essential for organizations seeking faster decision-making, improved operational efficiency, and better utilization of computing resources. The proliferation of enterprise data, coupled with the increasing complexity of analytical workloads, has posed challenges in the areas of query performance, data storage management, and system scalability and performance. This paper discussed three great aspects of optimization, which are query processing, storage optimization, and enhancement methods. It looked at popular techniques such as query transformation, access path selection, join optimization, partitioning, indexing, materialized views, memory and buffer management, workload management, resource allocation, parallel processing, and load balancing. The advantages and disadvantages of the recent approaches were discussed along with the recent trends regarding scalable & distributed analytical environment. The results show that there is no single optimization method which is capable of resolving all the performance issues. Rather, by combining several optimization techniques, significant gains can be achieved in query execution speed, space savings, system throughput, and overall analytical performance. Future research should aim to create a single optimization framework to optimize the query execution, storage organization, workload scheduling and resource management in both on-premises and cloud-based environments. Adaptive optimization, efficient support for real-time analytical workloads, automated performance tuning and optimization of distributed and hybrid architectures will help to create more scalable, reliable and efficient analytical systems that can evolve to better address the needs of business and data processing.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

The authors would like to acknowledge the academic and technical resources that supported the preparation of this survey manuscript. No personal relationships or individual acknowledgments are included.

Funding Source

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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