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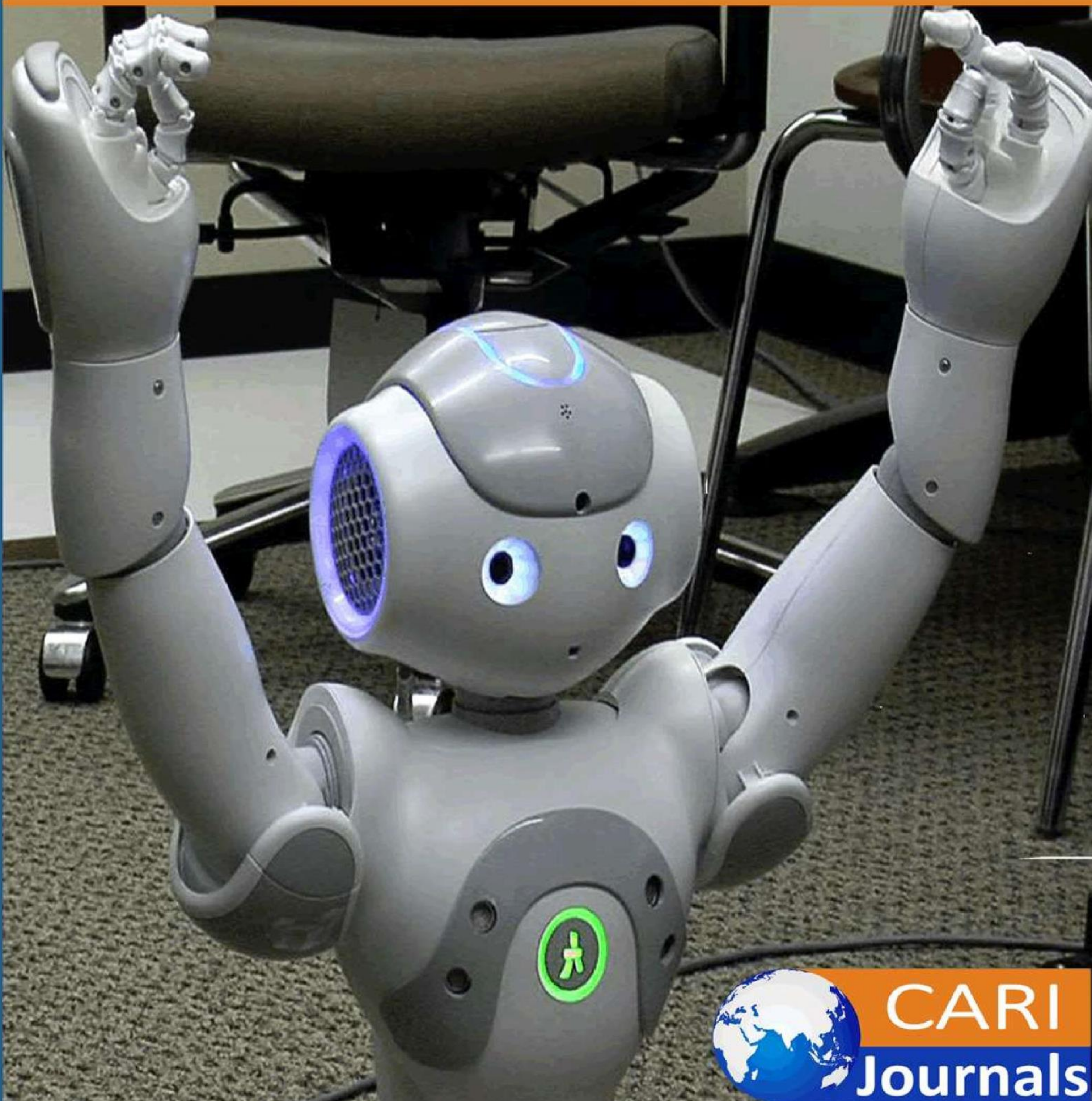

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Real-Time Data Streaming and AI Enhancements: E-Commerce Live Streaming Shopping

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Abstract

This paper explores the transformative potential of real-time data streaming and artificial intelligence (AI) in the context of e-commerce live streaming shopping. By leveraging advance technologies such as Storm, Trident, Samza, and Spark Streaming, businesses can process and analyze data in real-time, enhancing consumer engagement and driving sales in real time. This paper reviews the literature on live streaming selling, product promotion, and multichannel sales, and discusses the challenges and opportunities associated with these technologies. The findings provide valuable insights for businesses and researchers aiming to harness the power of real-time data streaming in the dynamic landscape of social commerce using real time streaming.

Keywords: *Real-Time Data Streaming, Artificial Intelligence, E-Commerce, Live Streaming Shopping, Consumer Engagement.*

I. INTRODUCTION

The digital landscape is rapidly evolving, with social media and e-commerce converging to create new opportunities for businesses. Real-time data streaming has emerged as a key technology in this transformation, enabling businesses to process and analyze data as it is generated. This capability is particularly valuable in the context of e-commerce live streaming, where real-time interactions with consumers can drive engagement and sales.

The proliferation of social media platforms and mobile devices has led to an explosion of user-generated content, creating a vast reservoir of data. Traditional batch-oriented data processing approaches are insufficient for capturing the fleeting value of this data, necessitating the adoption of real-time data streaming technologies [1]. Technologies such as storm, trident, samza, and spark streaming empower businesses to process and analyze streaming data in milliseconds, enabling highly responsive and scalable systems [1][2].

In e-commerce, live streaming has become a powerful tool for engaging consumers and fostering brand loyalty. by leveraging the immediacy and interactivity of live video, retailers can showcase products, demonstrate features, and interact with consumers in real-time [6][8]. this approach not only enhances the shopping experience but also taps into the potential of social commerce, where influencer recommendations carry significant weight [9][8] and real time data processing that can help achieve this and have key performance indicator (KPI) generated.

However, the adoption of real-time data streaming in social media and e-commerce live streaming presents challenges, including data privacy concerns and the complexity of revenue sharing models [9]. It aims to explore these challenges and provide insights into maximizing the benefits of real-time data streaming for social media and e-commerce.

II. METHODOLOGY

Reference No.	Studies	Focus Area	Key Findings
1.	Wingerath, Wolfram, Gessert, Felix, Friedrich, Steffen and Ritter, Norbert. "Real-time stream processing for Big Data"- it Information Technology, vol. 58, no. 4, 2016, pp. 186-194.	Real-time stream processing technologies	Discusses the capabilities and limitations of Storm, Trident, Samza, and Spark Streaming in processing big data in real-time. Highlights the trade-offs between latency, fault tolerance, and processing guarantees.

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2.	Xiao Zeng, Biyi Fang, Haichen, Shen, and Mi Zhang. 2020. Distream: scaling live video analytics with workload-adaptive distributed edge intelligence. In Proceedings of the 18th Conference on Embedded Networked Sensor Systems (SenSys '20)	Live video analytics	Introduces Di stream, a system for scaling live video analytics using distributed edge intelligence. Emphasizes workload-adaptive mechanisms to handle varying data loads.
3.	Andrew Psaltis, Streaming Data: Understanding the real-time pipeline, Manning, 2017	Real-time data pipelines	Provides a comprehensive guide on building and managing real-time data pipelines. Covers various technologies and best practices for implementing real-time data streaming solutions.
4.	Wang, Tong-Yuan & Chen, Yi& Mardani, Abbas & Chen, Zhen-Song. (2024). Live Streaming Service Introduction and Optimal Contract Selection in an E-Commerce Supply Chain. IEEE Transactions on Engineering Management.	E-commerce live streaming and supply chain management	Examines the introduction of live streaming services in e-commerce supply chains. Analyzes optimal contract selection and the impact on supply chain performance.
5.	B. K. Sunny, P. S. Janardhanan, A. B. Francis and R. Murali, "Implementation of	Real-time recommendation systems	Describes the implementation of a self-adaptive real-time

	a self-adaptive real time recommendation system using spark machine learning libraries”, 2017 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES).		recommendation system using Spark ML lib. Highlights the benefits of real-time data processing for personalized recommendations.
6.	Xu, Xiaoyu et al. “What Drives Consumer Shopping Behavior in Live Streaming Commerce.” Journal of Electronic Commerce Research 21 (2020): 144.	Consumer behavior in live streaming commerce	Investigates factors influencing consumer shopping behavior in live streaming commerce. Identifies key drivers such as streamer attractiveness, para-social relationships, and information quality.
7.	Apasrawirote, Darlin & Yawised, Kritcha. (2022). Factors Influencing the Behavioral and Purchase Intention on live-streaming Shopping. Asian Journal of Business Research. 12. 39-56.	Behavioral and purchase intention in live streaming shopping	Explores the factors that influence consumer behavior and purchase intentions in live-streaming shopping. Emphasizes the role of real-time interactivity and trust in streamers.
8.	Wang, Y., Lu, Z., Cao, P. et al. How Live Streaming Changes	Impact of live streaming on	Analyzes how streaming affects shopping decisions in e-commerce live. Highlights the

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	Shopping Decisions in E-commerce: A Study of Live Streaming Commerce. Comput Supported Coop Work 31, 701–729 (2022).	shopping decisions	role of live streaming as a decision support system and market intermediary.
9.	Hwang, S.B., Kim, S. (2006). Dynamic Pricing Algorithm for E-Commerce. In: Sobh, T., Elleithy, K. (eds) Advances in Systems, Computing Sciences and Software Engineering. Springer, Dordrecht.	Dynamic pricing in e- commerce	Discusses dynamic pricing algorithms for e-commerce. Examines the impact of real-time data on pricing strategies and consumer behavior.
10.	Zheng, T., Chen, G., Wang, X. et al. Real-time intelligent big data processing: technology, platform, and applications. Sci. China Inf. Sci. 62, 82101 (2019).	Real-time big data processing	Reviews technologies and platforms for real-time intelligent big data processing. Discusses applications in various domains, including e-commerce and social media.

Table 1. Characteristics of the included studies

III. LITERATURE REVIEW

The literature on real-time data streaming and e-commerce live streaming can be categorized into three main areas: live streaming selling, product promotion, and multichannel sales.

A. Live Streaming Selling

Research on live streaming selling focuses on its impact on consumer behavior and the perceived value of live streaming e-commerce [4]. Studies have shown that live streaming influences consumers' willingness to make purchases due to real-time interactivity, trust in streamers, and shopping guidance [6][8]. Streamers' product trials and interactive behaviors can enhance consumers' purchasing intentions, and their emotions can affect consumer behavior, displaying a negative U-shaped trend over time [7][8].

B. Product Promotion

In the context of supply chain product promotion, most literature focuses on interfirm collaboration and supply chain coordination from the perspective of advertising investments. Studies discuss the impact of such alliances on the dominant retailer, with the manufacturer setting wholesale prices and investing in advertising to enhance competitive advantage [6][8].

Research indicates that when the manufacturer is dominant, they exert the least quality effort, while the retailer invests the least in advertising [6][8].

C. Multichannel Sales

Research on multichannel sales often addresses pricing, channel selection, and contract design in the supply chain without considering the role of live streaming services. This paper differs by considering the live streaming spillover effect of the influencer live streaming model and incorporating the streamers’ flow effect to analyze its impact on supply chain members’ decisions [6][8].

IV. TECHNOLOGIES ENABLING REAL-TIME DATA STREAMING

A. Storm

Storm provides low latency but does not offer ordering guarantees and is often deployed without delivery guarantees, as the per-tuple acknowledgment required for at-least-once processing effectively doubles messaging overhead [1].

B. Trident

Stateful exactly once processing is available in Trident through idempotent state updates, but this has a notable impact on performance and fault-tolerance in some failure scenarios [1].

C. Samza

Samza is another native stream processor that focuses more on providing rich semantics, particularly through a built-in concept of state management, rather than low latency [1].

D. Spark Streaming

Spark Streaming effectively unifies batch and stream processing and offers a high-level API, exactly once processing guarantees, and a rich set of libraries, which can greatly reduce the complexity of application development [1]. Throughput can be optimized by buffering data and processing it in batches to reduce the impact of messaging and other overhead per data item, although this increases the in-flight time of individual data items [1][3][5].

```
from pyspark.sql import SparkSession
from pyspark.sql.functions import explode, split

# Initialize Spark Session
spark = SparkSession.builder \
    .appName("Real-Time Product Recommendations") \
    .getOrCreate()

# Read data from Kafka
df = spark \
    .readStream \
    .format("kafka") \
    .option("kafka.bootstrap.servers", "localhost:9092") \
    .option("subscribe", "user-activity") \
    .load()

# Convert the value column to string
df = df.selectExpr("CAST(value AS STRING)")

# Split the value column into words
words = df.select(
    explode(
        split(df.value, " ")
    ).alias("word")
)

# Generate running word count
wordCounts = words.groupBy("word").count()

# Write the output to console
query = wordCounts \
    .writeStream \
    .outputMode("complete") \
    .format("console") \
    .start()

query.awaitTermination()
```

Figure 1. Python code using Spark Streaming

Technology	**Latency**	**Fault Tolerance**	**Processing Guarantees**	**Key Features**
Storm	Low	No ordering guarantees	At-least-once processing	Low latency, high throughput
Trident	Moderate	Stateful exactly once processing	Idempotent state updates	High fault tolerance
Samza	Moderate	Rich semantics	Built-in state management	Focus on state management
Spark Streaming	Moderate to High	Exactly once processing	High-level API, batch processing	Unifies batch and stream processing

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Table 2. Comparison of Real-Time Data Streaming Technologies

V. IMPACT ON CONSUMER ENGAGEMENT AND SALES

A. Consumer behavior

Real-time data streaming and AI significantly influence consumer behavior in live streaming settings. Streamer attractiveness, para-social relationships, and information quality have direct effects on cognitive assimilation and arousal, which in turn affect impulsive consumption, hedonic consumption, and social sharing [6][8][10].

B. Case Studies

Empirical results from case studies reveal that live streaming as a decision support system improves the evaluation of products and online stores at the information search and alternative evaluation stages, while market intermediaries influence consumers at the shopping need awareness stage [6][8].

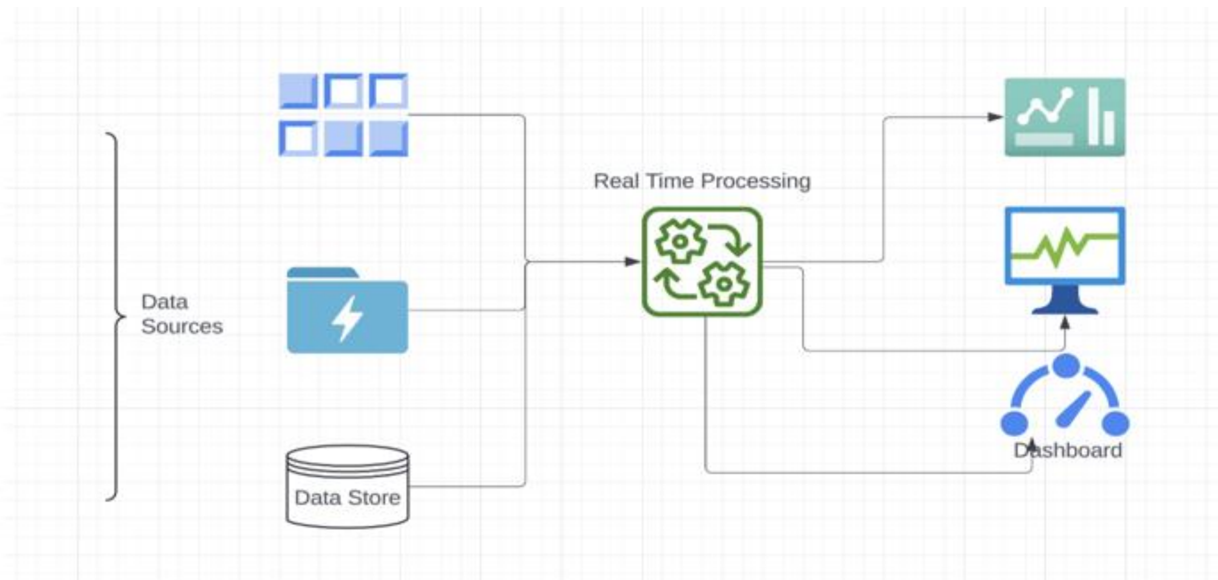

Figure 2. Real time processing system

VI. CHALLENGES AND CONSIDERATIONS

A. Data Privacy and Security

Ensuring data privacy and security is a significant challenge in real-time data streaming for social media and e-commerce live streaming. Businesses must implement robust measures to protect consumer data and comply with regulatory requirements [9].

B. Revenue-Sharing Models

Navigating the complexities of revenue-sharing models and influencer partnerships is another critical consideration. Businesses need to establish fair and transparent revenue-sharing agreements to foster long-term partnerships with influencers [9].

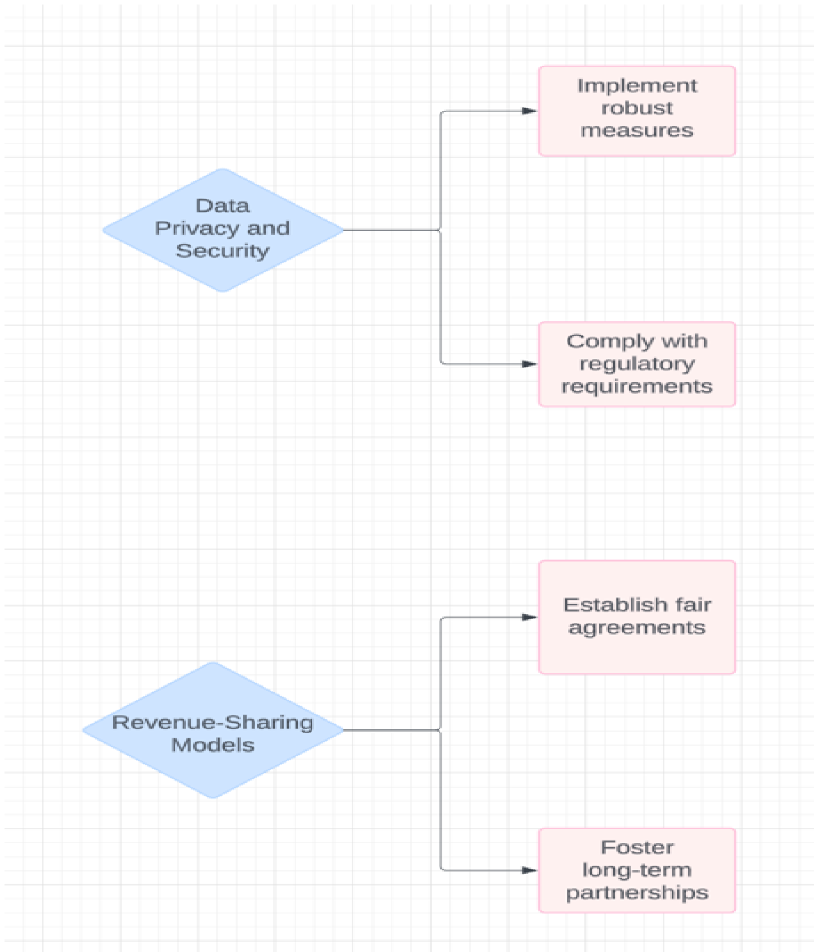

Figure 3. Flowchart to address Challenges in Real-Time Data Streaming

VII. DISCUSSION

This section integrates the findings from the literature review and empirical analysis, discussing how real-time data streaming and AI can be optimized to overcome the identified challenges. Future research directions include exploring the impact of the streamers effort on optimal decision-making and studying the introduction strategies of live streaming services in a competitive environment involving multiple manufacturers [6][8].

VIII. CONCLUSION

This paper has explored the transformative potential of real-time data streaming and AI in e-commerce live streaming shopping. By leveraging these technologies, businesses can enhance consumer engagement, drive sales, and foster brand loyalty. However, challenges such as data privacy and revenue-sharing models must be addressed to unlock the full potential of this technology. Future research should focus on optimizing these technologies and exploring new strategies to further enhance their impact on e-commerce.

IX. FUTURE DIRECTIONS

Research Area	Description	Potential Impact
Streamer Effort on Decision-Making	Exploring how streamers' efforts influence optimal decision-making	Improved strategies for influencer partnerships
Introduction Strategies in Competitive Environments	Studying strategies for introducing live streaming services in competitive markets	Enhanced competitive advantage for businesses

Table 3. Future Research Directions

X. REFERENCES

[1] Wingerath, Wolfram, Gessert, Felix, Friedrich, Steffen and Ritter, Norbert. Real-time stream processing for Big Data" it- Information Technology, vol. 58, no. 4, 2016, pp. 186-194. https://doi.org/10.1515/itit-2016-0002.

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