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Mapping the Social Sphere: A Critical Analysis of Big Data Visualization Techniques and Challenges

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Abstract: *The exponential growth of social media data presents unique challenges and opportunities for visualization. This paper explores key techniques for visualizing large-scale social media datasets, including network graphs, sentiment heatmaps, and geospatial analytics. We identify technical challenges such as scalability and real-time processing, alongside non-technical barriers like cognitive overload and privacy concerns. Through case studies on misinformation tracking and marketing analytics, we analyze how these challenges impact decision-making. The paper concludes with recommendations for future research, emphasizing AI-driven and immersive visualization tools.*

Index Terms: *Big Data, Data Visualization, Social Media, Challenges, Decision-Making*

I. INTRODUCTION

The rise of social media platforms like Twitter, Facebook, Instagram, and TikTok has fundamentally transformed how individuals and organizations communicate, share information, and make decisions. With over 4.7 billion active social media users globally [1], these platforms generate vast amounts of unstructured data every second. This includes text (tweets, posts, comments), images, videos, geospatial data, and meta-data such as timestamps and user locations. The sheer volume, velocity, variety, veracity, and value of this data—commonly referred to as the “5 Vs” of big data—pose significant challenges for traditional data analysis techniques [2].

Big data visualization serves as a critical bridge between raw, complex datasets and actionable insights. By converting intricate patterns into intuitive visual formats such as charts, graphs, maps, and interactive dashboards, visualization enables stakeholders—from marketers to policymakers—to identify trends, outliers, and correlations that would otherwise remain hidden. For example, sentiment heatmaps can reveal public opinion shifts during political campaigns, while geospatial maps can track the spread of viral content or misinformation across regions.

However, the unique characteristics of social media data introduce additional layers of complexity. Unlike structured datasets, social media data is highly dynamic, heterogeneous, and often noisy. Real-time interactions, multimedia content, and the interconnected nature of user networks demand advanced visualization techniques that can handle both scale and complexity. Moreover, the virality of social media amplifies the need for rapid insights, making real-time processing a critical requirement.

This paper aims to address these challenges by exploring key visualization techniques tailored to social media data, analyzing the technical and non-technical barriers to effective visualization, and evaluating their impact on decision-making processes. Through case studies and a review of emerging trends, we provide a comprehensive analysis of the current state of big data visualization in social media and offer recommendations for future research.

II. RELATED WORK

The field of big data visualization in social media has garnered significant attention from researchers and practitioners alike. Existing literature provides valuable insights into the techniques, tools, and challenges associated with visualizing large-scale social media datasets.

Visualization Techniques Several studies have explored innovative methods for representing social media interactions. Javalkoti et al. [3] conducted a comprehensive survey of visualization techniques specifically designed for platforms like Twitter and Facebook. They highlighted the use of network graphs to model user interactions, where nodes represent users and edges denote relationships such as retweets, mentions, or follows. Tools like Gephi and D3.js have been widely adopted for creating interactive network visualizations, enabling analysts to identify influencers, communities, and clusters within social networks. Additionally, Qi et al. [4] demonstrated the effectiveness of temporal visualizations, such as timelines and heatmaps, in capturing the evolution of trends and sentiments over time.

Sentiment analysis visualization has also emerged as a powerful tool for understanding public opinion. Techniques such as word clouds, sentiment heatmaps, and bar charts aggregate textual data to highlight positive, negative, or neutral sentiments. These visualizations are particularly useful for brands and organizations seeking to monitor campaign performance or gauge customer feedback. Similarly, geospatial mapping tools like Tableau and ArcGIS allow analysts to visualize user activity across geographic regions, aiding in applications such as disaster response and marketing localization [4].

A. Challenges in Visualization

Despite advancements in visualization techniques, several challenges persist. Wang et al. [2] identified scalability as a major hurdle, emphasizing the difficulty of rendering billions of data points in real-time without compromising performance. Social media data's heterogeneity further complicates visualization, as it often combines text, images, videos, and metadata, requiring sophisticated integration methods.

Non-technical challenges, such as cognitive overload and privacy concerns, have also been extensively studied. SpringerOpen [5] highlighted how overly complex visualizations can overwhelm users, leading to misinterpretation or disengagement. Privacy remains another critical issue, as anonymizing sensitive data while preserving its utility for analysis is a delicate balance. Javalkoti et al. [3] noted that improper handling of personal information in visualizations can lead to ethical and legal ramifications.

B. Emerging Trends

Recent research has begun exploring the potential of augmented reality (AR) and virtual reality (VR) in social media visualization. SpringerOpen [5] demonstrated how AR/VR dashboards can reduce cognitive load by providing immersive, interactive environments for data exploration. Similarly, SCIRP [6] highlighted the role of AI-driven tools in automating insight generation, enabling real-time anomaly detection and predictive analytics. These innovations not only address existing challenges but also pave the way for more intuitive and scalable visualization solutions.

In summary, prior work has laid a strong foundation for understanding the complexities of social media data visualization. However, gaps remain in addressing scalability, cognitive limitations, and ethical considerations. This paper builds on these insights to propose a framework for overcoming these challenges and enhancing decision-making through effective visualization.

III. TECHNIQUES FOR SOCIAL MEDIA DATA VISUALIZATION

Visualizing social media data requires specialized techniques that can handle its scale, complexity, and heterogeneity. Below, we discuss six key techniques—network graphs, sentiment analysis visualization, geospatial mapping, temporal analysis, immersive dashboards, and advanced machine learning integration—and their applications in social media analytics.

A. Network Graphs

Social media platforms are inherently interconnected, making network graphs a natural choice for visualizing relationships between users, content, and interactions. Nodes represent entities such as users or posts, while edges denote relationships like retweets, mentions, or follows. These graphs are particularly useful for identifying influencers, detecting communities, and analyzing the spread of information. Tools like Gephi [7] and D3.js enable the creation of interactive and scalable network visualizations. For example, DeepTwitter [8] and FluxFlow [8] use network graphs to model retweet cascades, revealing patterns in misinformation propagation. Clusters of nodes often represent communities discussing specific topics, such as political campaigns or brand crises [8]. Advanced tools like D-Map [8] extend this by visualizing ego-centric diffusion patterns, aiding in identifying "super-spreaders" of viral content.

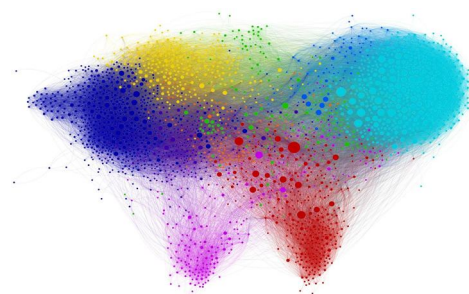


Fig. 1. Example of a network graph visualizing retweet cascades. [9]

B. Sentiment Analysis Visualization

Sentiment analysis transforms unstructured text data (e.g., tweets, comments) into visual summaries like heatmaps, word clouds, or polarity timelines. Tools such as SentiView [8] and VADER [10] classify sentiments into positive, negative, or neutral categories, while hybrid approaches combine lexicon-based methods with machine learning (e.g., SVM, Naive Bayes) for higher accuracy [10]. For instance, during the early stages of the COVID-19 pandemic in early 2020, sentiment heatmaps were instrumental in tracking public reactions to lockdown policies across different countries. These visualizations revealed spikes in negative sentiment correlated with policy announcements, such as school closures and travel restrictions [10].

However, challenges like slang, multilingual data, and sarcasm require advanced NLP techniques [10]. Recent innovations include multimodal sentiment analysis, which integrates text with audio/visual cues (e.g., emojis, video reactions) for richer insights [10]. Figure 2 illustrates a sentiment heatmap tracking public reactions to lockdown policies across four major regions—London, the USA, India, and Australia—during March-April 2020. The heatmap highlights how sentiment evolved over time, with notable negative sentiment spikes coinciding with significant policy changes.

C. Geospatial Mapping

Geospatial mapping is a powerful technique for visualizing social media activity across geographic locations, enabling analysts to track regional trends and identify spatial patterns. Tools like Tableau, ArcGIS, and CARTO leverage geotagged posts to provide insights into political campaigns, marketing

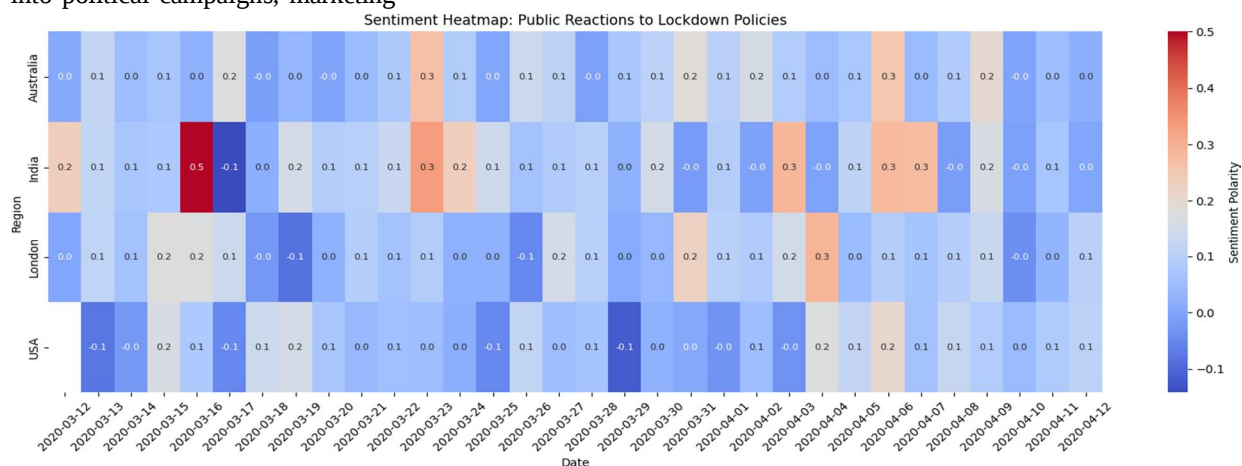


Fig. 2. Sentiment heatmap of tracking public reactions to lockdown policies. [10]

localization, and community engagement [11]. For instance, GenAI-powered geospatial maps have been used to prioritize network resources during high-traffic events, such as viral social media campaigns or live-streamed concerts. These maps help organizations allocate bandwidth dynamically by identifying regions with spikes in user activity, ensuring seamless connectivity for users.

Beyond resource allocation, tools like ScatterBlogs2 [8] employ hexbin maps to aggregate high-volume data, reducing visual clutter while preserving spatial patterns. Hexbin maps divide geographic areas into hexagonal bins, each representing the density of social media activity within that region. This approach is particularly useful for visualizing large datasets without overwhelming the viewer. Similarly, probabilistic geolocation algorithms have been developed to infer the likely location of non-geotagged posts, which account for approximately 60% of tweets [12]. These algorithms analyze linguistic cues, user profiles, and historical data to estimate post locations, though they introduce uncertainties that must be carefully managed to ensure accurate interpretations.

GenAI-driven geospatial tools further enhance these capabilities by integrating real-time analytics with predictive modeling. For example, CARTO's 2024 innovations in geospatial visualization enable dynamic updates and interactive dashboards, allowing users to explore trends in social media activity at both local and global scales [11]. Such advancements are critical for understanding how information spreads across regions and identifying key influencers within specific communities.

D. Temporal Analysis

Temporal analysis leverages time-series visualizations, such as line charts, bar charts, and animated timelines, to reveal trends, bursts, and seasonality in social media activity. Tools like TwitInfo [12] aggregate tweets into timeline-based displays, enabling analysts to identify peaks in activity during events such as political speeches, product launches, or viral

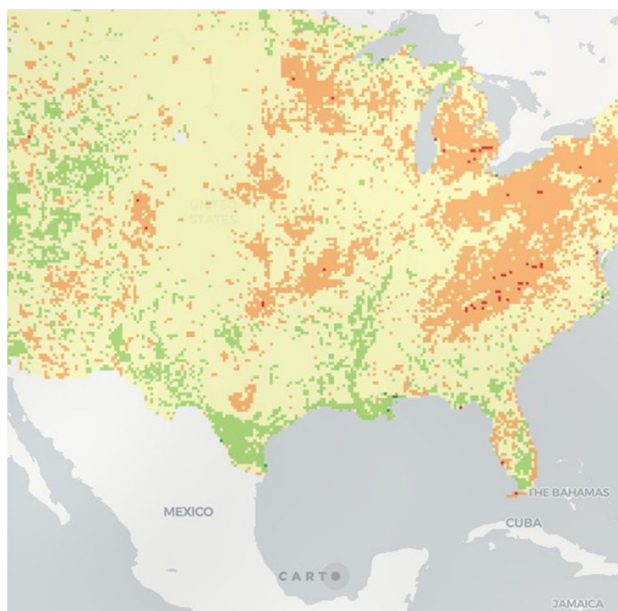


Fig. 3. A GenAI-powered geospatial map visualizing regional variations in social media activity during a viral campaign. The map highlights areas with high user engagement, aiding in resource prioritization and trend analysis [11].

campaigns. For example, during the 2016 U.S. presidential election, temporal visualizations highlighted spikes in tweet volume corresponding to key debates and policy announcements, providing real-time insights into public engagement.

E-Map [8] extends temporal analysis by incorporating spatial dimensions, allowing analysts to track the evolution of events across both time and space. For instance, the spread of hashtags like #BlackLivesMatter was visualized using E-Map, revealing how the movement gained momentum in different regions over time. Such visualizations are invaluable for understanding the dynamics of social movements and identifying influential nodes within networks.

Real-time streaming analysis tools like VARTTA [12] are particularly crucial for crisis management and stock market predictions. By processing live data streams, these tools enable organizations to respond quickly to emerging trends or anomalies. For longitudinal studies, seasonal-trend decomposition techniques separate noise from meaningful patterns, as demonstrated in analyses of Twitter's Gross National Happiness (GNH) index [12]. GNH visualizations revealed periodic fluctuations in public mood, correlating with holidays, weekends, and major global events.

Temporal analysis not only uncovers short-term bursts but also identifies long-term trends, making it an essential tool for understanding the temporal dynamics of social media data.

E. Immersive and Interactive Dashboards

Emerging visualization tools leverage augmented reality (AR) and virtual reality (VR) to create immersive analytics environments, addressing cognitive overload and enhancing user engagement. For example, SocialOcean [8] uses 3D bubble visualizations to explore "social media bubbles," where users can interactively navigate through clusters of interconnected posts. This approach allows analysts to drill down into subsets of data dynamically, uncovering hidden patterns and relationships.

FluxFlow [8] combines anomaly detection with interactive dashboards to flag atypical retweet threads, helping identify misinformation campaigns or coordinated bot activities. Similarly, WeSeer [8] integrates predictive modeling with visual analytics to forecast information cascades for WeChat articles. By simulating potential outcomes, these tools empower decision-makers to anticipate trends and mitigate risks proactively.

Despite their advantages, immersive dashboards face challenges related to accessibility and computational costs. High-end hardware requirements and steep learning curves limit their adoption, particularly for small organizations or individual users [13]. Additionally, ensuring seamless integration with existing systems remains a technical hurdle. Nevertheless, as AR/VR technologies become more affordable and user-friendly, their role in social media analytics is expected to grow significantly.

These tools exemplify the future of data visualization, where interactivity and immersion enhance the depth and clarity of insights derived from complex datasets.

F. Advanced Machine Learning Integration

Modern machine learning frameworks, such as Apache Spark [14] and NeuroSymbolic AI [10], automate insight generation from massive social media datasets. These frameworks employ advanced algorithms to process high-dimensional data, revealing latent structures and patterns that traditional methods might miss. For example, manifold learning algorithms reduce high-dimensional social media data into 2D or 3D projections, enabling analysts to visualize clusters of user demographics, bot accounts, or trending topics [14].

SentimentTree [8] uses hierarchical clustering to map sentiment evolution over time, providing a nuanced understanding of how public opinion shifts during events like elections or natural disasters. Similarly, IdeaFlow [8] applies topic modeling to visualize discourse shifts, helping organizations track emerging themes and adapt their strategies accordingly. Hybrid approaches that combine neural networks with traditional visualization techniques are gaining traction for real-time trend forecasting on platforms like Instagram [15]. For instance, convolutional neural networks (CNNs) analyze image-based content to detect visual trends, while recurrent neural networks (RNNs) model temporal dependencies in text-based data. Together, these methods enable comprehensive analyses of multimodal social media content.

While machine learning integration offers unprecedented capabilities, it also introduces challenges such as interpretability, scalability, and ethical considerations. Ensuring transparency in algorithmic decisions and addressing biases in training data are critical for maintaining trust and fairness in social media analytics. Table I presents a summary of various tools available for big data analysis.

TABLE I
KEY TOOLS FOR BIG DATA VISUALIZATION

Technique	Tools	Purpose
Network Graph	Kepler.gl, ArcGIS, Gephi	Geospatial & graph data
Sentiment Viz.	Graphana, VADER, Kibana	Social media, real-time data
Geospatial Mapping	Amazon LS, BigQuery GIS, GRASS GIS	Mapping & tracking (AWS, scientific)
Temporal Analysis	Apache Druid, Amazon TS, TF Time Series	Time-series trends
Immersive Dashboards	Cesium.js, Deck.gl, Unity3D	3D & VR visualization
ML Integration	AutoTS, Superset + MLflow, Azure BI	Forecasting, AI dashboards

IV. CHALLENGES

Visualizing social media data presents both technical and non-technical challenges that impact scalability, usability, and ethical considerations.

A. Technical Challenges

Rendering billions of data points in real-time remains a significant hurdle, as platforms like Twitter generate over 500 million tweets daily [2]. Traditional tools like Tableau struggle with latency during crises, such as misinformation outbreaks, though distributed frameworks like Apache Spark and GPU-accelerated rendering partially mitigate this issue [6]. Data heterogeneity further complicates visualization, as integrating text, images, videos, and metadata requires advanced preprocessing pipelines [4]. For instance, correlating hashtags with image content on Instagram demands multimodal analysis, increasing system complexity [16]. Real-time processing adds another layer of difficulty, as streaming platforms like TikTok demand sub-second latency for trend detection, often forcing compromises between granularity and performance [5]. Additionally, noisy datasets—containing spam, bots, and duplicates—distort analyses, while dimensionality reduction techniques like t-SNE and UMAP risk oversimplifying nuanced patterns [3]. Table II presents a summary of technical challenges along with the solutions.

TABLE II
TECHNICAL CHALLENGES IN BIG DATA VISUALIZATION

Challenge	Description	Solution
Scalability	Big dataset handling	Use Hadoop/Spark
Processing Speed	Real-time processing	In-memory computing, faster algorithms
Data Integration	Mixed data types	ETL pipelines, data lakes
Storage & Retrieval	Large data volumes	NoSQL, cloud storage
Data Cleaning	Inconsistencies in data	ML-based cleaning automation
Interactive Visuals	Smooth interactivity	GPU acceleration
Security & Privacy	Data protection	Encryption, access control
Device Constraints	Performance on devices	Graphics optimization

B. Non-Technical Challenges

Cognitive overload is a persistent issue, as complex visualizations (e.g., multilayer networks) overwhelm non-expert users, leading to misinterpretation [5]. Simplified dashboards like Twitter’s “Trending Topics” improve readability but may omit critical context [3]. Privacy concerns also arise when visualizing user-generated data, as anonymization techniques like k-anonymity reduce fidelity, while differential privacy introduces noise that distorts network structures [2]. User training and accessibility remain barriers, as advanced tools like Gephi require programming skills, excluding non-technical stakeholders [17]. Ethical risks, such as algorithmic bias in sentiment analysis, disproportionately affect marginalized groups, while cross-cultural differences in symbol interpretation (e.g., color schemes) necessitate localized design adaptations [4]. Table III presents a summary of non-technical challenges along with the solutions.

V. CASE STUDIES

To illustrate the practical implications of the techniques and challenges discussed, we examine two case studies: misinformation tracking during elections and AR/VR marketing dashboards.

A. Misinformation Tracking During Elections

During the 2020 U.S. elections, delays in visualizing Twitter data hindered timely fact-checking efforts [3]. The sheer volume of tweets overwhelmed traditional visualization tools, leading to missed opportunities to counteract false narratives. For example, network graphs revealed coordinated misinformation campaigns but were rendered too late to influence

TABLE III
NON-TECHNICAL CHALLENGES IN BIG DATA VISUALIZATION

Challenge	Description	Solution
Cognitive Load	Info overload	Clear, simple visual design
Interpretation Bias	Misinterpretation risk	Provide context, transparency
UX Design	Intuitive interfaces	Focus on usability & access
Domain Requirements	Industry-specific needs	Align with domain use cases
Implementation Cost	Infra expenses	Use open-source/cloud tools
Collaboration	Tech-business gap	Training, communication dashboards
Ethical Concerns	Deceptive visuals	Adhere to data ethics
Change Mgmt	Tool adoption	Train users, give documentation

public discourse effectively. This highlights the critical need for scalable, real-time processing frameworks that can handle high-velocity social media streams without compromising accuracy or speed.

A. AR/VR Marketing Dashboards

In contrast, a prototype AR dashboard demonstrated how immersive technologies can reduce cognitive load for marketers analyzing Instagram trends [5]. By visualizing engagement metrics and sentiment patterns in a 3D environment, the dashboard enabled users to "drill down" into specific demographics or regions dynamically. This approach not only improved decision-making efficiency but also enhanced user engagement by providing an intuitive interface. However, the high computational costs and limited accessibility of AR/VR tools remain barriers to widespread adoption.

These case studies underscore the dual nature of social media visualization: while technical challenges like scalability and real-time processing persist, innovations in immersive technologies offer promising solutions to non-technical barriers such as cognitive overload.

VI. FUTURE TRENDS

The future of social media data visualization lies in leveraging AI-driven tools and immersive technologies to address existing limitations. AI-powered frameworks, such as NeuroSymbolic AI and Apache Spark, automate insight generation from massive datasets, enabling real-time trend forecasting and anomaly detection [6]. For instance, neural networks can analyze multimodal content (e.g., text, images, videos) to detect emerging themes, while manifold learning algorithms project high-dimensional data into interpretable 2D/3D spaces. Similarly, VR-based collaborative dashboards are gaining traction for their ability to create shared, interactive environments where teams can explore complex datasets together [5]. These tools not only enhance collaboration but also reduce cognitive overload by allowing users to focus on subsets of data dynamically. As hardware costs decrease and software becomes more user-friendly, AR/VR technologies are expected to play a pivotal role in democratizing access to advanced visualization capabilities. Table IV shows a summary of future trends in Big Data Visualization

TABLE IV
FUTURE TRENDS IN BIG DATA VISUALIZATION

Trend	Description	Impact
AI-Powered Visualization	ML automates smart visual creation	Enhances predictions, reduces manual load
Real-Time Visuals	Stream IoT/sensor data	Enables fast, critical decisions
AR & VR	Immersive 3D data experiences	Boosts spatial insights in health/finance
NLP Integration	Voice/text-driven visuals	Increases access for non-experts
Edge Computing	Data near source (e.g., IoT)	Cuts latency, eases networks
Cloud Visualization	On-demand visual compute	Aids scalability & collaboration
Quantum Computing	Ultra-fast processing	Unlocks new analytic frontiers

However, ethical considerations must remain at the forefront of these advancements. Ensuring transparency in algorithmic decisions, addressing biases in training data, and respecting user privacy will be crucial for maintaining trust and fairness in social media analytics.

VII. CONCLUSION

Effective visualization of social media data requires striking a balance between technical scalability and user-centric design. Techniques such as network graphs, sentiment heatmaps, and geospatial mapping have proven invaluable for extracting insights from large-scale datasets. However, challenges like scalability, data heterogeneity, cognitive overload, and privacy concerns continue to pose significant hurdles.

Through case studies on misinformation tracking and AR/VR marketing dashboards, we have seen how these challenges impact decision-making and how innovative solutions can mitigate their effects. Looking ahead, advancements in AI-driven tools and immersive technologies promise to address many of these limitations, paving the way for more intuitive, scalable, and accessible visualization methods.

As social media continues to shape global communication and decision-making, the role of visualization in bridging raw data and actionable insights will only grow more critical. By embracing these innovations while addressing ethical and technical barriers, researchers and practitioners can unlock the full potential of big data in social media analytics.

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