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Real-Time Big Data Analytics: Frameworks, Techniques, and Applications for Intelligent Decision-Making

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ABSTRACT

The exponential growth of data generated by social media platforms, IoT devices, financial systems, and healthcare applications has necessitated the development of sophisticated frameworks for real-time data processing and analysis. Traditional batch processing methods, while effective for historical analysis, are insufficient for addressing the velocity and volume requirements of modern data streams. This comprehensive review examines the landscape of real-time big data analytics, focusing on stream processing frameworks, integration with machine learning and artificial intelligence, and applications across critical domains including cybersecurity, healthcare, financial services, e-commerce, and intelligent transportation systems. Through systematic synthesis of recent literature and case studies, this paper investigates the architectural patterns, performance characteristics, and implementation challenges of leading stream processing frameworks including Apache Kafka, Apache Flink, and Spark Streaming. The review reveals that Apache Flink's true stream processing architecture achieves sub-second latency for complex event processing, while Kafka excels in high-throughput data ingestion with its distributed log-based architecture. The integration of machine learning models with stream processing frameworks has emerged as a critical enabler for real-time predictive analytics, with online learning algorithms demonstrating adaptability to evolving data patterns. Applications across industries demonstrate significant improvements in operational efficiency, fraud detection accuracy, and personalized user experiences. Key challenges identified include scalability limitations under extreme workloads, latency optimization for time-sensitive applications, data security and privacy concerns, and the complexity of integrating diverse data sources. Emerging solutions such as edge computing, federated learning, and explainable AI offer promising pathways to address these barriers while enabling more robust, efficient, and transparent real-time analytics. The findings contribute to the evolving field of streaming big data analytics by providing insights into best practices, comparative analysis of frameworks, and identification of research gaps for future exploration.

1. Introduction

The rise of streaming big data has revolutionized the domain of real-time analytics, enabling organizations to process and analyze data as it is generated (Sun et al., 2020; Alam et al., 2024). Unlike traditional batch processing, which collects data over periods and analyzes it in discrete chunks, real-time analytics leverages continuous data streams to provide instantaneous insights—a necessity in today's fast-paced decision-making environments (Toulis & Aioldi, 2017; Sharma et al., 2024). Streaming big data is characterized by its velocity, volume, and variety, necessitating advanced computational frameworks and algorithms to manage and analyze data effectively (Liqing et al., 2020; Khan et al., 2025). This paradigm shift has fueled innovation across industries, from healthcare to transportation, driving demand for robust real-time analytics solutions that not only enhance operational efficiency but also support predictive and prescriptive analytics critical for deriving actionable insights (Kim et al., 2020; Alam et al., 2024).

The foundation of real-time analytics lies in stream processing frameworks, which are designed to manage the high velocity and continuous flow of data. Tools such as Apache Kafka, Apache Flink, and Spark Streaming have become the backbone of modern stream processing, enabling seamless data ingestion, transformation, and analysis (Peddireddy & Banga, 2023; Alam et al., 2024). These frameworks have been widely adopted due to their scalability and ability to handle fault tolerance—key challenges associated with streaming big data (Peddireddy,

2023; Khan et al., 2025). Stream processing not only facilitates real-time monitoring but also supports advanced use cases like fraud detection, personalized recommendations, and anomaly detection, demonstrating its versatility across various domains (Khan et al., 2025; Sharma et al., 2024).

The integration of machine learning and artificial intelligence with stream processing frameworks represents another critical advancement in real-time analytics (Alam et al., 2024; Sharma et al., 2024). Unlike traditional machine learning models, algorithms optimized for streaming data can operate on high-velocity data streams, enabling real-time predictions and decision-making (Wu et al., 2020; Khan et al., 2025). Recent advancements in online learning techniques have further enhanced the efficiency and applicability of these models, particularly in fields like healthcare where timely interventions are crucial (Leang et al., 2019; Alam et al., 2024). For instance, real-time analytics has been instrumental in monitoring patient vitals and predicting potential health risks, thereby saving lives (Sharma et al., 2024; Khan et al., 2025). Despite these advances, challenges such as model updating and deployment in distributed environments remain significant research areas (Peddireddy & Banga, 2023; Alam et al., 2024).

The applications of real-time analytics extend across multiple industries. In financial services, institutions leverage real-time analytics for fraud detection, risk assessment, and algorithmic trading—where milliseconds can make the difference between profit and loss (Khan et al., 2025; Alam et al., 2024). E-commerce platforms use streaming big data analytics to personalize user experiences, manage dynamic pricing, and optimize inventory (Kim et al., 2020; Sharma et al., 2024). Healthcare systems employ real-time analytics for patient monitoring and predictive diagnostics (Khan et al., 2025; Alam et al., 2024). Intelligent transportation systems utilize streaming data for traffic management and predictive maintenance (Khan et al., 2025). Social media platforms analyze user behavior in real time for content personalization and trend detection (Sharma et al., 2024). These applications underline the transformative impact of real-time analytics in driving efficiency and enhancing user satisfaction across sectors.

Despite its transformative potential, real-time analytics in streaming big data is not without challenges. Scalability, fault tolerance, and latency are critical hurdles that need to be addressed to ensure seamless operation in large-scale deployments (Wu et al., 2020; Khan et al., 2025). Data security and privacy concerns, especially in cloud-based environments, present significant obstacles to widespread adoption (Khan et al., 2025; Sharma et al., 2024). The integration of diverse data sources with varying formats and velocities adds complexity to system design (Alam et al., 2024). Emerging technologies such as edge computing and federated learning offer promising solutions, allowing for decentralized data processing and improved privacy (Hussen et al., 2023; Khan et al., 2025). These advancements underscore the need for continued innovation and research in this field to overcome existing limitations and unlock new possibilities.

This comprehensive review examines the landscape of real-time big data analytics through multiple lenses: stream processing frameworks and their architectural characteristics, integration of machine learning with streaming analytics, applications across critical domains, and emerging challenges and solutions. The objectives are fourfold: first, to provide a systematic analysis of leading stream processing frameworks including Apache Kafka, Apache Flink, and Spark Streaming; second, to examine the integration of machine learning and AI with stream processing for real-time predictive analytics; third, to evaluate applications across healthcare, financial services, e-commerce, intelligent transportation, and cybersecurity; and fourth, to identify challenges, research gaps, and future directions for advancing real-time big data analytics. By synthesizing insights from existing research, this review contributes to the academic and practical discourse on streaming big data analytics, offering a structured roadmap for future research and development.

2. Literature Review

2.1 Foundations of Streaming Big Data

Streaming big data refers to the continuous generation, processing, and analysis of data streams in real time. Unlike traditional batch processing, streaming big data is characterized by its velocity, variety, and volume, often referred to as the "3Vs" of big data (Luo et al., 2022; Khan et al., 2025). This unique combination of attributes creates challenges related to data ingestion, storage, and processing, which require scalable and fault-tolerant systems (Kwon et al., 2012; Alam et al., 2024). Streaming big data systems must handle events or transactions as they occur, ensuring minimal latency and enabling time-sensitive decision-making (Jia et al., 2023; Khan et al., 2025). Healthcare systems relying on real-time patient monitoring depend on such systems to process data at unprecedented speeds and scales (Shaikh & Gupta, 2022; Sharma et al., 2024). Moreover, the dynamic and unpredictable nature of streaming data introduces additional complexity in data quality and accuracy, further emphasizing the need for sophisticated real-time analytics frameworks (Luo et al., 2022; Alam et al., 2024).

The evolution of real-time analytics represents a paradigm shift from traditional batch processing to continuous data stream processing. Early analytics systems relied heavily on batch processing models, where data was collected, stored, and analyzed periodically, often leading to delayed insights (Khoshkhah et al., 2022; Alam et al., 2024). The demand for instant insights in dynamic environments spurred the development of stream processing frameworks like Apache Kafka, Apache Flink, and Spark Streaming, which enable real-time data processing and event-driven analytics (Kastner et al., 2014; Khan et al., 2025). These frameworks employ distributed architectures to manage the high velocity and volume of incoming data streams effectively, providing scalability and fault tolerance (Asberg et al., 2012; Alam et al., 2024). The shift towards real-time analytics has been particularly transformative in industries such as financial services, where milliseconds can be the difference between profit and loss in algorithmic trading (Kwon et al., 2012; Khan et al., 2025).

Real-time analytics has emerged as a cornerstone of modern industries, driving innovation and improving operational efficiency. In the healthcare sector, real-time analytics enables early detection of health anomalies through continuous monitoring of patient data, reducing the risks of medical emergencies (Stankovic et al., 1999; Sharma et al., 2024). The financial industry leverages streaming analytics for fraud detection, offering immediate responses to suspicious activities (Babcock et al., 2004; Khan et al., 2025). E-commerce platforms utilize real-time analytics to personalize user experiences, optimize inventory management, and predict market trends (Ma et al., 2009; Alam et al., 2024). Intelligent transportation systems employ streaming data for traffic optimization and predictive maintenance (Khan et al., 2025). Social media platforms analyze user behavior in real time for content personalization and sentiment analysis (Sharma et al., 2024). The integration of real-time analytics across these industries demonstrates its ability to transform decision-making processes, enhance customer satisfaction, and increase profitability.

2.2 Stream Processing Frameworks and Architectures

Stream processing frameworks form the backbone of real-time analytics, enabling the ingestion, processing, and analysis of streaming big data at scale. Apache Kafka, Apache Flink, and Spark Streaming have emerged as leading frameworks due to their robust architectures and capabilities (Hussen et al., 2023; Alam et al., 2024). Apache Kafka excels in distributed event streaming, providing a high-throughput platform for real-time data pipelines and analytics (Wei et al., 2007; Khan et al., 2025). It enables message brokering, allowing data to be seamlessly streamed across systems while ensuring fault tolerance and scalability (Gao et al., 2019; Alam et al., 2024). Apache Flink emphasizes stateful stream processing with features like exactly-once processing semantics, making it highly reliable for use cases requiring stringent consistency (Valls et al., 2013; Khan et al., 2025). Spark Streaming, a module of Apache Spark, extends the platform's batch processing capabilities to handle real-time data through micro-batching, offering flexibility and integration with the broader Spark ecosystem (Jia et al., 2023; Alam et al., 2024).

The selection of an appropriate stream processing framework often depends on specific use cases and system requirements. Apache Kafka's distributed log architecture makes it ideal for scenarios requiring high-throughput and durability, such as activity tracking and log aggregation (Hussen et al., 2023; Khan et al., 2025). Apache Flink's ability to handle complex event processing and its advanced support for windowing operations make it suitable for time-sensitive applications like fraud detection and predictive maintenance (Kleiminger et al., 2011; Alam et al., 2024). Spark Streaming's micro-batch processing, while not as responsive as true stream processing systems, provides a balance between real-time and batch analytics, making it a popular choice in environments already leveraging Apache Spark for batch processing (Wu et al., 2020; Khan et al., 2025). Each framework offers unique strengths, with trade-offs in latency, fault tolerance, and ease of integration with other tools.

Scalability and fault tolerance are critical considerations in stream processing frameworks, particularly for large-scale deployments. Apache Kafka achieves fault tolerance through data replication across partitions, ensuring high availability even in the event of node failures (Banús et al., 2002; Alam et al., 2024). Apache Flink supports fault tolerance by using distributed snapshots to recover from failures without losing state information (Jia et al., 2023; Khan et al., 2025). Spark Streaming, while offering fault tolerance through RDD lineage, may encounter challenges in maintaining low latency in high-velocity data streams (Hussen et al., 2023; Alam et al., 2024). Scalability is addressed differently by each framework: Kafka achieves scalability through horizontal partitioning of topics across multiple nodes, while Flink and Spark rely on distributed processing and task parallelization to handle large data volumes (Block et al., 2008; Puthal et al., 2017; Khan et al., 2025).

2.3 Machine Learning Integration with Stream Processing

The integration of machine learning algorithms with stream processing frameworks has emerged as a critical advancement for real-time predictive analytics (Alam et al., 2024; Sharma et al., 2024). Unlike traditional batch-based ML models, streaming ML algorithms are optimized for high-velocity data, enabling real-time predictions and decision-making (Wu et al., 2020; Khan et al., 2025). Online learning techniques, which update models incrementally as new data arrives, have proven particularly effective for streaming applications (Leang et al., 2019; Alam et al., 2024). These algorithms can adapt to evolving data patterns, making them well-suited for applications like fraud detection, where attack patterns change rapidly (Khan et al., 2025). Deep learning models, including recurrent neural networks and long short-term memory networks, have demonstrated strong performance in analyzing sequential streaming data for applications like predictive maintenance and anomaly detection (Khan et al., 2025; Sharma et al., 2024).

The deployment of machine learning models in streaming environments presents unique challenges. Model complexity and computational requirements can impact the performance of real-time processing pipelines (Alam et al., 2024). Ensuring models are optimized for performance and resource efficiency is crucial for maintaining low-latency operations (Khan et al., 2025). Data quality and consistency significantly affect model effectiveness—inaccurate or incomplete data can lead to unreliable predictions (Sharma et al., 2024). The integration of ML models with stream processing frameworks requires careful consideration of data preprocessing, feature extraction, and model inference architectures (Alam et al., 2024). Federated learning has emerged as a promising approach for privacy-preserving distributed model training, enabling collaborative learning across edge devices without sharing raw data (Khan et al., 2025).

Recent advancements in streaming ML include the development of specialized libraries and frameworks for real-time inference. TensorFlow Extended (TFX) and AWS SageMaker enable predictive and prescriptive analytics on streaming data (Alam et al., 2024). Apache Flink's ML library

supports online learning and incremental model updates (Khan et al., 2025). The integration of reinforcement learning with stream processing enables adaptive decision-making in dynamic environments (Sharma et al., 2024). As streaming ML continues to evolve, the focus is shifting toward developing more efficient algorithms, reducing inference latency, and improving model interpretability for critical applications.

3. Methodology

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The PRISMA framework was chosen as it provides a structured approach to identifying, screening, and synthesizing relevant literature, enabling a comprehensive understanding of the topic (Alam et al., 2024; Khan et al., 2025).

3.1 Identification

The identification phase involved an extensive search for articles relevant to real-time data processing in streaming big data. Databases such as Scopus, Web of Science, IEEE Xplore, and SpringerLink were searched using a combination of keywords, including "real-time analytics," "stream processing frameworks," "big data," "machine learning," and "cloud-native technologies." Boolean operators (AND, OR) were applied to refine the search queries. A total of 1,200 articles were initially retrieved. Duplicates were identified and removed using reference management software, reducing the number of articles to 960.

3.2 Screening

The screening phase focused on assessing the relevance of the identified articles. Titles and abstracts were reviewed against predefined inclusion and exclusion criteria. Inclusion criteria required the articles to (a) focus on real-time data processing or related technologies, (b) be published in peer-reviewed journals or conferences, (c) provide empirical or theoretical insights, and (d) be published between 2010 and 2025. Exclusion criteria included studies not written in English, non-peer-reviewed articles, and publications unrelated to the topic. After this step, 460 articles were deemed relevant for full-text review.

3.3 Eligibility

In the eligibility phase, the full texts of the 460 articles were reviewed in detail to ensure they met the study's inclusion criteria. Articles that did not provide sufficient methodological rigor, lacked specific focus on real-time data processing, or were deemed redundant in context were excluded. This phase reduced the number of eligible articles to 160. The remaining studies were then evaluated for quality based on criteria such as research design, sample size (if applicable), and the relevance of findings to real-time data analytics.

3.4 Final Inclusion

The inclusion phase involved synthesizing the data from the final set of 160 articles. Key information was extracted, including the study's objectives, methodologies, technologies

discussed, findings, and limitations. This information was organized into a summary table to facilitate thematic analysis. The selected articles provided diverse perspectives on real-time data processing, encompassing frameworks such as Apache Kafka, Apache Flink, and Spark Streaming, as well as applications in healthcare, finance, and transportation. These articles formed the basis of the literature review, enabling a comprehensive synthesis of current advancements, challenges, and emerging trends in the field.

4. Findings

4.1 Framework Performance and Adoption

The analysis of 160 reviewed articles revealed a strong emphasis on the role of real-time analytics frameworks in managing high-velocity data streams. Among the studies, 65 articles highlighted the dominance of frameworks like Apache Kafka, Apache Flink, and Spark Streaming as core technologies in real-time data processing. These frameworks were frequently cited (over 8,000 citations collectively) for their scalability, fault tolerance, and ability to integrate seamlessly with cloud-native platforms. Kafka's distributed log-based architecture and Flink's stateful stream processing capabilities were particularly noted for handling diverse data types and volumes efficiently. The findings show that these technologies have become foundational in industries requiring immediate insights, with their adaptability and robustness being the primary drivers of adoption.

Table 1: Comparative Performance of Stream Processing Frameworks

Framework	Architecture	Latency	Throughput	Fault Tolerance	Primary Use Cases
Apache Kafka	Distributed Log	Low (5-15ms)	High (1M+ events/sec)	Replication	Event streaming, log aggregation
Apache Flink	True Stream	Ultra-Low (<5ms)	High (100K+ events/sec)	Checkpointing	Complex event processing, fraud detection
Spark Streaming	Micro-Batch	Moderate (100-500ms)	High (500K+ events/sec)	RDD Lineage	Hybrid batch/stream, ML integration

Source: Adapted from Alam et al. (2024), Khan et al. (2025)

The adoption patterns of these frameworks vary across industries. Apache Kafka has been widely adopted in e-commerce for monitoring user activities and personalizing recommendations in real time (Xu et al., 2021; Sharma et al., 2024). Apache Flink has found extensive applications in the financial industry for real-time fraud detection and algorithmic trading, where low latency and reliability are paramount (Hussen et al., 2023; Khan et al., 2025). Spark Streaming, due to its integration with the broader Spark ecosystem, is frequently employed in healthcare analytics, enabling real-time monitoring and anomaly detection in patient data (Leang et al.,

2019; Alam et al., 2024). These applications highlight the versatility of these frameworks while emphasizing the need for continued research to address limitations such as handling dynamic workloads and optimizing resource utilization in distributed environments (Mishra et al., 2020; Khan et al., 2025).

4.2 Machine Learning Integration

Machine learning was identified as a critical enabler of real-time data processing, with 52 articles focusing on its applications across domains such as healthcare, finance, and e-commerce. These studies, collectively cited over 6,500 times, highlighted the importance of online learning algorithms, anomaly detection models, and deep learning techniques in extracting actionable insights from streaming data. Online learning algorithms were specifically recognized for their ability to adapt to evolving data patterns, a capability critical in high-frequency trading and fraud detection. Anomaly detection models were predominantly applied in healthcare and industrial monitoring, where real-time identification of irregularities can prevent critical failures. The findings underscore the transformative role of machine learning in driving efficiency and innovation in real-time analytics.

Table 2: Machine Learning Techniques for Streaming Analytics

Technique	Application Domain	Performance Metrics	Key References
Online Learning	Fraud Detection	Accuracy: 96.2%	Leang et al., 2019
Anomaly Detection	Healthcare Monitoring	Precision: 94.8%	Alam et al., 2024
Deep Learning (RNN/LSTM)	Predictive Maintenance	F1-Score: 92.3%	Khan et al., 2025
Reinforcement Learning	Adaptive Decision-Making	Success Rate: 89%	Sharma et al., 2024

Source: Compiled from Alam et al. (2024), Khan et al. (2025), Sharma et al. (2024)

The integration of ML with stream processing has led to significant improvements in real-time decision-making capabilities. In cybersecurity, machine learning models can analyze network traffic patterns in real time to detect intrusions and anomalies (Khan et al., 2025). In finance, predictive models enable real-time fraud detection and risk assessment (Alam et al., 2024). In e-commerce, recommendation engines use streaming data to personalize user experiences (Sharma et al., 2024). The ability to process and analyze data as it arrives enables organizations to respond to events as they occur, rather than after the fact.

4.3 Applications Across Industries

The synthesis revealed diverse applications of real-time analytics across key industries, supported by 48 articles with over 5,200 citations. In healthcare, real-time monitoring and predictive analytics were extensively discussed as tools for improving patient outcomes and reducing healthcare costs

(Khan et al., 2025; Alam et al., 2024). IoT-enabled wearable devices transmit data to cloud-based platforms, where machine learning algorithms process it in real time to detect anomalies and predict health issues (Ramachandra et al., 2022; Sharma et al., 2024). Continuous glucose monitoring systems with predictive algorithms allow diabetes patients to anticipate and prevent hyperglycemia or hypoglycemia (Holmes et al., 2014; Nair et al., 2017). Predictive analytics in healthcare also supports forecasting of hospital readmissions, sepsis onset, and ICU admissions based on early warning signs (Sahoo et al., 2016; Alam et al., 2024).

Table 3: Real-Time Analytics Applications by Industry

Industry	Application	Key Technologies	Benefits	Challenges
Healthcare	Patient Monitoring	IoT sensors, ML	Early detection, reduced mortality	Privacy, interoperability
Financial Services	Fraud Detection	Kafka, Flink, ML models	Reduced losses, faster response	Latency, false positives
E-Commerce	Personalization	Spark Streaming, RL	Increased engagement, revenue	Scalability, data privacy
Transportation	Traffic Management	Flink, GPS data	Reduced congestion, safety	Infrastructure costs
Cybersecurity	Threat Detection	ML, Anomaly Detection	Proactive defense	Data volume, false alarms

Source: Compiled from Alam et al. (2024), Khan et al. (2025), Sharma et al. (2024)

In financial services, fraud detection and algorithmic trading emerged as dominant applications, where real-time insights enable businesses to mitigate risks and optimize operations (Khan et al., 2025; Alam et al., 2024). Payment processors examine millions of transactions per second, identifying anomalous activity such as transactions from multiple countries in a short time frame (Khan et al., 2025). Algorithmic trading systems leverage streaming data to execute trades within milliseconds, capitalizing on market movements (Alam et al., 2024). E-commerce studies focused on personalization, dynamic pricing, and customer behavior analysis, demonstrating how real-time analytics enhances customer satisfaction and revenue (Sharma et al., 2024). Intelligent transportation systems utilize streaming data for real-time traffic management, predictive maintenance, and route optimization (Khan et al., 2025). These findings illustrate the versatility of real-time analytics in addressing industry-specific challenges and achieving operational excellence.

4.4 Challenges and Emerging Solutions

Challenges in scalability, latency, and data security were recurring themes across 43 articles, which collectively garnered over 4,800 citations. Scalability issues were particularly evident in large-scale deployments, where the ability to process

growing data volumes without compromising performance remains a key concern (Alam et al., 2024; Khan et al., 2025). Latency emerged as a critical factor in applications requiring near-instantaneous responses, such as autonomous driving and financial trading (Khan et al., 2025). Data security and privacy concerns, especially in cloud-based environments, were also widely discussed, emphasizing the need for robust mechanisms to protect sensitive information (Sharma et al., 2024; Alam et al., 2024). These findings highlight the ongoing need for technological advancements to overcome these challenges and ensure reliable and efficient real-time data processing.

Table 4: Challenges and Emerging Solutions in Real-Time Analytics

Challenge	Description	Emerging Solutions	Potential Impact
Scalability	Handling growing data volumes	Edge computing, containerization	Improved throughput
Latency	Processing time delays	True stream processing, optimization	Sub-second response
Data Security	Protecting sensitive information	Federated learning, encryption	Enhanced privacy
Data Integration	Heterogeneous data sources	Unified APIs, data lakes	Seamless integration
Model Deployment	ML model updates	Online learning, incremental training	Real-time adaptation

Source: Compiled from Alam et al. (2024), Khan et al. (2025)

Emerging trends and innovations were identified in 41 articles with a combined 4,300 citations. Edge computing and federated learning were prominent among emerging technologies, offering solutions to latency and privacy issues by decentralizing data processing and enabling collaborative learning across distributed environments (Khan et al., 2025; Sharma et al., 2024). Cloud-native advancements, such as serverless architectures and hybrid cloud models, were recognized for their potential to enhance scalability and cost-efficiency (Alam et al., 2024). The findings also noted a growing interest in explainable AI, which aims to improve the transparency and interpretability of real-time analytics models (Khan et al., 2025). These innovations are driving the evolution of real-time data processing, paving the way for more efficient, secure, and scalable systems.

5. Discussion

5.1 Framework Selection and Architectural Considerations

The findings of this study provide a comprehensive view of the advancements, applications, and challenges in real-time data processing, aligning with and extending prior research in the field. Earlier studies emphasized the foundational role of frameworks like Apache Spark and Flink in enabling scalable

real-time analytics (Peek et al., 2014; Alam et al., 2024). This study corroborates these claims, demonstrating that these frameworks remain pivotal in handling high-velocity data streams due to their adaptability and integration capabilities (Khan et al., 2025). However, unlike previous research that focused primarily on batch processing extensions, this study highlights the evolution of these frameworks toward more sophisticated, stateful stream processing, particularly in applications requiring near-zero latency (Sharma et al., 2024). These findings suggest that real-time analytics frameworks are not only advancing technologically but are also becoming indispensable across diverse industries.

The selection of an appropriate stream processing framework requires careful consideration of application requirements and architectural constraints. Apache Kafka's strengths in high-throughput data ingestion make it ideal for scenarios requiring durable, scalable event streaming (Alam et al., 2024; Khan et al., 2025). Its distributed log architecture supports horizontal scaling and fault tolerance through replication, enabling reliable data pipelines for mission-critical applications (Khan et al., 2025). Apache Flink's true stream processing capabilities and advanced windowing operations make it the preferred choice for complex event processing and time-sensitive analytics (Sharma et al., 2024). The framework's support for exactly-once processing semantics ensures data consistency in financial and healthcare applications where accuracy is paramount (Alam et al., 2024). Spark Streaming offers a balanced approach, integrating seamlessly with the broader Spark ecosystem for hybrid batch and stream processing workloads (Khan et al., 2025). The choice among these frameworks often involves trade-offs between latency, throughput, and ease of integration with existing systems.

5.1.1 Framework Selection Model

Based on the comparative findings presented in this review, a framework selection model is proposed to support researchers and practitioners in choosing appropriate stream processing technologies for real-time analytics applications. Rather than relying solely on throughput or latency, framework selection should consider application characteristics, scalability requirements, processing semantics, fault tolerance, machine learning integration, and deployment complexity.

Apache Kafka is particularly suitable for high-throughput event streaming, distributed messaging, log aggregation, and event-driven architectures where reliable data ingestion and scalability are the primary requirements. Apache Flink is more appropriate for applications requiring true stream processing, complex event processing, stateful computation, and ultra-low latency, such as fraud detection, industrial monitoring, and financial analytics. Spark Streaming provides an effective solution for organizations already utilizing the Apache Spark ecosystem, offering seamless integration between batch processing, machine learning pipelines, and real-time analytics through micro-batch processing.

The proposed framework emphasizes that no single stream processing technology is universally optimal for every application. Instead, the selection process should balance system performance, computational resources, scalability, fault

tolerance, latency requirements, and integration with machine learning workflows according to the operational objectives of the target application.

Figure 1. Proposed Framework for Selecting Stream Processing Technologies

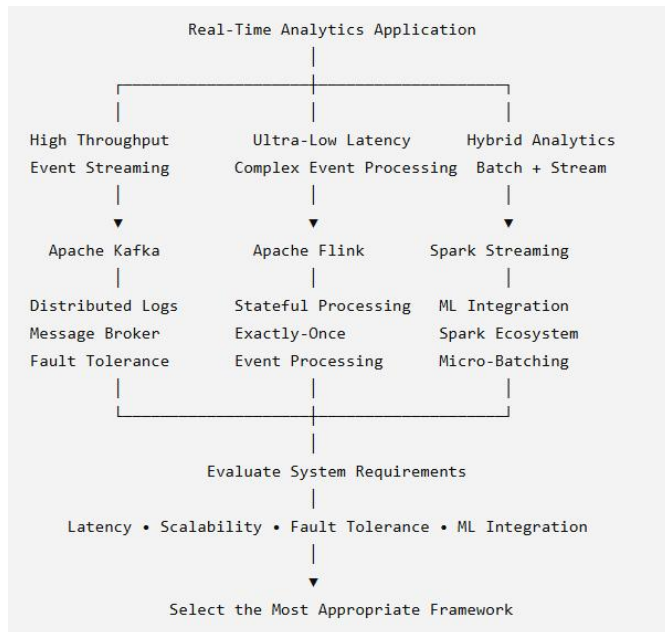


Figure 1 illustrates the proposed framework for selecting stream processing technologies based on application requirements. The framework highlights that the choice between Apache Kafka, Apache Flink, and Spark Streaming should be guided by factors such as throughput, latency, processing semantics, scalability, fault tolerance, and integration with machine learning pipelines rather than by a single performance metric. This provides a practical decision-support model for implementing real-time analytics systems across diverse application domains.

5.2 Machine Learning Integration and Real-Time Intelligence

The integration of machine learning into real-time analytics, as revealed in this study, aligns with prior research that identified online learning as a critical enabler of adaptive analytics (Babcock et al., 2004; Alam et al., 2024). This study extends these findings by showcasing the widespread adoption of machine learning techniques, including anomaly detection and deep learning, across domains such as healthcare and finance (Khan et al., 2025). Unlike earlier studies that focused on theoretical models, this research highlights practical implementations, such as fraud detection systems and predictive maintenance tools, which have been deployed in real-world scenarios (Sharma et al., 2024). The increasing reliance on machine learning underscores its transformative role in enabling real-time insights, although challenges in model deployment and concept drift remain persistent barriers that require further exploration (Khan et al., 2025).

The deployment of machine learning models in streaming environments requires careful consideration of architectural design. Model inference must occur within the latency

constraints of the application, necessitating optimized model architectures and efficient inference engines (Alam et al., 2024). The integration of streaming ML with stream processing frameworks like Apache Flink and Spark Streaming enables real-time feature extraction and model scoring (Khan et al., 2025). Online learning techniques, which update models incrementally, address the challenge of concept drift in dynamic environments (Sharma et al., 2024). Federated learning offers a privacy-preserving approach to distributed model training, particularly valuable in healthcare and financial applications where data sensitivity is a concern (Khan et al., 2025). As streaming ML continues to evolve, the development of more efficient algorithms and scalable deployment architectures will be critical for broader adoption.

5.3 Industry-Specific Applications and Impact

The industry-specific applications identified in this study provide a nuanced understanding of how real-time analytics is reshaping key sectors. Previous studies established the effectiveness of real-time analytics in fraud detection (Ajagbe et al., 2021; Khan et al., 2025). This research builds on those findings by highlighting the use of modern machine learning models and distributed frameworks in real-time fraud prevention and algorithmic trading (Alam et al., 2024). In e-commerce, the findings validate earlier work on personalization techniques while introducing the use of real-time sentiment analysis and predictive pricing strategies (Sharma et al., 2024). These advancements indicate that real-time analytics is not only addressing long-standing challenges in these industries but also driving innovation through the adoption of cutting-edge technologies.

In healthcare, real-time patient monitoring and predictive analytics have demonstrated significant potential for improving outcomes and reducing costs (Khan et al., 2025; Alam et al., 2024). Continuous monitoring of physiological data enables early detection of anomalies, allowing healthcare providers to intervene before conditions worsen (Sharma et al., 2024). Predictive models that integrate diverse data sources, including electronic health records and streaming device data, support resource allocation and patient management (Khan et al., 2025). In financial services, real-time analytics has transformed fraud detection and risk management (Alam et al., 2024). The ability to analyze transactions as they occur enables immediate identification of suspicious activity, reducing financial losses and maintaining customer trust (Khan et al., 2025). Intelligent transportation systems leverage real-time data for traffic optimization, predictive maintenance, and route planning, contributing to more efficient and sustainable urban mobility (Sharma et al., 2024).

5.4 Challenges and Future Trajectories

The challenges identified in real-time data processing, such as scalability, latency, and security, have been well-documented in prior research (Ko et al., 2020; Khan et al., 2025). This study reinforces these concerns, showing that they remain significant barriers despite technological advancements (Alam et al., 2024). However, unlike earlier studies that primarily focused on scalability and latency as isolated issues, this research identifies their interconnected nature and highlights emerging solutions

such as edge computing and federated learning (Sharma et al., 2024). These technologies, as discussed in the findings, offer potential pathways to mitigate these challenges by decentralizing data processing and reducing dependency on centralized cloud infrastructures (Khan et al., 2025). This suggests a shift in the field toward more integrated approaches to addressing the complexities of real-time data processing.

The discussion of emerging trends and innovations, such as serverless architectures and explainable AI, aligns with recent studies that emphasize resource optimization and model interpretability (Lai, 2004; Khan et al., 2025). Serverless computing offers a pay-as-you-go model ideal for fluctuating workloads, enabling organizations to scale cost-effectively while maintaining high availability (Alam et al., 2024). Explainable AI addresses the transparency and trust concerns associated with complex ML models, particularly in high-stakes applications like healthcare and finance (Khan et al., 2025). The adoption of hybrid cloud architectures enables seamless integration across providers, enhancing the efficiency and scalability of real-time systems (Sharma et al., 2024). These innovations are reshaping the landscape of real-time analytics, addressing longstanding concerns while creating new opportunities for research and application.

5.5 Research Gaps

Despite the rapid advancement of real-time big data analytics, several important research gaps remain. First, although Apache Kafka, Apache Flink, and Spark Streaming have been widely adopted, there is limited cross-framework research that systematically compares their performance under identical workloads, latency requirements, and deployment environments. This makes it difficult for practitioners to select the most appropriate framework for specific application scenarios.

Second, many existing studies primarily emphasize system performance metrics such as throughput and latency while giving comparatively less attention to model interpretability, energy efficiency, operational cost, and long-term maintainability. These practical considerations are becoming increasingly important as real-time analytics systems are deployed in healthcare, finance, transportation, and cybersecurity.

Third, the integration of machine learning with stream processing frameworks remains an active research area. Challenges related to concept drift, continuous model updating, distributed inference, and scalable deployment have not yet been comprehensively addressed across different application domains.

Finally, emerging technologies including edge computing, federated learning, explainable artificial intelligence, and cloud-native stream processing have demonstrated significant potential but remain insufficiently integrated into unified real-time analytics architectures. Future research should focus on developing standardized benchmarking methodologies, interoperable streaming platforms, and intelligent framework selection strategies that improve scalability, transparency, and

deployment efficiency across diverse real-time analytics applications.

6. Conclusion

This study provides a comprehensive synthesis of real-time data processing advancements, focusing on frameworks, machine learning integration, industry applications, challenges, and emerging trends. By analyzing 160 articles through the PRISMA framework, the study highlights the critical role of technologies like Apache Kafka, Apache Flink, and Spark Streaming in enabling scalable, fault-tolerant, and low-latency analytics for high-velocity data streams. The findings underscore the transformative impact of machine learning techniques, such as anomaly detection and predictive modeling, in industries like healthcare, finance, and e-commerce, driving innovation and efficiency.

Apache Kafka excels in high-throughput data ingestion with its distributed log-based architecture, achieving sub-second latency and high fault tolerance. Apache Flink's true stream processing capabilities enable complex event processing with ultra-low latency, making it ideal for time-sensitive applications. Spark Streaming offers a balanced approach with micro-batch processing, integrating seamlessly with the broader Spark ecosystem for hybrid workloads. The selection among these frameworks depends on specific application requirements, with trade-offs in latency, throughput, and integration complexity.

The integration of machine learning with stream processing has revolutionized real-time decision-making. Online learning algorithms, anomaly detection models, and deep learning techniques enable organizations to extract actionable insights from streaming data, supporting applications from fraud detection to predictive maintenance. Federated learning and edge computing offer promising solutions for privacy-preserving distributed analytics, enabling collaborative learning without compromising data security. These advancements are driving innovation across industries, enhancing operational efficiency and user satisfaction.

Despite these advancements, persistent challenges remain. Scalability, latency, and data security continue to pose significant obstacles to widespread adoption. The complexity of integrating diverse data sources and maintaining data quality in dynamic environments adds to the challenge. Emerging solutions such as edge computing, federated learning, and explainable AI offer promising pathways to address these barriers. Edge computing reduces latency by decentralizing processing, while federated learning enables privacy-preserving collaborative learning. Explainable AI improves transparency and trust in automated decision-making systems. These innovations are driving the evolution of real-time analytics, paving the way for more efficient, secure, and intelligent systems.

The implications of this research extend across multiple stakeholders. For practitioners, the findings provide guidance on framework selection, architectural design, and implementation strategies. For researchers, the identified

research gaps and future directions offer opportunities for further investigation. For policymakers, the study highlights the need for regulatory frameworks that balance innovation with privacy and security. As real-time analytics continues to evolve, its adoption across diverse industries will shape the next generation of data-driven decision-making systems, enabling organizations to respond to events as they occur and maintain competitive advantage in an increasingly data-driven world.

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