Journal of Computer Science and Technological Enquiry
e-ISSN 3135-0372
Vol: 2, Issue: 1 (2026)
https://doi.org/10.65496/jcste.2025.72

ORIGINAL RESEARCH - OPEN ACCESS

Data-driven Public Perception and Media Impact Analytics of Political Event: Tarunner Somabesh

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Article History
Received: 10 December 2025
Revised: 02 January 2026
Accepted: 25 January 2026
Published: 28 February 2026

How to Cite:
M.F. Rabbi, M. Ashiqussalehin, M. Sanaullah, A. Bashar and A. K. Bitto, "Data-driven Public Perception and Media Impact Analytics of Political Event: Tarunner Somabesh," Journal of Computer Science and Technological Enquiry (JCSTE), Vol-02 Issue 01, pp. 19–33, https://doi.org/10.65496/jcste.2025.72.

ABSTRACT

In today's fast-paced political world, understanding how media shapes public views on big events is key for leaders and analysts. Works like this one are vital as they use modern AI tools to dig deep into data from news, videos, and searches, giving real facts over guesswork. This study introduces a comprehensive framework that integrates advanced data mining techniques and artificial intelligence (AI) tools to evaluate the media impact and public perception of a significant political event- "Tarunner Somabesh" organized by the Bangladesh Nationalist Party (BNP). Leveraging Python-based data acquisition from Google News, YouTube APIs, and Google Trends, combined with natural language processing (NLP) algorithms trained for multilingual sentiment analysis, the study elucidates the dynamic interaction between traditional media coverage, digital commentary, and public search behavior. The findings illustrate the dominant narrative strategies employed by media outlets, reflect regional variances in public sentiment, and underscore the pivotal role of AI in facilitating scalable and rigorous political media analytics. Overall, this approach sets a strong example for future studies on political media in places like Bangladesh.

KEYWORDS

Media Impact Measurement, Public Sentiment Analytics, Google Trends, YouTube Data Mining

1. Introduction

In an era marked by rapid transformation in political communication, the lines between traditional media and digital platforms continue to blur, resulting in intricate feedback mechanisms that significantly shape public opinion and civic participation. The proliferation of social media, online news outlets, and search engines has created a vast and diverse information landscape, demanding sophisticated analytical approaches to make sense of the data. For developing democracies such as Bangladesh, understanding how these platforms influence political discourse and public perception is particularly crucial.

The political gathering "Tarunner Somabesh," hosted by the Bangladesh Nationalist Party (BNP), serves as a valuable case study to investigate the interplay between media representation and public reaction. Featuring a combination of seminars and rallies conducted in multiple regions, the event provides insight into how different formats of political mobilization and regional contexts are covered in the media and echoed in public dialogue.

This research introduces a reproducible analytical framework powered by artificial intelligence, integrating data from a range of sources-such as print and broadcast news, YouTube comment sections, and Google Trends to offer a holistic view of media narratives and public sentiment. By applying advanced natural language processing methods adapted for both Bangla and English content, the framework analyzes emotional tone and framing strategies to reveal nuanced patterns in how media coverage affects public engagement and perception.

By zooming in on regional and event-specific differences, we reveal how media coverage and public reactions vary in key cities like Dhaka, Chattogram, Khulna, and Bogura. These findings offer valuable insights for political strategists, media analysts, and policymakers who seek to better understand and respond to the changing political communication landscape in Bangladesh. Moreover, our work contributes to the wider conversation about how AI and data-driven approaches can enhance media impact analysis and support democratic participation. Key contributions of this research includes:

- Developed a comprehensive AI-powered framework that integrates multi-source data mining from traditional news media, YouTube comments, and Google Trends to measure political event impact.
- Advanced multilingual natural language processing techniques tailored for Bangla and English textual data, enabling accurate sentiment and narrative analysis in a complex sociolinguistic context.
- Provided granular, region-specific insights into media coverage and public perceptions across Bangladesh's major urban centers, capturing variations in sentiment and engagement by event type.
- Demonstrated the effectiveness of combining automated large-scale mining with qualitative validation to produce robust, actionable intelligence for political communication strategy.
- Contributed a replicable methodology and toolset applicable to political media analysis in emerging democracies, enhancing transparency and data-driven decision-making in electoral contexts.

2. Literature Review

1.1 AI and Data-Driven Approaches in Political Media Analysis

The utilization of artificial intelligence has transformed political media analysis by enhancing researchers' ability to process vast quantities of unstructured textual data with high speed and accuracy. Recent advances in natural language processing, particularly the adoption of transformer-based models such as BERT and other large language models, have equipped analysts with powerful tools to detect sentiment, stance, and nuanced public attitudes across multilingual datasets (HybridS Project, 2025) [3]. Acemoglu et al. (2025) further emphasize the economic and social ramifications of AI-powered media monitoring, highlighting its capacity to reveal subtle patterns of influence and agenda setting that were previously inaccessible [1].

Importantly, AI methods go beyond mere sentiment classification. They facilitate the detection of bias, misinformation, and the authenticity of media content, which is especially crucial in volatile political environments subject to misinformation campaigns and digital manipulation, including deepfakes (Insight7, 2025) [2]. The application of such technologies thus enhances not only descriptive analyses but also critical evaluative functions necessary for transparent political discourse.

Advances in AI have not been uniformly received by the public or across nations. Cross-national studies reveal that news media frequently frame AI-related risks differently according to local political biases, shaping social narratives and levels of public trust in AI tools [26]. These divergent frames influence not only how the public perceives AI's societal role but also how regulatory debates unfold, particularly in electoral contexts.

1.2 AI Algorithms and Media Polarization

Recent research emphasizes how AI-driven recommendation algorithms used by social media and digital news platforms can reinforce political polarization by filtering and amplifying certain opinions and narratives. How systems shape user exposure and encourage echo chambers, effectively segmenting audiences along ideological lines and limiting cross-cutting discourse related concerns are raised in the 2025 Isentia Report, which demonstrates the role of AI-driven curation in the emergence of filter bubbles during highly charged election periods [28]. Understanding this dynamic is crucial for analysts and policymakers seeking to foster a more balanced media environment.

1.3 Media Influence on Public Sentiment and Political Behavior

The ways in which people consume news online are changing quickly, particularly in the context of elections. According to the 2025 Digital News Report, there has been a notable rise in both political engagement and digital news consumption across South Asia, with Bangladesh witnessing particularly intense fluctuations in how public discourse is shaped [27]. These developments highlight the urgent need for advanced analytical methods capable of tracking real-time changes in public sentiment during key political moments.

A substantial body of research confirms that the way media frames and structures narratives plays a critical role in shaping public opinion and influencing political actions. Joshi (2018) emphasizes that news organizations do more than report events they actively shape societal understanding by emphasizing specific angles or frames, which in turn guide how audiences interpret political developments [4]. Likewise, Frontiers in Communication (2024) points out that digital platforms like YouTube intensify this influence by offering interactive environments where users not only consume content but also comment, share, and discuss, leading to the emergence of shared public attitudes [6].

In Bangladesh, the widespread availability of mobile internet and the active role of both national and regional media outlets accelerate the formation of public discourse. This evolving conversation is often mirrored in online search trends, revealing a reciprocal relationship between media coverage and public sentiment. Rather than flowing in one direction, influence circulates in a feedback loop, where media narratives and audience reactions continuously shape each other. This coevolution is further mediated by the nature of political events, cultural dynamics, and broader socio-political conditions.

1.4 Gaps and Challenges in Current Methods

Despite these advancements, challenges remain in political media analytics. Automated methods sometimes falter when confronted with local dialects, code-switching, or the use of sarcasm and nuanced rhetoric common in political commentary (TRT World, 2024) [7]. Furthermore, many studies focus on single media channels or broad national data, overlooking regional disparities and event-specific characteristics that are vital for accurate interpretation.

Recent progress in natural language processing, such as transformer models specifically designed for low-resource and morphologically rich languages like Bangla, has improved the accuracy and cultural relevance of sentiment and narrative analysis [14, 23]. However, ongoing work is needed to adapt these advances across regional variants and emerging social media formats.

This research confronts these gaps by employing a multistage, cross-platform analytic approach tailored to the Bangladeshi socio-political context, enabling a granular and context-aware measurement that integrates qualitative validation with quantitative rigor.

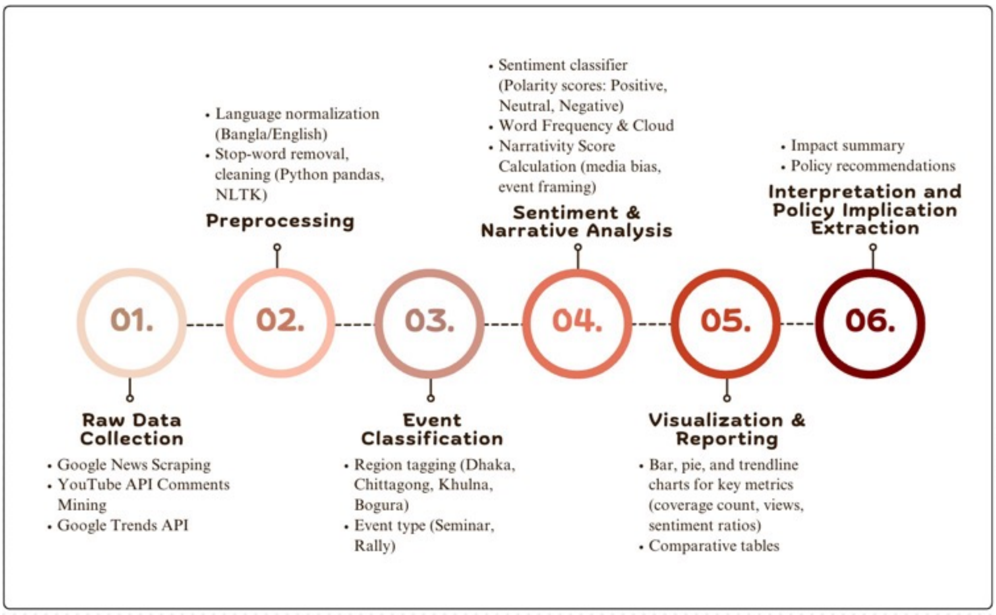

Fig. 1 Research Methodology for Data and AI-Driven Measurement and Analytics of Media Impact and Public Perceptions for Political Event.

3. Data and Methodology

The methodology employs a multi-tiered, complex data processing and analytic architecture to manage the vast and heterogeneous datasets obtained. Central to this is a modular flowchart designed to clearly delineate the sequence and logic of data acquisition, cleansing, annotation, analytic processing, visualization, and interpretation. This ensures replicability and transparency in the face of multilanguage and multi-platform complexity.

The research utilized a triangulated data acquisition approach encompassing multiple digital sources to obtain a comprehensive dataset. News articles were crawled from Google News through customized Python scripts, targeting Bengali and English language outlets to ensure wide coverage of “Tarunner Somabesh” events in May 2025. These scripts combined official API access with advanced scraping techniques to capture metadata, article text, publication timestamps, and source identification. YouTube data collection employed the YouTube Data API v3 integrated within Python environments, extracting video metadata alongside a detailed comment corpus from numerous event-related videos. Using a list of curated video IDs relevant to different regions and event types, comments were mined to assess public sentiment and engagement. Additionally, Google Trends data were gathered to measure public interest over time and geography by tracking search query volumes related to the event. This enabled correlation analyses between media exposure and public curiosity, completing the data triangulation.

1.1 Data Acquisition and Integration

The system begins with diverse raw input streams:

- **Google News API and Scraping Scripts:** Extract news articles from Bengali and English media, with structured metadata capture including source, timestamp, and regional tagging.

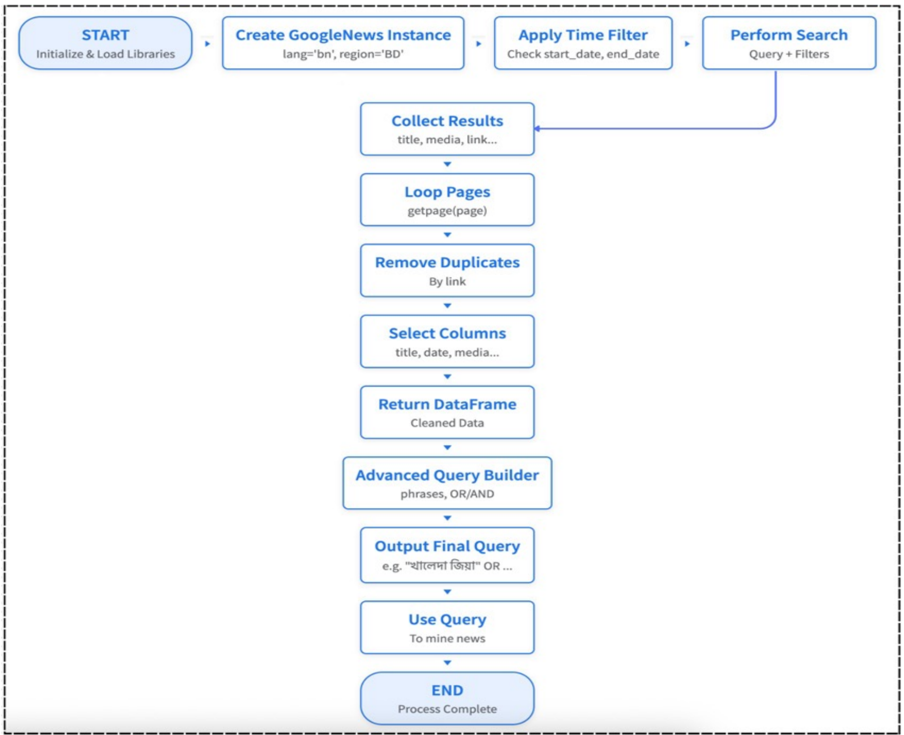

Fig. 2 Sequence of steps involved in Google News API and Scraping Scripts using Python Script.

This process kicks off by loading the GoogleNews library and setting the foundational search parameters, like the language (Bangla) and the region (Bangladesh). Once these essentials are set, an instance of the GoogleNews client is created to manage all subsequent queries.

If specific date ranges are needed, the system applies a time range filter to focus searches on news published during that period. Then, an initial search is launched using the constructed query, pulling back news articles that match the defined keywords and filters. To ensure a thorough search, the system doesn't stop at just the first page; it loops through multiple pages of search results, collecting more articles until either it reaches a preset maximum or the pages run dry. Throughout this paging process, brief pauses are inserted as a courtesy to the server and to avoid triggering access restrictions.

Once all results are gathered, duplicates are removed based on their links, so the dataset consists only of unique articles. The dataset is streamlined by selecting only the necessary fields like title, media source, publication date, description, and link making it easier to analyze.

Separately, an advanced query construction function takes user inputs such as exact phrases to match, keywords to include or exclude, site and file-type restrictions, date ranges, and grouped logical conditions to build a precise and flexible search string. This query string is then used in the Google News search process.

Ultimately, this modular and iterative approach allows for gathering a wide yet focused collection of news articles, perfectly tailored to the research needs around the political events under analysis.

- **YouTube API Mining:** To gather video metadata and comment-level information from selected YouTube videos linked to the “Tarunner Somabesh” events, we developed a sophisticated Python script tailored for this purpose. This script plays a central role in our research by acting as an automated tool that systematically collects and structures public discourse found in the comment sections of regionally relevant channels. It starts by processing a pre-identified list of specific video IDs associated with the event. Through a secure connection to the official YouTube API, the script retrieves essential details about each video, including its title, the uploading media channel, publication date, and the video’s URL. This metadata provides important contextual background, ensuring that every comment captured is tied to accurate temporal and source-based information. By preserving this context, the script enables a more meaningful analysis of public sentiment not only capturing user opinions but also situating them within the time and platform where they emerged. With the metadata in place, the script proceeds to collect user comments for each video. It efficiently manages the pagination process, navigating through potentially hundreds or even thousands of comments per video, ensuring comprehensive coverage and minimizing data loss. For every comment retrieved, the script records essential information: the author’s name, the text of the comment, the timestamp of when it was posted, and its visibility status (i.e., whether it is publicly viewable). This data is then organized into a structured format, such as a tabular dataset, making it suitable for subsequent analysis.

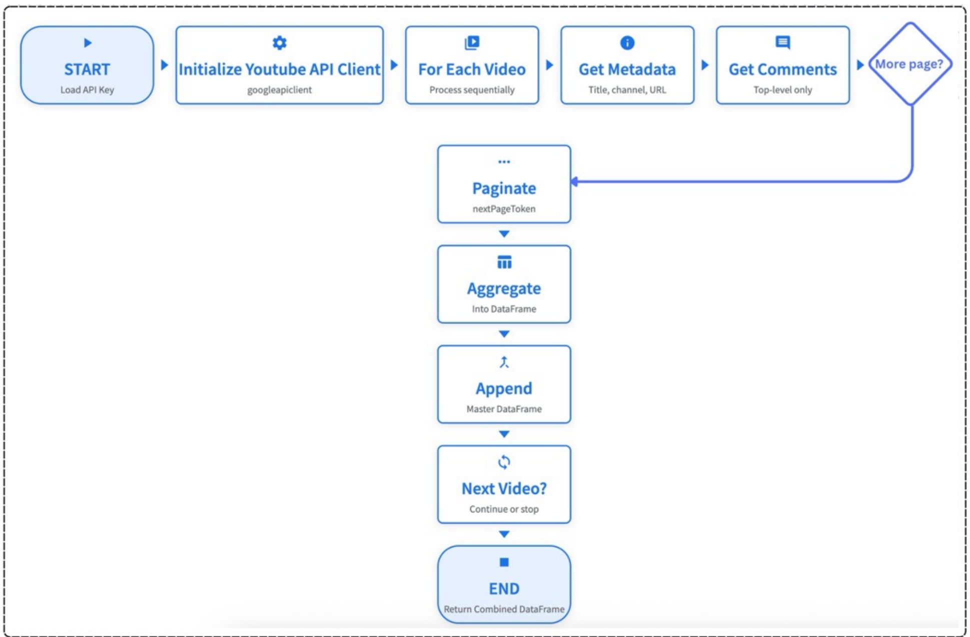

Fig. 3 This flowchart represents the sequence of steps for YouTube API Mining using Python Script.

The real strength of this tool lies in its capacity to aggregate comments from multiple videos and various regional media channels into one cohesive dataset. By consolidating inputs across different sources, it captures a broad spectrum of public opinions, reflecting regional variations and diverse audience perspectives. This enriched dataset becomes the foundation for our sentiment analysis enabling us to identify shifts in public emotion, compare reactions across geographic areas, and track overall public sentiment in response to the political events under study.

Ultimately, the script serves to convert the vast, unstructured landscape of YouTube comments often fragmented and noisy into a systematic, organized, and analyzable resource. This transformation allows us to derive meaningful, data-driven insights that directly support the core findings of our research.

- **Google Trends API:** Aggregates search query frequencies over time and region, enabling public attention tracking. This flowchart outlines the procedure for analyzing Google search trends using the PyTrends library in Python. The process starts by installing and importing the required Python packages, followed by initializing a PyTrends request object configured specifically for the Bengali language and targeted to the Bangladesh region. This regional and linguistic customization ensures that the collected data reflects locally relevant search behavior

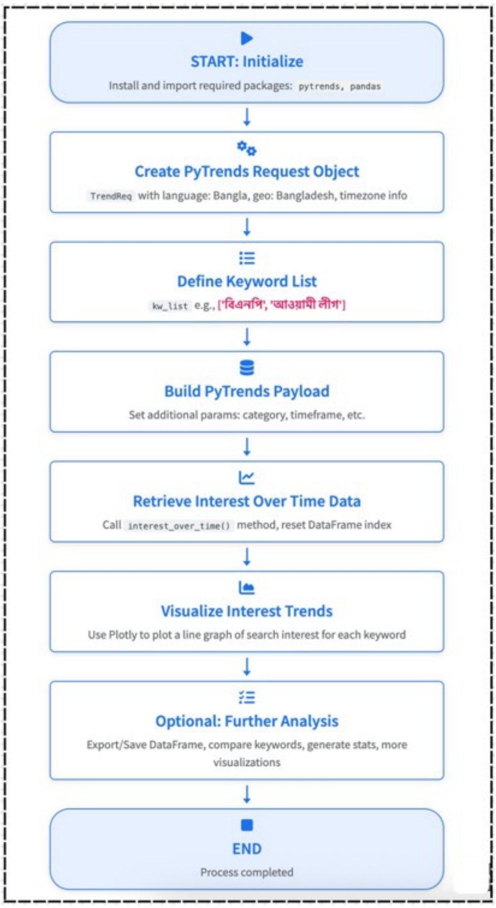

Fig. 4 This figure illustrates the steps involved in Google Trends API implementation through Python Script.

Next, the user specifies a set of keywords to analyze such as names of major political parties or event-related terms. These keywords are used to construct a search payload, where additional parameters like search category, time range, and geographic focus are defined. These settings shape the query sent to Google Trends, ensuring accurate and context-specific results.

Once the payload is submitted, the script pulls the relative search interest data over time. This data, which shows how frequently each keyword was searched relative to the total search volume, is then cleaned and organized into a structured pandas data frame. This format makes it easier to manipulate, analyze, and integrate with other datasets.

To support visual interpretation, the time-series search data is plotted using the Plotly library, generating interactive line graphs. These visualizations allow researchers to observe fluctuations in public interest for each keyword across the selected period, highlighting peaks, dips, and broader trends. The system is designed to be flexible and modular, enabling users to export raw data, conduct comparative studies across keywords, or create alternative visual representations based on research needs.

In sum, this method provides a simple yet effective way to monitor and interpret changes in public attention through digital search behavior. By capturing realtime shifts in what people are searching for, it adds valuable context to political media analysis, helping to uncover patterns in public interest tied to key political events or narratives.

Data streams feed into preprocessing systems where integration occurs.

1.5 Data Preprocessing and Natural Language Processing Pipeline

Given the multilingual nature of the dataset, preprocessing included normalization steps such as Unicode standardization, stop-word removal specific to Bangla and English, and lexical disambiguation. Pandas and NLTK libraries, supplemented with Bangla NLP resources, facilitated cleaning textual data for consistent analysis. Sentiment classification was conducted using a supervised machine learning model fine-tuned on political communication corpora encompassing positive, negative, and neutral categories. Narrative framing scores were generated through thematic parsing and frequency analysis of key political lexicons, further enhanced by word cloud visualizations to illustrate dominant themes. The complete analytics pipeline comprised sequential stages from raw data ingestion through preprocessing, tagging by region and event type, sentiment and narrative analytics, culminating in visualization and interpretive reporting.

To handle the bilingual and noisy nature of the data:

- **Unicode normalization and encoding standardization** ensure character consistency.
- **Stopword filtering, punctuation removal, and tokenization** are conducted separately for Bangla and English corpora, using custom lexicons.
- **Deduplication algorithms** remove repeated news articles or comments.

Event and region tagging algorithms assign each data item a classification (seminar/rally; Dhaka/Chattogram/Khulna/Bogura) based on metadata and content keywords.

1.6 Complex Multistage Analytics Pipeline

A carefully structured, multistage analytical pipeline that transforms raw heterogeneous data into meaningful political media insights through a sequence of interlocking modules:

I. **Raw Data Input:** The process begins by aggregating three primary types of data: news articles sourced via Google News APIs and web scraping, YouTube

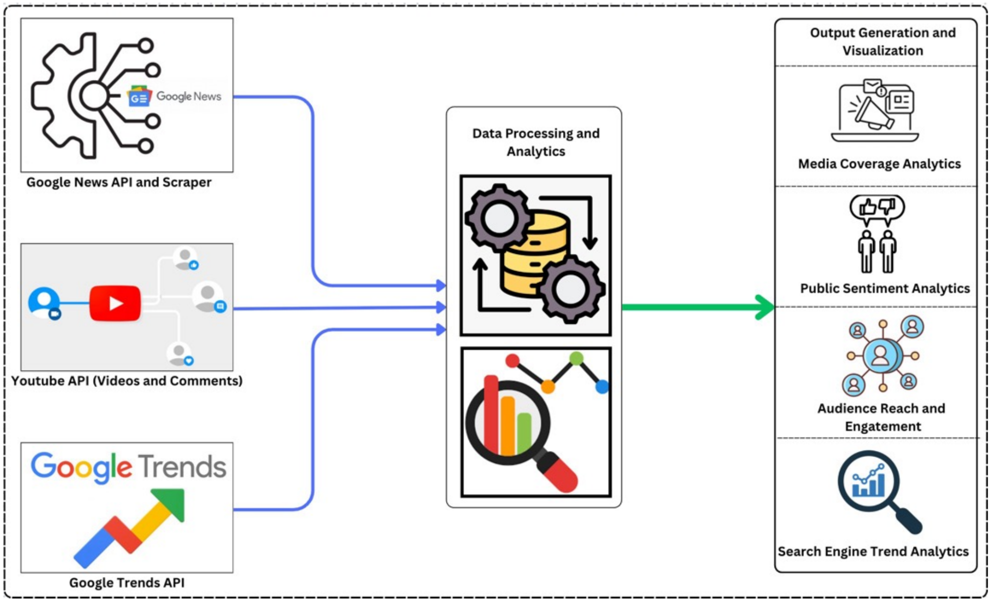

Fig. 5 High-Level System Architecture of the system for Data and AI-Driven Measurement and Analytics of Media Impact and Public Perceptions for Political Event.

video metadata and user comments extracted through the YouTube Data API, and public interest metrics from Google Trends capturing search volume over time and regions. These diverse data sources provide layered perspectives on political event coverage, public discourse, and engagement patterns.

I. **Data Preprocessing Module:** Given the multilingual (Bangla and English) and noisy nature of the collected data, an essential early stage involves extensive preprocessing. This includes Unicode normalization for consistent character encoding, language detection to route texts into appropriate processing pipelines, and thorough cleaning such as removing stop words, punctuation, and irrelevant tokens. Deduplication algorithms identify and remove repeated content while data is tokenized for finer analysis. This module ensures data integrity, uniformity, and readiness for advanced parsing.

II. **Event Classification Module:** Preprocessed texts undergo detailed annotation to classify the type of political event they describe, distinguishing between seminars and rallies leveraging keyword-based and contextual textual parsing. Concurrently, metadata and topical content are analyzed to assign precise geographic tags (e.g., Dhaka, Chattogram, Khulna, Bogura), facilitating region-specific stratification of the analysis. This classification enables granular disaggregation of results by key dimensions relevant to political interpretation.

III. **Sentiment Analysis Engine:** A central component, this module applies advanced NLP models fine-tuned for Bangla and English to classify each textual snippet's sentiment into positive, neutral, or negative categories. The model incorporates confidence scoring to quantify classification reliability and flags cases with low certainty for further manual review. This blend of automated precision and human oversight balances scalability with contextual nuance critical for political discourse.

I. **Narrative Framing & Thematic Analysis:** Beyond sentiment, the pipeline computes keyword frequency distributions identifying dominant thematic clusters. Word cloud generation visually summarizes these themes to highlight recurring motifs such as "youth," "unity," or "development," relevant to the political event's narrative. Additionally, algorithms estimate narrative polarity and measure media bias scores by analyzing tone, framing patterns, and source characteristics, providing an evaluative layer on media portrayal.

II. **Aggregation & Visualization Generator:** Processed data is aggregated into structured statistical summaries and visualized through time-series trendline plots, bar charts, and pie charts representing coverage volume, sentiment proportions, and regional differences. These visualizations serve as intuitive tools for interpreting complex multilayered data and identifying temporal and spatial dynamics in media impact and public perception.

III. **Validation & Interpretation Layer:** Recognizing the limits of automated processes, this final stage includes manual spot-checks of data samples particularly borderline sentiment cases and regionally ambiguous classifications and qualitative validations using selected exemplary texts. Synthesizing these with the aggregated quantitative findings, the module compiles summarized policy implications and strategic insights, closing the analytic feedback loop with actionable interpretations.

Together, these modules constitute an integrated, replicable pipeline that balances automated scalability with contextual sensitivity, enabling rigorous and insightful measurement of political media influence and public sentiment in multilingual, multi-regional contexts.

The framework is scripted primarily in Python, utilizing libraries such as Pandas for data management, NLTK and SpaCy for NLP tasks, Matplotlib and Seaborn for visualizations, and Google API clients for data acquisition. The YouTube comment mining script implements multi-video comment retrieval with pagination handling, ensuring comprehensive coverage of public discourse.

4. Results

4.1 Quantitative Overview of Media Coverage

The media coverage analysis reveals a pronounced preference for rallies over seminars, with rallies accounting for approximately 90% of total reported instances. This imbalance underscores rallies as the primary spectacle attracting media attention, likely due to their visual appeal and potential to mobilize mass audiences. Region-wise, Dhaka emerged as the most intensively covered area, receiving nearly double the news volume of other targeted regions such as Bogura and Khulna. Temporal spikes aligned directly with scheduled event dates, attesting to active media synchronization with political calendars.

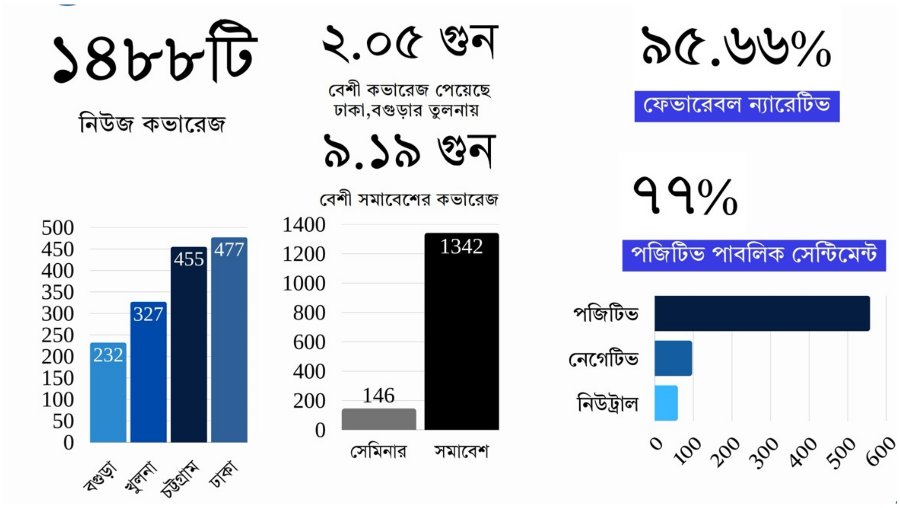

Fig. 6 Analysis of Media Coverage. Total number of news is 1488 where rallies got 9.19 times higher coverage than seminars. Dhaka got 2.05 times more coverage than Bogura. Favourable narrative percentage is 95.66 and positive public sentiment appeared around 77%.

4.2 Public Sentiment Patterns

Sentiment analysis across regions indicates strong predominance of positive public perceptions, with Khulna and Bogura reporting positivity rates exceeding 81%. In contrast, Chattogram exhibited comparatively higher negative sentiment proportions, hinting at localized challenges or political contestation.

The proportion of favorable media framing was consistently high across all areas, ranging from 93% to 98%, suggesting concerted media efforts in generating supportive narratives for the events. These results were further supported by word cloud analyses accentuating terms like “youth,” “development,” and “unity,” portraying narratives designed to emotionally engage supporters.

4.3 Audience Reach and Engagement Metrics

Evaluation of YouTube video views and user engagement demonstrated extensive reach, with flagship Dhaka event videos amassing over 2.4 million views. Major news channels including Channel 24, Somoy TV, and Jamuna TV dominated both video presence and viewership statistics.

The simultaneous monitoring of Google Trends revealed synchronization between peak search interest and event occurrences, reinforcing the close coupling of media visibility and public attention

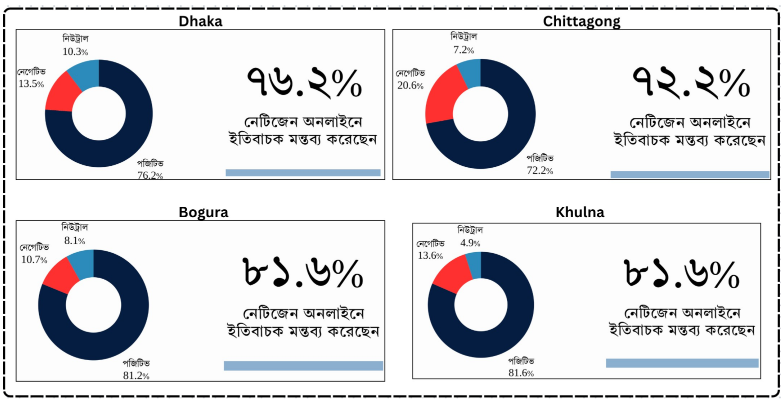

Fig. 7 Analysis of Public Sentiment Patterns. The percentage of positive comments for Dhaka, Chittagong, Bogura and Khulna are 76.2%, 72.2%, 81.6% and 81.6% respectively.

4.4 Trend on Search Engines

The temporal analysis of Google Search Trends for the “Tarunner Somabesh” events reveals significant and localized spikes in public interest that closely align with the timing of organized rallies across key regions in Bangladesh. The data encapsulated in the figure highlights three main clusters of search activity corresponding to the three major urban centers Chattogram, Khulna, and Dhaka each exhibiting a pronounced surge during their respective event periods.

Starting with Chattogram, the earliest peak in search volume occurred between May 7 and May 11, coinciding directly with the scheduled political mobilization in this region. This spike suggests an intense public curiosity and engagement driven by media coverage and word-of-mouth circulation around the event. The rapid rise and fall of search activity in this window suggest a focused and temporally limited surge in awareness among local populations.

Following Chattogram, Khulna experienced its most notable burst of search interest between May 15 and May 21. Though slightly lower in magnitude compared to Chattogram, the pattern reflects a clear cause-and-effect relationship, with public attention sharply heightening in response to live events or online media dissemination during this timeframe.

The final and most substantial peak occurred in Dhaka from May 26 to May 31. This surge not only registers the highest search volumes among the three regions but also illustrates a sustained period of augmented interest. Dhaka’s status as the capital and media hub likely amplifies the scale and duration of this digital engagement, reflecting the combined impact of large-scale rallies, intensified media promotion, and heightened public discourse.

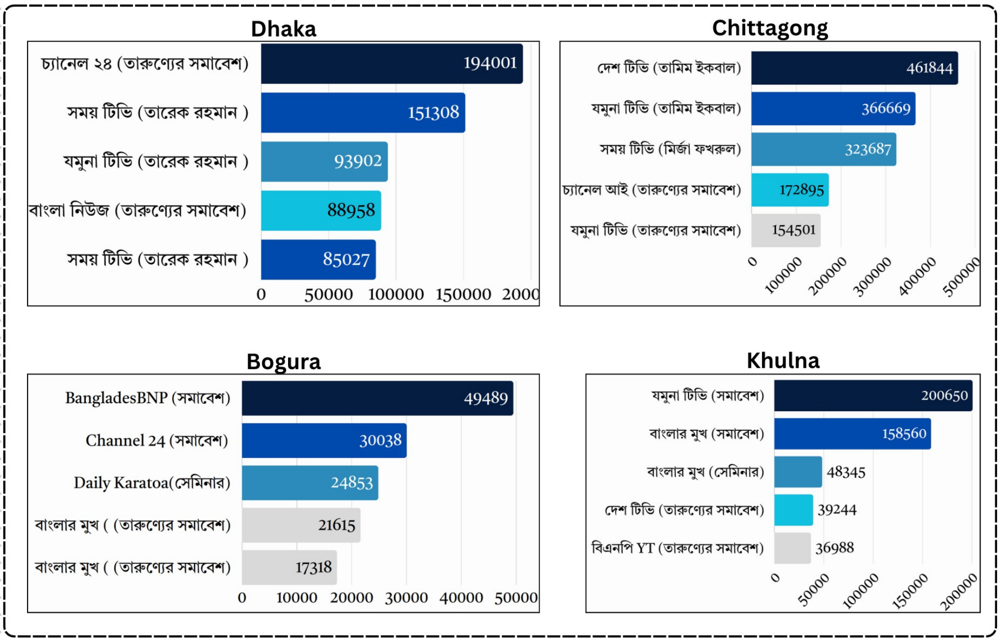

Fig. 8 Analysis of Public Reach and Engagement. Represents the views of contents and videos through digital media.

Overall, these regional search interest trajectories demonstrate how digital footprints, as captured by search engine query volumes, effectively mirror the physical occurrence and media coverage of political events. The distinct, sequential spikes across different regions underscore the geographically targeted nature of the campaigns and the responsiveness of local populations to event-driven content. This alignment confirms that search engine trends serve as a valuable proxy for gauging public attention and engagement, complementing traditional media monitoring and sentiment analyses conducted in this study.

Given these patterns, political strategists and media analysts can leverage search trend data to optimize the timing and regional focus of campaign activities, ensuring peak public exposure and interaction. Furthermore, the demonstrated correlation between event occurrence and search behavior underscores the rising importance of digital analytics in contemporary political communication research within Bangladesh.

4. Discussion

The data substantiate the hypothesis that rally events attract substantially greater media and public attention than seminars, thereby intensifying the political narrative's reach and favorability. The striking alignment between positive media framing and public sentiment underscores the symbiotic nature of this relationship.

Regionally, variations in sentiment and coverage intensity indicate localized sociopolitical dynamics influencing public reception. The deployment of AI and NLP notably streamlined the extraction and synthesis of complex, multilingual textual data, though challenges around nuance interpretation persist.

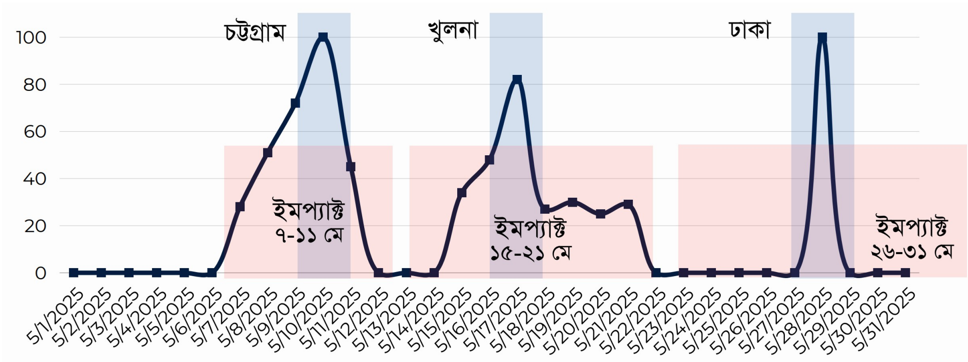

Fig. 9 Representation of Google Search Trend for "Tarunner Somabesh" with the timeline of event time.

5. Conclusion and Future Direction

This investigation confirms that advanced AI-driven methodologies applying large-scale, multi-source data mining and analysis significantly enrich our understanding of political event media impact and public sentiment dynamics in Bangladesh. The structured, multistage analytic flowchart detailed herein can serve as a replicable model for similar studies in emerging democracies.

Integrating these automated techniques with informed human oversight ensures both scalability and contextual sensitivity, vital for robust political communication research and strategy formulation.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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