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Research Article

Optimizing ETL Processes for High-Volume Data Warehousing in Financial Applications

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ABSTRACT

The Extract, Transform, Load (ETL) process is a critical backbone in financial data warehousing, where large-scale data volumes demand optimized performance to meet industry requirements. Financial institutions rely heavily on ETL systems to integrate, cleanse, and structure data for decision-making and regulatory compliance. This paper delves into the optimization of ETL processes for high-volume data warehousing in financial applications. By analyzing current challenges, exploring advanced architectures, and incorporating emerging technologies such as Big Data frameworks and cloud solutions, we present a comprehensive framework for enhanced ETL efficiency. The study also evaluates performance metrics and addresses critical concerns like data security and compliance, paving the way for scalable and resilient financial data warehousing systems.

Keywords: ETL optimization, financial data warehousing, high-volume processing, Big Data, cloud computing, compliance, performance metrics.

1. INTRODUCTION

A financial company deals with a vast and varied amount of data, including transactions, market feeds, regulatory reports, and customer interactions. ETL (Extract, Transform, Load) processes play a crucial role in extracting data from multiple sources, cleaning it, and converting it into a structured format that can be loaded into data systems for further use (Kola, 2024). Given that financial data is highly sensitive, and the industry demands both high performance and strict adherence to regulatory standards, the accuracy and speed of ETL processes are critical. The sector relies on fast and accurate data processing for real-time decision-making, continuous monitoring of operations, detecting fraud and illegal activities, and meeting legal requirements. As financial organizations face growing volumes of data, managing this data efficiently through ETL processes becomes even more important (Nookala, 2021). This research focuses on the challenges of high-velocity financial data processing and examines issues such as scalability, performance, and compliance with regulations. It also seeks to identify opportunities for improvement and propose innovative solutions (Salamkar, 2019). By analyzing technological advancements and making recommendations, the research aims to bridge the gap between current ETL practices and the future needs of financial data management. Additionally, it emphasizes the importance of standardizing ETL processes to improve data usability and efficiency, helping financial institutions stay competitive in an increasingly data-driven world.

2. LITERATURE REVIEW

2.1 Overview of ETL Processes and Architectures

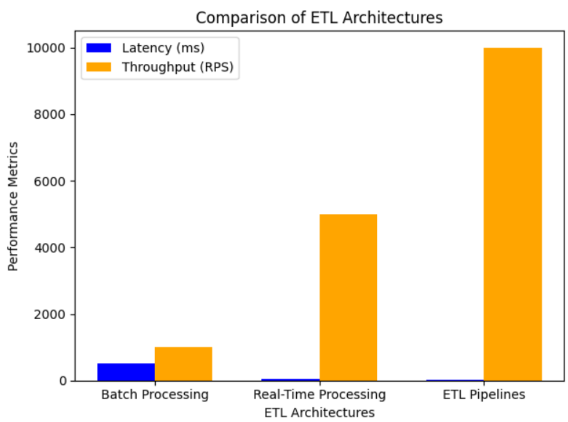

Figure 1: ETL Architectures

In figure 1 the comparison of ETL architectures highlights the differences in latency and throughput between batch processing, real-time processing, and ETL pipelines. ETL (Extract, Transform, Load) operation is considered as fundamental to data warehouse system as it provides both the mechanism for obtaining data as well as the means of transforming this data into a format that can be used for storage in the data warehousing system. This is culminated in the data extraction stage which pulls both structured, semi-structured and unstructured data from cross extractive sources including transactional databases, APIs and real-time feeds. The last phase ensures that the data collected, is cleansed, standardized and enriched, making it fit for analysis and the development of related decisions (Blake, 2024). Finally, what is known as the loading phase is used to load the information into a target structure that has been designed for querying and reporting.

There are two main categories of architectures which are used in traditional ETL processes: batch processing and real-time processing. A more modern approach is ETL pipelines which are essentially event-triggered processes which provide high elasticity to the changes in data source.

Table 1: Comparison of ETL Architectures

Architecture Type	Characteristics	Example Use Cases
Batch Processing	Scheduled, high latency	Historical data analysis, reporting
Real-Time Processing	Continuous updates, low latency	Fraud detection, real-time decision-making
ETL Pipelines	Event-driven, scalable, adaptable	Hybrid cloud data integration

Table 1 compares different ETL architectures, highlighting their characteristics and example use cases. Batch processing is suitable for historical data analysis due to its scheduled nature and high latency, while real-time processing offers low latency and supports tasks like fraud detection. ETL pipelines are event-driven, scalable, and adaptable, making them ideal for hybrid cloud data integration.

2.2 Challenges in High-Volume Data Warehousing

Exploiting high volume data warehousing in applications of financial is not without some challenges as brought out by this study. Trading firms deal with terabytes of data every day from trading floors, credit cards, and other obligatory reporting services. This mass of data is then exacerbated by the sheer variability of data types, from relatively orderly relational tables to semi-structured JSON files and completely unstructured datasets (Oliveira, 2021). This is to mean that advanced ETL systems are needed to handle the complexity of such data formats.

Another important problem is latency and performance. With financial operations requiring decision making in real-time, the delays that come with data processing impact essential business processes including fraud detection and algorithmic trading. High data velocity even aggravates these challenges because records run into millions per second needed to ensure business continuity.

Adding to the pot, regulatory compliance comes with another consideration. Laws like GDPR, SOX as well as BASEL III are the reason why financial regulations require the tracking of data such as audit trails, data privacy, as well as data retention policies (Bandyopadhyay, 2024). Such standards create demands for sturdy ETL processes, which must cope with large data flows in addition to compliance needs.

Data quality should also be considered which is a critical factor. Data errors, such as missing or duplicated data, lead to weak reliability of financial analytics. There are constraints in which data is cleaned, checked and normalized within the ETL processes prior to entering the warehouse. The failure to deal with these problems can result in impaired analyses, that therefore, impair decisions.

3. ETL ARCHITECTURE FOR FINANCIAL APPLICATIONS

3.1 Characteristics of Financial Data Sets

Financial datasets are therefore inherently diverse and are composed of structured, semi-structured and unstructured data. Structured data most often contains the transactions, the markets, and the customer accounts and is stored in a relational database (Biswas, 2022). Structured data is obtained from data generated through prescribed templates like XML/JSON for regulatory reporting and API interactions; while the unstructured data comprises of emails, financial news, social media sentiment, which is becoming more and more important in analysis.

Such volume is attributed by the real-time nature of the industry with constant transactions such as gate activity, credit sales, and fraud detection creating a flow of financial data. Also, the data which is financial is often enriched with attributes such as multidimensional time series data, geo-location data and categorical label data which require strong storage and querying system (Rizky et al., 2024). Due to these characteristics, ETL systems for financial data should therefore be made scalable, flexible and redundant. As depicted in Figure 2, the ETL workflow includes stages such as extraction, transformation, and loading, followed by data quality monitoring and a feedback loop for reprocessing if issues are identified.

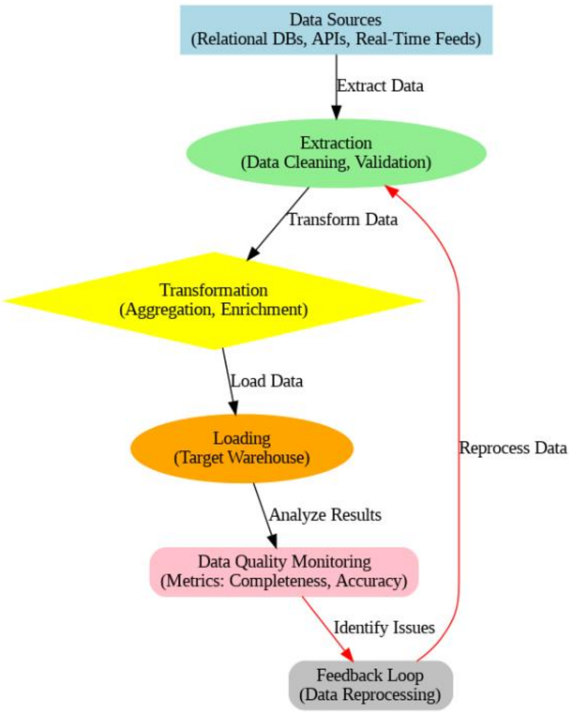

Figure 2 ETL Workflow

3.3 Integrating ETL with Data Warehousing Solutions

The management of financial information would not be complete without the use of ETL together with data warehousing. Contemporary ETL processes are more typically built to work with DWs that are located in the cloud, utilizing scalability and a pay-per-use, consumption-based pricing model that fits the irregular and unpredictable pattern of financial processing.

Other emerging implementation models consist of adopting both private and hybrid cloud architectures particularly where there is an emphasis on security and confidentiality of information together with the need for vast storage and processing power facilitated by cloud platforms (Mohanty, Jagadeesh, & Srivatsa, 2013). For example, the enterprise, for instance, a financial facility, can store personally identifiable information (PII) in an on-premises data warehouse due to legal requirements while using cloud data warehouse for analysis and reporting purposes.

Table 2: Comparison of Data Warehousing Solutions for Financial Applications

Solution Type	Characteristics	Example Use Cases
On-Premises Warehousing	High security, limited scalability	PII storage, regulatory compliance
Cloud Warehousing	Elastic, cost-efficient	Real-time analytics, large-scale reporting
Hybrid Warehousing	Balances security and scalability	Mixed sensitive and general analytics

As shown in Table 2, the comparison of data warehousing solutions outlines the characteristics and use cases of different approaches. For enhancing the efficiency of integration, most of the financial ETL systems embedded the orchestrations tools like Apache Airflow and AWS Step Functions (Maier, 2006). These tools enable the automation and tracking of plenty of operations which are associated with ETL and data warranty tasks.

Combined with the data warehousing technology ETL has also improved the speed and accuracy in which financial institutions handle and analyze large volumes of data. The next subcategory discusses issues that arise with large scale ETL in the case of financial applications.

4. CHALLENGES IN HIGH-VOLUME ETL PROCESSING

4.1 Data Volume and Velocity in Financial Applications

Financial applications are deployed in a big data environment that is highly volumetric and velocities oriented (Bengre & HoseinyFarahabady, 2021). Currently, global stock exchange markets accomplish billions of trades each day, credit card industries manage millions of transactions, and algorithmic trading systems produce continuous market reports. The velocity of generating the financial data requires the flag ETL systems that will work almost in real-time or in near-real-time mode. Even in high-frequency trading on its own the data stream processing can reach a rate higher than millions of messages per second, which means that the systems must be able to handle extremities of workloads without a breakdown.

The huge problem of traditional ETL systems is that they can hardly cope with the requirements of modern financial systems because of the batch-oriented processing. This limitation partly explains why stream-based ETL architectures, for high-velocity data ingestion and transformation, are prevalent in the market today. But to deliver very low-latency summarized results in such cases is possible only with specialized hardware, optimal algorithms, and well-protected networks. Figure 3 illustrates the relationship between data loss and throughput over time during the ETL process.

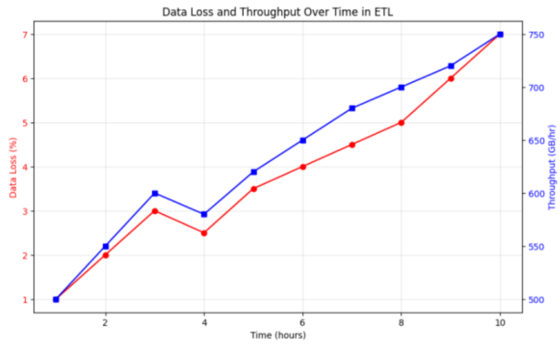

Figure 3 Data Loss

4.2 Latency and Performance Bottlenecks

One of the biggest difficulties of applying ETL is latency, especially in large-scale processes typical in financial applications (Paul, 2022). For instance, in fraud detection, a slight lag in data processing will mean that chances of preventing unauthorized transactions are missed. Likewise, the delays in data compilation during risk analysis can result in wrong estimations and cost and reputation losses in institutions.

There are several elementary sources of performance bottlenecks: I/O constraints, the transformational logic, and the networks' bandwidth (Grzegorowski et al., 2021). For example, using the traditional ETL tools may prove difficult if the tools' ability to perform transformation tasks consecutively translates into time delay when working with multiple terabytes of information. In order to overcome these problems financial organizations are starting to use parallel and distributed processing frameworks like Apache Spark and Flink. Such frameworks decompose workloads into numerous nodes and are able to perform ETL jobs in faster time. Figure 4 provides an advanced bottleneck analysis of ETL stages, highlighting metrics such as latency, resource usage, and error rates across extraction, transformation, and loading.

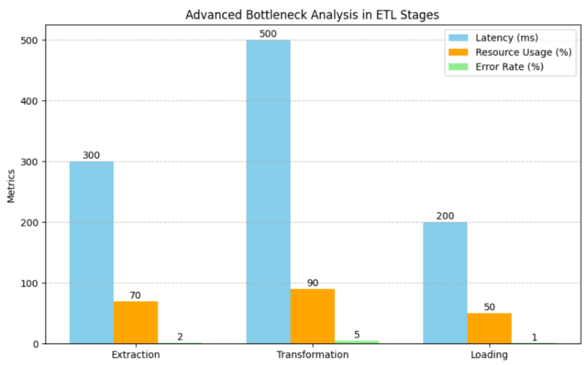

Figure 4 Bottleneck Analysis

4.3 Compliance and Regulatory Constraints

Lenders are faced with a broad body of regulation which enforces strict rules and standards of data management and reporting. Legal requirements like GDPR, SOX, HIPAA, PCI-DSS, require the protection of other types of data, which include PII and financial data (Fejzaj, 2021). ETL processes remain crucial in meeting compliance requirements through achieving data encryption and access control and, audit trails.

The issue here is selecting the right combination of compliance and performance objectives. To illustrate, when using encryption while in the ETL process, you find that big amounts of data slow down data processing (de Assis Vilela, Times, & de Campos Bernardi, 2023). Likewise, detailed audit trails enhance storage overhead or data complexity and add clumsiness in data management. These constraints call for the application of methodologies including hardware-based encryption and / or compression techniques in a bid to ensure compliance with these requirements but without prejudicing on performance results.

5. OPTIMIZATION TECHNIQUES FOR ETL PROCESSES

5.1 Parallel Processing and Distributed Computing

Both parallel processing and distributed computation are revolutionary solutions to enhance ETL activities in large databases (Salamkar & Allam, 2020). Through distribution of ETL workloads in a cluster, Apache Spark, and Hadoop and associated frameworks help in accelerating execution of ETL tasks. These frameworks also use distributed file systems like HDFS to replicate data, to achieve fault tolerant and high availability system.

In financial applications, parallel processing finds great use in functions such as risk assessment of a portfolio, and 'clearing' process for values to ensure they tally, both of which require massive numerical computations on data (Nambiar & Mundra, 2022). Another useful property of distributed computing is scalability, which enable organizations add or remove nodes depending on the traffic load.

5.2 Incremental Data Loading Approaches

One of the big optimization areas that has also evolved with time is the incremental data loading. At variance with full-load methods, where all tables in the data warehouse are loaded with full dataset, incremental loading deals with only that data that has been modified since the most recent ETL pass (Burle, 2024). This approach is efficient in the consumption of resources and time used to update the target warehouse.

Penalising minority update is beneficial in those applications where data change frequently, but changes will only affect few records at a time (Van der Putten, 2024). For example, while generating credit risk model, changes in customer credit ratings information could have partial impact to the risk data base. Due to working CDC and log-based replication techniques, ETL systems can effectively detect and load records that have been changed.

6. ROLE OF EMERGING TECHNOLOGIES

6.1 Big Data Frameworks for ETL Optimization

Apache Hadoop, Spark, and Flink have transformed the ETL process to the utilization of frameworks that support high distributed processing capability for exabyte scale. They both use parallelism for performing the ETL activities distributed across the nodes, and such an approach results in better performance and fault tolerance (Akhund, 2024). Apache Spark, for example, supports in-memory processing and real-time stream processing, meaning that it's best suited to low latency financial applications.

The Big Data frameworks are most beneficial in case of unstructured and semi-structured financial data which can include transactional logs, customer interactions and filings with appropriate regulatory agencies (Kola, 2024). When these frameworks are combined with ETL pipelines, organizations can clean and load different data types into distributed systems and do so in a manner that remains scalable and efficient. Further, the frameworks such as Flink comprise of stateful stream processing thus allowing analysis of streaming data in real-time such as trend analysis for the stock market of fraudulent activities.

Yet, use of Big Data frameworks is not without its issues such as lack of expertise in the management and fine tuning of distributed systems. As a result, financial institutions can benefit the most from training and recruiting data engineers with Big Data technologies.

6.2 Integration of AI and Machine Learning for ETL Automation

AI and ML are disrupting and revolutionizing, how data is being extracted, transformed, and loaded through ETL frameworks. ETL that powered by artificial intelligence could remove the hassle of recognizing the structure of the transformed data, search for anomalies, and suggesting data mapping on its own.

With regards use case, machine learning is more effective in identifying patterns and outliers within the financial datasets for improved data quality management (Nookala, 2021). For example, an ML model can isolate anomalous transactions for suspicious activities, or system errors such as theft or even false entries. Likewise, AI can forecast future changes on the schema to allow ETL suites to be promptly tweaked in reaction to shifting data source patterns.

Another area in financial applications is the use of AI and ML for business transformation logics, identification of the most relevant equations such as dynamic currency conversions or portfolio rebalancements (Salamkar, 2019). Not only do these technologies optimize ETL processing but also increase the quality of the result. Nevertheless, the application of AI and ML has significant costs and may be difficult for mid-large and especially small-scale financial organizations to apply.

The application of Big Data frameworks, cloud-based platform, and automation via artificial intelligence in ETL reflect advanced technologies to process large data sets at a far greater volume and velocity FEW in financial applications (Blake, 2024). The remaining parts of this article will discuss details of performance measurements, data protection, as well as governance concerns related to ETL processes.

7. PERFORMANCE METRICS AND EVALUATION

7.1 Key Performance Indicators for ETL Optimization

For high volume financial applications, the effectiveness of the ETL (Extract, Transform, Load) procedures needs to be measured. Key performance indicators give an exposure to understand how exactly the ETL system is contributing to the laid down objectives such as speed of the processing, the amount of resource being consumed on the process and overall data accuracy (Oliveira, 2021). In securities processing and financial ETL systems, throughput is one of the key measures that define the quantity of ingested data during a particular time period, normally measured in records per second (RPS) or bytes per second (BPS). For example, in a transaction processing system, throughput could be described in terms of the financial transactions per second.

Another significant KPI is latency that points to time required transitioning through all stages of the ETL process from extraction to transformation and subsequent loading of data into the data warehouse. Reducing latency is especially important in financial applications because the timeliness of data acquisition may influence a decision (Bandyopadhyay, 2024). To highlight this, using trading algorithms with high frequencies, even millisecond delay could lead to substantial losses. Figure 5 shows that ETL performance improves over time with increasing throughput and decreasing latency.

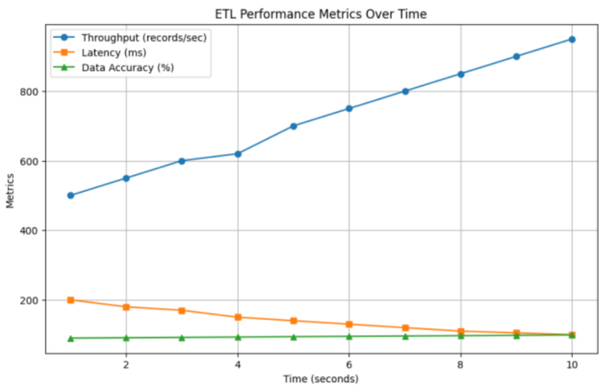

Figure 5 ETL Performance

In addition, an important parameter of financial ETL application is data accuracy, because one mistake can cost a lot of money – for example, incorrect evaluation of risks or violation of legislation. Bachelor of Science in Computer Science, Year 3, Semester 1, Assessment 2 – Question 5 Financials Institutions have a high level of quality check when transformation is going on to ensure the quality of loaded data by minimizing the condition created because of the duplication entries, missing values or wrong mappings.

7.2 Benchmarking Techniques for High-Volume Workloads

The most popular method of comparing the outcomes of ETL is used in transactions that require extensive calculations and high speeds – benchmarking. Benchmarking gives an organization an idea of the speed, scalability and efficiency of the ETL system in relation to other systems and ways that may be more efficient in the system (Biswas, 2022). The most typical benchmarking technique or tool is TPC-DS (Transaction Processing Performance Council – Decision Support) which measures the performance of data manipulation systems, including the ETL processing. Query execution and data loading and transformation benchmarks are used to measure resource utilization here and overall query speed.

Another relevant benchmarking tool used in financial applications is a TPCH – Transaction Processing Performance Council – Benchmark for Complex Queries (Rizky et al., 2024). This benchmark concentrates on assessing query performance and data loading which are two most important measures in financial data warehousing where petabytes of data involving financial transactions, market data and risk analysis are involved.

Another practical application of load testing is that organizations use the information they gather to simulate extreme workloads for organizations; this will help them to know how their ETL processes are fairing under actual working conditions (Mohanty, Jagadeesh, & Srivatsa, 2013). For example, stress-testing on ETL pipelines helps the financial institutions to learn the capacity constraint issues so that systems could effectively manage the transaction loads during the time of high traffic and no system slowness would be observed.

8. BEST PRACTICES AND FRAMEWORKS

8.1 Designing Scalable ETL Pipelines

One of the most important issues when developing ETL pipelines is scalability; in financial applications, it is often necessary to confront increasing volumes of data. To systematized ETL processes, efficient data partitioning, using of distributed computing, and load balancing come in handy (Maier, 2006). The first is horizontal scaling in which the ETL environment is added with more machines to partition the workload across the nodes. Cloud-based ETL is widely used in financial institutions where auto-scaling of resources through demand is used strategically. For example, AWS Glue provides a service that can automatically scale computation that is done on big volumes of data.

There is also important factor in scalable ETL pipelines and is the reduction of data movement. The throughput of financial applications can be enhanced by minimizing the I/O pressure between the systems that feed in data to the data warehouse and the warehouse in question (Bengre & HoseinyFarahabady, 2021). Approaches like, incremental data loading help financial institutions update only the altered/ new records, this takes a considerably shorter time from the existing records particularly when working with the big data.

In addition, batch processing is widely used while orchestrating large volumes of data within the financial ETL processes. Batch jobs involve processing of large amounts of data during a batch process where data is extracted, transformed, and loaded all at once (Paul, 2022). It is especially suitable for periodic reports where the data from several sources must be collected, consolidated and then sent to the data marts. However, special care is to be taken as to how much batch processing must be mingled with real-time streaming which is used with low latency data in trading systems or fraud detection system.

8.2 Strategies for Managing Evolving Financial Data

One of the challenges that financial institutions experience is the management of changing data that includes data schema and sources, additions and changes in the dataset, and changing business needs (Grzegorowski et al., 2021). For this, organizations apply change data capture (CDC) tools, which cause changes in source systems and pass only deltas. The tools like Apache Kafka or Oracle GoldenGate used by CDC can help financial ETL processes to identify alterations in real-time, which keeps the data warehouses fresh without having to perform full load all the time.

Moreover, documentation about ETL code and transformation logic is also critical when it comes to managing change on the processes involved in ETL processes (Fejzaj, 2021). Banks when it comes to finance and accounting use source control systems such as Git on ETL scripts, transformations and workflows. This makes it possible to work as a team, experiment on changes before implementing, and bringing back the previous state when something wrong is realized when updating.

Another strategic approach is metadata that is, the process of tagging the source, transformation, and target data concerning the ETL system (de Assis Vilela, Times, & de Campos Bernardi, 2023). Much to their benefit, metadata repositories can help financial institutions to trace not only the origin of a piece of data, but also all the transformations it has gone through in terms of audited data lineage. Some popular name which are used to keep a record of ETL process are Collibra or Informatica Axon.

9. LIMITATIONS AND FUTURE DIRECTIONS

9.1 Current Gaps in ETL Optimization for Finance

However, there are still some critical areas to be filled that financial institutions have to enhance their ETL techniques for better pipelines. The first by nature is data latency which may be a major drawback. While Financial applications need data of real time or near real time for decision making many traditional ETL systems continue with a request for batch processing (Salamkar & Allam, 2020). This can result in lack of timely update of other key financial reports such as balance of risk, price, among others. Incorporating streaming ETL process that can facilitate continuous data ingestion and transformation is one way of bridging this gap but issues to do with system design and resource availability are next.

One more direction of ETL optimization that is not used enough is in-memory computing. Despite a shared vision of an embedded memory era that has been seen with solutions such as Apache Spark and Hadoop, a number of financial applications remain firmly based within the disk model (Nambiar & Mundra, 2022). Computationally intense queries that require complex calculations, or implicating return tallies of ratios and percentages, with potentially large data sets, can also be substantially enhanced with in-memory computing when compared to conventional approaches to database queries and data transformations. Slowly but steadily, in-memory databases like SAP HANA or MemSQL are implemented; still, financial institutions have to generate a need for those rapidly to develop.

Also, data quality still poses a great challenge in the financial ETL processes As such. Missing, incorrect or dirty data may be due to variability in source systems providing data, data duplication or erroneous data mapping procedures (Burle, 2024). Traditional ETL principles may not have a strict error checking and handling mechanism in place to guarantee that the data is correct and standard when loaded into the organisation's data warehouse. A few firms apply such frameworks as Informatica Data Quality or Talend Data Fabric to support data quality validation and data cleansing; however, their usage remains far from perfect.

9.2 Potential Areas for Research and Development

It is important to identify several potential directions for further research and development in the sphere of ETL optimization for financial applications. One such area in which innovation has been observed is the use of machine learning algorithm for data transformation. Presently, most ETL processes only use simple rules and mapping to perform the transformation risks (Van der Putten, 2024). However, in Static XSLT transformations, one primary drawback is that logic can be changed only at design time and not during runtime But in case of Machine learning algorithms, the transformations logic can be adjusted during runtime based on data history and current trending behavior. This could assist the financial institutions to transform its data pipeline to adhere to the changes in the business needs or market and without one having to struggle with so many data transformations.

One more crucial field is the use of real-time data processing in ETL business processes. Existing ETL solutions were designed to support a batch approach that does not meet the requirements of real-time analytics. The trend of the financial apps requiring more and more frequent insights might be served by integrating streaming analytics as part of the ETL processes to load, transform, and analyze data in real-time (Akhund, 2024). Kafka Streams and AWS Kinesis are newer tools that help with this, but there is much more potential for developing new uses of these technologies in financial apps.

In addition, it should be noted that edge computing means a certain chance of lowering data processing time thanks to the proximity to the sources of data. In financial applications it could be used for pre-processing of data collected at local points before sending to the data warehouse which would save time and cost of transmitting loads of information... Advanced studies in the edge-based ETL may help the financial institutions gather the required data directly from their source and improve their efficiency at different stages of data processing.

10. CONCLUSION

10.1 Summary of Findings

Thus, the research synthesis of optimisation of ETL in high volume data warehousing in financial applications comprises of technical issues and best practices. Financial institutions process humongous volume of data on an everyday basis in the form of transactional data, market data and regulators' reports. ETL best practices need to be followed in order to obtain accurate, easily accessible, and compliant data. Literature section also reflects to major concerns like data delay, size, and data quality assurance and at the same time poses recent successful efforts that were made such as parallelism use of distributed computing and in-memory processing.

The analysis of ETL for financial applications shows that there are certain features of finance data, which makes it highly sensitive, and since it is usually updated very frequently, it requires real-time processing. Smooth functioning of today's financial systems requires constant data processing, and as such proper incorporation of advanced technologies like cloud-based ETL platforms and machine learning for automation is very relevant. Also, a sustainable data governance through the metadata management, encryption and pertinent, internationsl rules such as GDPR and MiFID II continues to be a concern.

10.2 Implications for Financial Data Warehousing

The implications of the present research can be considered regarding to the FDI data warehousing practices of financial companies. Lenders have to transition from implementing batch processing to real-time and streaming ETL for handling the constantly increasing volume of data and offering up-to-date insights. In-memory computing, distributed computing, and use of cloud-based data warehouse are critical requirements for scalability, low latency, and for the required performance of the system.

Furthermore, figures protection and governance have no room for compromises in financial applications since a data leakage or a noncompliance event can lead to enormous losses or damage reputations. Data security must be assured by implementing proper encryption, data masking and also the right access control for handling the financial data that is moved in the ETL pipelines. In SOX, MiFID II, and GDPR there are retention requirements, auditability and accountability that are only probable through efficient metadata management together with data lineage control.

The future development of techniques for the improvement of ETL include machine learning for the dynamic mapping of data transformation, integration ETL with real-time analytics, and distributed edge platforms for reducing latency in application sectors such as finance. The next generation technologies if adopted by financial institutions help them in making sure that the ETL mechanisms are adaptive, productive and sufficiently prepared to address the ever changing data environment.

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