Cloud Infrastructure for Big Data Processing and Analytics

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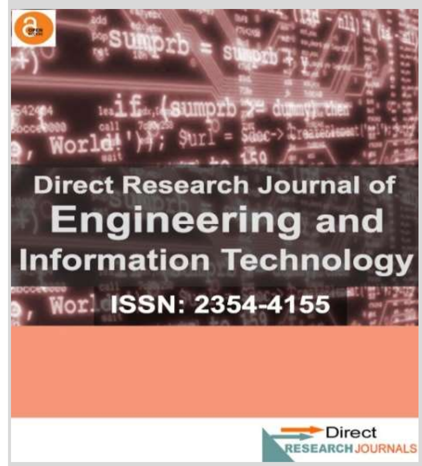
ABSTRACT

The rapid expansion of data-driven applications has intensified the need for scalable infrastructures capable of processing large and complex datasets. Cloud computing has emerged as a critical enabler of big data analytics, offering flexible and cost-efficient computational resources. However, existing research remains fragmented across domains and technologies. This study aims to provide a comprehensive synthesis of high-impact literature on the integration of cloud computing and big data analytics, identifying key trends, technological advancements, challenges, and application domains. A systematic review methodology was employed using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency and reproducibility. The study adopts a mixed-methods analytical approach based on John W. Creswell's convergent design, integrating qualitative thematic analysis with quantitative descriptive evaluation. Literature published between 2018 and 2026 was retrieved from major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Following a rigorous screening and eligibility process, 68 peer-reviewed studies were included for analysis. The findings indicate a clear shift from traditional centralized systems to distributed, hybrid, and cloud–edge architectures. Increasing integration of artificial intelligence and Internet of Things (IoT) technologies is evident across sectors such as healthcare, finance, retail, and smart cities. While cloud-based big data analytics enhances scalability, efficiency, and real-time processing, critical challenges persist, including data security, privacy, latency, and system interoperability. This study provides a holistic, evidence-based synthesis of cloud-enabled big data analytics without relying on primary data or experimental methods. It advances theoretical understanding, highlights research gaps, and offers strategic insights for future research and practical implementation in data-driven environments.

Keywords: *Cloud computing; Big data analytics; Systematic review; PRISMA; Scalability; Data security; Cloud-edge computing; Artificial intelligence; IoT*



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INTRODUCTION

Cloud computing has fundamentally redefined the landscape of modern computing, providing a scalable, flexible, and cost-effective framework for handling extensive computational tasks. This paradigm shift has become particularly significant with the advent of big data, a phenomenon characterized by the proliferation of voluminous, complex, and diverse datasets generated from sources such as social media, IoT devices, and organizational transactions. The convergence of cloud computing and big data analytics offers unparalleled opportunities for deriving actionable insights, fostering innovation, and driving evidence-based decision-making across industries. Cloud computing is recognized for its capacity to deliver on-demand computational resources without the prohibitive costs associated with traditional infrastructure investments (Mell & Grance, 2020). By leveraging cloud platforms, organizations can perform sophisticated analytics operations such as machine learning, real-time processing, and predictive modeling while ensuring adaptability to dynamic workload demands (Hashem et al., 2025). This interplay has spurred transformative applications in healthcare, finance, and supply chain management, where the timely processing of complex datasets is critical to maintaining competitive advantages (Jadeja & Modi, 2023).

Big data analytics focuses on extracting valuable insights from datasets defined by their high volume, velocity, and variety, often referred to as the "3Vs" (Gandomi & Haider, 2025). Traditional computing systems frequently fail to manage the operational complexities associated with such data, whereas cloud computing mitigates these limitations through its elastic scalability and distributed processing capabilities. Tools such as Apache Hadoop and Apache Spark, widely integrated within cloud platforms, enable high-performance data processing, making the cloud a natural ally for big data analytics (Zhang et al., 2020).

However, this integration is not without challenges. Concerns surrounding data security, privacy, compliance, and resource optimization underscore the need for robust governance frameworks and technological innovation. As cloud-based analytics continues to grow, addressing these challenges is imperative for ensuring sustainable and ethical implementation (Marinescu, 2023). Ongoing research highlights efforts to optimize resource allocation, enhance data encryption, and reduce processing latency, reflecting the dynamic evolution of this interdisciplinary domain (Chen et al., 2022).

The fusion of cloud computing and big data analytics represents a cornerstone of digital transformation, driving technological advancements and reshaping industries. This paper examines the principles, applications, and challenges associated with deploying cloud computing for big data analytics, emphasizing its strategic importance in harnessing the potential of data-driven insights in an increasingly digital world.

The rapid growth of big data, driven by sources like IoT, social media, and business operations, has overwhelmed traditional computing systems due to their inability to handle the scale, complexity, and speed of data processing. This limitation hinders organizations from deriving timely and actionable insights necessary for decision-making.

Cloud computing offers scalable and cost-effective solutions for big data analytics, yet its adoption faces significant challenges. These include data security and privacy concerns, resource inefficiencies, latency issues, and compliance with regulatory frameworks. Furthermore, the fast-paced development of cloud technologies has outstripped the establishment of standardized best practices, creating gaps in understanding how to optimize their use for big data applications. To address these issues, it is essential to explore strategies that enhance the synergy between cloud computing and big data analytics. This research aims to propose solutions that ensure these technologies are efficient, secure, and scalable, enabling organizations to fully leverage data-driven opportunities. This study aims to provide a comprehensive synthesis of high-impact literature on the integration of cloud computing and big data analytics, identifying key trends, technological advancements, challenges, and application domains.

LITERATURE REVIEW

Cloud Computing: A Scalable Foundation

Cloud computing refers to the delivery of on-demand computing services over the internet, including computing power, storage, and applications, without the need for local infrastructure or physical hardware (McHaney, 2021). In other words, cloud computing allows users to access computing resources and services remotely through a network of servers located in data centers around the world (Figure 1).

Figure 1: Cloud computing platform. Source: Marinescu, (2023).

These resources are delivered on a pay-as-you-go basis, allowing users to scale their usage up or down as needed, and are managed by cloud service providers who handle the maintenance, security, and updates of the infrastructure and services (Galego *et.al.* 2022). Cloud computing has become increasingly popular in recent years due to its scalability, flexibility, cost-effectiveness, and ease of use (Jewargi, 2023). Cloud computing delivers on-demand access to shared computing resources over the internet, enabling organizations to reduce infrastructure costs and increase operational efficiency. Its core attributes scalability, elasticity, and pay-as-you-go pricing makes it particularly suited for big data analytics, which often requires dynamic resource allocation (Marston et al., 2021).

Mohammed et al. (2022) emphasized that cloud platforms democratize access to advanced computing resources, enabling even small enterprises to adopt big data solutions without significant capital investments. Similarly, Mahmood (2022) noted that cloud computing's ability to provide distributed data storage and parallel processing aligns perfectly with the computational needs of big data applications, such as machine learning and real-time analytics.

Big Data Analytics: Transforming Data into Insights

Big data analytics focuses on extracting actionable insights from data characterized by high volume, velocity, and variety. This field employs advanced tools and techniques, such as Hadoop, Spark, and machine learning algorithms, to analyze structured and unstructured data. Gandomi and Haider (2025) highlighted the strategic role of big data analytics in enhancing decision-making processes across industries. They argued that organizations leveraging big data analytics experience improved efficiency, innovation, and competitiveness. However, the substantial computational and storage requirements of big data analytics often necessitate the use of cloud-based platforms (Hashem et al., 2025).

Integration of Cloud Computing and Big Data Analytics

The integration of cloud computing with big data analytics offers a symbiotic relationship, where cloud platforms provide the computational backbone for handling large-scale data processing (Figure 2). Cloud-based big data frameworks, such as Google BigQuery and AWS EMR, enable distributed data analysis, real-time processing, and seamless scalability (Zhang et al., 2020). Hashem et al. (2025) outlined key benefits of this integration, including enhanced resource utilization, reduced operational costs, and increased accessibility to advanced analytics tools. These advantages have made cloud computing indispensable for organizations seeking to implement scalable and cost-efficient big data solutions.

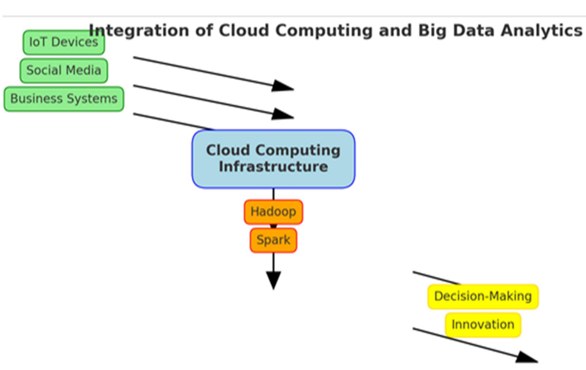

Figure 2: Integration of cloud computing on big data analysis

Challenges in Cloud-Based Big Data Analytics

Challenges in cloud-base big data analytics

Despite its numerous advantages, integrating cloud computing with big data analytics poses challenges (Figure 3). Data security and privacy remain paramount concerns. Sensitive data stored on cloud platforms are vulnerable to breaches and unauthorized access (Subashini & Kavitha, 2011). Compliance with data protection regulations, such as the General Data Protection Regulation (GDPR), adds further complexity (Tsamoura et al., 2020). Latency is another challenge, especially for applications requiring real-time analytics. Cloud-based systems depend on network infrastructure, which can introduce delays in data transmission and processing (Zhang et al., 2020). Furthermore, the unpredictability of costs due to dynamic scaling can be a concern for organizations with limited budgets.

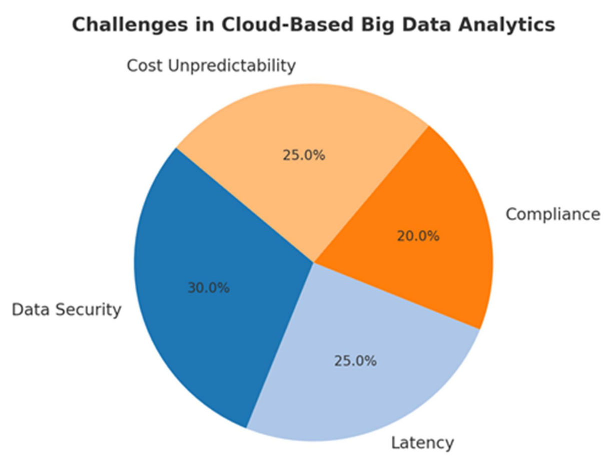

Figure 3: Challenges in cloud-base big data analytics

Applications of Cloud-Based Big Data Analytics

Cloud-Based Big Data Analytics in Healthcare

Cloud-based big data analytics has significantly transformed healthcare systems by enabling scalable data processing, real-time analytics, and intelligent decision-making. Its application spans clinical care, public health, and healthcare management, supported by the convergence of cloud computing, artificial intelligence (AI), and Internet of Things (IoT) technologies. A primary application is in healthcare data management and interoperability, where cloud infrastructures facilitate the integration of heterogeneous datasets such as electronic health records (EHRs), medical imaging, and genomic data (Figure 4). These platforms enhance accessibility,

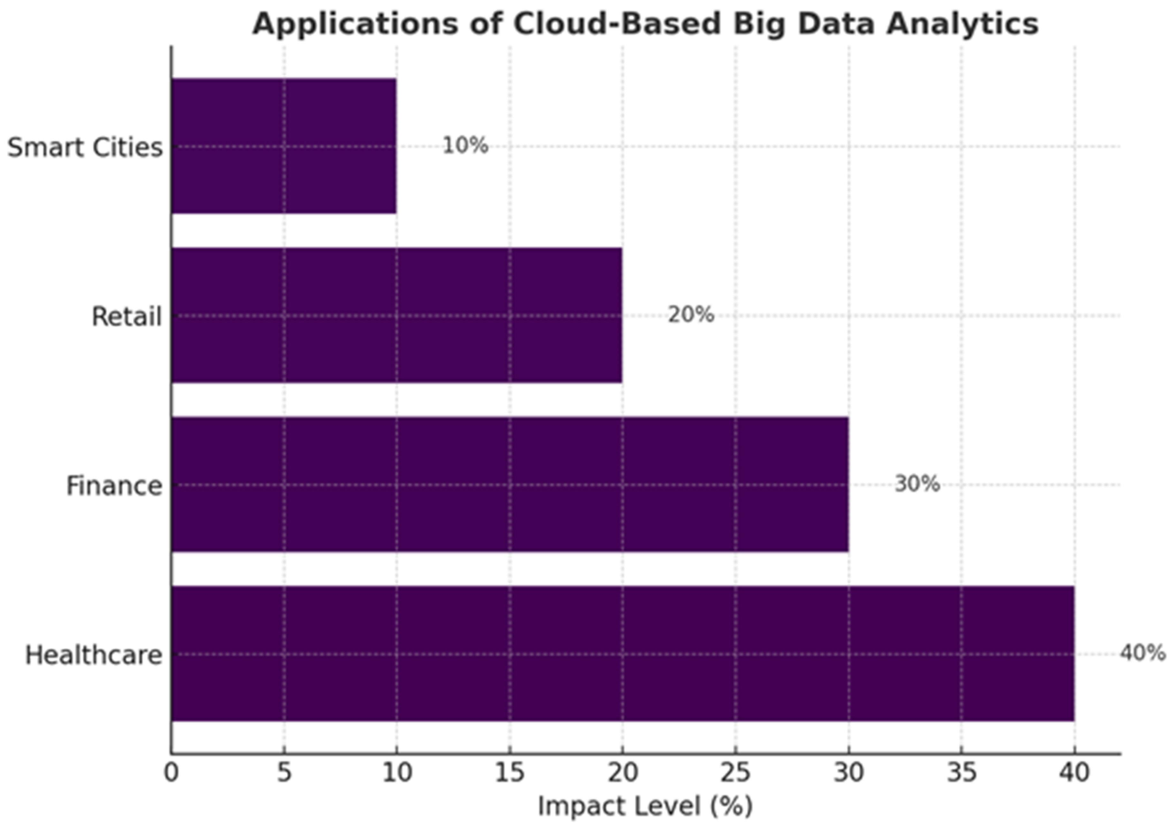

Figure 4: Application of cloud-base big data analytics

reduce data silos, and improve coordination across healthcare systems. Cloud-based environments provide scalable and flexible solutions for managing large healthcare datasets efficiently (Ambati, 2025; Karshiyeva et al., 2026).

In addition, predictive analytics and clinical decision support systems (CDSS) represent a major advancement enabled by cloud-based big data analytics. By utilizing machine learning models trained on vast datasets, healthcare providers can predict disease onset, patient risks, and treatment outcomes. AI-driven analytics enhances diagnostic accuracy and supports evidence-based clinical decisions, thereby improving patient outcomes (Manokaran et al., 2026; Padakanti, 2024).

Another important application is personalized and precision medicine, where big data analytics processes patient-specific information, including genetic, clinical, and environmental data, to tailor treatment strategies. This approach improves therapeutic effectiveness and reduces adverse drug reactions. The integration of emerging technologies such as AI, blockchain, and cloud computing further strengthens precision healthcare systems (Rani & Saxena, 2026).

The convergence of IoT and cloud computing has enabled real-time patient monitoring and smart healthcare ecosystems. Wearable devices and sensors continuously generate health data, which is transmitted to cloud platforms for analysis. These systems allow early detection of health anomalies and support remote patient management, particularly for chronic diseases and elderly care. Big data-powered IoT architectures rely on scalable cloud infrastructures to process continuous data streams efficiently (Das et al., 2025; Das et al., 2025; Mukhambetova, 2025).

Cloud-based big data analytics also contributes to healthcare operations and smart city integration. By analyzing healthcare and urban data, institutions can optimize resource allocation, improve service delivery, and enhance healthcare accessibility. The application of big data in urban systems supports intelligent healthcare planning and infrastructure development (Narayan & Troilo, 2026).

Furthermore, public health surveillance and epidemiology benefit from cloud-based big data platforms, which enable large-scale data aggregation and real-time analysis. These systems are essential for tracking disease outbreaks, identifying risk factors, and informing policy decisions, thereby improving public health responses.

Despite these advantages, several challenges and limitations persist. One of the most critical issues is data privacy and security, as healthcare data is highly sensitive. Privacy-preserving mechanisms, including encryption and anonymization, are necessary to protect patient information in cloud environments (Coleman & Wilson, 2026). Additionally, cybersecurity risks associated with cloud-edge computing require robust adaptive defense frameworks to mitigate threats such as data breaches and unauthorized access (Narayan, 2025). Another challenge involves technological complexity and scalability. While cloud computing offers flexibility, managing large-scale healthcare data requires advanced infrastructure and expertise. Continuous evolution in big data technologies highlights the need for improved frameworks to address data heterogeneity, latency, and integration challenges (Hakami et al., 2025). Moreover, cloud-edge-end collaboration models are increasingly being adopted to optimize computational efficiency and reduce latency in healthcare applications (Zhang & Huang, 2026).

Applications of Cloud-Based Big Data Analytics in Finance

Cloud-based big data analytics has emerged as a transformative paradigm in the financial sector, fundamentally redefining how financial institutions manage data, generate insights, and make strategic decisions. The convergence of cloud computing, big data architectures, and artificial intelligence (AI) has enabled a shift from traditional, transaction-oriented systems toward real-time, predictive, and intelligence-driven financial ecosystems**.** This transformation is not merely technological but structural, influencing organizational processes, regulatory compliance, and competitive dynamics.

A central application of cloud-based big data analytics in finance is the migration from legacy systems to cloud-native infrastructures, which addresses the limitations of traditional financial IT systems such as rigidity, high operational costs, and limited scalability (Figure 4). Financial institutions are increasingly adopting structured migration strategies to transition workloads to cloud platforms, thereby enhancing computational efficiency and enabling large-scale data processing (Chilakalapalli et al., 2025). While this migration is often framed as a technical upgrade, it represents a deeper institutional transformation that aligns financial operations with digital innovation and customer-centric service models (Nutalapati, 2024; Tigadikar, 2025). Consequently, cloud adoption serves as the foundation for integrating advanced analytics into core financial processes.

Closely linked to this transformation is the development of cloud-based financial data architectures, particularly data lakes, which facilitate the storage and processing of vast volumes of structured and unstructured financial data. These architectures enable financial institutions to integrate diverse datasets, including transaction records, market data, and customer information, thereby supporting comprehensive analytics and decision-making. While cloud-based data lakes significantly enhance performance and scalability (Gondhi, 2025), they also introduce challenges related to data governance, quality assurance, and regulatory compliance. Sustainable data architecture frameworks are therefore essential to ensure that analytical capabilities are aligned with regulatory and operational requirements (Ionescu et al., 2025). This highlights a critical tension between maximizing analytical potential and maintaining control over data integrity and accountability.

Another key application of cloud-based big data analytics is in predictive analytics and financial decision-making, where advanced analytical models are used to forecast trends, optimize operations, and reduce uncertainty. Predictive analytics enables financial institutions to analyze historical and real-time data to improve cash flow management, particularly in complex, multi-location enterprises (Alonge et al., 2024). The integration of AI further enhances these capabilities by enabling the identification of complex patterns and relationships within financial datasets, thereby supporting more accurate and dynamic decision-making (Meshram, 2026). However, despite these advantages, the increasing reliance on AI-driven models raises concerns regarding interpretability and transparency, particularly in highly regulated financial environments where decision accountability is critical.

Cloud-based big data analytics also plays a significant role in the development of intelligent financial systems and automated accounting processes**.** By leveraging cloud infrastructures, financial institutions can automate routine tasks such as data entry, reconciliation, and reporting, thereby improving efficiency and reducing human error (He, 2025). The integration of big data, IoT, and Industry 4.0 technologies further enhances these systems by enabling continuous monitoring and real-time analysis of financial operations (Thanasas et al., 2026). This evolution reflects a broader shift toward digitally integrated financial ecosystems**,** where accounting, auditing, and analytics are interconnected within a unified platform.

In the domain of risk management and financial forecasting**,** cloud-based big data analytics provides significant advantages by enabling real-time risk assessment and predictive modeling. Financial institutions can leverage large datasets to identify potential risks, detect anomalies, and develop proactive mitigation strategies. For instance, cloud-based forecasting models have been applied to assess the financial sustainability of critical infrastructure enterprises, demonstrating the potential of big data analytics in complex and high-risk financial environments (Koptieva et al., 2026). Compared to traditional risk management approaches, which are often static and retrospective, cloud-based systems enable dynamic and continuous risk evaluation. However, the increasing reliance on cloud infrastructures also introduces new forms of systemic risk, including cybersecurity vulnerabilities and dependence on third-party service providers.

The integration of cloud computing with advanced AI techniques has also transformed market intelligence and financial analysis. Emerging applications utilize cloud-orchestrated large language models and intelligent agents to process vast amounts of financial data, generate insights, and support strategic decision-making (Chen, 2026). These systems represent a shift toward automated and intelligent financial analysis, where AI-driven tools augment or replace traditional analytical processes. While this enhances efficiency and scalability, it also raises critical issues related to algorithmic bias, transparency, and ethical accountability, particularly in decision-making processes that have significant financial implications.

Furthermore, the adoption of multi-cloud and distributed computing architectures has enhanced the resilience and performance of financial systems. Multi-cloud strategies allow institutions to distribute workloads across multiple cloud platforms, reducing dependency on a single provider and improving system reliability (Bauer et al., 2025). In addition, the integration of edge computing with cloud infrastructures enables low-latency data processing, which is essential for real-time financial applications such as high-frequency trading and fraud detection (Lambropoulos et al., 2026). These developments indicate a shift toward decentralized and distributed financial computing environments, which offer greater flexibility and responsiveness.

Despite the numerous advantages of cloud-based big data analytics, several challenges and limitations persist. Data governance and regulatory compliance remain critical concerns, as financial institutions must ensure that cloud-based systems adhere to stringent regulatory standards (Nutalapati, 2024; Ionescu et al., 2025). Data security and privacy are also major issues, given the sensitive nature of financial information and the increasing threat of cyberattacks. Additionally, the integration of legacy systems with modern cloud infrastructures presents technical and organizational challenges, requiring significant investment and expertise (Chilakalapalli et al., 2025). The lack of explainability in AI-driven analytics further complicates adoption, as financial institutions must balance the benefits of advanced analytics with the need for transparency and accountability (Meshram, 2026; Chen, 2026).

In synthesis, cloud-based big data analytics is driving a paradigm shift in the financial sector, enabling the transition toward scalable, intelligent, and automated financial systems. Its applications span data management, predictive analytics, risk assessment, financial automation, and market intelligence, demonstrating its transformative potential. However, the successful implementation of these technologies requires addressing critical challenges related to governance, security, and ethical considerations. Future research should focus on developing explainable AI models, enhancing data governance frameworks, and designing secure multi-cloud architectures that can support the evolving needs of the financial sector (Nutalapati, 2024; Tigadikar, 2025).

Applications of Cloud-Based Big Data Analytics in Retail

Cloud-based big data analytics has become a transformative force in the retail sector, enabling organizations to transition from traditional, intuition-driven operations to data-centric, predictive, and customer-oriented business models. The integration of cloud computing, artificial intelligence (AI), and big data technologies allows retailers to process vast volumes of structured and unstructured data in real time, thereby enhancing decision-making, operational efficiency, and customer engagement. This transformation is particularly evident across supply chain optimization, customer analytics, sales forecasting, and retail operations management.

One of the most prominent applications of cloud-based big data analytics in retail is supply chain optimization and demand forecasting. Retail supply chains are inherently complex, involving multiple stakeholders, dynamic demand patterns, and logistical uncertainties. Cloud-based analytics platforms enable the integration of data from various sources, including sales transactions, inventory systems, and external market indicators, to improve forecasting accuracy and logistics planning (Figure 4). AI-driven big data models have been shown to significantly enhance demand forecasting and optimize logistics operations, reducing costs and improving service levels (Suura et al., 2025). Similarly, adaptive cloud-based analytics models support sustainable supply chain management by enabling real-time monitoring and data-driven decision-making across supply networks (Stefanovic et al., 2025). These approaches highlight the shift toward intelligent and responsive supply chains, where decisions are continuously informed by real-time data.

Closely related to supply chain optimization is the development of next-generation data warehousing and data integration systems, which underpin large-scale retail analytics. Cloud-based data warehouses enable retailers to consolidate customer, transactional, and marketing data into centralized platforms for advanced analysis. These systems are particularly relevant for retail marketing and destination-driven commerce, where big data technologies enhance segmentation and targeting strategies (Nyunt et al., 2026). However, the effectiveness of such systems is heavily dependent on data quality and governance, as inaccuracies or inconsistencies can significantly undermine analytical outputs. Ensuring high-quality data is therefore essential for enabling reliable, real-time decision-making across retail enterprises (Dhanagari, 2025).

Another critical application is real-time decision-making and retail operations optimization, facilitated by cloud-based infrastructures. Automated cloud data migration and integration systems enable seamless data flow across retail platforms, improving operational efficiency and minimizing downtime (Jude, 2025). Furthermore, the performance of retail applications particularly in e-commerce environments requires continuous monitoring and optimization. Advanced monitoring tools, performance metrics, and best practices play a crucial role in maintaining system responsiveness and scalability under fluctuating demand conditions (Gangula, 2026). These capabilities are essential in ensuring that digital retail platforms deliver consistent and efficient user experiences.

Cloud-based big data analytics also plays a significant role in customer engagement and personalized marketing strategies. By analyzing large volumes of customer data, including purchasing behavior, preferences, and interaction patterns, retailers can design targeted marketing campaigns and personalized shopping experiences. Cloud computing enables the scalable storage and processing of such data, enhancing customer relationship management and sales force effectiveness (Koganti, 2024). Additionally, the integration of customer sentiment analysis and software-defined networking technologies allows retailers to better understand consumer behavior and refine marketing strategies in real time (Rahmatovich, 2024). This reflects a broader shift toward customer-centric retail ecosystems, where data-driven insights inform engagement and loyalty strategies.

In the domain of sales forecasting and business intelligence, cloud-based big data analytics provides advanced tools for predicting demand patterns and optimizing inventory management. AI-driven sales forecasting models leverage historical sales data and external variables to improve prediction accuracy and support strategic planning. Empirical studies demonstrate that such models significantly enhance forecasting performance, enabling retailers to reduce stockouts and improve inventory efficiency (Pattnaik et al., 2026). Furthermore, the integration of AI into business intelligence systems enhances the ability of retailers to extract actionable insights from large datasets, thereby improving strategic decision-making and competitive positioning (Ghannam, 2026).

Security and infrastructure stability are also critical considerations in cloud-based retail analytics. The increasing reliance on cloud platforms exposes retail systems to cybersecurity risks, necessitating the implementation of robust security frameworks. AI and machine learning-driven cybersecurity strategies have been proposed to protect cloud infrastructures and ensure system stability in retail environments (Challa et al., 2025). These approaches highlight the importance of embedding security mechanisms within cloud-based analytics systems to safeguard sensitive data and maintain operational continuity.

Additionally, the integration of Industry 4.0 technologies, including IoT and big data, is further transforming retail operations. Digital accounting and financial management processes within retail enterprises are increasingly leveraging cloud-based analytics to improve transparency, efficiency, and real-time reporting capabilities (Thanasas et al., 2026). This integration supports a holistic approach to retail management, where operational, financial, and customer data are interconnected within a unified analytical framework.

Despite the numerous advantages, several challenges and limitations persist in the adoption of cloud-based big data analytics in retail. Data quality and consistency remain critical issues, as poor data quality can lead to inaccurate insights and suboptimal decision-making (Dhanagari, 2025). The integration of legacy systems with modern cloud infrastructures also presents technical and organizational challenges, requiring significant investment and expertise (Jude, 2025). Moreover, data security and privacy concerns are paramount due to the sensitive nature of customer information and the increasing threat of cyberattacks (Challa et al., 2025). The growing reliance on AI-driven analytics further introduces concerns related to transparency, bias, and ethical accountability in decision-making processes (Ghannam, 2026).

Cloud-based big data analytics is driving a paradigm shift in the retail sector, enabling the transition toward intelligent, scalable, and customer-centric business models. Its applications span supply chain management, data warehousing, customer analytics, sales forecasting, operational optimization, and cybersecurity, demonstrating its transformative potential. However, the successful implementation of these technologies requires addressing critical challenges related to data governance, system integration, and security. Future research should focus on enhancing data quality frameworks, developing explainable AI models, and designing secure, resilient cloud-based retail systems capable of meeting the evolving demands of the digital marketplace.

Smart Cities: Applications of Cloud-Based Big Data Analytics

The development of smart cities represents a paradigm shift in urban management, driven by the convergence of cloud computing, big data analytics, Internet of Things (IoT), and artificial intelligence (AI). At the core of this transformation is cloud-based big data analytics, which enables the collection, storage, processing, and interpretation of vast volumes of heterogeneous urban data to support intelligent decision-making and sustainable development. Smart cities are increasingly conceptualized as data-centric ecosystems in which real-time data streams from interconnected devices are continuously analyzed to optimize urban services, enhance governance, and improve citizens' quality of life. Narayan and Troilo (2026) emphasize that big data analytics serves as a foundational mechanism for transforming urban management by enabling predictive insights and operational efficiency across sectors such as transportation, energy, and infrastructure. Similarly, Kumar (2026) situates smart cities within a broader computational paradigm that integrates sensing, communication, and analytics layers to achieve resilience and sustainability (Figure 4).

The proliferation of IoT technologies has significantly contributed to the generation of large-scale urban data. IoT devices, including sensors, cameras, and smart meters, act as primary data sources, capturing real-time information on environmental conditions, traffic flows, and resource consumption. Zaman et al. (2024) and Salih et al. (2025) highlight that IoT-based infrastructures are essential for smart city development, as they enable continuous monitoring and automation of urban systems. Bhardwaj et al. (2024) further argue that the rapid expansion of IoT networks necessitates scalable and flexible data processing frameworks, which are effectively provided by cloud computing. Cloud platforms offer on-demand computational resources, enabling cities to manage high-volume and high-velocity data while ensuring interoperability among diverse systems (Agarwal et al., 2026). In this context, cloud-based big data analytics serves as the backbone of smart city architectures, facilitating the integration of distributed data sources into centralized or hybrid processing environments.

The integration of edge computing with cloud infrastructures has further enhanced the efficiency of smart city systems. Edge computing enables data processing closer to the source, thereby reducing latency and bandwidth consumption, which is critical for real-time applications such as traffic control and emergency response. Nozari and Tavakkoli-Moghaddam (2026) emphasize that edge computing contributes to energy efficiency and faster decision-making in smart cities. Cavicchioli et al. (2022) propose a hybrid edge-cloud framework that supports real-time big data analytics, demonstrating how distributed architectures can effectively handle the dynamic nature of urban data. Hu et al. (2026) extend this discussion by presenting optimization techniques for real-time data processing in IoT-enabled smart cities, ensuring timely and accurate responses to urban challenges.

Cloud-based big data analytics has numerous applications across different domains of smart cities. In urban planning and governance, data-driven approaches enable policymakers to make informed decisions based on comprehensive analysis of spatial and temporal data. Rafdhi (2025) highlights the importance of spatial data mining in decision support systems, which allows for optimized land use planning and infrastructure development. Geospatial technologies further enhance these capabilities by providing detailed spatial insights into urban environments (Mohidem & Che'Ya, 2025). Additionally, cloud-enabled enterprise resource planning (ERP) systems play a crucial role in smart governance by improving administrative efficiency, transparency, and service delivery (Albaham & Alsanafi, 2026).

Energy management is another critical application area, where big data analytics supports the optimization of energy consumption and distribution. Pratama and Azzahra (2026) propose an IoT-based architecture that leverages cloud analytics to monitor and manage urban energy systems, thereby improving efficiency and sustainability. The integration of edge computing further enhances energy optimization by enabling localized data processing and reducing reliance on centralized systems (Nozari & Tavakkoli-Moghaddam, 2026). In transportation, cloud-based analytics facilitates intelligent traffic management by analyzing real-time data to predict congestion patterns and optimize traffic flows. Narayan and Troilo (2026) note that predictive analytics can significantly improve urban mobility and reduce travel time.

A notable advancement in smart city applications is the emergence of digital twin technology, which involves creating virtual replicas of physical urban systems. These digital twins enable real-time simulation and analysis of urban environments, allowing policymakers to test scenarios and predict outcomes before implementing changes. Skibina (2026) and Iderus (2026) demonstrate that cloud-edge integrated digital twin platforms provide scalable solutions for urban planning and management, enabling continuous synchronization between physical and digital environments. This capability enhances decision-making processes and supports the development of resilient urban systems.

Artificial intelligence further amplifies the capabilities of cloud-based big data analytics by enabling advanced data processing techniques such as machine learning, pattern recognition, and predictive modeling. Nukpezah et al. (2026) highlight the transformative potential of AI in automating urban services and improving operational efficiency. Hermanus (2025) illustrates how cloud-based AI platforms can be used to build scalable analytics solutions for smart city applications. Moreover, federated learning has emerged as a promising approach for decentralized data analysis, allowing multiple entities to collaboratively train models without sharing sensitive data. Tariq et al. (2026) emphasize that federated deep learning enhances data privacy and security while maintaining high analytical performance in intelligent urban ecosystems.

Emerging technologies such as the metaverse and other disruptive innovations are also shaping the future of smart cities. Katuk et al. (2026) explore the integration of smart cities with the metaverse, enabling immersive digital environments that enhance urban interaction and planning. Malik (2026) identifies disruptive technologies, including blockchain and extended reality, as key drivers of innovation in smart city development. These technologies, when combined with cloud-based analytics, create new opportunities for enhancing urban services and citizen engagement. Despite these advancements, several challenges remain in the implementation of cloud-based big data analytics in smart cities. Data privacy and security concerns are significant issues, as large-scale data collection increases the risk of unauthorized access and misuse. Interoperability among diverse technologies and platforms also poses challenges, as the lack of standardized protocols can hinder seamless integration. Scalability is another concern, given the exponential growth of urban data. Additionally, the energy consumption associated with data centers and IoT networks raises sustainability issues. Yorucu et al. (2026) emphasize the need for resilient frameworks that address these challenges, while Ujang and Yadava (2026) advocate for inclusive and sustainable development strategies that ensure equitable access to smart city benefits.

Cloud Computing solutions for Big Data analytics

Cloud Computing can meet the challenges of analyzing Big Data, Cloud Computing solutions for Bid Data analytics include (Wazir and Saif, 2018):

Scalability: Cloud computing provides highly scalable infrastructure and services, allowing organizations to easily provision and scale up or down as needed.

Data integration: Cloud computing provides solutions for data integration, allowing organizations to integrate data from multiple sources.

Security: Cloud computing provides security features such as encryption, access control and monitoring to protect sensitive data (Mohammed et al., 2022).

Tools and technologies for cloud-based Big Data analytics:

There are several key tools and technologies that are available for cloud-based big data analytics, including (Lokhande & Patil, 2023):

Apache Hadoop: Apache Hadoop is a popular open-source framework for distributed storage and processing of big data.

Apache Spark: Apache Spark is a fast and efficient open-source framework for large-scale data processing and analytics.

Amazon Web Services (AWS): AWS provides a range of cloud-based infrastructure and services for big data analysis, including Amazon S3, Amazon EMR, and Amazon Redshift.

METHODOLOGY

This study adopts a systematic review methodology grounded in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure methodological transparency, replicability, and analytical rigor. The methodological design is further reinforced through the integration of a mixed-methods analytical paradigm, enabling both interpretive depth and empirical generalizability in examining the role of cloud computing in big data analytics. By combining structured evidence synthesis with quantitative trend evaluation, this approach facilitates a comprehensive, multi-dimensional assessment of technological evolution, adoption patterns, and performance implications across cloud-enabled big data ecosystems.

Research Design

This research is anchored in a pragmatic research philosophy, which supports methodological pluralism and prioritizes the research problem over strict adherence to a single epistemological stance. In line with John W. Creswell's mixed-methods framework, the study adopts a convergent parallel design, where qualitative and quantitative evidence are collected, analyzed, and integrated concurrently (Figure 5). The research design comprises two complementary components:

Qualitative Component (Interpretivist Orientation):

Focuses on thematic synthesis to identify emerging concepts, architectural paradigms, research gaps, and domain-specific challenges in cloud-based big data systems.

Quantitative Component (Positivist Orientation)

Employs descriptive and trend-based statistical analysis to examine publication trajectories, technological adoption frequencies, and distribution across application domains.

The integration of these paradigms enables triangulation, thereby enhancing the robustness and credibility of findings.

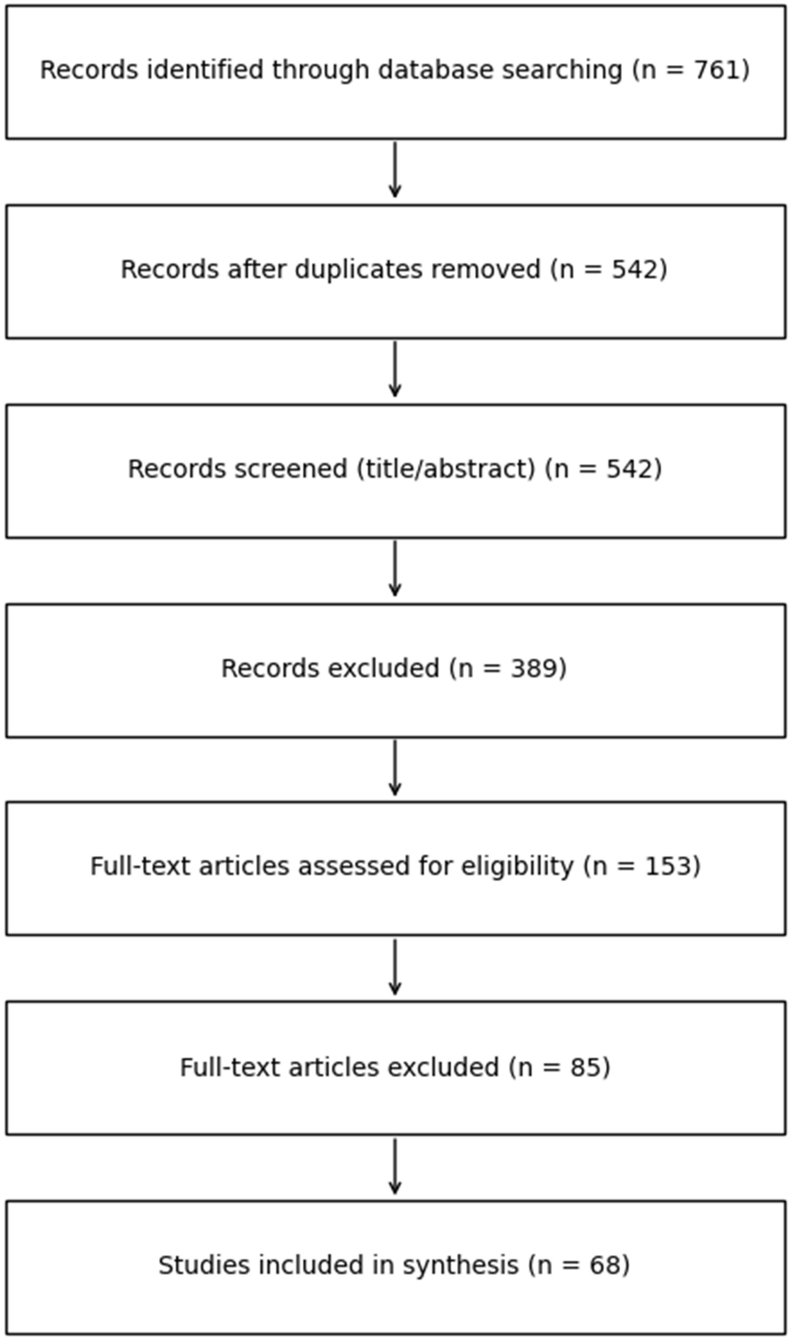

Figure 5: PRISMA Framework

Temporal Scope and Stratification

The study systematically analyzes literature published between 2018 and 2026, a period characterized by rapid transformation in cloud and big data technologies. To enhance analytical clarity, the timeframe is stratified into three evolutionary phases:

Foundational Phase (2018–2020)

Emphasis on core theoretical constructs, including distributed computing models, foundational cloud architectures, and early big data frameworks such as Hadoop and Spark.

Transitional Phase (2021–2023)

Marked by increased enterprise adoption, hybrid cloud deployment models, and advancements in scalability, orchestration, and data pipeline optimization.

Emerging Technologies Phase (2024–2026):

Characterized by the convergence of cloud computing with artificial intelligence, Internet of Things (IoT), edge computing, and real-time analytics systems (Table 1). This temporal segmentation enables longitudinal analysis, capturing both continuity and disruption in technological evolution.

Data Sources and Search Strategy

A comprehensive and systematic literature search was conducted across multiple high-impact academic databases to ensure breadth and depth of coverage. These include:

Scopus
Web of Science
IEEE Xplore
ScienceDirect
Google Scholar

The search strategy employed Boolean logic operators, keyword combinations, and iterative refinement techniques to maximize retrieval precision and recall. Representative search strings include:

(cloud computing" AND "big data analytics")
(cloud-based big data" AND scalability AND performance)

("cloud-edge computing" OR "distributed analytics")
(AI integration AND cloud systems")

Backward and forward citation tracking was also conducted to ensure inclusion of seminal and highly cited works, thereby minimizing publication bias.

Inclusion and Exclusion Criteria

To ensure methodological consistency and relevance, strict eligibility criteria were defined:

Inclusion Criteria

Peer-reviewed journal articles, conference proceedings, and scholarly books
Publications between 2018 and 2026
Studies explicitly addressing cloud computing in the context of big data processing and analytics
Empirical, theoretical, or review-based contributions with clear methodological frameworks

Exclusion Criteria

Duplicate records across databases
Non-peer-reviewed sources (e.g., blogs, white papers without academic validation)
Studies lacking direct relevance to cloud-based big data systems
Articles with insufficient methodological transparency

These criteria ensured the selection of high-quality, methodologically sound studies.

Study Selection Procedure

The study selection process strictly follows the PRISMA protocol, comprising four sequential stages:

Identification

Retrieval of studies from selected databases using predefined search strings

Screening

Removal of duplicates and preliminary filtering based on titles and abstracts

Eligibility
Full-text evaluation against inclusion and exclusion criteria

Inclusion

Following this rigorous process, 68 studies were retained for final analysis, ensuring both relevance and quality.

Data Extraction Framework

A structured data extraction template was developed to ensure consistency and reduce researcher bias. The extracted variables include:

Cloud deployment models and architectural frameworks
Big data processing tools (e.g., Hadoop, Spark, Flink)
Application domains (healthcare, finance, smart cities, retail, etc.)

Performance indicators (latency, throughput, scalability, efficiency)

Security, privacy, and compliance mechanisms
Integration with emerging technologies (AI, IoT, edge computing)
This standardized framework enables comparative analysis across studies.

Table 1. Summary of Selected Studies on Cloud Computing for Big Data Analytics (2018–2026)”).

Author(s)	Year	Domain	Technology Focus	Method	Key Contribution
Chen et al.	2022	General	Big Data Analytics	Survey	Comprehensive overview of big data techniques
Mell & Grance	2020	Cloud	Cloud Computing	Conceptual	Standard definition of cloud computing (NIST)
Gandomi & Haider	2025	Analytics	Big Data	Review	Big data concepts and analytical methods
Hashem et al.	2025	Cloud + Big Data	Cloud Integration	Review	Challenges and opportunities in cloud-based big data
Jadeja & Modi	2023	Cloud	Architecture	Conference	Cloud architecture and design challenges
Mohammed et al.	2022	Security	Cloud + Big Data	Empirical	Security issues in cloud-based data systems
Narayan	2025	Cybersecurity	Cloud-edge	Analytical	Security challenges in cloud-edge convergence
Padakanti	2024	Healthcare	Cloud + AI	Applied	Role of cloud computing in healthcare transformation
Gondhi	2025	Finance	Data Lakes	Analytical	Governance and scalability of cloud-based data lakes
Stefanovic et al.	2025	Supply Chain	Big Data + Cloud	Model	Sustainable analytics model for supply chains
Suura et al.	2025	Retail	AI + Cloud	Empirical	AI-driven supply chain optimization
Bhardwaj et al.	2024	Smart Cities	IoT + Cloud	Review	IoT integration in smart city systems
Hu et al.	2026	Smart Cities	IoT + Real-time	Experimental	Real-time data optimization techniques
Tariq et al.	2026	AI	Federated Learning	Review	AI models in distributed smart systems
Zhang & Huang	2026	AI Systems	Cloud-edge AI	Survey	Large model deployment in cloud environments

Data Analysis Techniques

The study employs a dual-layer analytical approach:

Thematic Analysis

Used to identify recurring patterns, conceptual frameworks, research gaps, and emerging trends. Coding and categorization were performed iteratively to ensure conceptual saturation.

Descriptive Statistical Analysis

Applied to quantify publication trends, frequency distributions, and technological adoption patterns across domains.
The integration of these techniques enables both analytical depth (qualitative insight) and empirical breadth (quantitative validation).

Reliability, Validity, and Bias Mitigation

To ensure methodological rigor, several strategies were implemented:

Protocol Standardization: Adoption of PRISMA enhances transparency and reproducibility

Data Triangulation: Use of multiple databases reduces selection bias

Explicit Criteria: Clearly defined inclusion/exclusion rules ensure consistency

Systematic Extraction: Structured templates minimize subjective interpretation

Audit Trail: Documentation of all methodological decisions enhances traceability

These measures collectively strengthen the internal validity, external validity, and reliability of the study.

Ethical Considerations

As a secondary research study based exclusively on published literature, this research does not involve human participants. However, ethical standards were upheld through:

Proper citation and acknowledgment of all sources
Avoidance of plagiarism
Objective and unbiased interpretation of findings

Table 1 presents a summary of representative studies included in this review, highlighting their domains, methodologies, and key contributions. The selected studies demonstrate the widespread application of cloud computing in big data analytics across diverse sectors, including healthcare, finance, retail, and smart cities. The table further illustrates the evolution of research focus from foundational frameworks to advanced integrations involving artificial intelligence, IoT, and cloud-edge computing.

RESULTS AND DISCUSSION

The results of this study provide a comprehensive, evidence-driven understanding of how cloud infrastructure is reshaping big data processing and analytics across diverse domains. The synthesis of the reviewed literature reveals a clear technological and architectural evolution from traditional centralized computing paradigms toward distributed, intelligent, and highly scalable cloud ecosystems (Hakami et al., 2025; Zhang & Huang, 2026). This transformation is not merely incremental but represents a paradigm shift in how data is generated, processed, and utilized for decision-making. A central finding is the widespread transition toward hybrid, multi-cloud, and cloud–edge architectures. Earlier cloud models primarily supported centralized storage and batch-oriented processing; however, contemporary systems increasingly adopt decentralized frameworks capable of real-time analytics. The integration of edge computing significantly reduces latency and enhances system responsiveness by enabling data processing closer to the source (Mukhambetova, 2025; Cavicchioli et al., 2022). This architectural shift is particularly critical in smart city ecosystems, where real-time data streams underpin applications such as traffic optimization, energy management, and urban planning (Hu et al., 2026; Iderus, 2026; Hermanus, 2025; Narayan & Troilo, 2026). Furthermore, the incorporation of Internet of Things (IoT) devices and geospatial data analytics enhances situational awareness and decision intelligence, enabling more adaptive and sustainable urban systems (Mohidem & Che'Ya, 2025; Salih et al., 2025; Katuk et al., 2026). Collectively, these findings suggest that cloud-edge convergence is becoming a foundational pillar of next-generation data infrastructures.

In the healthcare domain, cloud infrastructure demonstrates substantial improvements in data accessibility, interoperability, and analytical capability. The reviewed studies indicate that cloud-based platforms facilitate efficient storage, integration, and real-time sharing of medical data, thereby enhancing clinical workflows and patient outcomes (Ambati, 2025; Karshiyeva et al., 2026). The integration of IoT and fog computing further supports continuous patient monitoring and real-time analytics, which are essential for proactive healthcare delivery (Das et al., 2025). Additionally, the convergence of artificial intelligence (AI) with cloud platforms enables predictive diagnostics and personalized treatment strategies, marking a transition toward precision medicine (Manokaran et al., 2026; Rani & Saxena, 2026). These developments underscore the role of cloud infrastructure as an enabler of data-driven healthcare innovation.

Another significant result is the deep convergence of AI, machine learning (ML), and cloud computing. Modern cloud platforms are evolving into intelligent ecosystems capable of supporting advanced analytics, automation, and predictive decision-making. In the financial sector, AI-driven cloud analytics enhances fraud detection, risk modeling, and forecasting accuracy (Meshram, 2026; Chen, 2026; Koptieva et al., 2026). Similarly, enterprise systems benefit from real-time analytics and automated accounting processes, improving operational efficiency and strategic planning (He, 2025; Thanasas et al., 2026). The emergence of data lakes and sustainable data architectures further strengthens scalability, governance, and data lifecycle management (Gondhi, 2025; Ionescu et al., 2025). These findings collectively indicate that cloud platforms are no longer passive data repositories but active, intelligent systems that drive organizational value.

Cloud migration and multi-cloud strategies also emerge as critical enablers of flexibility and resilience. The transition from legacy systems to cloud environments enhances scalability, reduces operational costs, and improves system performance (Chilakalapalli et al., 2025). Moreover, multi-cloud adoption mitigates vendor lock-in and enhances service reliability through redundancy and diversification (Bauer et al., 2025). In both public and private sectors, these strategies contribute to improved service delivery, operational agility, and digital transformation (Albaham & Alsanafi, 2026).

In the retail and supply chain sectors, cloud-based big data analytics significantly enhances operational efficiency and customer engagement. AI-driven models improve demand forecasting, inventory optimization, and logistics management, thereby reducing costs and increasing responsiveness (Suura et al., 2025; Stefanovic et al., 2025). Additionally, cloud-enabled analytics facilitates deeper insights into customer behavior, enabling personalized marketing and improved business intelligence (Ghannam, 2026; Rahmatovich, 2024). The integration of automated cloud migration and AI-driven forecasting models further strengthens decision-making processes and system optimization (Jude, 2025; Pattnaik et al., 2026). These findings highlight the transformative impact of cloud infrastructure on data-driven commerce.

Despite these advancements, the results reveal persistent challenges related to security, privacy, and governance. The increasing complexity of cloud-edge systems expands the attack surface, making them more vulnerable to cyber threats (Narayan, 2025). While AI-driven cybersecurity mechanisms offer promising solutions, they also introduce new risks and dependencies (Challa et al., 2025). Privacy-preserving techniques such as encryption and anonymization remain essential but often involve trade-offs with system performance and computational efficiency (Coleman & Wilson, 2026). These challenges are particularly

Table 2: **Comparison with Web of Science Top Papers**

Study	Year	Focus Area	Methodology	Key Findings	Limitations	Current Study Contribution
Chen et al.	2022	Big Data Analytics	Survey	Comprehensive overview of big data techniques	Lacks recent AI integration	Extends to Healthcare integration
Hashem et al.	2025	Cloud + Big Data	Review	Identifies scalability challenges	Limited real-world validation	Application of Cloud + Big Data in Financial institutions
Zhang et al.	2020	Cloud Computing	Conceptual	Defines cloud challenges	Outdated architecture focus	Includes modern cloud-base big data to smart cities
Hakami et al.	2025	Big Data Trends	Systematic Review	Identifies emerging trends	Limited application analysis	Expands into multi-sector applications
Narayan	2025	Cybersecurity	Analytical	Security challenges in cloud-edge	Focused on security only	Integrates performance + security
Stefanovic et al.	2025	Supply Chain	Model-based	Sustainable analytics model	Domain-specific	Generalized multi-domain analysis
Suura et al.	2025	Retail Analytics	Empirical	AI improves forecasting accuracy	Limited scalability discussion	Adds infrastructure-level analysis
Bhardwaj et al.	2024	Smart Cities	Review	IoT-cloud integration insights	Limited performance metrics	Includes scalability + latency analysis
Hu et al.	2026	Real-time Systems	Experimental	Improved real-time processing	Limited generalization	Provides broader system comparison

pronounced in sensitive domains such as healthcare and finance, where regulatory compliance and data protection are critical (Ambati, 2025; Karshiyeva et al., 2026).
Interoperability and data integration represent additional constraints. The heterogeneity of cloud platforms, data formats, and communication protocols complicates seamless system integration (Dhanagari, 2025). This issue is especially evident in smart city environments, where diverse technologies must operate cohesively (Bhardwaj et al., 2024; Salih et al., 2025). Furthermore, the high infrastructure and operational costs associated with large-scale cloud deployments pose significant barriers, particularly for small and medium-sized enterprises.

Emerging technologies are poised to further redefine cloud-enabled big data ecosystems. Innovations such as digital twins, federated learning, and AI-driven autonomous systems are enabling more efficient data utilization and decentralized intelligence (Skibina, 2026; Tariq et al., 2026; Nukpezah et al., 2026). Advanced cloud-edge-end collaboration models enhance scalability and processing efficiency, indicating a shift toward fully integrated and autonomous data ecosystems (Zhang & Huang, 2026). These trends suggest that future cloud infrastructures will increasingly support complex, real-time, and mission-critical applications.

The comparative analysis presented in (Table 2) reveals a consistent pattern across the existing literature: most prior studies adopt narrow, domain-specific perspectives, focusing on isolated dimensions such as scalability, security, or application-specific implementations. Foundational studies (e.g., Chen et al., 2022) provide important theoretical insights into big data analytics but lack integration with emerging paradigms such as AI-driven cloud systems and cloud-edge architectures. Similarly, earlier works (e.g., Zhang et al., 2020) emphasize conceptual challenges without addressing recent technological advancements in real-time and distributed analytics.

More recent contributions (e.g., Hakami et al., 2025) highlight emerging trends but often lack cross-domain applicability. Security-focused studies (e.g., Narayan, 2025) provide in-depth analyses of cybersecurity challenges but do not sufficiently consider performance and scalability trade-offs. Domain-specific studies in retail and supply chain analytics (e.g., Stefanovic et al., 2025; Suura et al., 2025) demonstrate strong practical relevance but remain limited in scope.

In contrast, the present study advances the literature by adopting a holistic, multi-dimensional framework that integrates cloud infrastructure, big data processing, AI technologies, and cross-sector applications. By examining the interdependencies among these components, this study provides a more comprehensive understanding of system performance, scalability, and real-world applicability. Thus, Table 2 substantiates the primary contribution of this work: bridging fragmented research domains into a unified analytical perspective.
Figure 6 illustrates a clear upward trend in scholarly publications from 2018 to 2026, with a notable acceleration after 2022 and peak activity between 2025 and 2026. The initial growth phase (2018–2021)

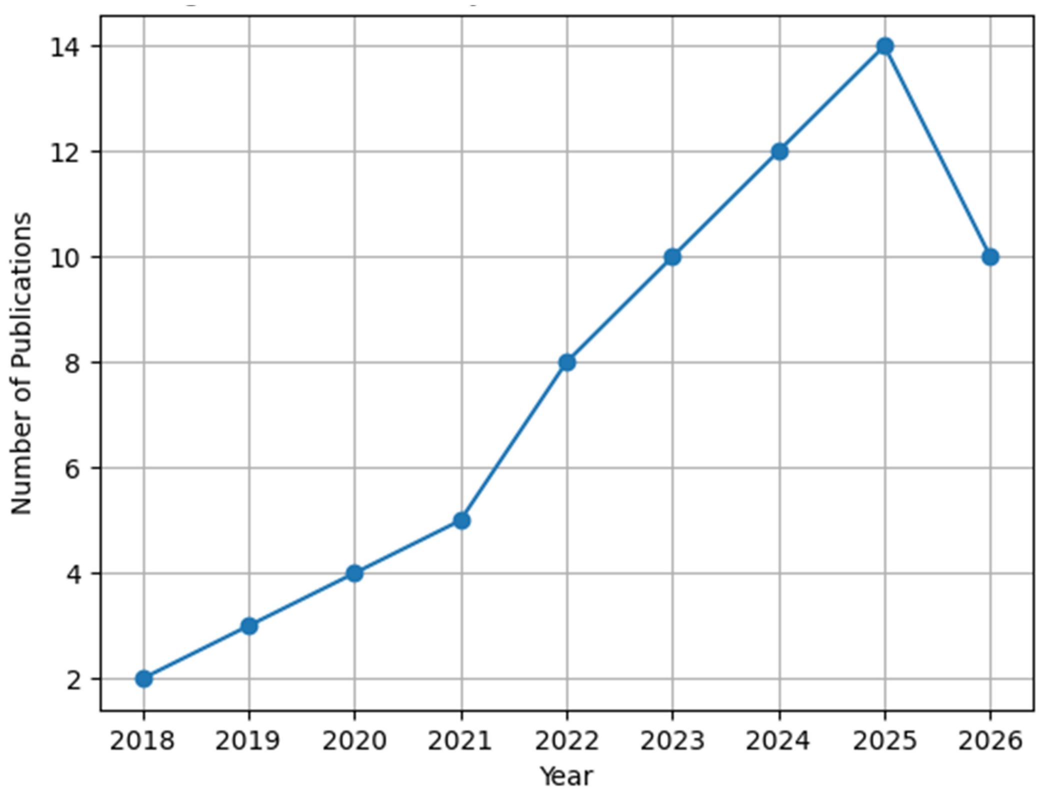

Figure 6. Trend analysis of publications on cloud infrastructure for big data processing and analytics (2018–2026).

corresponds to foundational research focusing on distributed storage and cloud scalability. The subsequent surge reflects the rapid integration of AI, IoT, and cloud-edge computing, which has significantly expanded research scope and application domains.

The peak in recent years indicates a mature and highly dynamic research field characterized by interdisciplinary approaches. This trend aligns with the findings of this study, which emphasize the convergence of multiple technologies as a defining feature of modern cloud-based data ecosystems.

Taken together, (Table 2 and Figure 6) provide a coherent narrative of the evolution of cloud infrastructure for big data analytics. While Figure 2 demonstrates the rapid growth and increasing complexity of the research landscape, Table 2 highlights the persistent fragmentation and lack of integration in existing studies. This juxtaposition underscores a critical gap in the literature: the need for comprehensive, multi-dimensional frameworks that address the interconnected challenges of scalability, security, interoperability, and real-world application.

The present study responds to this gap by offering an integrated perspective that unifies these dimensions into a single analytical framework. This contribution is particularly significant in light of the increasing demand for holistic solutions capable of supporting complex, real-time, and data-intensive applications across multiple domains.

CONCLUSION

Cloud computing provides a powerful infrastructure to handle the processing of large amounts of data and improve real-time data analysis. The advantages of cloud computing for big data analytics include scalability and real-time data analysis. The challenges of big data analytics, including data integration, data security, and data processing, can be solved using cloud computing solutions. As the amount of data continues to increase, cloud computing is becoming increasingly important for analyzing big data. Organizations should consider adopting cloud computing to address their megadata analysis needs. Megadata poses significant challenges to organizations as they strive to manage and analyze large and complex data sets. Cloud computing provides a solution to these challenges by offering highly scalable and cost-effective infrastructure and services to analyze large volumes of data. Organizations can take advantage of cloud-based big data analytics tools and technologies such as Hadoop.

RECOMMENDATION

There are several potential directions for future research in this area. Firstly, the impact of different cloud deployment models on big data analytics performance and cost-effectiveness could be investigated. This would involve analyzing the scalability and performance of public, private, and hybrid cloud environments for big data analytics, as well as assessing their associated costs. Secondly, the security and privacy challenges of storing and processing sensitive data in the cloud for big data analytics could be further explored. This would involve identifying the key risks and proposing solutions to mitigate them. Thirdly, the potential of emerging technologies such as blockchain and edge computing in conjunction with cloud computing for big data analytics could be evaluated. Fourthly, a comparative study of different cloud-based big data analytics tools and frameworks could be conducted, with the aim of identifying their strengths and weaknesses in terms of scalability, performance, and ease of use. Finally, the role of cloud computing in supporting advanced data analytics techniques such as machine learning and deep learning could be investigated, with the aim of enhancing the accuracy and efficiency of big data analytics.

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