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Social media analytics for investigations: A survey of recent trends, challenges and future research direction

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Highlights:
- Social media analytics revolutionizes investigations through advanced machine learning and real-time data analysis.
- Key challenges include data validity, bias reduction, ethical compliance, and misinformation management.
- Future research calls for standardized frameworks, adaptive ethics, and robust privacy protection measures.

Abstract

Social media analytics has emerged as a critical tool for investigations, providing valuable insights into user interactions, trends, and behaviors across various platforms. With over 4.76 billion active social media users globally, this vast data source has proven useful in government investigations and criminal litigations. However, extracting reliable information from social media presents significant challenges, including data representativeness, ethical and legal concerns, user behavior interpretation, and the growing issue of misinformation. This paper reviews recent trends in social media analytics, particularly its application in investigations, highlighting the increasing use of machine learning for data processing and analysis. Our analysis reveals its transformative impact, enabling advanced evidence collection, suspect identification, criminal network mapping, and proactive crime prevention. However, significant challenges persist regarding data validity, bias minimization, ethical responsibilities, and misinformation. Additionally, the paper offers future research directions, emphasizing the need for standardized frameworks, adaptive ethical guidelines, AI-driven real-time multimodal analysis, and robust privacy protection measures. These advancements aim to enhance the reliability and effectiveness of social media analytics for investigative purposes.

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1. Introduction

Social media platforms are widely used by users for business, sharing news and information, engaging with family and friends, and expanding networks for various organizations and groups (Murphy, 2013). Figure 1 displays the number of users across different social media platforms. Social media has proven highly effective in various applications such as brand awareness, targeted advertising, customer engagement, real-time news, collaborative communities, and activism (Aichner, Grünfelder, Maurer, & Jegeni, 2021). These platforms generate user data, including posts, images, videos, opinions, engagements, and connections that reveal networks and relationships among users. This extensive data can offer valuable information and insights applicable in multiple domains, such as government investigations and criminal litigation. However, extracting reliable and meaningful information from social media data is challenging. Social media analytics has become a crucial investigative tool, providing insights into user interactions, trends, and behaviors across different platforms (Batrinca & Treleaven, 2015).

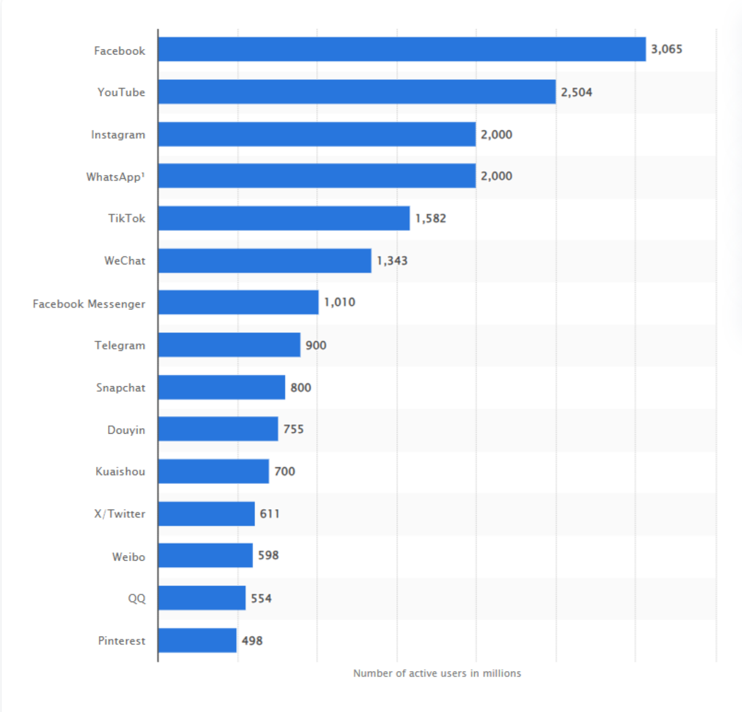

Figure 1. Number of monthly active users in different social media platforms (as of April 2024)[1]

Social media data provides valuable insights and information regarding the user and events. It has shown a critical role in identifying potential risk and managing crises effectively, such as in disaster management (Phengsuwan et al., 2021), conservation science and practice (Di Minin, Tenkanen, & Toivonen, 2015) and, tourism and hospitality (Rashidi, Abbasi, Maghrebi, Hasan, & Waller, 2017). In recent years, the application of social media data has increased in criminal investigations and crime prevention (Walsh & O'Connor, 2019). This data has been vital for law enforcement during evidence collection, suspect identification and profiling, network analysis, real-time monitoring, sentiment and trend analysis, and public engagement and crowdsourcing. These activities have helped law enforcement agencies to identify, analyze, and solve crime more efficiently and effectively.

Although using social media data for crime prediction and prevention has shown numerous benefits, it also provides many drawbacks and challenges. Data representativeness can be challenging and can show algorithmic bias towards a certain race, ethnicity, or social status. Relying on data from specific platforms, like Twitter, can lead to biased samples that do not accurately reflect broader populations (Tufekci, 2014; Sriram, Adhiraju, Kalangi, & Sathiyamoorthi, 2021). Furthermore, user behavior and socio-cultural complexities complicate the ability to interpret user interactions accurately. Investigators must address these difficulties to ensure their findings are valid and represent the larger context they are analyzing. They present challenges in

[1] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/

the accuracy and reliability of the collected data. The ethical and legal ramifications of social media data and data quality introduce further complications (Baier, 2019). Investigators must maintain compliance with different regulatory frameworks across nations and platforms while balancing the necessity for information and privacy concerns. Misuse of data or invasion of privacy are prime issues with using social media data. Misinformation is another significant challenge (Bayer, Kaufhold, & Reuter, 2021; Kaufhold, Rupp, Reuter, & Habdank, 2020). Misinformation can distort findings and lead to inaccurate conclusions as it can take many forms, such as fabricated news, manipulated images or videos, and false narratives.

Investigators need to implement stringent methods to verify the authenticity of the data and cross-check facts using sophisticated tools capable of identifying suspicious trends and content. Addressing these challenges requires combining methodological rigor, ethical consideration, and the latest technological innovations to ensure that social media analytics remains a reliable tool for investigators.

For this paper, we conducted a comprehensive literature search, which, while extensive, does not adhere to the strict protocol of a systematic literature review, but rather aims to provide a broad survey of the field. Our methodology involved targeted queries across various academic databases, including IEEE Xplore, ScienceDirect, ACM Digital Library, and Google Scholar, using keywords such as “social media analytics for criminal investigations”, “crime prediction using social media analytics”, and “social media analytics in court proceedings.” We augmented this with general search engine queries to capture a diverse range of sources, including relevant news articles, case studies, and practical applications. To identify enduring concepts and foundational developments, our search encompassed literature from the early 2010s to the present, to reflect the rapid evolution in social media and AI. The inclusion criteria prioritized materials demonstrating direct relevance to criminal investigations, crime detection, prediction, prevention, and their integration into criminal justice processes. Exclusion criteria involved studies primarily focused on non-investigative or non-criminal contexts. The collected materials were then systematically analyzed to extract key descriptors, evaluate their practical relevance, and highlight notable applications, challenges, and emerging trends in leveraging social media data. This approach allowed us to identify both established practices and recent innovations in the field.

Most of the existing surveys using social media analytics have been limited on specific applications of social media analytics. Authors in (Rathore, Kar, & Ilavarasan, 2017), have surveyed based on its application in business, in (Dong & Lian, 2021) surveyed on public opinion analyses, and in (Rodríguez-Ibánez, Casánez-Ventura, Castejón-Mateos, & Cuenca-Jiménez, 2023) authors have studied sentiment analysis. In (Balaji, Annavarapu, & Bablani, 2021) authors have presented a survey on tools and methods like machine learning algorithms used for social media analysis. This paper offers a focused and extensive survey of social media analytics tailored specifically to criminal investigations. While numerous reviews exist across related fields like crime prevention and digital forensics, our work uniquely synthesizes the application of social media analytics in diverse criminal contexts, examining its evolving role from foundational concepts to recent trends and challenges. This distinctive focus allows for a granular exploration of how this technology aids crime detection, prediction, prevention, and evidence collection within the criminal justice framework, setting it apart from broader or more domain-specific reviews. Likewise, this paper explores the application of data-driven methodologies, particularly social media analytics, in investigative contexts. Examining the integration of machine learning (ML), sentiment analysis, and natural language processing (NLP) to analyze vast social media datasets address key topics such as AI-based surveillance, privacy protection, and the ethical implications of data usage. The challenges and opportunities highlighted in the paper including combating misinformation and developing standardized frameworks for cross-platform analysis, aligning with the broader focus on advancing security measures, enhancing investigative tools, and promoting responsible technology deployment. This contribution lays a foundation for understanding how emerging technologies can transform digital investigations while upholding ethical and legal standards. The main contributions of this paper are:

- *Review of recent trends*: This paper examines current trends in social media analytics, focusing on investigative applications. We discuss real-world case studies and the increasing use of ML for data extraction, processing, and interpretation in investigations.
- *Identification of key challenges*: We categorize critical challenges in social media analytics, including data representativeness, user behavior analysis, data collection issues, ethical/privacy concerns, and the rise of information overload and misinformation.
- *Future research directions*: We propose future research on AI-driven multimodal analysis, ethics, and explainable AI, combating misinformation, and cross-platform integration for more efficient investigative workflows.

The paper is organized as follows: Section 2 presents the recent trends for social media analytics for investigations. Section 3 shows the different challenges investigators have while working on social media analytics. In Section 4 we present important future directions that social media analytics might follow. Finally, we present our conclusions in Section 5.

2. Recent Trends

With an increasing number of users and data on social media platforms, it has been a popular and important data source for many applications. With the development of big data analytics and ML in recent decades, this data from social media have provided great value in data mining and visual analytics that can be used for spatiotemporal situational awareness (Deng et al., 2023). Figure 2, shows that the increasing use of social media analytics worldwide can be demonstrated by the number of times it has been searched on the internet.

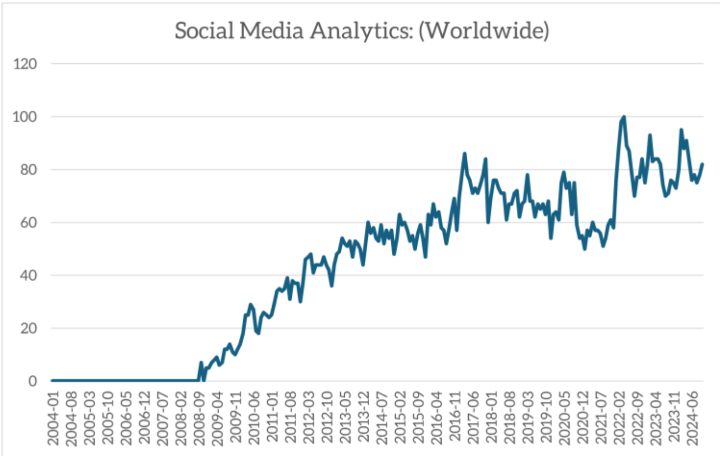

Figure 2. Social Media analytics web search number worldwide. (Google Trends)

Information from criminal justice records can provide links and motives behind crime and help to study crime and understand criminal networks (Bright, Brewer, & Morselli, 2022). In studying the engagement of groups in activities such as drug trafficking and terrorism, these network methods have been used in different criminological research. Social media data involves two types of sources: (i) open source, which is public information, and (ii) private data, which requires privileged access to be used for any purpose. This data can be used for information extraction and social networks that provide insights into criminal investigations and play a helpful role in criminal justice (Yu, 2023). Analyzing the data collected from different social media platforms on a specific person and group can provide an understanding of the purpose and possible threats that can help in identifying, predicting, and neutralizing the threats before they happen. This data helps to describe the patterns that include the opinions, expressions, sentiments, and social behaviors of diverse communities and people. Hence, much work has been performed in recent years, that apply different tools and techniques with predictive analysis techniques, using sources for preventing criminal activities and investing after those events happen.

Many countries have been applying social network analysis to determine criminal networks engagement with public. A study (Duijn & Klerks, 2014), details examination about intelligence-led policing has been provided in Dutch Law enforcement. Using advanced network analysis methodology and crime scripting techniques, criminal analysts collect information about habitual lawbreakers and criminal networks and identify intelligence gaps and potential informants. Generating hot-spot maps, studying background knowledge, neighborhood social fabrics, mobile network activities, and observing socio-behavioral impacts can provide insights into the key factors of certain demographics influencing certain criminal activities. Likewise, a study has been performed to find if social media context can provide social behavior signals for crime predictions (Aghababaei & Makrehchi, 2016). Authors have used Twitter data to develop a predictive model to predict the crime rates in four different cities in the United States. The study shows that social content correlates with crime trends and can be used as a predictive indicator for determining the crime rate index. Also, analyzing the sentiment toward individuals and organizations can be a strong indication of possible crime in the near future. These negative sentiments or emotions can influence and drive a group of people to take direct actions that can cause civil unrest. This information is usually circulated through social media, which can provide information about the location and time of the protest and can be used to predict violent disorders or riots. Similarly, Twitter data has been used to detect disruptive events, prevent riots, and increase public safety (Alsaedi, Burnap, & Rana, 2017). The study evaluates the event detection system to detect riots in England in August 2011, using Twitter data posted during those events. It shows that it can predict well as compared to the actual truth collected by the London Metropolitan Police Service.

Research has been conducted to detect radical groups using social media data that analyze circumstances, trends, and gaps (Adek, Ula, et al., 2021). These radical and extremist groups and organizations use social media platforms to deliver hate speech, spread propaganda, recruit new members, operate virtually, and reach worldwide audiences, focusing on their missions and furthering their goals (Arunachalam & Sarkar, 2013).

Different tools, techniques, approaches, and algorithms have been applied to monitor the presence of such radicalizing content in the online platform. A real-time system is developed in (Abrar, Arefin, & Hossain, 2019) for detecting tweets that support terrorism. Likewise, in (Moussaoui, Zaghdoud, & Akaichi, 2019), a graph mining method has been used to detail the process of processing the extracted tweets with semantic processing and classifying the clusters into non-terrorist, terrorist-sympathizer, and terrorist.

Social media platforms have been used as a medium to communicate police authority with the community for crime prevention (Hu & Lovrich, 2019). Sharing information regarding crime, accidents, community engagement and criminal activities is increasing in social media by the law enforcement authorities (Boateng & Chenane, 2020). Police personnel in China are using Social media like WeChat to manage their image, communicate risks, and enhance legitimacy. They analyzed six types of posts: image building, civil service, political broadcasting, crime broadcasting, crime prevention advocacy (Liu, Ma, & Xia, 2024). They use this information for security intelligence and to promote public safety.

Hence with social media, transforming the way people communicate and share information, the use of this information through open-source intelligence has increased extensively in recent years to find answers, solve crimes, predict criminal activities, and capture criminals. These analytics help investigators in collecting evidence and solving criminal cases. With more cases using this intelligence and the increase in the adoption of this information in justice, and social media data and its analytics have proven to be very crucial in criminal investigations. The following Section presents some of the cases that have used social media and the information obtained from these platforms in criminal court proceedings.

2.1. Case Studies

The use of social media data has increased in recent years to identify suspects, detect crimes or events, and solve crimes. The data collected provides information to further the investigations and solve crimes more rapidly. Many cases involve identifying the suspects and/or witnesses through photos and videos posted on social media. In early 2013, in the Bradley vs. State case, the victim of an armed robbery identifies his assailants through publicly available Facebook photos. In the Hoffman v. State case, photos and comments posted on the Myspace page were used as evidence for the convict of vehicular manslaughter. In the USA vs. Anderson case, Facebook was used to identify and lure victims. In the Zimmerman vs. Weis Markets Inc. case, the defendant used social media profiles to support their claim. Also, in the People vs Mendez case, investigators used TikTok videos to trace the defendant's movement leading up to the crime that linked him to the scene.

Similarly, individuals are convicted based on the threat posts or pictures or videos posted on different social media platforms. In recent years, Ukraine used the statement made by officials on social media platforms like Telegram as evidence to demonstrate the existence of dispute[2]. In 2018, Davis Wright was charged and convicted for posting threats on social media targeting a police officer and received a sentence that included time in prison. In 2019, Tiffany Smith was charged with conspiracy to commit robbery based on posting her plans to rob a bank. In 2018, Morgan Roof was arrested for posting threatening messages on Snapchat directed at students protesting gun violence.

Social media data has been used in investigations not only in criminal cases but also in some high-profile terrorist cases. In 2017, the authorities analyzed the social media data of the bomber of Manchester Arena bombing, analyzing his movement and communication to understand his connections and the radicalization process. In 2022, German authorities utilized social media data to prevent terror plots of an extremist group. They track the communication and plans from platforms where this content was shared. Also, Canadian

[2] https://www.ejiltalk.org/statements-by-officials-on-social-media-as-evidence-before-the-icj

authorities have used social media to identify potential threats and monitor radicalization trends and specific individuals linked to terror plots. In 2016, Cleveland police used social media monitoring to identify threats and were able to prevent the potential violence during the Republican National Convention. US domestic terrorism investigations also used social media to explore various cases. In 2021, after the capitol riot on January 6, law enforcement agencies analyzed social media platforms to identify the people who participated in that riot. They used videos, pictures, posts, livestreams, and communications as evidence to prosecute the individuals involved in the riot.

In the Uvalde school shooting in 2022, the investigator used the shooter's social media activity to analyze the posts and communications that hinted at the shooter's intentions and potential motivations3. Apart from that, many schools in the US have implemented monitoring systems to predict the shooting threats in the school. The Broward County school district in Florida used a monitoring program that analyzed students' posts for possible threats. Proactive monitoring methods have proven effective, as several potential threats have been detected and addressed before any harm occurred. Hence, social media data has been used in various cases, such as criminal cases, employment investigations, divorce and custody disputes, libel cases, terrorism, and national security. Acceptance of this data in such cases has increased. Still, it also adds challenges regarding ethical and legal considerations and to consider the relevance and the authenticity of the evidence to be able to be used in those cases and be admissible in the court.

2.2. Machine Learning in Social Media Analytics (Tools Used for Analytics)

In recent years, ML has played a significant role in extracting information from social media data, providing analytics to law enforcement personnel for crime prediction and investigations. ML algorithms are mostly used to extract meaningful insights from the large amount of unstructured data collected from various social media platforms. ML algorithms also help in social media analytic tasks such as sentiment analysis, user behavior prediction, trend detection, and content recommendation.

2.2.1 Automating Data Collection and Processing

ML has been used to enhance the automation of data collection, preprocessing, filtration, and efficient monitoring of the data from social media platforms in real-time. Web scraping techniques (Khder, 2021) or Application Programming Interfaces (APIs) can be used to access and extract accurate, consistent, and structured data from social media sites. These collected data can be stored securely and more efficiently in the database for easy access and analysis. These APIs requests or web scraping tasks can be run periodically and automatically using tools or script. Tools like Postman, CURL, Insomnia, Python requests library, HTTPie, can be used for API requests whereas Beautiful Soup, Scrapy, Selenium, Puppeteer, Requests-HTML, Octoparse, ParseHub, WebHarvy, Apify can be used for web scraping. Other automation tools like Zapier, IFTTT or Integromat can be used for connecting different apps, devices and online services to automate complex workflows. This data can be further filtered and analyzed, and useful insights can be extracted with relevant information using different ML algorithms in real time.

2.2.2 Advanced Sentiment Analysis and Emotion Detection

Different sentiment analysis techniques, which include ML algorithms such as Naive Bayes (Babu & Kanaga, 2021), Support Vector Machines (SVM) (Sabharwal & Sharma, 2019; Pate, Patil, Patil, & Raut, 2023), and Deep Learning (DL) algorithms such as Recurrent Neural Networks (RNN) (Jayachandran & Dumala, 2023) and Bidirectional Encoder Representations from Transformer (BERT) (Boukabous & Azizi, 2022), are used to analyze the sentiment through social media data. With recent advancements in machine learning algorithms, the ability for sentiment analysis capabilities has been increased and has shown great potential in sectors such as e-commerce, finance and investment, healthcare, entertainment, and hospitality. Different algorithms can be used to categorize the data points into various sentiment categories, whereas other ML algorithms can capture contextual information by analyzing the sequential text input data. They have been used to determine public sentiment towards events, individuals, or topics. NLP techniques can be used to gauge public sentiments regarding crime and safety.

In criminal investigation, law enforcement agencies are using sentiment analysis with advanced NLP and extracting useful insights from various forms of social media data. Different ML algorithms help to identify potential threats by analyzing the posts, comments, pictures, and patterns and creating a flag for unusual

[3] https://www.texastribune.org/series/uvalde-texas-school-shooting

activities. They generate sentiment forecasts that provide insightful information to find patterns and predict prospective criminal activity. This helps in crime detection and prevention. Also, monitoring the sentiment trends helps to indicate rising tension in specific communities that can increase crime. Also, analyzing the sentiments of suspect interaction can provide evidence of their mental state or intention.

2.2.3 Predictive Analytics for Trend Forecasting

By analyzing social media analytics, law enforcement authorities can analyze and identify potential threats or criminal activities. This can help these agencies to respond proactively and stop or prevent crime. Predictive analytics use historical data, such as social media interactions and patterns, to predict the likelihood of future potential criminal outcomes. They use users to express sentiments and behaviors and use it as a baseline to understand and predict the potential time and place of the crime. Different ML algorithms and computer vision approaches (Shah, Bhagat, & Shah, 2021), such as regression models, classification models, ensemble models and DL models, can be used to identify patterns and make predictions. Analyzing this data in real-time can help law enforcement to act more efficiently and effectively by making automated monitoring and policing strategies for preventing crime4. However, this comes with challenges like data privacy, biasing to a certain community, quality issues or reliability in the effectiveness of these predictive models (Alassafi et al., 2023).

2.2.4 Personalized Content Recommendations

ML and data analytics can be used to tailor information, suggestions based on preference, and contextual factors to analyze evidence by providing relevant information for decision-making. ML algorithms can be used to analyze collected data from various sources, including case files, criminal databases, and social media platforms. Analyzing this data, ML algorithms can suggest preferences based on similar users or investigators with relevant lead and forensic evidence that improve decision-making and successful case resolutions. This will increase efficiency, improve decision-making, and optimize resources. However, this also surrounds challenges such as privacy, bias, integration with existing systems, and ethical standards regarding law enforcement practices.

2.2.5 Combating Cybercrime Through Social Media Analytics

ML plays a vital role in combating cybercrime. Analyzing the data effectively provides insights for detecting cyber threats, identifying the perpetrators, and device preventive measures to prevent future incidents. ML algorithms can be used to recognize patterns indicative of malicious behaviors on social media, such as phishing and spam detection. ML algorithms use graph analytics in understanding the connection among users, highlighting networks that may propagate harmful content. Different ML techniques like Random Forest (RF), Decision Tree (DT), SVM, and DL algorithms like Convolutional Neural network (CNN) and Recurrent Neural Networks (RNNs) are used to classify phishing websites by analyzing features such as URL length, HTTP, and the use of certain keywords. Also, ML algorithms are used to investigate automated bots on social media platforms, which are used for spreading misinformation and manipulating public sentiment. Hence advanced ML algorithms and analytics can help in developing security measures, address threats and create secure digital environment.

2.2.6 Enhancing Fraud Detection and Security

By analyzing vast amounts of data generated on social media platforms, organizations can identify fraudulent activities, assess risks, and improve the overall security posture. ML algorithms can analyze social media profiles to identify accounts that exhibit suspicious behavior. By analyzing the profile of individuals to detect anomalies, ML models can flag anomalies indicative of fraud, detecting unlikely account activity or unusual posting patterns. Also, using social media networks, ML algorithms can identify connections among users that can uncover organized fraud schemes operating within social networks.

In this section, the challenges of processing the vast amounts of unstructured data generated on social media platforms are discussed. ML is highlighted as a key tool for extracting insights from this data, with applications in data collection, analytics, automation, and the prediction and classification of criminal activities. Social media analytics tools use methods like sentiment analysis, sentiment classification, and supervise learning to analyze user behavior and content. Additionally, native analytics platforms such as TikTok, Facebook,

[4] https://jatheon.com/blog/social-media-law-enforcement/

Twitter, and YouTube provide metrics on user activities, posts, and network interactions, which can support crime prediction and prevention efforts.

3. Challenges in Social Media Analytics

Social media analytics has become an essential tool for investigations, offering insights into human behavior, trends, and events. However, the field faces several challenges that can impact the effectiveness and reliability of these analyses. In this section, we will review some of the challenges presented in the literature regarding the use of social media analytics. Figure 3 shows the main challenges identified for social media analytics for investigations. Each of these categories will be addressed in the following sections.

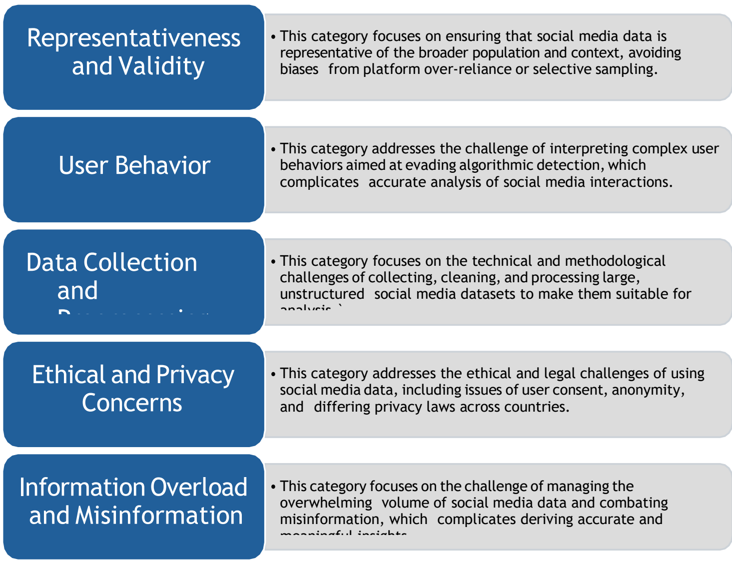

Figure 3. Main Challenges for Social media analytics for investigations

3.1. Representativeness and Validity

In social media analytics, ensuring data representativeness and validity is crucial for deriving insights that are generalizable to more general populations. Due to the diverse nature of social media platforms, different demographics, and user behaviors can introduce biases that skew data collection. These differences can result in findings that reflect only specific user groups, limiting their applicability. Both representativeness and validity are critical in overcoming these challenges, as outlined by (Tufekci, 2014; Sriram et al., 2021).

A common issue in social media research is the risk of sampling bias, mainly when studies recruit participants through specific online platforms. For instance, autism studies recruiting via social media have shown notable demographic skews, including reversed sex ratios, higher education levels, and lower rates of intellectual disability, leading to findings that are difficult to generalize to the broader autism population (Rødgaard, Jensen, Miskowiak, & Mottron, 2022). For example, in the context of brand monitoring, a representativeness-aware approach was developed in (Liao et al., 2017) to select social media posts and aspects that provide a broader coverage of user opinions, accounting for noise and varying post impacts. This work emphasizes the importance of optimizing both data coverage and relevance, demonstrating that careful algorithmic approaches can enhance the validity of insights in brand-related social media studies.

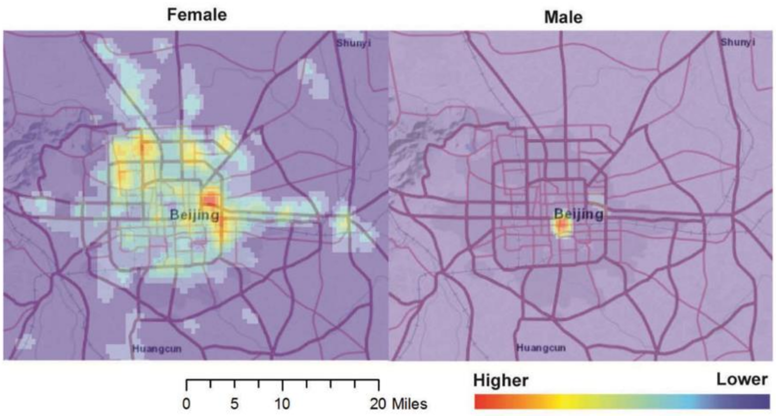

Figure 4. Point density distribution of male and female users in Beijing (Yuan et al., 2018). (CC BY 4.0)

Gender representativeness is another concern, as demonstrated in research on location-based social media data (Yuan, Wei, & Lu, 2018). The study found gender biases in usage patterns, with women being more likely to use the platform, and noted strong regional variations in these patterns across China. Figure 4 shows a that male and female users follow distinct patterns. These results highlight the importance of considering demographic biases when analyzing social media data, especially when conducting studies in specific regions or focused on subgroups. To address these challenges, different strategies are needed to help ensure that insights from social media analytics are representative and valid, making them more useful for policy, healthcare, and market analysis applications.

3.2. User Behavior

Understanding and interpreting user behavior is one of the most critical challenges in social media analytics for investigations. Social media users often adopt various techniques to evade detection, complicating the analysis of their activities. A key aspect of user behavior on social media involves using indirect communication. Sub tweeting (i.e., mentioning individuals or topics without directly naming them) and mock-retweeting are common practices designed to obscure the meaning of posts, making them harder to track with standard keyword-based algorithms. Such tactics have been used in scenarios where individuals attempt to avoid detection or monitoring. For example, screen captures can be used to respond to critics, further bypassing algorithmic visibility (Yadav et al., 2023; Viswanath et al., 2014).

Users also evade detection by posting screenshots of text instead of using actual words, or by embedding meaning in memes, emojis, and coded language. Figure 5 illustrates how a meme can be used for sarcasm, where the comment is in context to the image. Beyond these textual evasion techniques, users also rely on visual methods, such as sharing sensitive content through screenshots instead of text. This action effectively bypasses keyword detection algorithms, adding another layer of complexity to investigations. Using coded language, memes, and emojis further complicates efforts to decipher social media content. These non-traditional forms of communication can obscure the intended message, making it harder to draw accurate conclusions from the data collected (Fernández-Gavilanes, Costa-Montenegro, García-Méndez, González-Castaño, & Juncal-Martínez, 2021; Reuter & Lee, 2019). The rapidly evolving nature of social media platforms introduces another challenge for investigators. Platforms constantly update their features, introducing new ways for users to interact and communicate. ML is increasingly required to stay ahead of these changes by recognizing patterns in user behavior that traditional analysis might miss (Balaji et al., 2021; Abkenar, Kashani, Mahdipour, & Jameii, 2021; Habibi & Cahyo, 2021). ML models can adapt to detect subtle shifts in user activity, such as abrupt changes in language patterns or imagery that suggest attempts to evade detection (Gulyás & Imre, 2013).

Figure 5. *A sarcastic comment with images (Sharma, Singh, Agarwal, Kim,& Sharma, 2022). (CC BY 4.0)*

Despite the advancements in ML, a crucial need remains to understand the socio-cultural context behind user behaviors. Cultural references, inside jokes, or community-specific memes can drastically alter the interpretation of a message. Without the necessary contextual knowledge, investigators may misinterpret key elements of user interactions, potentially leading to flawed conclusions (Duffy & Meisner, 2023).

3.3. Data Collection and Preprocessing

Data collection and preprocessing are fundamental steps, and therefore, they represent some of the most significant challenges. These challenges stem from technical limitations, ethical concerns, and the complexity of handling large volumes of dynamic, unstructured, and multimodal data. Addressing these obstacles ensures investigators can generate reliable and actionable insights.

Collecting data from social media platforms often involves navigating technical challenges such as platform-specific APIs, rate limits, and differing data formats, which complicate data access. These APIs, although useful, impose restrictions on the amount of data that can be collected over a specific period, making large-scale investigations particularly challenging when timely insights are required (Park, Chae, & Kwon, 2020; Stieglitz, Mirbabaie, Ross, & Neuberger, 2018). Additionally, platforms often update their APIs and access policies, creating a moving target for investigators who must constantly adapt their data collection strategies. This issue is worsened by platform policies that are frequently revised to address privacy concerns and regulatory compliance requirements. Figure 6 shows a framework to gather, preprocess data, and extract pertinent information from it (i.e., topics and sentiment analysis).

The real-time nature of social media data is another important challenge. Social media platforms generate vast amounts of content on a minute-to-minute basis, and data that is collected too late may no longer be relevant for investigative purposes (Nirmal, Jiang, & Liu, 2023; Jeong, Ding, & Liu, 2021). The constant evolution of social media content requires investigators to develop adaptive and flexible data collection techniques to keep pace with the rapid changes in the online environment. These techniques must also account for the dynamic nature of user interactions, hashtags, and trending topics, ensuring that investigators capture the most pertinent information.

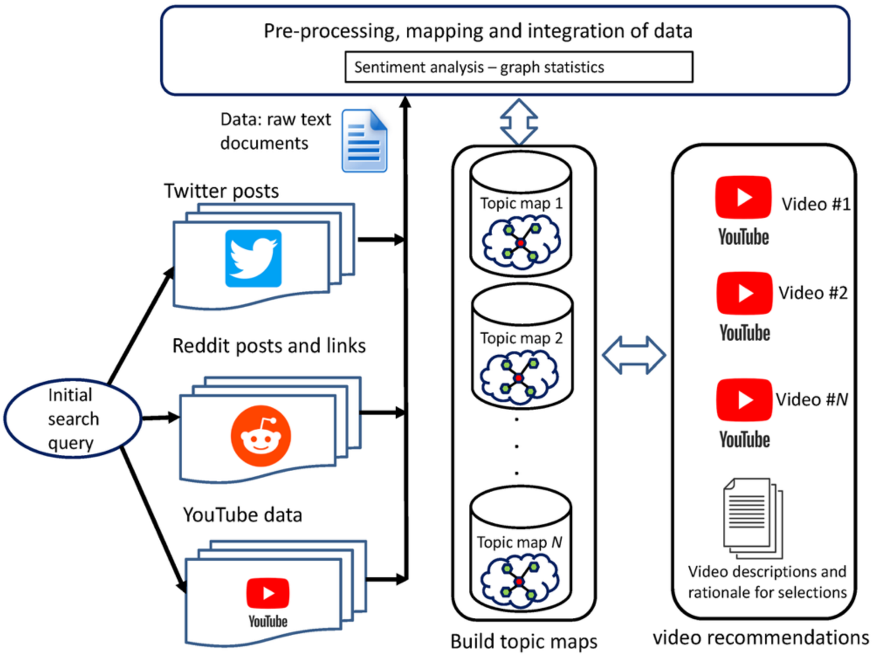

Figure 6. *Framework for social media analytics (SMA) (McGarry, 2023) (CC BY 4.0)*

Once collected, preprocessing is essential to clean and prepare social media data for analysis. This data is typically noisy, incomplete, and unstructured, necessitating significant effort to make it usable. For instance, filtering spam, advertisements, and irrelevant posts is crucial but time-consuming (Chandra, Khatri, & Som, 2019).

Moreover, social media data is highly multimodal and multilingual, adding layers of complexity. It often includes text, images, videos, and metadata, demanding specialized techniques to normalize and ensure consistency, which can be computationally expensive (Al Bashaireh, Zohdy, & Sabeeh, 2020). For text, beyond tokenization and stop word removal, advanced methods like Named Entity Recognition (NER) for entities and sarcasm/irony detection for sentiment are vital. For image and video data, techniques such as object detection, facial recognition with pose estimation, and activity recognition are required to extract useful information.

The multilingual nature further complicates preprocessing, requiring tools for various languages and dialects, along with linguistic analysis for informal content (Laxmi Narasamma & Sreedevi, 2016). Future advancements are needed in robust cross-lingual embedding models and unsupervised domain adaptation to handle low-resource languages and evolving slang.

Finally, social media's real-time and evolving nature means that data collection and preprocessing methods must be highly adaptable. Unlike static datasets, social media data is constantly changing, requiring dynamic approaches to data collection and preprocessing. Investigators must stay updated on platform policy changes, which can affect the availability of certain types of data or restrict their access (Ho, Goh, & Tan, 2022).

3.4. Ethical and Privacy Concerns

A foundational ethical issue in social media analytics is the matter of user consent. Social media users often share content publicly but may not fully understand how their data could be used in investigations. Research indicates that users are rarely asked for explicit consent before their publicly shared posts are analyzed at scale, creating a significant ethical dilemma (Baier, 2019; Islam, Mohammed, & Alhadidi, 2024). This issue is especially critical when dealing with sensitive data, such as mental health discussions, where users may not expect their content to be used for investigative or analytical purposes (Mahoney, Le Louvier, & Lawson, 2022). Furthermore, many users are unaware of the extent to which their data is gathered, aggregated, and used by third parties for investigations. Ensuring that informed consent is obtained, or at least that users know how their data might be used, remains a significant challenge.

Although anonymization techniques are commonly employed to protect privacy, they are not foolproof (Bkakria et al., 2021). Studies have demonstrated that even anonymized data can be re-identified, particularly when cross-referenced with other datasets (Brady, 2016; Gangarde, Sharma, & Pawar, 2022).Re-identification risks increase when investigators use sophisticated algorithms or have access to auxiliary information that can connect anonymized data points to specific individuals. The result is a growing concern that anonymization alone is insufficient to protect privacy, requiring more robust data protection measures (Mahoney et al., 2022; Carlton & Malik, 2024). Figure 7 illustrates the various types of data collected/processed in social networks, as well as the information that requires privacy preservation when an online social network is represented as a graph. For example, having profession information can lead to income disclosure.

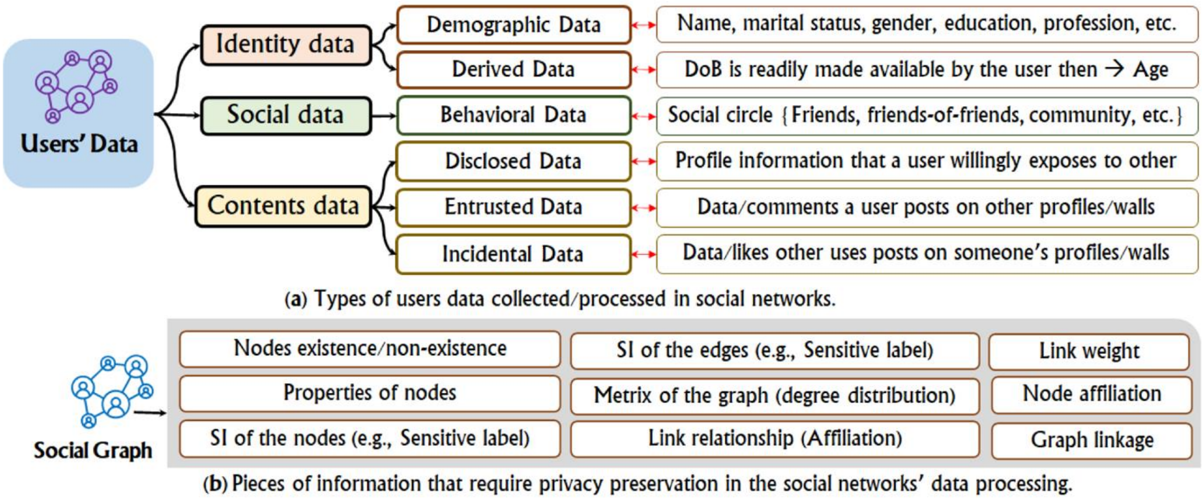

Figure 7. Different types of social network data and pieces of information concerning privacy in social graphs (Majeed, Khan, & Hwang, 2022). (CC BY 4.0)

Investigations often involve data from vulnerable populations, such as those discussing mental health or social justice issues (Smith, Szongott, Henne, & Von Voigt, 2012). When analyzing data from these groups, it is crucial to consider the context in which the data was shared. For instance, posts about personal trauma or marginalized identities could be misused if the analytical context strips away the nuance and sensitivity of these topics. Social media posts often lack the depth and detail required to interpret the full meaning behind a user's words, especially in situations involving vulnerability or distress (Mahoney et al., 2022). Researchers must be cautious not to decontextualize posts in ways that could lead to harmful outcomes, such as further stigmatization or the potential misuse of data for purposes other than those the user intended.

A key ethical principle in social media analytics is transparency. Investigators must be clear about how data is collected, how it will be used, and the potential consequences for the individuals whose data is analyzed (Escamilla, Fraccastoro, & Ehrlich, 2019). Lack of transparency can deteriorate public trust and lead to negative outcomes, such as individuals being unaware that their data is part of an investigation. As stressed in (Mahoney et al., 2022), researchers should commit to full disclosure of their methods and the limitations of their analysis. Ensuring that the data is used responsibly and that findings are reported in a way that minimizes harm is crucial for maintaining ethical standards in social media analytics.

The ethical and privacy challenges of using social media analytics in investigations are multifaceted and require careful consideration. The potential harm to individuals from misused social media data cannot be overstated. Investigators must balance the need to analyze social media data with the obligation to protect individuals from undue harm. By adopting a transparent, cautious, and context-sensitive approach, investigators can mitigate potential harm and ensure that their social media data operates within legal and ethical boundaries.

3.5. Information Overload and Misinformation

One of the primary challenges investigators face is the overwhelming volume of content on social media platforms. Information overload occurs when a large amount of data makes it challenging to go through irrelevant content to find meaningful insights. This phenomenon is particularly problematic during crises, where rapid decisions must be made based on available data (Bayer et al., 2021; Kaufhold et al., 2020). Information overload is a critical bottleneck that delays the extraction of relevant insights, which can be detrimental in time-sensitive situations where real-time data is required.

Figure 8 presents a comparison of the ability of users across different social media platforms to keep up with reading and responding to posts (Bontcheva, Gorrell, & Wessels, 2013). The Figure shows that 82.3% of Social Networking Site (SNS) users can mostly or always keep up with posts, which is the highest among the platforms, while 73.4% of Personal Network Site (PNS) users can do so. Interestingly, despite a lower sense of overload among PNS users, they are less consistent in keeping up compared to SNS users. The micro bloggers, however, face the greatest challenge, with only 55.6% managing to keep up, leaving 44.4% failing to keep pace.

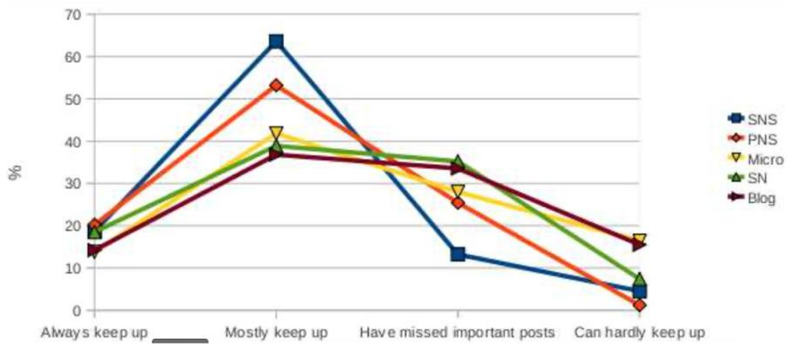

Figure 8. *Ability to keep up with posts received. (Figure reproduced with permission of (Bontcheva et al., 2013))*

Different approaches (Bontcheva et al., 2013; Matthes, Karsay, Schmuck, & Stevic, 2020; Sabarky, Karyanta, & Anggarani, 2023) aim to filter and organize large volumes of social media posts during crises, reducing the burden of managing vast datasets by automatically identifying and prioritizing relevant content. Clustering algorithms, in particular, enable investigators to group similar content, making it easier to navigate and interpret social media data. However, these solutions are still evolving, and further research is needed to develop more efficient, scalable systems capable of handling the continuous growth of social media data. The relationship between information overload and misinformation is also significant (Y. Zhang, 2023). Overloaded users are more prone to sharing false information, either because they fail to evaluate the content critically or because they rely on heuristics and shortcuts to process the overwhelming amount of information available. Studies have shown that cognitive overload increases users' susceptibility to misinformation, underscoring the importance of simultaneously addressing both challenges.

False information can spread more rapidly than facts, often reaching large audiences before any fact-checking or verification can be completed. This problem creates a significant risk for researchers, investigators, and decision-makers who rely on social media data to inform their conclusions. The consequences of relying on misinformation can be severe, including the spread of false narratives during political campaigns and public health crises (Apuke, Omar, Tunca, & Gever, 2022; Guo, Apuke, Tunca, & Gever, 2023). Previous studies have explored the various factors contributing to the spread of misinformation, including cognitive ability, digital literacy, and the intentional spreading of disinformation (Melchior & Oliveira, 2024). Researchers are actively developing techniques to combat misinformation, including machine learning algorithms that automatically categorize and flag false content and fact-checking tools that verify the accuracy of shared information (An, Huang, Danjuma, Apuke, & Tunca, 2023). However, these tools are still in their infancy. The fast-paced nature of social media means that misinformation can outpace correction efforts, necessitating continuous advancements in automated verification systems to keep up with the evolving landscape of online communication.

In this section, we discussed the growing importance of social media analytics as a tool for understanding human behavior, trends, and events. However, this field faces challenges, including ensuring fair representation of diverse populations, accurately interpreting user behavior, addressing technical and ethical concerns in data collection, and safeguarding user privacy. These issues highlight the need for a thoughtful approach that combines technical innovation with ethical responsibility. Researchers can address these challenges effectively by improving algorithms, gaining deeper insights into user behavior, and adopting better data practices. Future work in this area should aim to develop tools and methods that are efficient and socially responsible, ensuring the benefits of social media analytics are widely accessible and impactful.

4. Future Research Directions

To effectively harness the potential of social media analytics, it is essential to explore future research directions that address key areas. This section outlines these emerging directions, highlighting their significance in advancing the field and improving the efficacy of investigations.

4.1. AI-Driven Real-Time Multimodal Analysis

AI-driven real-time multimodal analysis is a promising future direction in social media investigations. This approach aims to integrate various data types, such as text, images, videos, and audio, into unified analysis systems, enhancing the ability to identify patterns and behaviors across different modalities. Recent advances in AI, particularly in ML and DL (Krylov et al., 2021; Shchepina & Surikov, 2022), have shown how multimodal data can be processed and analyzed in real-time, significantly improving investigative outcomes.

By leveraging NLP for text analysis and computer vision for image and video data, future systems can provide richer, context-aware insights. For instance, these models can help investigators track changes in sentiment, detect emerging trends, and even identify threats more effectively than relying on a single data source. Moreover, this fusion of data types is vital for handling the complex, fast-paced environment of social media platforms. Figure 9 shows a fusion technique to combine visual and textual data for sentiment classification.

4.2. Ethics, Privacy, and Explainable AI

Integrating AI in social media analytics has raised critical ethical considerations, particularly regarding privacy and accountability. As highlighted in (Shi & Wang, 2023; Salminen, Mustak, Corporan, Jung, & Jansen, 2022), the growing reliance on AI technologies necessitates robust ethical frameworks to safeguard user data while ensuring compliance with regulations. Researchers stress the importance of establishing ethical guidelines that govern the collection and use of social media data, emphasizing the need for transparency in these processes.

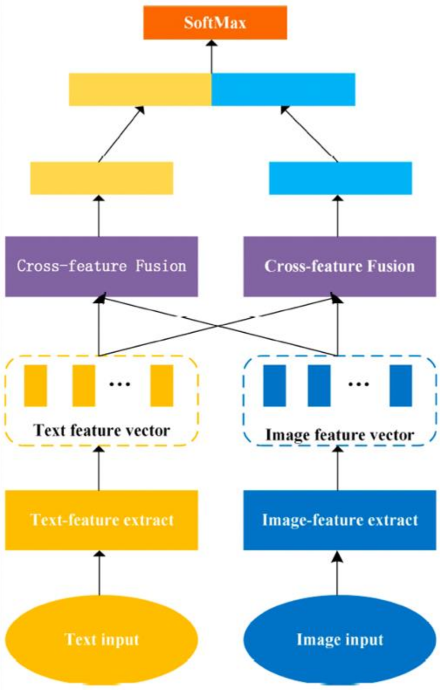

Figure 9. *Social media multimodal data fusion technique (K. Zhang, Geng, Zhao, Liu, & Li, 2020). (CC BY 4.0)*

Privacy concerns advocating for methodologies that prioritize user consent and data protection. Future research should focus on developing algorithms that not only comply with privacy standards but also empower users by providing them with control over their personal information.

Moreover, explainable AI is becoming increasingly crucial in social media analytics (Mehta & Passi, 2022; Pérez-Landa, Loyola-González, & Medina-Pérez, 2021). For example, Figure 10 shows the use of the Local

Interpretable Model-Agnostic Explanations (LIME) explainer model and a logistic regression model. The Figure shows how each word in a Tweet contributes in the detection for hate speech.

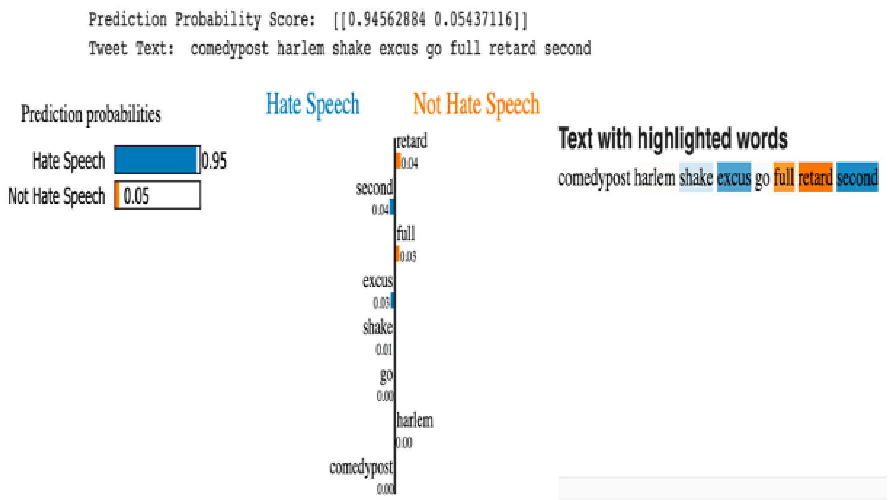

Figure 10. *Explainability using Machine Learning models (Mehta & Passi, 2022).* (CC BY 4.0)

Therefore, the absence of transparency in AI decision-making can lead to distrust among users. Future directions must prioritize explainable AI, allowing stakeholders to understand the rationale behind AI-driven conclusions and decisions. By focusing on ethics, privacy, and explainability, researchers can create AI systems that are not only effective but also responsible and trustworthy, ultimately fostering public confidence in these technologies.

4.3. Combating Misinformation and Disinformation

The rapid spread of misinformation and disinformation on social media platforms poses significant challenges to information integrity and public trust. As outlined in (Srivastava, Singh, & Singh, 2021), the prevalence of false information can deform public perception and influence decision-making processes. Future research should focus on developing AI-driven solutions (see Figure 11) to identify and mitigate the spread of misleading content effectively.

Other works (He et al., 2017; Bayer et al., 2021; Kaufhold et al., 2020), emphasize the importance of enhancing social media analytics tools to improve the detection of false narratives and the actors behind them. Employing advanced machine learning algorithms can enable real-time tracking of misinformation campaigns, allowing for timely intervention. This proactive approach can help platforms flag or remove harmful content before it reaches a larger audience.

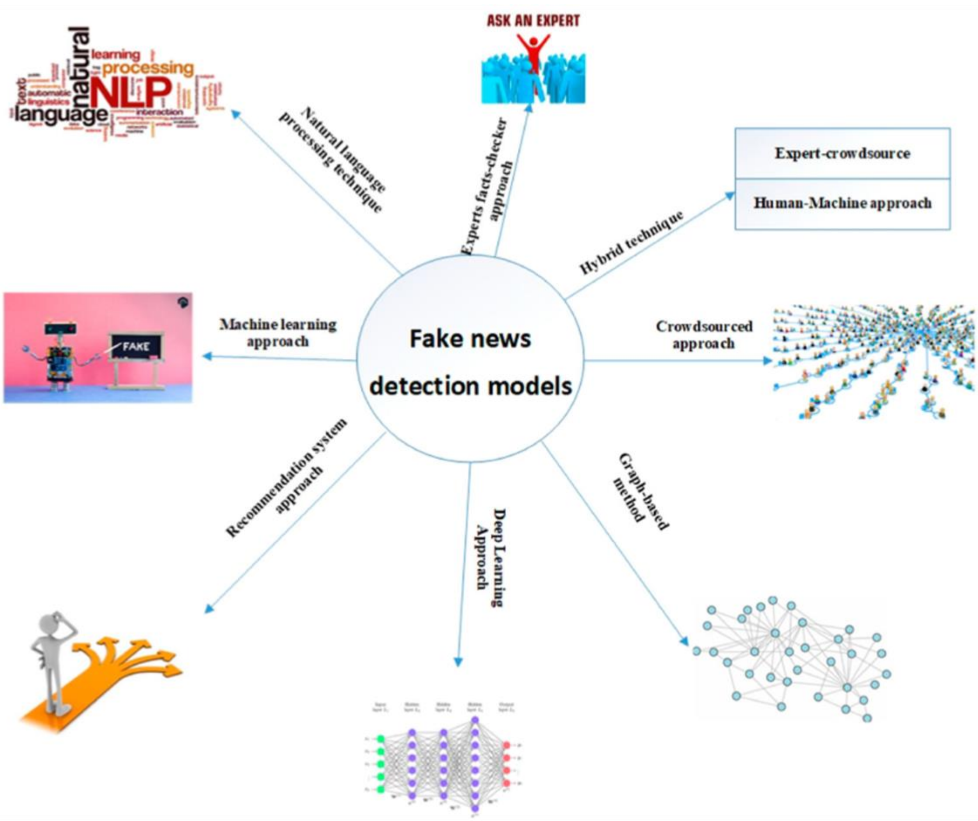

Figure 11. Fake news detection models (Collins, Hoang, Nguyen, & Hwang, 2021). (CC BY 4.0)

Additionally, fostering media literacy among users is crucial in combating misinformation. Therefore, educating users about identifying credible sources and recognizing deceptive information can empower them to evaluate content critically. Future strategies should integrate educational initiatives alongside technological advancements to create a comprehensive response to the misinformation crisis.

By combining AI technologies with user education and robust analytical frameworks, researchers can significantly contribute to the fight against misinformation and disinformation, promoting a more informed and resilient society.

4.4. Cross-Platform Integration and Automated Workflows

Cross-platform integration and automated workflows are crucial for enhancing the efficiency and effectiveness of social media analytics. Research by Murić et al. (2020) and Oliveira et al. (2022) emphasizes the need for unified systems that can aggregate data from various social media platforms, allowing researchers to conduct comprehensive analyses without the limitations of platform-specific tools. This integration will enable a holistic understanding of user interactions and information dissemination across diverse channels. Figure 12 shows how different social media networks (SMNs) are combined to generate more comprehensive raw data and create more complete SMNs for social computing applications (Zhou, Liang, Zhang, & Ma, 2015).

Automated workflows are essential for streamlining the data collection, processing, and analysis stages. Studies (Ross & Redhead, 2021, 2023) demonstrate the potential of using automation to reduce manual effort, increase data processing speed, and ensure real-time insights. By implementing automated pipelines that handle tasks such as data cleaning, sentiment analysis, and trend identification, researchers can focus on interpreting results and developing strategies rather than on the labor-intensive aspects of data management. Moreover, the synergy between cross-platform data integration and automation can lead to the development of more sophisticated AI-driven tools (Krylov et al., 2021; Shchepina & Surikov, 2022). These tools could provide real-time dashboards, enabling stakeholders to monitor social media dynamics effortlessly. Future research should prioritize building frameworks that facilitate seamless integration and automation, ultimately enhancing the scalability and applicability of social media analytics in various domains.

This section highlights the transformative potential of emerging research directions in social media analytics. Researchers can integrate diverse data types for deeper, real-time insights by leveraging AI-driven multimodal analysis. Prioritizing ethics, privacy, and explainable AI fosters trust and accountability, ensuring technological advancements align with societal values. Addressing the spread of misinformation through advanced AI tools and media literacy initiatives strengthens information integrity and public resilience.

Additionally, cross-platform integration and automated workflows promise to enhance efficiency, scalability, and actionable outcomes. These pathways collectively pave the way for a future where social media analytics drives meaningful, responsible, and impactful solutions to complex challenges.

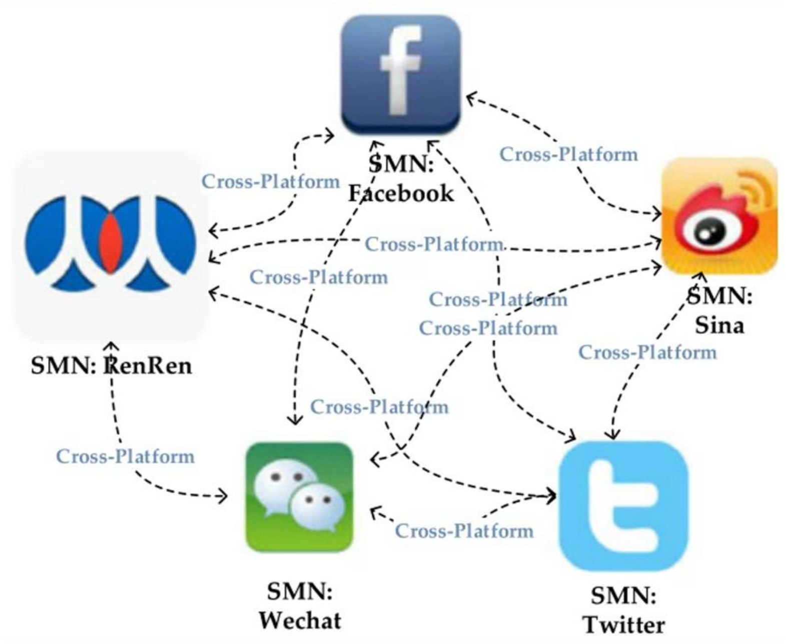

Figure 12. *Cross-platform merging a variety of SMNs (Zhou et al., 2015). (CC BY 4.0)*

5. Conclusions

This paper examines the transformative impact of social media analytics in modern investigative contexts, highlighting its evolution from a supplementary tool to an indispensable component of law enforcement and investigative frameworks. Integrating advanced technologies, particularly machine learning, natural language processing, and sentiment analysis, has revolutionized how digital evidence is collected, processed, and analyzed in investigative scenarios.

The exponential growth in social media usage, enhanced by widespread internet accessibility and smart device proliferation, has created an unprecedented landscape for data-driven investigations. This digital transformation has proven particularly valuable for law enforcement agencies, who have successfully leveraged these technologies across multiple dimensions. Social media analytics has evolved into a powerful tool for collecting evidence through public participation, enabling investigators to piece together critical information from posts, comments, images, and videos shared by individuals. Advanced facial recognition systems, combined with social data and location tracking, have significantly improved the capability to identify and track suspects, making the investigative process more efficient and effective. Technology has proven invaluable in mapping criminal networks, allowing the identification of group crimes, gang members, and organized crime syndicates through the analysis of social connections and interaction patterns. Through sentiment analysis and tone assessment of social media data, law enforcement agencies can now proactively identify potential criminal activities, enabling preventive intervention before crimes occur.

However, this research has also uncovered significant challenges that demand careful consideration. Ensuring the validity and representativeness of social media data remains a complex challenge, particularly given the diverse nature of user behaviors and platform dynamics. Managing and preprocessing extensive information while minimizing biases requires sophisticated technical solutions and standardized methodologies. The balance between technological effectiveness and ethical responsibilities, particularly regarding privacy protection and fair use, presents ongoing challenges that require careful navigation. Additionally, the risk of information overload and the spread of misinformation necessitates robust filtering and verification mechanisms.

Several key areas emerge as critical for future development. In terms of methodological advancement, the field requires the development of standardized frameworks that address current limitations while maintaining analytical rigor, integrating AI-driven real-time multimodal analysis systems, and creating more sophisticated preprocessing techniques for complex social media data.

The ethical and legal framework demands the establishment of adaptive ethical guidelines that evolve with technological capabilities, the development of robust privacy protection measures, and the creation of mechanisms to ensure transparency and accountability in investigative processes. Technical integration requires implementing cross-platform solutions for seamless data analysis, developing automated workflows to streamline operations, and incorporating explainable AI technologies to maintain transparency. From an operational perspective, success in this field requires investment in research and development of advanced analytical tools, forming cross-functional teams combining technical, legal, and ethical expertise, implementing regular assessment frameworks to evaluate effectiveness, and developing standardized protocols for data collection and analysis.

The future of social media analytics in investigative contexts is promising and characterized by increased automation, enhanced privacy measures, and more sophisticated analytical capabilities. However, realizing this potential requires a delicate balance between technological innovation and ethical responsibility. As social media platforms continue to evolve, the methodologies and approaches for their analysis must similarly advance, ensuring that these powerful tools serve the interests of justice and public safety while respecting individual rights and privacy concerns.

The success of social media analytics in investigations will ultimately depend on the researchers' ability to address technical and ethical challenges while maintaining public trust. The paper provides a foundation for future work in this critical field, emphasizing the need for continued innovation while upholding strict ethical standards and professional integrity. Considering these factors and the continuous development of robust frameworks, social media analytics can be a powerful force for good in investigative contexts, contributing to a safer and more just society.

Statement of Researchers

Researchers' contribution rate statement:

SRS: Conceptualization, methodology, investigation, validation, writing- original draft preparation, writing - review & editing.

EC-V: methodology, investigation, validation, writing- original draft preparation, writing - review & editing.

Conflict statement:

The authors declare that they have no conflict of interest.

Data Availability Statement:

The data supporting this study's findings are available from the corresponding authors upon reasonable request.

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Ethical Considerations:

As this is a review article, no ethics committee approval certificate has been obtained.

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6. References

Abkenar, S. B., Kashani, M. H., Mahdipour, E., & Jameii, S. M. (2021). Big data analytics meets social media: A systematic review of techniques, open issues, and future directions. *Telematics and informatics*, *57*, 101517. https://doi.org/10.1016/j.tele.2020.101517

Abrar, M. F., Arefin, M. S., & Hossain, M. S. (2019). A framework for analyzing real-time tweets to detect terrorist activities. In *the 2019 International Conference on Electrical, Computer, and Communication Engineering (ECCE)* (p. 1-6). https://doi.org/10.1109/ECACE.2019.8679430

Adek, R. T., Ula, M., et al. (2021). Systematics review on the application of social media analytics for detecting radical and extremist group. In *IOP conference Series: Materials Science and Engineering* (Vol. 1071, p. 012029). https://doi.org/0.1088/1757-899X/1071/1/012029

Aghababaei, S., & Makrehchi, M. (2016). Mining social media content for crime prediction. In *2016 IEEE/WIC/ACM International Conference on Web Intelligence (WI)* (p. 526-531). https://doi.org/10.1109/WI.2016.0089

Aichner, T., Grünfelder, M., Maurer, O., & Jegeni, D. (2021). Twenty-five years of social media: A review of social media applications and definitions from 1994 to 2019. *Cyberpsychology, Behavior, and Social Networking*, *24*(4), 215-222. https://doi.org/10.1089/cyber.2020.0134

Alassafi, M., Alghamdi, W., Naveena, S., Alkhayyat, A., Tolib, A., & Ugli, I. (2023) Machine learning for predictive analytics in social media data. *E3S Web of Conferences*, *399*. https://doi.org/10.1051/e3sconf/202339904046

Al Bashaireh, R., Zohdy, M., & Sabeeh, V. (2020). Twitter data collection and extraction: A method and a new dataset, the UTD-MI. In *Proceedings of the 2020 the 4th International Conference on Information System and Data Mining* (pp. 71–76). https://doi.org/10.1145/3404663.3404686

Alsaedi, N., Burnap, P., & Rana, O. (2017). Can we predict a riot? Disruptive event detection using twitter. *ACM Transactions on Internet Technology 17*(2). https://doi.org/10.1145/2996183

An, Y., Huang, Y., Danjuma, N. U., Apuke, O. D., & Tunca, E. A. (2023). Why do people spread fake news? Modelling the factors that influence social media users' fake news sharing behaviour. *Information Development*, 41(1). https://doi.org/10.1177/02666669231194357

Apuke, O. D., Omar, B., Tunca, E. A., & Gever, C. V. (2022). Information overload and misinformation sharing behaviour of social media users: Testing the moderating role of cognitive ability. *Journal of Information Science*, 50(6) (pp 1371-1381). https://doi.org/10.1177/01655515221121942

Arunachalam, R., & Sarkar, S. (2013). The new eye of government: citizen sentiment analysis in social media. In *Proceedings of the IJCNLP 2013 Workshop on Natural Language Processing for Social Media (SocialNLP)* (pp. 23–28). https://aclanthology.org/W13-4204/

Babu, N. V., & Kanaga, E. G. M. (2021, November). Sentiment analysis in social media data for depression detection using artificial intelligence: A review. *SN Comput. Sci.*,*3*(1). https://doi.org/10.1007/s42979-021-00958-1

Baier, A. L. (2019). The ethical implications of social media: Issues and recommendations for clinical practice. *Ethics & Behavior*, *29*(5), 341–351. https://doi.org/10.1080/10508422.2018.1516148

Balaji, T., Annavarapu, C. S. R., & Bablani, A. (2021). Machine learning algorithms for social media analysis: A survey. *Computer Science Review*, 40. https://doi.org/10.1016/j.cosrev.2021.100395

Batrinca, B., & Treleaven, P. C. (2015). Social media analytics: A survey of techniques, tools and platforms. *AI & Society*, *30,* 89–116. https://doi.org/10.1007/s00146-014-0549-4

Bayer, M., Kaufhold, M.-A., & Reuter, C. (2021). Information overload in crisis management: Bilingual evaluation of embedding models for clustering social media posts in emergencies. IN *Deep Learning in Textual Low-Data Regimes for Cybersecurity. Technology, Peace and Security* I Technologie, Frieden und Sicherheit. Springer Vieweg, Wiesbaden. https://doi.org/10.1007/978-3-658-48778-2_6

Bkakria, A., Cuppens, F., Boulahia Cuppens, N., & Tasidou, A. (2021). Information theoretic-based privacy risk evaluation for data anonymization. *Journal of Surveillance, Security and Safety*, *2*, 83–102. https://doi.org/10.20517/jsss.2020.20

Boateng, F., & Chenane, J. (2020, 06). Policing and social media: A mixed-method investigation of social media use by a small-town police department. *International Journal of Police Science and Management*, *22*(3). https://doi.org/10.1177/1461355720927429

Bontcheva, K., Gorrell, G., & Wessels, B. (2013). Social media and information overload: Survey results. *arXiv.* https://doi.org/10.48550/arXiv.1306.0813

Boukabous, M., & Azizi, M. (2022). Crime prediction using a hybrid sentiment analysis approach based on the bidirectional encoder representations from transformers. *Indonesian Journal of Electrical Engineering and Computer Science*, *25*(2), 1131-1139. https://doi.org/10.11591/ijeecs.v25.i2.pp1131-1139

Brady, L. L. (2016). Canaries in the ethical coal mine? Case vignettes and empirical findings for how psychology leaders have adopted Twitter. *Ethics & Behavior*, *26* (2), 110–127. https://doi.org/10.1080/10508422.2014.994064

Bright, D., Brewer, R., & Morselli, C. (2022). Reprint of: Using social network analysis to study crime: Navigating the challenges of criminal justice records. *Social Networks*, *69*, 235–250. https://doi.org/10.1016/j.socnet.2022.01.008

Carlton, J., & Malik, H. (2024). A data privacy survey on personal identifiable information (PII) left on rental vehicle infotainment systems. *Journal of Surveillance, Security and Safety*, *5*(4), pp(198-212). http://dx.doi.org/10.20517/jsss.2024.07

Chandra, N., Khatri, S. K., & Som, S. (2019). Natural language processing approach to identify analogous data in offline data repository. *System Performance and Management Analytics*, 65–76. Springer. https://doi.org/10.1007/978-981-10-7323-6_6

Collins, B., Hoang, D. T., Nguyen, N. T., & Hwang, D. (2021). Trends in combating fake news on social media–a survey. *Journal of Information and Telecommunication*, *5*(2), 247–266. https://doi.org/10.1080/24751839.2020.1847379

Deng, Z., Weng, D., Liu, S., Tian, Y., Xu, M., & Wu, Y. (2023). A survey of urban visual analytics: Advances and future directions. *Computational visual media*, *9*(1), 3–39. https://doi.org/10.1007/s41095-022-0275-7

Di Minin, E., Tenkanen, H., & Toivonen, T. (2015). Prospects and challenges for social media data in conservation science. *Frontiers in Environmental Science*, *3*, 63. https://doi.org/10.3389/fenvs.2015.00063

Dong, X., & Lian, Y. (2021). A review of social media-based public opinion analyses: Challenges and recommendations. *Technology in Society*, *67*, 101724. https://doi.org/10.1016/j.techsoc.2021.101724

Duffy, B. E., & Meisner, C. (2023). Platform governance at the margins: Social media creators' experiences with algorithmic (in) visibility. *Media, Culture & Society*, *45*(2), 285–304. https://doi.org/10.1177/01634437221111923

Duijn, P. A. C., & Klerks, P. P. H. M. (2014). Social network analysis applied to criminal networks: Recent developments in Dutch law enforcement. In: Masys, A. (eds) Networks and Network Analysis for Defence and Security. Lecture Notes in Social Networks (pp. 121–159). Springer, Cham: https://doi.org/10.1007/978-3-319-04147-6_6

Escamilla, C. A., Fraccastoro, K. A., & Ehrlich, E. (2019). The impact of social media on fraternal organizations: Ethical concerns. *Journal of Business Case Studies (Online)*, *15*(2), (pp. 45-54). https://doi.org/10.19030/JBCS.V15I2.10316

Fernández-Gavilanes, M., Costa-Montenegro, E., García-Méndez, S., González-Castaño, F. J., & Juncal-Martínez, J. (2021). Evaluation of online emoji description resources for sentiment analysis purposes. *Expert Systems with Applications*, *184*, 115279. https://doi.org/10.1016/j.eswa.2021.115279

Gangarde, R., Sharma, A., & Pawar, A. (2022). Clustering approach to anonymize online social network data. In *2022 international conference on sustainable computing and data communication systems (ICSCDS)* (pp. 1070–1076). IEEE. https://doi.org/10.1109/ICSCDS53736.2022.9760742

Gulyás, G. G., & Imre, S. (2013). Hiding information in social networks from de-anonymization attacks by using identity separation. In De Decker, B., Dittmann, J., Kraetzer, C., Vielhauer, C. (eds) Communications and Multimedia Security. CMS 2013. Lecture Notes in Computer Science, vol 8099. Springer, Berlin, Heidelberg). https://doi.org/10.1007/978-3-642-40779-6_15

Guo, M., Apuke, O. D., Tunca, E. A., & Gever, C. V. (2023). Modelling the information abundance factors that predict fake news sharing behaviour of social media users: Testing the moderating role of resilience. *Journal of Asian and African Studies*, 60(2). https://doi.org/10.1177/00219096231192312

Habibi, M., & Cahyo, P. W. (2021). A social network analysis: Identifying influencers in the COVID-19 vaccination discussion on twitter. *Compiler*, *10*(2), 99–108. https://doi.org/10.28989/compiler.v10i2.1074

He, W., Tian, X., Tao, R., Zhang, W., Yan, G., & Akula, V. (2017). Application of social media analytics: A case of analyzing online hotel reviews. *Online Information Review*, *41*(7), 921–935. https://doi.org/10.1108/OIR-07-2016-0201

Ho, I., Goh, H. N., & Tan, Y. F. (2022). Preprocessing impact on sentiment analysis performance on malay social media text. *Journal of System and Management Sciences*, *12*(5), 73–90. https://doi.org/10.33168/JSMS.2022.0505

Hu, X., & Lovrich, N. (2019). Social media and the police: A study of organizational characteristics associated with the use of social media. *Policing an International Journal of Police Strategies and Management*, *42*(4), 654-670. https://doi.org/10.1108/PIJPSM-09-2018-0139

Islam, T. U., Mohammed, N., & Alhadidi, D. (2024). Privacy preserving vertical distributed learning for health data. *Journal of Surveillance, Security and Safety*, *5*(1), 1–18. https://doi.org/10.20517/jsss.2023.28

Jayachandran, S., & Dumala, A. (2023). Recurrent neural network based sentiment analysis of social media data during corona pandemic under national lockdown. *Journal of Intelligent & Fuzzy Systems*, *44* (2), 2131–2146. https://doi.org/10.3233/JIFS-221883

Jeong, U., Ding, K., & Liu, H. (2021). FBAdtTracker: An interactive data collection and analysis tool for Facebook advertisements. *arXiv.* https://doi.org/10.48550/arXiv.2106.00142

Kaufhold, M.-A., Rupp, N., Reuter, C., & Habdank, M. (2020). Mitigating information overload in social media during conflicts and crises: Design and evaluation of a cross-platform alerting system. *Behaviour & Information Technology*, *39* (3), 319–342. https://doi.org/10.1080/0144929X.2019.1620334

Khder, M. A. (2021). Web scraping or web crawling: State of art, techniques, approaches and application. *International Journal of Advances in Soft Computing & Its Applications*, *13*(3), pp(145-168). https://doi.org/10.15849/IJASCA.211128.11

Krylov, D., Poliakov, S., Khanzhina, N., Zabashta, A., Filchenkov, A., & Farseev, A. (2021). Improving multimodal data labeling with deep active learning for post classification in social networks. In *Multimedia understanding with less labeling on multimedia understanding with less labeling* (pp. 17–25). https://doi.org/10.1145/3476098.3485055

Laxmi Narasamma, V., & Sreedevi, M. (2016, November). Modeling of tweet summarization systems using data mining techniques: A review report. *Indian J. Sci. Technol.*, *9*(44). https://doi.org/10.17485/ijst/2016/v9i44/102441

Liao, L., He, X., Ren, Z., Nie, L., Xu, H., & Chua, T.-S. (2017). Representativeness-aware aspect analysis for brand monitoring in social media. *Proceedings of the 26th International Joint Conference on Artificial Intelligence,* Melbourne, Australia, 2017 August 19 - 25. 310-316. https://doi.org/10.24963/ijcai.2017/44

Liu, T.-H., Ma, Z., & Xia, Y. (2024). Serving on WeChat: Understanding the logics of police's engagement with the public in chinese contexts. *International Journal of Law, Crime and Justice*, *77*, 100665. https://doi.org/10.1016/j.ijlcj.2024.100665

Mahoney, J., Le Louvier, K., & Lawson, S. (2022). The ethics of social media analytics in migration studies. In *Information and communications technology in support of migration* (pp. 333–346). Springer. https://doi.org/10.1007/978-3-030-93266-4_19

Majeed, A., Khan, S., & Hwang, S. O. (2022). A comprehensive analysis of privacy-preserving solutions developed for online social networks. *Electronics*, *11* (13), 1931. https://doi.org/10.3390/electronics11131931

Matthes, J., Karsay, K., Schmuck, D., & Stevic, A. (2020). "Too much to handle": Impact of mobile social networking sites on information overload, depressive symptoms, and well-being. *Computers in Human Behavior*, *105,* 106217. https://doi.org/10.1016/j.chb.2019.106217

McGarry, K. (2023). Analyzing social media data using sentiment mining and bigram analysis for the recommendation of YouTube videos. *Information*, *14*(7), 408. https://doi.org/10.3390/info14070408

Mehta, H., & Passi, K. (2022). Social media hate speech detection using explainable artificial intelligence (XAI). *Algorithms*, *15*(8), 291. https://doi.org/10.3390/a15080291

Melchior, C., & Oliveira, M. (2024). A systematic literature review of the motivations to share fake news on social media platforms and how to fight them. *New Media & Society*, *26* (2), 1127–1150. https://doi.org/10.1177/14614448231174224

Moussaoui, M., Zaghdoud, M., & Akaichi, J. (2019). A possibilistic framework for the detection of terrorism-related twitter communities in social media. *Concurrency and Computation: Practice and Experience*, *31*(13), https://doi.org/10.1002/cpe.5077

Murić, G., Tregubov, A., Blythe, J., Abeliuk, A., Choudhary, D., Lerman, K., & Ferrara, E. (2020). Massive cross-platform simulations of online social networks. In *Proceedings of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS)* (pp. 895–903).

Murphy, A., Justin P. Fontecilla. (2013). Social media evidence in government investigations and criminal proceedings: A frontier of new legal issues. *19 Rich. J.L. & Tech 11*. Available at: https://scholarship.richmond.edu/jolt/vol19/iss3/4

Nirmal, A., Jiang, B., & Liu, H. (2023). SocioHub: An interactive tool for cross-platform social media data collection. *arXiv.* https://doi.org/10.48550/arXiv.2309.06525

Oliveira, L. S. D., Costa, W., Vaz De Melo, P. O. S., & Benevenuto, F. (2022). How politicians communicate in social media: A cross-platform study. In *Proceedings of the Brazilian Symposium on Multimedia and the Web* (pp. 75–83). https://doi.org/10.1145/3539637.3558232

Park, E., Chae, B., & Kwon, J. (2020). The structural topic model for online review analysis: Comparison between green and non-green restaurants. *Journal of Hospitality and Tourism Technology*, *11* (1), 1–17. https://doi.org/10.1108/JHTT-08-2017-0075

Pate, R., Patil, S., Patil, M., & Raut, R. (2023). Sentiment analysis of tweets using machine learning algorithms. In *2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC)* (p. 1-6). https://doi.org/10.1108/JHTT-08-2017-0075

Pérez-Landa, G. I., Loyola-González, O., & Medina-Pérez, M. A. (2021). An explainable artificial intelligence model for detecting xenophobic tweets. *Applied Sciences*, *11*(22). https://doi.org/10.3390/app112210801

Phengsuwan, J., Shah, T., Thekkummal, N. B., Wen, Z., Sun, R., Pullarkatt, D., Thirugnanam, H., Ramesh, M. V., Morgan, G., James, P., & Ranjan, R. (2021). Use of social media data in disaster management: A survey. *Future Internet*, *13*(2), 46. https://doi.org/10.3390/fi13020046

Rashidi, T. H., Abbasi, A., Maghrebi, M., Hasan, S., & Waller, T. S. (2017). Exploring the capacity of social media data for modelling travel behaviour: Opportunities and challenges. *Transportation Research Part C: Emerging Technologies*, *75* , 197–211. https://doi.org/10.1016/j.trc.2016.12.008

Rathore, A. K., Kar, A. K., & Ilavarasan, P. V. (2017). Social media analytics: Literature review and directions for future research. *Decision Analysis*, *14*(4), 229-249. https://psycnet.apa.org/doi/10.1287/deca.2017.0355

Reuter, K., & Lee, D. (2019). Evaluating patients' perspectives on social media: the importance of clearly reporting data search, cleaning and processing. *British Journal of Dermatology*, *181* (1), 222. https://doi.org/10.1111/bjd.17868

Rødgaard, E.-M., Jensen, K., Miskowiak, K. W., & Mottron, L. (2022). Representativeness of autistic samples in studies recruiting through social media. *Autism Research: Official journal of the International Society for Autism Research*, *15* (8), 1447–1456. https://doi.org/10.1002/aur.2777

Rodríguez-Ibánez, M., Casánez-Ventura, A., Castejón-Mateos, F., & Cuenca-Jiménez, P.-M. (2023). A review on sentiment analysis from social media platforms. *Expert Systems with Applications*, 223. https://doi.org/10.1016/j.eswa.2023.119862

Ross, C. T., & Redhead, D. (2021). DieTryin: An R package for data collection, automated data entry, and post-processing of network-structured economic games, social networks, and other roster-based dyadic data. *Behavior Research Methods*, 54, 611-631. https://doi.org/10.3758/s13428-021-01606-5

Ross, C. T., & Redhead, D. (2023). Automatic entry and coding of social networks and dyadic peer ratings. *Methodological Innovations*, *16*(2), 138–148. https://doi.org/10.1177/20597991231160281

Sabarky, M. A., Karyanta, N. A., & Anggarani, F. K. (2023). Information overload as a mediator in the relationship between instagram's social media use intensity and social media fatigue in emerging adulthood. *Jurnal ASPIKOM*, *8*(2), 305–318. http://dx.doi.org/10.24329/aspikom.v8i2.1274

Sabharwal, M., & Sharma, D. (2019). Sentiment analysis for social media using SVM classifier of machine learning. *International Journal of Innovative Technology and Exploring Engineering*, *8* , 39-47. https://doi.org/10.35940/ijitee.I1107.0789S419

Salminen, J., Mustak, M., Corporan, J., Jung, S.-G., & Jansen, B. J. (2022). Detecting pain points from user-generated social media posts using machine learning. *Journal of Interactive Marketing*, *57* (3), 517–539. https://doi.org/10.1177/10949968221095556

Shah, N., Bhagat, N., & Shah, M. (2021). Crime forecasting: a machine learning and computer vision approach to crime prediction and prevention. *Visual Computing for Industry, Biomedicine, and Art*, *4*(1), 9. https://doi.org/10.1186/s42492-021-00075-z

Sharma, D. K., Singh, B., Agarwal, S., Kim, H., & Sharma, R. (2022). Sarcasm detection over social media platforms using hybrid auto-encoder-based model. *Electronics*, 11 (18), 2844. https://doi.org/10.3390/electronics11182844

Shchepina, E., & Surikov, A. (2022). Modeling the trajectories of interests and preferences of users in digital social systems. *Procedia Computer Science*, *212,* 104–113. https://doi.org/10.1016/j.procs.2022.10.212

Shi, B., & Wang, H. (2023). An AI-enabled approach for improving advertising identification and promotion in social networks. *Technological Forecasting and Social Change*, *188.* https://doi.org/10.1016/j.techfore.2022.122269

Smith, M., Szongott, C., Henne, B., & Von Voigt, G. (2012). Big data privacy issues in public social media. In *2012 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST)* (pp. 1–6). https://doi.org/10.1109/DEST.2012.6227909

Sriram, A., Adhiraju, P. R., Kalangi, P. K., & Sathiyamoorthi, V. (2021). A comprehensive study of data analytics in social perspectives. In *Challenges and applications of data analytics in social perspectives* (pp. 257–274). IGI Global. https://doi.org/10.4018/978-1-7998-2566-1.ch014

Srivastava, S., Singh, M. K., & Singh, Y. N. (2021). Social media analytics: Current trends and future prospects. In *Communication and intelligent systems: Proceedings of ICCIS 2020* (pp. 1005–1016). Springer. https://doi.org/10.1007/978-981-16-1089-9_78

Stieglitz, S., Mirbabaie, M., Ross, B., & Neuberger, C. (2018). Social media analytics – Challenges in topic discovery, data collection, and data preparation. *International journal of information management*, *39* , 156–168. https://doi.org/10.1016/j.ijinfomgt.2017.12.002

Tufekci, Z. (2014). Big questions for social media big data: Representativeness, validity and other methodological pitfalls. In *Proceedings of the International AAAI Conference on Web and Social Media,* 8(1), 505–514. https://doi.org/10.1609/icwsm.v8i1.14517

Viswanath, B., Bashir, M. A., Crovella, M., Guha, S., Gummadi, K. P., Krishnamurthy, B., & Mislove, A. (2014). Towards detecting anomalous user behavior in online social networks. In *23rd USENIX Security Symposium (USENIX Security 14)* (pp. 223–238).

Walsh, J. P., & O'Connor, C. (2019). Social media and policing: A review of recent research. *Sociology Compass*, *13* (1). https://doi.org/10.1111/soc4.12648

Yadav, A., Alahmar, M., Singh, A., Sharma, K., Agrawal, R., & Sharma, C. B. (2023). Analyzing user behavior in social media through big data analytics. In *2023 IEEE International Conference on ICT in Business Industry & Government (ICTBIG)* (pp. 1–5). https://doi.org/10.1109/ICTBIG59752.2023.10456112

Yu, S. (2023). Social media intelligence: AI applications for criminal investigation and national security. In *Handbook of Research on Artificial Intelligence Applications in Literary Works and Social Media* (pp. 152–170). IGI Global. https://doi.org/10.4018/978-1-6684-6242-3.ch00

Yuan, Y., Wei, G., & Lu, Y. (2018). Evaluating gender representativeness of location-based social media: A case study of Weibo. *Annals of GIS* , *24* (3), 163–176. https://doi.org/10.1080/19475683.2018.1471518

Zhang, K., Geng, Y., Zhao, J., Liu, J., & Li, W. (2020). Sentiment analysis of social media via multimodal feature fusion. *Symmetry*, *12* (12), 2010. https://doi.org/10.3390/sym12122010

Zhang, Y. (2023, October). A study of the impact of information overload in social media in the simple medium network - The case of the university students majoring in communication studies. *Communications in Humanities Research*, *7* (1), 262–268. https://doi.org/10.54254/2753-7064%2F7%2F20230892

Zhou, X., Liang, X., Zhang, H., & Ma, Y. (2015). Cross-platform identification of anonymous identical users in multiple social media networks. *IEEE Transactions on Knowledge and Data Engineering*, *28* (2), 411–424. https://doi.org/10.1109/TKDE.2015.2485222