Adaptive Architectures and Real-time Decision Support Systems: Integrating Streaming Analytics for Next-Generation Business Intelligence

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Abstract- The development of new technologies within the last few years and the enormous increase in the availability of real-time data have changed the concept of Business Intelligence (BI). Difficulty in providing real-time, aggregated OLAP information with slow data mining limited ability to accommodate strategic decision support needs through traditional BI systems. This paper looks at the role that streaming analytics can have in serving as an extension of adaptive BI to foster the evolution of RT-DSS. Like using real-time data from IoT, financial transactions data, and social media data, next-generation BI systems can provide predictive and prescriptive analytics information in real-time. The work highlights the drawbacks of the conventional BI architectures and demonstrates the adaptive architectures that can scale depending on the data traffic and various processing loads. Event stream processing, real-time data pipeline, and machine learning algorithms are analyzed as the core technologies enabling efficient and scalable, non-faulty systems. Examples from the financial, healthcare, and retail sectors include showing how RT-DSS can create an environment that promotes anticipatory action and organizational performance. While real-time analytics has been postulated, providing analytical responses to business questions in almost real-time, there are essential limitations yet to be effectively addressed, including latency issues, data integration, and the questions of ethical AI decision-making. Finally, this paper provides insights on where the BI systems are going in the future and focuses on the ongoing adaptation of BI architectures to use real-time data.

Indexed Terms- Streaming Analytics, Real-time Decision Support Systems (RT-DSS), Adaptive Architectures, Business Intelligence (BI), Data Integration.

I. INTRODUCTION

Given the recent technological progress coupled with the continuous expansion of data, companies are forced to accept that timing is a key factor that dictates success in most organizational decisions. Conventional business intelligence (BI) systems that are burdened with large volumes of structured historical data and processed in batches need to be revised to meet the changing requirements of contemporary businesses. With volume, variety, and velocity constantly increasing, there is a pressing need for real-time systems to process and analyze information to keep up with the dynamics of the market and consumers.

Streaming analytics is a critical feature in this new world, enabling organizations to analyze information as it is received from a wealth of sources, including IoT gadgets, open forums, and transaction systems. This capability is crucial in promoting real-time decisions since it enables an organization to get insights on decisions as soon as they are made, unlike most cases where reports take time to produce. However, stream analytics integration into existing BI frameworks presents many issues, such as data quality, system scalability, and low latency.

Due to these challenges, adaptive architectures have been introduced. Below, we define adaptive architectures simply as those that can scale up or down to fit changes in the amount of data and the business needs. Incorporating event stream processing and machine learning in these architectures promotes the kinds of Real-time Decision Support Systems (RT-DSS) that feed the decision maker with events and facts in real-time, duly filtered and fashioned according to the demands of an organization.

This paper aims to establish how and where streaming analytics can be best integrated within adaptive architectures to strengthen the decision support capacity. By mapping the BI systems development, outlining the technological prerequisites for streaming analytics, and commending the adaptive architecture for streaming analytics strategies, this work aims to explain how real-time data can be valuable for organizational competitive advantage attainment. It will expand on the concrete implications and examples of its application in which to show the experiences of the successful adoption of RT-DSS across industries before turning to the discussion on the potential growth paths in the field of Business Intelligence.

II. BACKGROUND AND LITERATURE REVIEW

Structurally, earlier business intelligence (BI) systems were mainly backward-looking and employed batch-processing paradigms. Though these systems have served their respective purposes well, they possess inherent architectural flaws, which hinder scalability and responsiveness. Traditional BI tools and technologies work towards analyzing data stored within data warehouses, which are usually more structured and often result in a lag between data generation and when the data is available for consumption in decision-making. Lack of ability to consume information in real-time prevents organizations from reacting to the dynamic market, changing consumer base, and internal issues. More importantly, these static systems are more discrete and often create barriers to integrating data for analysis, thus providing restricted results in most cases.

Thus, with the call for near-real-time reports enhancing BI systems, the technology has moved toward more real-time BI. Great technological and data analysis improvements have made this shift from simple reporting to dynamic dashboards possible. Real-time BI allows entities to work with live streams of data and instant reporting and data visualization. This shift has proved most effective in enterprises like finance and retail since quick decision-making may greatly affect the performance and positioning of the business. The addition of real-time analysis into BI systems positively impacts organizational flexibility. It allows for strategic action at the appropriate time rather than just a behind-the-scenes approach to remedial actions.

BI would only be complete by mentioning Decision Support Systems (DSS), which have completed the tools used for analysis and decision-making. The prior DSS models are generally implemented for structured decision-making and involve several algorithms and reference data. However, with the increasing use of minute-to-minute data, these systems need reconsideration. Current RT-DSS are transitioning into systems that can handle streaming data to enable organizations to make real-time decisions from data in real-time as opposed to historical data alone. Such evolution is possible due to machine learning and artificial intelligence improvements, which allow for prediction analysis and adaptable decision strategies applications.

Adaptive architectures have emerged and taken root primarily in the face of real-time data processing issues. One distinguishing feature of adaptive architecture is the ability of systems to scale to cope with data rate variability and other changing business needs. It is becoming imperative to design BI systems capable of responding to changes in workload and operations environment. It was revealed that by using event stream processing and cloud support, adaptive architectures could foster an efficient and timely generation of RT-DSS that would meet organizational real-time needs in a precise manner.

A few challenges are associated with streaming analytics and adaptive architectures. The key challenges are data integration, latency, and system scalability, which hamper organizations from benefiting from real-time analytics. Data Protection and Regulation EU 2016/679 on the use of information technology also raises challenges about the rights of data subjects and objective decision-making information data processing and use in organizations based on real-time data. Therefore, this literature review aims to foreground the issue of further research and development of real-time BI, focusing on architecture complexity, streaming analysis, and decision-making tools.

III. TECHNOLOGICAL FOUNDATIONS OF STREAMING ANALYTICS

The increasing adoption of streaming analytics mainly stems from the ever-increasing importance of real-time analysis across companies. This section examines the technologies central to streaming analytics and identifies their roles, importance, and inefficiencies in business settings.

Understanding the nature of streaming data is one of the most significant and initially challenging ideas connected to streaming analytics. Real-time data is the unceasing data streams collected from different sources such as IoT, finance, social networks, etc. Compared with classical data streams, which are gathered and stored at once, they differ in being continuous, massive, and heterogeneous. This information may be structured or unstructured and, as such, requires complex mechanisms to analyze and accumulate data.

The heart of streaming analytics is formed by event stream processing (ESP) engines that allow continuous data streams to work in real-time. These engines enable entities to carry out low latency or initial processing techniques like filtering, aggregation, and data enrichment. ESP systems work on processing information in 'flight' rather than on 'shelf,' which is typical of data warehousing platforms. With the help of technologies like Apache Kafka, Apache Flink, and Apache Spark, Streaming makes it easy to build highly scalable and highly available architectures capable of processing stream data.

Table 1: Comparison of Different Streaming Analytics Technologies

Technology	Features	Advantages	Use Cases
Apache Kafka	Distributed messaging system; high throughput; fault-tolerant	Scalable, resilient, and widely adopted	Real-time data pipelines; log aggregation
Apache Flink	Stream processing framework; stateful computations	Low latency; exactly-once processing	Stream processing applications; ETL processes
Apache Storm	Real-time computation system; processing of unbounded streams	High fault tolerance; supports complex event processing	Real-time analytics; machine learning model serving
Amazon Kinesis	Fully managed service; data stream processing; integration with AWS ecosystem	Scalable and easy to use; low operational overhead	IoT data processing; real-time dashboarding
Google Cloud Dataflow	Unified stream and batch processing; auto-scaling	Managed service; supports Apache Beam	Data processing and ETL jobs; analytics pipelines

Real-time data pipelines are important in integrating and processing real-time data. I will define these pipelines as conveying data from numerous origins to analytics platforms to make information ready for use. Apache NiFi and AWS Kinesis make transferring the data as easy as possible and provide a simple data flow of different sources. Subsequently, organizations can guarantee that they acquire information about a specific situation in real time, preparing them to make fast decisions resulting from the available data.

Continuous queries are always another big part of streaming analytics. In general, and contrary to the traditional queries that work on fixed data stores, continuous queries are used to track data streams and deliver the data as soon as new data becomes available. This capability provides the organization with real-time alerts and condition-based analysis for more effective management of situations. For instance, an organization in the retail business can establish permanently run queries to track consumers' buying habits and thus intervene with promotional methods in case of a shift in trends.

However, only by acknowledging the benefits of streaming analytics can several issues be solved to achieve greater results. An important issue is the question of scalability because the amount of data is constantly growing, and organizations need to have confidence that their analytics solutions will not require extensive changes. Latency is another constraint; organizations must immediately afford the necessary sophisticated analytics. However, they must maintain the quality of their data. Also, another problem that may be faced when working with streaming contexts in terms of data is ensuring that the data being collected and analyzed is of high quality and integrity, a task complicated by the characteristics of the streaming nature of data.

The increased use of streaming analytics as a decision tool signifies that implemented technologies must be incorporated into BI strategies. Through streaming analytics, it is therefore possible for organizations to improve their capacity to deal with constantly evolving business contexts, gain real-time insight from streaming data, and consequently perform better and become more competitive.

IV. ADAPTIVE ARCHITECTURES FOR REAL-TIME BUSINESS INTELLIGENCE

Adaptive architectures aim to increase the functionality of Business Intelligence (BI) systems, but mostly when conducting real-time analysis. These architectures are recognized by their capacity to be adaptable, extensible, and reactive, allowing an organization to adapt to changes in its data surroundings and its business. This section examines adaptive architectures' principles, elements, and advantages in real-time BI.

Fundamental points in adaptive architectures include flexibility in the use of resources as well as the throughput capacity for data flows and analytical needs. Compared to the conventional BI platforms that are preprogrammed, adaptive architectures are based on the cloud, known as distributed systems, to assign them when they are needed. This flexibility enables an organization to easily deal with fluctuating demands and observe optimal performance levels regardless of high workloads. Because cloud technology is a highly flexible and elastic environment, organizations can easily increase their analytical capacity similarly and adapt quickly to changes in the business environment. Also important for adaptive architectures is the seamless connection with event-driven design concepts. Real-time event processing can escalate systems to process real-time events and changes within data flows, thus responding to urgent business conditions. This design approach is appropriate for organizations like the financial and healthcare industries undertaking real-time decisions. Organizations must have an event-driven approach to build efficient data and insights streams to respond to opportunities and threats as they happen.

The microservices concept is based on adaptive architectures, which operate as individual and decentralized micro-applications. The advantages of microservices include that this approach enables organizations to develop more malleable and sustainable systems since each service can be upgraded or altered without destabilizing the structure. This kind of approach also improves flexibility while at the same time fostering a culture of constant search for improvement, leading to increased innovation that will help organizations meet the market needs promptly. For example, in a retail firm, microservices can bring the ability to handle customer actions, inventory, and sales performance data as individual services, enabling the business to enhance specific attributes without affecting the firm continually.

The adaptive architectures also require data integration and interoperability. Thus, information from different sources, such as IoT, social media, and old IT systems, should be collected in real-time BI contexts. Adaptive systems rely on data integration products and services and the use of APIs to enable the flow and collection of data so that all relevant stakeholders receive timely and relevant information. This capability improves the quality of analysis gathered from analytics since decision-makers in organizations can make decisions based on an organizational performance overview.

Table 2: Examples of Industries Utilizing Adaptive Architectures in BI Systems

Industry	Adaptive Architecture Implemented	Specific Benefits Realized
Healthcare	Cloud-based data lakes with microservices for patient data management	Improved patient outcomes through real-time analytics and personalized treatment plans
Finance	Event-driven architecture for transaction processing and fraud detection	Enhanced security and rapid response to fraudulent activities, reducing losses
Retail	Microservices architecture for inventory management and customer insights	Increased operational efficiency and enhanced customer experience through personalized recommendations
Manufacturing	IoT-enabled adaptive architecture for supply chain management	Greater visibility into supply chain operations, leading to optimized inventory levels and reduced costs
Telecommunications	Real-time data streaming for network performance monitoring	Proactive network management and quicker issue resolution, improving service reliability
Transportation	Cloud-based analytics for fleet management and route optimization	Reduced operational costs and improved delivery times through efficient route planning

This paper has discussed how and why adaptive architectures are valuable in real-time BI and demonstrated the advantages of these changes, which are not merely technical. As such, these architectures allow organizations to collect live data and adapt quickly to current conditions, which provides decision-makers with valuable information. This capability drives organizational culture in that its various teams plan and are ready to counter the challenges of shifting market trends, internal issues of poor organizational structure or design, or, on the other end, search for solutions to improve the general experiences of customers. Adaptive architectures help organizations continue some strategies and also show the ability to change quickly due to external forces, making them relevant more often than not.

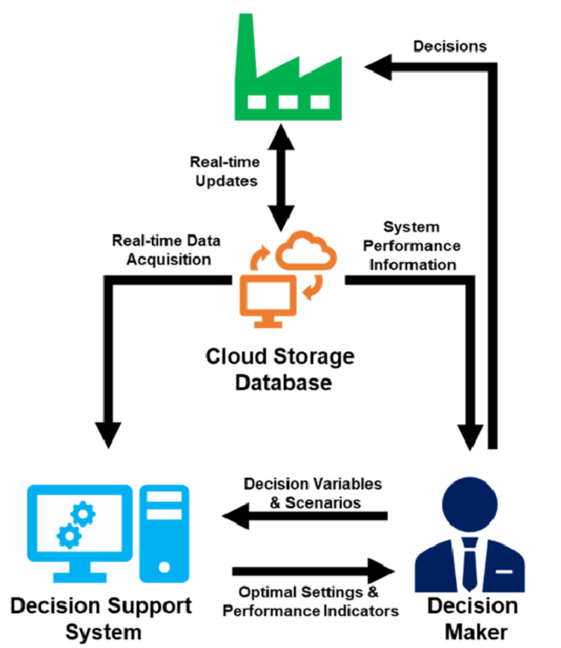
Some issues arise while integrating adaptive architectures. To operationalize NLG within an organization, organizations must invest in the relevant tools, human capital, and organizational enablers to overcome prevailing BI systems. Besides, the permanence and consistency of approaches and techniques for data usage, compliance, and security are critical when operating in the modern world: organizations collect larger amounts of data and face various challenges in their utilization.

Adaptive architectures are a revolutionary solution for real-time Business Intelligence that provides an opportunity to use streaming analytics for decision-making. Following principles of elasticity, event-driven design, microservices, and data integration, organizations can build proper BI systems that meet the modern requirements of business environments. With the ever-changing nature of how organizations use data, implementing adaptive architectures will remain the key to success in organizations that leverage data.

V. REAL-TIME DECISION SUPPORT SYSTEMS (RT-DSS)

Real-time Decision Support Systems (RT-DSS) are complex systems that offer real-time data and information to support real-time decisions. While most decision support systems, as currently well implemented, are based upon historical data and batch processing, RT-DSS uses streaming analytics to provide timely information that can truly make a difference to real-time operations and strategic planning activities. This section analyses the main characteristics of RT-DSS and their advantages and limitations considering the contemporary business environments.

Figure 1: Decision support system process



The defining feature of RT-DSS is that data analysis takes place in real time. Ingesting data from various sources at the speed of real-time: With the help of technologies such as event stream processing or real-time data pipeline, these systems can easily ingest real-time data feed. Such capability makes it possible for such organizations to assess key performance indicators (KPIs) and other important factors as they evolve, allowing for decision-making in response to the change and informed by it. For example, in the case of the financial market, changes can be immediately analyzed in the work of the stock exchange or any other market. When the trader decides whether to buy or sell the shares, offer him the necessary information. The first advantage of RTS-DSS is the improvement of situational awareness. It implies that the reliability and timeliness of the data mean that decision-makers can also respond to new challenges and opportunities. This capability is of great significance for large and volatile industries like healthcare, where patient data availability may significantly affect the decision-making process and outcome. Some applications include eliciting information from the patient's electronic health records, from patient monitors, and others to construct a complete picture of the patient's condition for timely decision-making.

Also, given its design features, RT-DSS can use powerful and promising methods such as machine learning and artificial intelligence to improve decision-making. It especially helps to give a forecast based on earlier patterns and tendencies combined with current information, which allows further action. For instance, the RT-DSS can be employed by a retail organization whereby actual purchase behavior is used to predict customers' demand, when stock levels are to be managed, or when marketing campaigns are to be initiated.

Another huge strength of the RT-DSS is the program's flexibility. These systems are flexible and may be implemented depending on the nature of business of the various industries and organizations. For example, a logistics firm may use an RT-DSS to monitor shipments, delay occurrences, and dynamic routes due to traffic congestion. It also guarantees the application can cope with different businesses' needs and provide value in multiple industries.

However, some issues related to RT-DSS characteristics have to be considered, as follows. One of the major challenges is the high difficulty experienced while integrating real-time data from various sources; this may be felt most especially while handling medium- and large-scale applications, including legacy systems. If data quality is low in the first place, one can only imagine the wrong pictures that will be painted and the wrong conclusions that will be drawn. Furthermore, organizations also have to consider issues concerning the security and privacy of data, especially when working on such information in real time.

A second significant issue is designing interfaces to enable employee-oriented decision-making. Managers could be faced with an information flood originating from various sources in real-time, which, in turn, requires the creation of proper data visualization tools and the appropriate interfaces that sit on top of them so as not to overload the person who has to make decisions. Training and change management are also important because the stakeholders benefitting from RT-DSS must understand how to do so.

Real-time decision support systems are a step from business intelligence tools as they allow organizations to employ streaming analytics to make better decisions. Enabling immediate data accessibility for decision-making, supporting predictive analysis, and enhancing the structures' adaptability across sectors, RT-DSS enhances organizational performances and longevity in increasingly dynamic business contexts. In light of this ratio, RT-DSS integration will remain crucial as organizations embark on real-time analytics for competitive advantage and higher performance.

VI. INTEGRATING STREAMING ANALYTICS IN NEXT-GENERATION BUSINESS INTELLIGENCE

The deployment of methods such as streaming analytics into the next generation of Business Intelligence (BI) systems is indeed changing the face of analytics today. As such, systems that permit real-time processing of data and analysis to produce near real-time data output allow organizations to get timely information and take action as appropriate within a dynamic market environment. This section looks at the issues of methodology, advantages, and risks of adopting stream analytics in today's BI environments.

Table 3: Case Studies of Organizations Integrating Streaming Analytics into BI Systems

Organization	Industry	Challenges Faced	Outcomes Achieved
Netflix	Entertainment	Managing large volumes of streaming data from millions of users	Improved content recommendation algorithms leading to higher user engagement and retention rates
Amazon	E-commerce	Ensuring real-time processing of millions of transactions and user interactions	Enhanced customer experience through personalized recommendations and faster order processing
Uber	Transportation	Real-time tracking and analysis of rides and user behavior	Optimized pricing and routing strategies, resulting in reduced wait times and increased customer satisfaction
Spotify	Music Streaming	Integrating diverse data sources for real-time user insights	Data-driven music recommendations that enhance user engagement and increase listening time
Zalando	Fashion Retail	Analyzing real-time data from various channels to optimize	Improved inventory management and reduced stockouts through accurate

		inventory	demand forecasting
Walmart	Retail	Handling massive volumes of data from various sources for inventory management	Enhanced supply chain efficiency and reduced operational costs through real-time analytics

One of the most straightforward methods of incorporating streaming analytics into BI is to create an infrastructure for a single batch and stream data system. This type of architecture enables organizations to include past and real-time information feeds, thus providing a clear picture of business activities. Applying hybrid data models will help organizations avoid situations wherein only one type of data informs all decisions. This integration requires efficient data management and tools to ease data movement from different systems/ sources.

Innovative technologies in data processing, including event stream processing (ESP) and data streaming platforms, are essential to the convergence. These technologies enable organizations to consume, transform, and analyze big volumes of data in real time. With the help of systems like Apache Kafka or Amazon Kinesis, organizations can develop effective data flows containing continuously incoming data and their analysis. Such platforms help consume real-time data from various sources like IoT, social media, and transaction systems, providing the latest information to the stakeholders.

It brings additional value to next-generation BI systems when machine learning and artificial intelligence are adapted for streaming analytics. With the help of predictive and prescriptive analytics, an organization cannot only summarize the existing patterns but also predict what is likely to happen next, considering the actual current data. For instance, in the case of retail firms, real-time purchase patterns can be identified using machine learning algorithms, allowing for sales marketing to be done in line with new preferences. This integration will enable organizations to achieve timely and relevant insights to inform decisions and strive for higher customer interaction and organizational effectiveness.

Another important element related to visualizing streaming data and their integration into BI is that advanced data visualization tools are critical for managers to simplify ambiguous information into usable formats to make informed decisions. Performance reports that show updated metrics and company goals provide the organization with a way to view the progress as it happens without delays. If designed to be very simple and easy to understand, organizations can help the decision-makers get an at-a-glance idea of the myriad of available data, leading to better decisions.

That said, there are several issues organizations need to overcome and tackle when using streaming analytics for BI integration. A major problem is maintaining data quality and consistency standards in categories where data is collected in real-time. Since streaming data is often large, complex, and consists of various types of data, a high degree of accuracy and reliability is vital for decision-making. To minimize such risks, data validation and cleansing are needed to help produce good and quality data.

Companies must manage technical issues related to data integration processes, various technologies, and data sources. Moreover, due to the implementation of such systems, there is an acute demand for qualified personnel capable of administering and supporting the systems. These problems can be solved during the attempt to get the most out of the BI systems by training the existing workers and employing new specialists in stream analytics and data engineering.
Streaming analytics into the next-generation BI system is a promising shift in coping with difficulties in predicting real-time data for organizations. The BI frameworks that help to make the organization noticeable can be developed by implementing the following steps:

- Creating the consolidated data infrastructure
- Using sophisticated processing platforms

- Integrating the BI system with machine learning tools

Though the issues persist, organizations stand with high prospects of risk-free inclusion of streaming analytics as the business world advances to a world that highly depends on data.

VII. CHALLENGES AND FUTURE DIRECTIONS

When extended to Business Intelligence (BI) systems, Streaming analytics has advantages but challenges that organizations need to quell to achieve optimum impact. A summary of the main research questions pertinent to tapping the potential of streaming analytics and the implication for future study of the emerging area is provided in this section.

Data quality and integrity are two of the biggest problems organizations often face when data is in real-time. Data streaming can come from a wide variety of sources and, in response, can be structured, unstructured, or semi-structured in format or structure. This data type normally contains irrelevant noise and may have several inconsistencies as it is frequently updated; thus, it contains much real-time data. To avoid such problems, organizations need to devote sufficient resources to implementing proper data governance frameworks that define data accuracy, verification, and cleaning guidelines. Appropriate solutions that include automated data profiling and monitoring can assist in the early detection of problems related to data quality, allowing decision-makers to gain access to high-quality information.

The last of the essential challenges of streaming analytics is scalability. When organizations create and process more data, their analytics solutions must meet this demand. However, persistent growth in the volume of data requires a scalable system that can respond to these loads as smoothly as possible. With the help of cloud computing solutions and distributed computing architectures, resource management processes that are performed in organizations can be highly flexible. However, the technical implementation of such solutions may hinder many organizations due to the skills required and resource constraints on training.

The specifications and rules are especially crucial as organizations work with personal data in real-time analytics contexts. The main challenges of stream analytics integration include data processing, which often includes personal data, financial information, and other sensitive data; in this regard, it is possible to question data protection rules. Enhancing security is imperative in organizations; achieving either encryption, controlling, or auditing on databases where sensitive information is stored needs to be properly done to meet regulatory requirements. Another important area here is to train employees of the organizations to adopt proper security measures for data protection.

That is why further developments in streaming analytics and BI systems are expected. This is because technologies like artificial intelligence and machine learning will continue to progress, further boosting the effectiveness of real-time decision support systems. For example, incorporating complex algorithms like machine learning into streaming analytics is likely to improve the mechanisms of using them in making developmental predictive models and decisions in streaming analytics. With these technologies developing further, there will be more potential to use real-time analysis for strategic planning needs in an organization, leading to better business value.

One potential area of future work is the work done in federated learning together with private analysis. In a world where data ownership is increasingly important but there is a need to leverage information, federated learning enables training models on distributed data without central ownership of data. This approach has the potential to allow organizations to extract knowledge from different data sources while respecting the regimes governing the protection of data and the privacy of users at the same time.

Also, the availability of advanced and more comprehensive Internet of Things (IoT) capabilities portends a revolutionary role in the future of streaming analytics. IoT devices will result in streaming data generation amounting to petabytes, offering organizations a window into real-time opportunities. More studies in this area should aim to identify solutions for creating architectures that can handle massive amounts of IoT data in real-time to support organizational improvements and provide a better understanding of clients.

As already revealed, when it comes to integrating streaming analytics into next-generation business intelligence systems, several challenges can be encountered, and numerous opportunities can be explored. By so doing, concerns inherent to data quality, scalability, security, and privacy can be addressed, expanding the possibilities of producing real-time analytics. Challenges include The next evolution of streaming analytics, which will be refined by artificial intelligence and the Internet of Things, and the demand for integrated privacy-preserving technology, thus positioning organizations for success in a world that is becoming more data-dependent.

CONCLUSION

Adopting streaming analytics into the adaptive archetypes and real-time decision-assist systems is a drastic change in the business intelligence (BI) systems landscape. Due to the rising competence of real-time data in the organization's operations, the need for complex analytics tools persists. As highlighted in this paper, the technology supports adaptive architectures that underpin streaming analytics, and there is a discussion of how Real-time Decision Support Systems (RT-DSS) enable organizations.

By deploying streaming analytics, organizations introduce radical changes in how they analyze data. Real-time management and data analysis allow organizations to improve control over the environments within which they operate and the ability to respond to market dynamics. Significantly for businesses, this delivers the ability to exploit these opportunities, avoid these risks, and improve the company's performance. In addition, streaming analytics with other higher-order technology enablers, such as machine learning and artificial intelligence, supports intelligence generation in decision-making and promotes and supports strategic thinking.

Nevertheless, the process of expanding the opportunities for the use of streaming analytics is filled with difficulties. Companies need certain information quality, volume, security, and privacy factors to guarantee that analytics solutions work correctly and can provide value. Simple ways of enabling real-time analytics will include Creating proper data governance and leadership, Integrating scalability, and Ensuring that appropriate security is in place and pursued vigorously by the organizational leadership.

Prospective-wise, there are enormous opportunities to enhance the streaming analytics framework. Advancements in IoT devices and the development of artificial intelligence will help organizations get more value from huge data streams. Organizations will have to catch up with new and developing technologies as their respective industries, as well as society at large, become more reliant on data.

The adoption of streaming analytics into the next generation of business intelligence systems is crucial for organizations planning to succeed in the current dynamic business environment. By implementing adaptive architectures and integrating the real-time decision support system, organizations can capture and effectively use real-time insights within organizations to foster growth.

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