International Journal of AI, Big Data, Computational and Management Studies
Noble Scholar Research Group | Volume 5, Issue 3, 168-176, 2024
ISSN: 3050-9416 | https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I3P118

Cloud-Based Big Data Analytics Frameworks for Strategic Business Intelligence and Decision Support

Mr. Shashank Thota
Sr. Salesforce Engineer, USA.

Abstract: The multifold increase in digital information created by enterprise applications, social media, Internet of Things (IoT) operational apparatus, and transactional software applications has altered the way organizations gain strategic intelligence. The scope, speed, diversity, accuracy and worth of the present-day big data cannot be dealt with by traditional data processing and decision supporting systems. Cloud computing stands out as a paradigm shift that comes with more scalable, elastic, and cost-effective infrastructures that can fulfill the large-scale data analytics. To this end, big data analytics frameworks in the form of clouds have been enablers of core strategy business intelligence (BI) and decision support systems (DSS). This essay is a thorough and methodical discussion of cloud-based big data analytics designs and their implication on improving strategic business intelligence and business decision-making. The paper will examine the architecture features, analytics tiers, and processing frameworks that can allow organizations to transform raw and heterogeneous data into actionable insights. The combination of distributed storage system, parallel processing engines, real time streaming analytics, and advanced machine learning models in the cloud environment is discussed in detail. Special consideration is made as to how these frameworks aid descriptive, diagnostic, predictive and prescriptive analytics in several business areas, such as finance, marketing, supply chain management and customer relationship management. The fine literature review encompasses previous research before 2024, which shows the development of the framework of big data analytics, the model of cloud services, and the business intelligence system. The survey explains why traditional on-premise analytics systems have serious drawbacks like the lack of scalability, the high cost of purchasing and installing systems and poor flexibility that cloud-based systems can handle. Moreover, issues regarding data security, privacy, governance, latency, and interoperability are also discussed its most critical. The team of the proposed methodology presents a layer-based cloud-based analytics system that encompasses the data ingestion, storage, processing, analytics, visualization and decision-support layers. The key features proposed in mathematical models and performance metrics are aimed at checking the efficiency of the system, its scalability and accuracy rate of decision making. The analysis of the effect of the cloud-based analytics on strategic decision-making is presented in the results and the discussion sections, where the authors observe the increase in the agility and accuracy in forecasting and responsiveness of the organization. The paper will end up by summarizing the important findings and explaining the future research directions of cloud-native analytics, explainable AI and intelligent decision support.

Keywords: Cloud Computing, Big Data Analytics, Business Intelligence, Decision Support Systems, Strategic Analytics, Distributed Computing, Data-Driven Decision Making.

1. Introduction
1.1. Background
The resulting digital revolution of business has resulted in a unanimous acceleration of data creation through innumerable varieties of heterogeneous sources including enterprise resource planning systems, customer relationship and interaction systems, sensor networks, mobile applications and online services. [1-3] This sudden increase in the amount of data, speed, and types has heightened the demand of highly analytical functions and processes that are capable of converting raw data into the usable information in strategic and operational decisions. The classical business intelligence systems were mainly optimized to examine the structured data saved in relational databases and generally were based on batch processing and preprogrammed reporting systems. Although they have proven to be effective in the stable and predictive data environment, these systems have massive restrictions when implemented to contemporary data ecosystems that encounter real-time streams, unstructured content, and fluidly changing data sources. The answer to these issues has been in the form of big data analytics which presents new distributed computing models that provide parallel processing of large clusters of computing interests. The big data analytics frameworks enable the effective analysis of large and challenging datasets that would not have been possible with standard tools by relying on the scalability of storage platforms and sophisticated analytic methods.

Simultaneously, cloud computing has transformed the computing infrastructural provision and management approach by providing elastic, on-demand computing, storage, and analytics services. This model enables companies to implement and scale analytics systems quickly without having to invest in large capital assets or have to maintain extensive infrastructure. The convergence of cloud computing and big data analytics thus forms a breakthrough method to the current business intelligent system and decision support systems that would allow organizations to gain a level of scalability, flexibility, and low costs and improve their power to derive timely and data-driven insights in a dynamic business environment.

1.2. Importance of Cloud-Based Big Data Analytics Frameworks

The cloud-based big data analytics frameworks are of essence in enabling organisations to have effective management, analysis and utilization of the large scaled data in making strategic decisions. Their significance can be viewed in several dimensions like the ones discussed in the sub sections below.

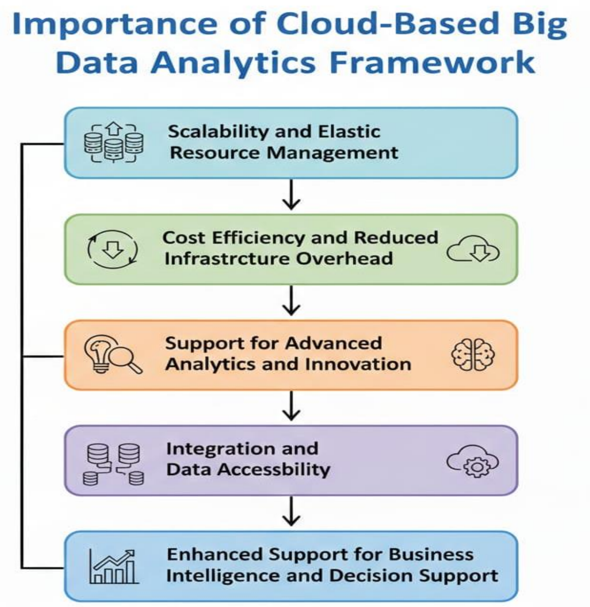

Figure 1: Importance of Cloud-Based Big Data Analytics Frameworks

- **Scalability and Elastic Resource Management:** Among the key benefits of cloud-based analytics models, one must note scalability of resources (dynamically in accordance with varying data loads, workloads, etc). Cloud computing resources are provisioned and de-provisioned on demand unlike traditional on-premise systems, which had a fixed capacity. This elasticity provides a steady operation with the maximum workload of the analysis, as well as will not lead to the wastage of resources when the load is weak. Consequently, businesses can effectively manipulate high volumes of data and real-time analytics without shutting down of the system.
- **Cost Efficiency and Reduced Infrastructure Overhead:** The capital and operational costs are greatly decreased by cloud based analytics model because it does not require initial investments of physical infrastructure. Pay-as-you-go pricing model allows an organization to pay only the resources that it uses and this better promotes transparency of costs and cost control. Moreover, cloud services providers do the infrastructure maintenance, upkeep, and fault tolerance which helps to reduce administrative overheads and allows companies to concentrate on analytics innovation than system operation.
- **Support for Advanced Analytics and Innovation:** It can also be deployed on cloud environments, which have access to high-performance computing environments and a vibrant ecosystem with analytics tools, allowing the application of sophisticated analytics models including machine learning, predictive analytics, and optimization methods. This ease of use speeds up experimentation and innovation as data scientists and analysts will be able to create, train, and deploy elaborate models effectively. Data-driven strategies, therefore, allow organizations to access more insights about their data and attain a competitive edge.
- **Integration and Data Accessibility:** The frameworks based on the clouds allow data of different sources to be easily integrated, such as structured enterprise data, unstructured social media data, and real-time IoT data. Centralized cloud data stores would improve the availability of data among different departments and analytical applications, and encourage collaboration and uniformity in decision-making. The single view of data data is critical to multipurpose business intelligence and enterprise wide analytics initiatives.
- **Enhanced Support for Business Intelligence and Decision Support:** Cloud-based analytics solutions based on big data data and infrastructure enable the enhancement of business intelligence and decision support systems through the integration of scalable infrastructure and sophisticated analytics capabilities. The fact that they stimulate faster generation of insights, real-time monitoring, scenario-based analysis, provides decision-makers with up-to-date and trustworthy information. This decision-support capability is more enhanced to increase strategic alignment of the organization, organizational agility and overall business performance in dynamic and competitive environment.

1.3. Strategic Business Intelligence and Decision Support

Strategic business intelligence (BI) and decision support system (DSS) are essential in helping organizations to convert data into actionable knowledge to support strategic planning (long-term) and competitive strategy. Compared to operational BI whose scope is limited to regular reporting and short-term performance analysis, strategic BI is more inclined to high-level analysis of past trends, [4,5] market movements, and capabilities of the organization. Strategic BI can help leaders and top managers clearly see the performance of an enterprise and its correspondence to the level of strategic goals by using data on various sources of information internal and external. This holism views facilitate sound decision making that concerns market growth, investment, risk management and resource distribution. The decision support systems augment the functions of strategic BI to include analytical models, forecasting methods as well as analysis involving scenarios to analyze alternative strategies and their resulting scenarios. DSS helps organizations predict the future, evaluate uncertainties and risk and opportunities by using predictive analytics.

Prescriptive analytics also allows augmenting decision support by offering the best courses of action based on the stated goals, limits, and business regulations. Combined, these competencies enable the decision makers to cease making decisions based on intuition and embrace evidence based strategic decisions. The strategic BI and DSS have been greatly empowered due to the integration of big data analytics and cloud computing, which allows analyzing large-scale diverse and real-time datasets. On-demand BI services offer scalable computing and perceptual instruments that get that incessant tracking and quick analysis findings. Such integration contributes to the agility of organizations because it enables them to react proactively to changes in the market, customer behavior, as well as competition. Besides, mutual dashboards and interactive visualization enhance dialogue and sync among the stakeholders so that strategic choices are made based on steady and dependable data. Consequently, the strategic business intelligence and decision support systems have become the indispensable part of the contemporary business aimed at long-term competitiveness and strategic position based on data.

2. Literature Survey

2.1. Evolution of Big Data Analytics Frameworks

The primary motivation behind the initial data analytics systems was to work with structured information that is stored in relational databases and it is based on centralized architectures and classic extract-transform-load (ETL) procedures. [6-8] The systems proved to be efficient in moderate volumes of data but were inefficient when organizations started to produce huge volumes of heterogeneous data that came through transaction systems, sensors, social media, and web applications. In order to address scalability and performance shortcomings distributed file systems and parallel processing paradigms were proposed so that data could be stored and processed over clusters of commodity hardware. Best frameworks that enabled handling of batch processing had made it possible to break down large data sets into small parts that could then be processed simultaneously leading to subdivision of process time. Nevertheless, first generation cluster solutions were complicated to setup, demanded administrative skill and capital costs were exorable. The later studies focused on making fault tolerance, data locality, and execution efficiency, which meant that a failure of nodes could not disrupt the processing, and computation would be brought as close to data storage as possible. Although these distributed analytics models were a development milestone when it came to processing high volumes of data, their on-premise implementation models limited scalability, constrained high-scale processing speed, and presented a challenge in coping with the dynamic business analytics needs.

2.2. Emergence of Cloud Computing for Analytics

With the introduction of techniques of big data analytics frameworks, the emergence of cloud computing has essentially changed how these frameworks are deployed and how they are managed by providing access to on-demand computation resources in the form of service oriented frameworks. IaaS, PaaS and Software as a Service (SaaS) models allowed companies to scale storage, compute and analytics tools without making physical infrastructure investments. One of the benefits of cloud-based analytics mentioned in literature is the use of elasticity which increases and decreases the volume of workloads when the data volume and processing requirements vary. The pay-as-you-go payment model also minimized financial risk and promoted the use of tried-out advanced analytics methods. Another observation made by the researchers was that cloud environments made deployment, monitoring, and maintenance more streamlined by use of automation and managed services. Cloud computing allowed processing, high-performance computers, and analytics platforms to work together in one ecosystem, which facilitated quicker data ingestion, processing, and visualization. Consequently, cloud-based analytics-systems proved to be more reliable and flexible to a traditional on-premise system especially when it comes to dealing with variable workloads as well as supporting business intelligence and decision support applications.

2.3. Business Intelligence and Decision Support Systems

Business intelligence (BI) systems have developed dramatically compared to the previous use of non-interactive and fixed reporting and dashboarding systems into dynamic, interactive analytics systems that are able to enable complicated decision-making processes. The early BI was limited in its support of predictive or prescriptive insights but aimed at the analysis of historical data and producing descriptive reports. As time went on, decision support systems (DSS) became integrated with analytical models, forecasting, optimization algorithms and simulation techniques to help the managers evaluate alternatives and possibilities. The adoption of big data analytics in the BI and DSS systems added more power to these systems as they were able to analyse high-volume, high-velocity and high-variety data. Literature suggests that any data-driven BI systems enhance accurate decision making, responsiveness as well as organizational agility through the delivery of timely action insights. Nevertheless, research also prescribes severe issues, such as quality management of data, complexity of data integration, privacy, and security risks, especially those encountered in clouds. Also, the absence of standardization of architectures, as well as the inability of analytics tools to work together, makes the desire to adopt analytics tools across the enterprise complex, which is why strong, scalable, and secure analytics systems in line with strategic decision-making goals are required.

2.4. Research Gaps Identified

Although the literature on big data analytics, cloud computing, and business intelligence is quite extensive, there are still several gaps, which are considered to be critical. First, most studies conducted in the field of technological performance research without suggesting integrative frameworks that clearly explain how cloud-based analytics services are aligned with strategic business intelligence goals. Second, minimal quantitative assessment of the impacts of analytics-driven decision support systems on the organizational outcomes in the quality of decisions, operational effectiveness, and strategic competitiveness are absent. Third, although the area of real-time and streaming analytics is gaining momentum, how the two are combined with long-term strategic planning and historical analysis of data is a topic that is not fully studied. The above gaps have shown that there is no alignment between technical analytics developments and its specialized use in enterprise decision-making. To deal with these limitations, an organized, stratified analytics model along with a strict assessment procedure that examines performance of the system and the efficiency of the decision support will be necessary to close the gap between cloud-based big data analytics and strategic business intelligence.

3. Methodology

3.1. Proposed Cloud-Based Analytics Framework

The cloud-based analytics structure proposed is built as a layered architecture to make it a scalable, flexible, and appropriate structure to the business intelligence (BI) and decision support system (DSS) needs. [9-11] Each layer does a specific job, and at the same time, it is closely connected with the neighboring layers to provide the smooth flow of data and analytics-oriented decision-making.

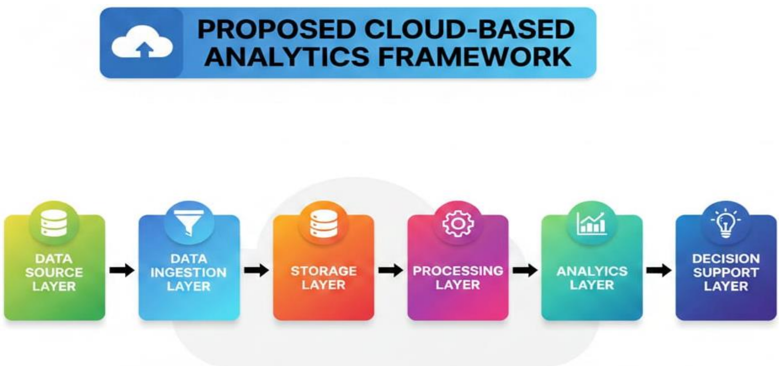

Figure 2: Proposed Cloud-Based Analytics Framework

- **Data Source Layer:** Data source layer is the source of raw data and consists of a broad spectrum of diverse sources such as enterprise transactional systems, Internet of Things (IoT) sensors, social media platforms, log files, and outside open-data repositories. These sources produce structured and unstructured pieces of information at varying speeds and quantities. This layer supports and allows a wide range of data formats and data sources, thus providing a complete coverage of data which could be utilized by the organization in order to gather both operational and customer as well as environmental data that can be utilized in strategic analysis.
- **Data Ingestion Layer:** The data ingestion layer will be in charge of taking up, filtering, or transferring data of various sources into the cloud environment. It advocates the batch ingestion of older data as well as the real-time streaming of high-velocity data produced by IoT centers and online websites. This layer is the one that ensures reliability of data by means of validation, transformation, and tagging as metadata so that downstream processing will be effective, and the latency and data loss are minimized.
- **Storage Layer:** The storage layer offers data repository that is not only scalable but also fault-tolerant to store large amount of structured, semi-structured and unstructured data. Distributed storage systems are used in order to achieve high availability, redundancy of data and to provide efficient access. It is a layer between storage and compute resources, which can be independently scaled and minimized cost, with long-term data retention and immediate access to data to drive analytics workloads.
- **Processing Layer:** The processing layer performs the computational tasks that are necessary in processing data that is required to be transformed, aggregated and analyzed. It facilitates a batch processing of large historical data and real-time processing of streaming data, thereby making access to timely insights possible. It uses distributed computing environments so as to exploit workloads in different nodes so that more processing is done very fast with less time and to provide fault-tolerance in cloud computing.

- **Analytics Layer:** The analytics layer applies sophisticated analysis tools to gain practical information on processed data. It enables it to use descriptive analytics to comprehend the past, predictive analytics to estimate future results, and prescriptive analytics to suggest the best actions. There are machine learning models, statistical and optimization algorithms incorporated in this layer in order to model decision-making based on data and drive the organizational goals.
- **Decision Support Layer:** The decision support layer is the interface between analytics output and end-users and converting insights into complex intelligence. It delivers interactive dashboards, visual reports, alerts and automated decision recommendations based on the various stakeholder roles. This layer will improve strategic planning, operational efficiency, and the quality of managerial decision-making by allowing real-time monitoring and analysis based on scenarios.

3.2. Analytical Models and Algorithms

The analytics layer is the heart of intelligence of the suggested cloud-based framework since it facilitates various analytical paradigms, which will transform data that has been processed into meaningful and actionable decisions. [12-14] All these paradigms, descriptive, predictive, and prescriptive analytics, are also worked in a complementary way so that organizations can get to know how they performed in the past, predict upcoming trends and act in the most optimal ways.

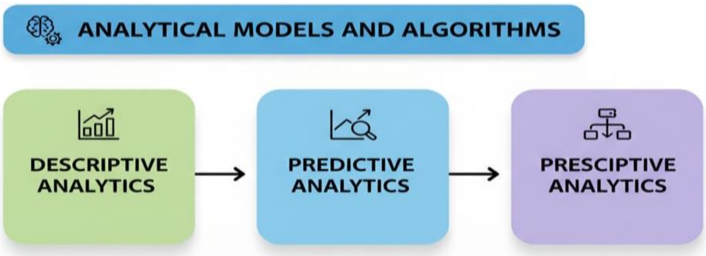

Figure 3: Analytical Models and Algorithms

- **Descriptive Analytics:** Descriptive analytics aims at summarizing past and real time data information with the aim of giving an understanding of what has happened in the system. It uses data aggregation and statistical summaries as well as visualization (charts, dashboards, key performance indicators or KPI) to represent information in a form that is easily understood. Descriptive analytics provides the primarily situational awareness of operational performance to the stakeholders by outlining patterns, trends, and anomalies and forms the background of more advanced analytics.
- **Predictive Analytics:** Predictive analytics focuses on predicting the future by establishing correlations and patterns in historic data. Statistical models, time-series analysis, and machine learning algorithms are used and include regression models, decision trees, and ensemble methods in this paradigm. Predictive analytics aids in making right assumptions of business metrics, risk evaluation, and demand planning by processing large-scale information in the cloud environment. Such forecasts also help organizations to react positively to emerging opportunities and threats.
- **Prescriptive Analytics:** Prescriptive analytics goes beyond prediction, and it advises on the best actions to adopt in order to meet the desired goals within specific limitations. It incorporates the approach of optimism, simulation models, and rule-based recommendation systems or learning-based systems in order to analyze various decision scenarios. The prescriptive analytics will offer practical prescriptive recommendations that can be used in strategic planning and operational effectiveness by including business rules, cost functions, and resource restrictions. Through this paradigm, the decision-makers can assess the trade-offs and execute data-driven strategies with confidence.

3.3. Performance Evaluation Metrics

In order to measure the efficiency and viability of the suggested cloud-based analytics framework, three indicators are established: scalability, accuracy of decision, and cost efficiency. [15-17] The entire metrics measure both the quality of the decision support and the economic viability as well as computational performance on the cloud environments.

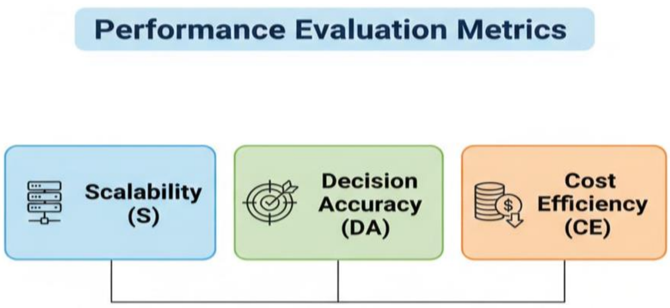

Figure 4: Performance Evaluation Metrics

- **Scalability (S):** Scalability is used to gauge capacity of the framework to enhance performance with increased allocation of computing resources. It is given as the ratio of the time that it takes to execute on one processing node to the time that it takes to execute on many nodes. Here, the time taken to execute a program on a single node can be considered as the baseline performing time and the time taken to execute the program on n node can be considered as the efficiency of parallel processing. Large values of scalability assure superior use of the distributed cloud resources and allow concluding that the framework is efficient in decreasing processing time with the increase in the number of nodes. This value is imperative in judging the architecture of the large analytics load associated with big data analytics.
- **Decision Accuracy (DA):** Decision accuracy determines the quality and reliability of the decisions made by the analytics-driven framework. It is measured in terms of the ratio of correct decisions to the total amount of decisions which the system presents. Recommendations offered by the system are compared with the real outcomes or standardized results to draw correct decisions and recommendations. An increased value of decision accuracy process means that the analysis model is a good representation of the underlying patterns of data and helps to make a good decision. This measure represents directly the effect of analytics on the effectiveness of business intelligence and the effectiveness of decision support.
- **Cost Efficiency (CE):** The cost efficiency evaluates the economics of the analytics structure by correlating the output about the operations cost of the analytics. Measurements provided in analytical output could be things like volume of data processed, number of data insights, or amount of analytical work done whereas operational cost considers cloud infrastructure, storage, computing and maintenance costs. A better cost efficiency value shows that it provides more analytical values of every unit cost, which points to its feasibility and cost-effectiveness to all the organizations that work in pay-as-you-go cloud environments.

3.4. Experimental Setup

The experiment structure will be planned to fully test, research, and verify the effectiveness of the offered cloud-based analytics infrastructure in terms of its performance, scalability, and instrumental support of decision-making during practical enterprise interactions. [18,19] Enterprise workloads are simulated to reflect 3 business use cases which are vital, namely sales forecasting, customer segmentation, and supply chain optimization. Such workloads are chosen since they represent typical analytics-based decision making situations that entail varied data properties such as: structured records of transactions, semi structured customer contact data, and records of time-series operational information. Synthetic and historical data is produced to simulate the different data volumes, speeds, and complexities and allows experimentation to be controlled and allows the real-world relevance to be maintained. The experiments are performed in cloud whereby computing, storage and analytics resources are provisioned dynamically. It conditions workload variability in a systematic manner that can be used to model peak and off-peak workload patterns including seasonal sales swings and unexpected demand spikes. This will enable the analysis of the elasticity of the framework, which will prove that it can expand or reduce its resources based on the varying analytical needs.

Tests of batch analytics tasks are performed to analyze historical trends, and real-time processing elements are investigated on the basis of streaming data inputs in order to determine the latency and responsiveness. In sales forecasting, predictive models are used to forecast the demand through the analysis of past sales and external influencing factors and calculating the demand estimates which are compared with baseline forecasts. Experiments Customer segmentation experiments use techniques of clustering and classification to group customers according to behavioral and demographic characteristics. Prescriptive analytics models to suggest inventory quantities and supply chain distribution strategies under different constraints are applied in supply chain optimization. Scalability is a performance measure whose measurement is documented over several trial runs as well as decision accuracy and cost efficiency. Using these workloads to assess forceful resource allocation, the experimental set-up displays the efficiency of the framework through scalable, precise and economical analytics of a cloud-based business intelligence and choice support structure.

4. Results and Discussion

4.1. Impact on Strategic Decision-Making

The results of the experiment indicate that the implementation of the cloud-based analytics frameworks can significantly positively influence the strategic decision-making process in the functions of the enterprise. Organizations can obtain timely, accurate, and valuable insights to should rely on in their strategic planning using scalable cloud infrastructure and advanced analytical models. This is because, since real-time and near-real-time analytics are available, decision-makers can make fast decisions based on the dynamics of the market, consumer behavior, and operational limitations and enhance organizational responsiveness. The proposed framework uses continuous processing and analysis of information with no periodic reporting as opposed to the traditional analytics systems that use periodic reporting to operate and thus make strategic decisions by use of the latest information available. Predictive analytics can be very useful to improve the accuracy of forecasting, detecting the patterns and trends on a large amount of historical and streaming data sets. With better system of demand forecasting, companies can better coordinate production strategies, inventory and distribution strategies, thereby decreasing uncertainty and minimizing operational risks. In like manner, the predicting of customer behavior is used to promote marketing campaign and personalized offerings of a service and helps to achieve customer satisfaction and increase in their revenues. According to the experimental results, predictive models run and deployed on cloud have the advantage of utilizing elastic computational resources that increase the efficiency of model training and allow the application of more complex algorithms without compromises in performance. Prescriptive analytics also enhances strategic decision making through transformation of predictive insights on the basis of recommendations that are taken. To propose the best resource assignments plan including inventory replenishment level, workforce planning, and distribution of supply chains, optimization models take into account various comings and restraints. Prescriptive analytics help executives choose the best decisions using numbers that indicate trade-offs and likely expected results of the business strategies. All in all, the findings prove that cloud-based analytics models not only enhance the quality of analytical accuracy but also the speed and effectiveness of strategic decision made under a dynamic business setting.

4.2. Scalability and Performance Analysis

The scalability and performance analysis findings reflect the efficiency of the set-out cloud-based analytics framework to manage the growth of data and computational loads. The framework has a distributed nature and thus is nearly linearly scalable, with the performance improvement being dependent on the number of computing resources that are added to the framework. The framework dynamically scales to add more compute nodes to deliver analytics services in parallel as workload intensity and data scale, without the system needing to go offline or manually add nodes to the system. This scaling elasticity makes it possible that the performance is not affected at all even when the load reaches its peak load, this is essential in the case of an enterprise environment where the analytics needs can fluctuate. According to performance analysis, distributed processing greatly decreases both the batch and real-time analytics workload execution time. Workload partitioning and data locality are useful in large-scale data processing when one wants computations to be performed closer to the data, and transferring data is not important. The obtained results demonstrate that the faster the number of processing nodes, the shorter the time required to accomplish the tasks, which confirms the efficiency of the framework in the use of the cloud resources.

In addition, the fault tolerance is integrated and this guarantees continuous running where automated reassignments are made in case nodes fail to protect system reliability and consistency of performance. The framework has also performed well with respect to mixed workloads both involving historical batch analytics and real-time streaming data processing. Policies of resource allocation dynamically balance the use of compute and memory among all workloads, avoiding resource contention and performance bottlenecks. This flexible nature allows organisations to operate several analytics applications simultaneously and achieve Quality of service improvement. In general, the scalability and performance analysis reveals that the suggested cloud-based analytics framework has the capacity to accommodate data intensive and large scale business intelligence and decision support applications with a consistent level of performance, high availability and operational resilience in the context of varying clouds.

4.3. Business Value and Organizational Benefits

Embracing cloud-based analytics platforms are of great business value and quantifiable organizational gains in the sense that they are changing the paradigm on how businesses use data to make strategic and operational decisions. Among the short-term benefits, it is possible to mention cost savings in infrastructure since organizations do not have to spend tremendous sums of money on initial investments in physical hardware and software placed on the premises. Cloud platforms, under the pay-as-you-go pricing model enable enterprises to weigh expenditure on analytics with the real usage leading to better cost control and finances. Moreover, the overheads on maintenance as well as management complexity are minimized through centralized cloud-based analytics environments, which allows IT personnel to concentrate on innovation, instead of managing infrastructure. Another rapidity that cloud-based analytics provides to the decision-making process is faster data ingestion, processing, and insight generation. Elastic compute resources and automated data pipelines have helped eliminate large and complex datasets analysis time to a significantly smaller size.

This leads to decision-makers having access to near-real-time insights to enable them to act promptly to the opportunities and threats that occur. Accelerated decision-making will result in better efficiency in business processes like marketing, finance, supply chain, and human resource; which in the long run will be better performance and competitiveness to the organization. Real-time analytics are also integrated which makes organizations more responsive to the changing market conditions. Organizations can recognize the changes in demand, customer preferences and operational performance immediately as they arise by continuously studying streaming information about customer interactions, transactions and external sources. This ability facilitates proactive operations, including the dynamic pricing adjustments, redistribution of inventory, and the customized approach to customer interaction. Furthermore, analytics systems on clouds facilitate strategic alignment because information-oriented insights are made available to departments and management levels. Through the culture of evidence-based decision-making, organizations are able to satisfy tactical measures with the long-term strategic plans, which result in the value of business over the long term as well as organizational agility.

4.4. Challenges and Limitations

Although cloud-based analytics structures have enormous benefits, there are a number of obstacles and issues that should be thoroughly dealt with to guarantee their effective implementation and successful functionality. Data security is one of the main issues, as the enterprise data which is confidential is kept and processed in common clouds. Companies should establish efficient security systems, such as encryption, access control, identity management, and real-time monitoring, to ensure that data and information are not accessed by unauthorized individuals and other cyber threats. Cloud systems are distributed, which further enlarges the attack surface and requires full security strategies to ensure a degree of trust in the analytics-driven decision systems. Another important issue is data privacy especially where the analytics frameworks handle personal, customer or confidential data. Organizations must adhere to stringent regulatory standards and data protection laws that bring limitations to data collection, storage, processing and cross-border data transfer. Compliance in a variety of jurisdictions may be challenging and multinational enterprises can have a complex time ensuring compliance. A non-compliance with the standards of regulations could lead to legal consequences and damage to reputation and losing customer trust.

Therefore, the privacy-by-design approach and the data governance policies need to be integrated into the cloud-based analytics designs. There are also major constraints of data governance and integrity in the environment of cloud analytics. Balancing between data quality, lineage, and data consistency between multiple sources and analytics pipelines is difficult, especially in real-time and batch data formation. Poor decision-making and unreliable analytics results can be achieved when inaccurate or incomplete data is used. Also, vendor dependency and interoperability problems can reduce the flexibility and raise the long-term expenses. These issues indicate why there is a need to have detailed governance systems, standard policies, and ongoing auditing systems to guarantee that data remains intact, and regulations are met and the cloud-based analytics systems operate effectively.

5. Conclusion

The paper has conducted an in-depth analysis of big data analytics solutions based upon the cloud-based computing platforms and how they support recommending strategic business intelligence and decision support in contemporary business. In a vast overview of the literature provided, the research has noted that the history of analytics systems has evolved with centralized and on-premise models that are now being replaced with scalable systems and cloud-native architectures, which can process large amounts of heterogeneous information. Based on these observations, a well-organized layered system was suggested to implement data ingestion, storage, processing, analytics, and decision support services in a single cloud platform. The architecture lays more stress on elasticity, fault tolerance, and interoperability and focuses on the major challenges related to the large-scale deployment of analytics. Additionally, the well-defined performance assessment metrics, including scalability, decision accuracy, and cost efficiency, were also presented, which helps understand that cloud-based analytics frameworks can be used to increase computational efficiency and the quality of the analytics-based decisions to a considerable extent. The experimental analysis and results discussion have proved that cloud-based analytics frameworks offer significant benefits over the traditional ones in that they can be scaled nearly-linearly, executing in less time and allocate resources dynamically without service degradation. The predictive and prescriptive analytics model integrations into the proposed framework were found to enhance the accuracy of the forecast, streamline resource use, and shorten the decision-making process.

All these abilities help to enhance the agility of organizations, their speed in responding to strategic changes, and the extent of matching analytical insights with the business goals. Cloud-based structures foster operational and strategic decision-making because they allow real-time and historical analytics in one platform, which reinforces their relevance as a core component of data-driven companies. In spite of these advantages, the study also recognized the prevailing issues of data security, privacy, governance and regulatory compliance. These concerns may be considered critical in making cloud-based analytics solutions more trustful, reliable, and sustainable. In this regard, future studies can build on the suggested framework by incorporating explainable artificial intelligence (XAI) platforms to improve the model transparency and the trust of the user in analytics-based recommendations. The administration overhead can also be minimized, and data integrity increased through the development of automated data governance and compliance operating in complex analytics pipelines. The discussion of hybrid and multi-cloud architectures is another prospective direction of the research, especially when it comes to organizations that have sensitive or regulated data. All in all, further studies and innovations in such fields will enhance the efficiency of cloud-based big data analytics systems as strategic facilitators of intelligent decision support.

References

1. Dean, J., & Ghemawat, S. (2008). MapReduce: simplified data processing on large clusters. Communications of the ACM, 51(1), 107-113.
2. Ghemawat, S., Gobioff, H., & Leung, S. T. (2003, October). The Google file system. In Proceedings of the nineteenth ACM symposium on Operating systems principles (pp. 29-43).
3. Khan, Z., Anjum, A., & Kiani, S. L. (2013, December). Cloud based big data analytics for smart future cities. In 2013 IEEE/ACM 6th International Conference on Utility and Cloud Computing (pp. 381-386). IEEE.
4. White, T. (2012). Hadoop: The definitive guide. "O'Reilly Media, Inc.".

5. Zaharia, M., Chowdhury, M., Franklin, M. J., Shenker, S., & Stoica, I. (2010). Spark: Cluster computing with working sets. In 2nd USENIX workshop on hot topics in cloud computing (HotCloud 10).
6. Armbrust, M., Fox, A., Griffith, R., Joseph, A. D., Katz, R. H., Konwinski, A., ... & Zaharia, M. (2009). Above the clouds: A berkeley view of cloud computing.
7. Mell, P., & Grance, T. (2011). The NIST definition of cloud computing.
8. Wang, L., Zhan, J., Shi, W., & Liang, Y. (2011). In cloud, can scientific communities benefit from the economies of scale?. IEEE Transactions on Parallel and Distributed Systems, 23(2), 296-303.
9. Botta, A., De Donato, W., Persico, V., & Pescapé, A. (2016). Integration of cloud computing and internet of things: a survey. Future generation computer systems, 56, 684-700.
10. Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS quarterly, 1165-1188.
11. Eckerson, W. W. (2010). Performance dashboards: measuring, monitoring, and managing your business. John Wiley & Sons.
12. Turban, E. (2011). Decision support and business intelligence systems. Pearson Education India.
13. Kambatla, K., Kollias, G., Kumar, V., & Grama, A. (2014). Trends in big data analytics. Journal of parallel and distributed computing, 74(7), 2561-2573.
14. Buyya, R., Yeo, C. S., Venugopal, S., Broberg, J., & Brandic, I. (2009). Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility. Future Generation computer systems, 25(6), 599-616.
15. Niu, Y., Ying, L., Yang, J., Bao, M., & Sivaparthipan, C. B. (2021). Organizational business intelligence and decision making using big data analytics. Information Processing & Management, 58(6), 102725.
16. Miah, S. J. (2015). A Cloud-based Business Analytics for Supply Chain Decision Support. Journal of Information Sciences and Computing Technologies, 4(1), 274-280.
17. Vögler, M., Schleicher, J. M., Inzinger, C., & Dustdar, S. (2017). Ahab: A cloud-based distributed big data analytics framework for the Internet of Things. Software: Practice and Experience, 47(3), 443-454.
18. M Alasiri, M., & Salameh, A. A. (2020). The impact of business intelligence (BI) and decision support systems (DSS): Exploratory study. International Journal of Management, 11(5).
19. Müller, O., Junglas, I., Brocke, J. V., & Debortoli, S. (2016). Utilizing big data analytics for information systems research: challenges, promises and guidelines. European Journal of Information Systems, 25(4), 289-302.
20. Fernández, A., Del Rio, S., López, V., Bawakid, A., Del Jesus, M. J., Benítez, J. M., & Herrera, F. (2014). Big Data with Cloud Computing: an insight on the computing environment, MapReduce, and programming frameworks. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 4(5), 380-409.
21. Khan, Z., Anjum, A., Soomro, K., & Tahir, M. A. (2015). Towards cloud based big data analytics for smart future cities. Journal of Cloud Computing, 4(1), 2.