Analyzing The October 7, 2023 War Events Based on Telegram Channels: A Sentiment and Temporal Analysis Approach

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Introduction

Social media platforms have transformed how information is disseminated during conflicts. Among them, Telegram [1] stands out for enabling rapid, unmoderated communication, playing a crucial role in crises and geopolitical events (Khaund et al. 2020). Its features, including broadcast channels, encryption, and minimal oversight, make it a powerful yet challenging medium, often prone to misinformation. The events of October 7, 2023 (Wikipedia contributors 2025), underscored Telegram's significance in shaping public perception, spreading narratives, and potentially aiding coordination. In this fast-moving and politically charged context, Telegram served both as an information source and a propaganda tool. Yet, the platform's openness raises concerns about information reliability, sentiment volatility, and narrative manipulation. To address these issues, this project aims to:

1. Analyze multilingual sentiment (Hebrew and Arabic) to detect shifts and trends related to real-world events.
2. Conduct temporal analyses to correlate sentiment changes with key conflict developments.

Our goal is to better understand Telegram's dual role as a real-time informational resource and a strategic communication tool in conflict zones.

Related Work

Recent research has highlighted the growing importance of social media analysis in crisis contexts, focusing on real-time sentiment tracking, misinformation detection, and event recognition. Studies have explored methods such as active learning, AI-based text classification, mixed-methods analysis, and social network analytics to understand public discourse and engagement during emergencies (Xu 2020; Swathi et al. 2020; Smith, Smith, and Knighton 2018). In particular, time series analysis and change-point detection techniques have been employed to uncover significant shifts in sentiment and behavior over time (Wu, Shang, and Gao 2021; Guralnik and Srivastava 1999). Deep learning and calibration methods further enhance the robustness of multilingual sentiment models, with applications in political, financial, and social domains (Moutidis and Williams 2020; Li et al. 2019; Schmidl, Wenig, and Papenbrock 2022). Despite these advances, Telegram remains understudied compared to platforms like Twitter and Facebook, especially in multilingual and high-conflict settings. Moreover, integrated analyses of Hebrew and Arabic sentiment during unfolding conflict events are lacking. Our work addresses this gap by applying sentiment and temporal analyses to Telegram channels active during the October 7, 2023 war, offering a real-time, dual-language perspective on narrative dynamics and information flow in modern conflict zones.

Methodology

This section details the methodology used to analyze Telegram communications' dissemination, sentiment dynamics, and event-related patterns surrounding the October 7, 2023 conflict. Through this multi-pronged methodology, combining rigorous preprocessing, rich visualization, time-series diagnostics, and statistical hypothesis testing, we establish a detailed map of sentiment evolution in relation to the key events of the October 7, 2023 conflict.

Data Collection and Preparation

We curated a set of Telegram groups relevant to the October 7, 2023 conflict, emphasizing channels frequently cited in media and active in prior events. To validate ideological alignment, especially for Arabic and pro-Palestinian sources, we enhanced our list with resources such as "Palestinian Territories Media Environment" (BBC Monitoring 2023). Messages were extracted via the Telegram API (Telegram Messenger Inc. 2025), with timezone handling and rate-limiting. Extracted fields included content, timestamps, metadata (e.g., sender, reply, forwards), media details, views, reactions, and derived features such as hour, weekday, and emoji count. All records were stored in a structured SQLite (Team 2025) database with composite keys and indexed timestamps to support efficient querying.

We also performed an EDA (exploratory data analysis, described in Appendix A). In the EDA, we merged a channel-level lookup table (shown in Appendix B) that labels every message by the channel's language and ideological class, enabling further comparisons of volume, engagement, and narrative dynamics across diverse communities.

[1] https://web.telegram.org/

Sentiment Analysis

We developed a modular pipeline to analyze multilingual Telegram messages. Language detection was first applied to filter empty texts and classify messages as Hebrew or Arabic, followed by manual correction of common misclassifications. Preprocessing was language-specific, involving duplicate removal and text normalization. For sentiment classification, we used pretrained models: DicataBERT-Sentiment for Hebrew (Shmidman, Shmidman, and Koppel 2023) and CAMeLBERT-DA for Arabic (Inoue et al. 2021), both applied without fine-tuning. Message-level predictions were then aggregated to compute average sentiment scores by channel group, language, and temporal windows (e.g., daily), forming the basis for subsequent time series analysis.

Sentiment Time Series Analysis

Sentiment Aggregation By Time. To capture temporal sentiment dynamics, we generated hourly, daily, and weekly aggregates for both Hebrew and Arabic messages. For each interval, we computed sentiment label counts and proportions, message volume, and average classifier confidence. Two key metrics were derived:

- *Net Sentiment*: $\big(\%\text{Positive} - \%\text{Negative}\big)$, reflecting the balance of sentiment.
- *Sentiment Index*: $\big((\#\text{Positive}-\#\text{Negative})/(\#\text{Positive}+\#\text{Neutral}+\#\text{Negative})\times 100\big)$, indicating overall polarity on a scale from -100 to $+100$.

We also analyzed message volume to detect activity spikes and explored hourly and weekday patterns to identify cyclical trends. These temporal aggregations underpin the subsequent time-series and event detection analyses.

Time Series Analysis Techniques. We analyzed daily sentiment scores for Hebrew and Arabic channels to uncover trends and patterns. Short-term fluctuations were smoothed with moving averages. Each series was then decomposed into observed, trend, seasonal, and residual components using classical seasonal decomposition. Stationarity was assessed via augmented Dickey–Fuller and KPSS tests. The residuals were inspected using time series graphs, histograms, QQ graphs, ACF analyses, and the Ljung-Box test to detect autocorrelation or anomalies. These steps provided a robust foundation for event detection and forecasting.

Group-type Aggregated Sentiment Time Series Analysis. We aggregated daily sentiment by channel type and conducted three analyses. First, we visualized the sentiment trajectories of each type with rolling averages of 14 days and examined their distributions using box plots and descriptive statistics. Second, we aligned Hebrew and Arabic series for corresponding channel types and computed correlation matrices to reveal cross-language synchrony and intertype relationships. Finally, we applied Granger causality tests on paired series (after differencing non-stationary data) to identify significant lead–lag influences in sentiment evolution.

Sentiment Event Detection

We applied a three-stage pipeline on the daily aggregated series: (1) change-point detection via CUSUM (Cumulative Sum) and PELT (Pruned Exact Linear Time); (2) time-lagged cross-correlation over ± 20 days to identify driving relationships between Hebrew and Arabic channels; and (3) event consolidation by counting all detected points across methods, metrics, and languages, per date, and selecting the top dates as significant sentiment events. This approach emphasizes robust, multi-metric shifts while suppressing isolated anomalies.

Sentiment Event Correlation Analysis

To analyze how sentiment shifts align with key conflict milestones, we merged detected sentiment events with structured time periods extracted from Wikipedia. Each period was mapped to a contiguous date range (see Appendix D). This enabled both visual and quantitative analyses of correlations between public sentiment and wartime developments.

Exploratory Visualization. We visualized sentiment trajectories for Hebrew and Arabic alongside conflict phases using overlay plots and rolling averages. We also used bar charts to summarize average sentiment by event type and conflict stage.

QuantitativeTime Series Analysis. We conducted a two-part quantitative analysis to examine sentiment dynamics around key conflict periods. First, we applied a window-based approach, computing average sentiment before, during, and after events, and tested for significant shifts using t-tests. Then, to explore temporal dependencies between public sentiment and conflict events, we computed cross-correlation functions on daily sentiment to identify potential lead–lag relationships.

Statistical Validation. We used two main statistical tests; we applied independent two-sample t-tests to compare sentiment on event versus non-event days, and we used one-way ANOVA to assess variation across event categories. Additionally, we fitted linear regression models with event and time controls to quantify and assess the impact of conflict events on Hebrew and Arabic sentiment.

Geopolitical and Linguistic Comparison. We compared event-related sentiment across ideological subgroups and between language communities. We computed daily sentiment divergence, summarized it by event type and group, and visualized temporal trends, scatter plots, and response pattern distributions to highlight nuanced differences in how distinct audiences perceived key conflict milestones.

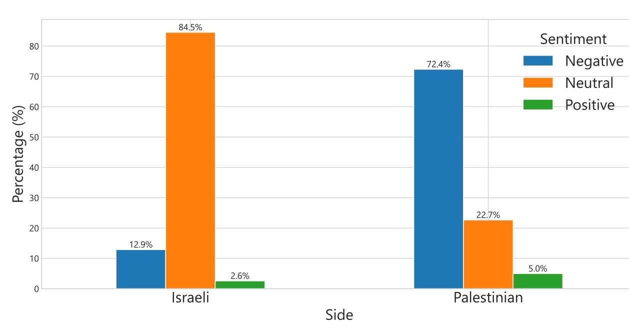

Figure 1: Sentiment distribution by side across all messages.

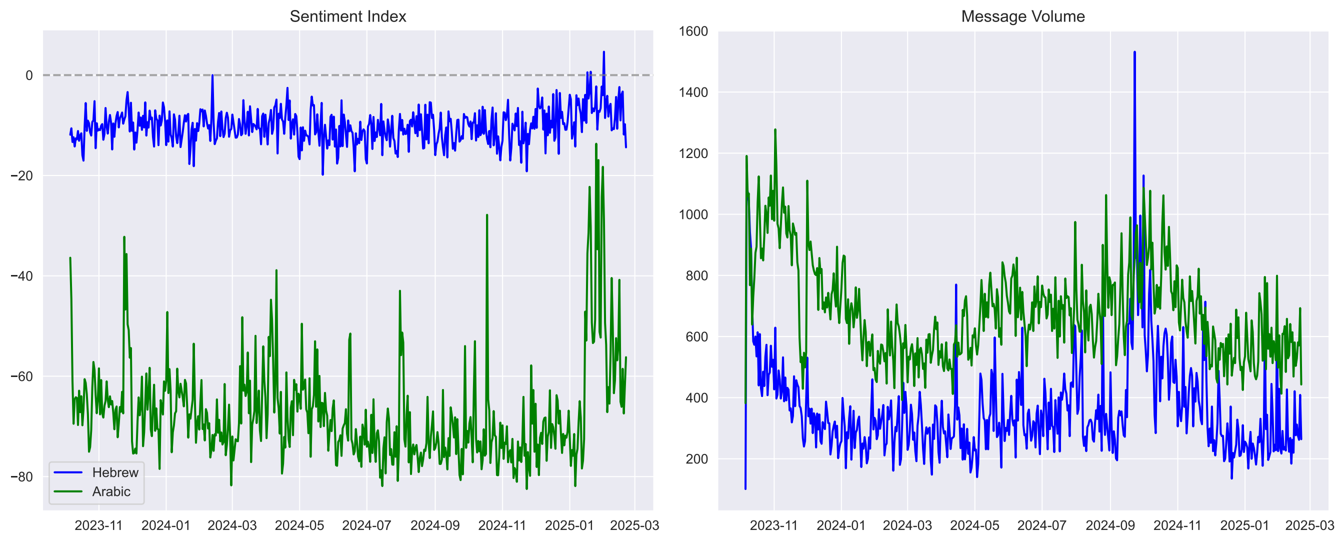

Figure 2: Daily sentiment index (left) and message volume (right) for Hebrew and Arabic Telegram channels between October 7th, 2023, and March 2025.

Results

We began by summarizing key characteristics of the processed Telegram dataset. The original collection comprised $611,484$ messages in Hebrew and Arabic. After removing empty texts (12.93%) and rare language mismatches (0.06%), $528,699$ messages remained; 65.28% in Arabic and 34.72% in Hebrew. Language detection aligned with metadata in 99.30% of cases. Although duplicates accounted for 6.50% of the data, they were retained due to their relevance for sentiment aggregation.

We first examined message distribution across group types, as categorized in Appendix B. Palestinian news groups were more active than official channels. From the Israeli perspective, commentary groups dominated activity, followed by Israeli news and Israeli side channels. This asymmetry in posting volume motivates further analysis of temporal, engagement, and sentiment patterns.

Sentiment Distribution. Figure 1 shows the sentiment distribution by side. Palestinian-affiliated channels were predominantly negative (72.4%), with 5.0% positive messages. In contrast, Israeli-affiliated channels were mostly neutral (84.5%), with only 2.6% positive sentiment. These results highlight differing emotional tones and narrative strategies across the two sides.

Sentiment Index Over Time. As seen in Figure 2, Hebrew sentiment was consistently negative (0% to –20%) with brief upticks in February 2024 and 2025. Arabic sentiment was more volatile (–85% to –15%), with upward spikes in October and December 2023, April and October 2024, and from February 2025 onward. Arabic channels maintained higher daily volume (400–1,100 messages) compared to Hebrew (100–800), with both peaking in October 2024. Volume and sentiment spikes are often aligned, especially in Arabic discourse.

Temporal Characteristics of Sentiment Series. Stationarity tests yielded mixed results for Hebrew sentiment: ADF ($p = 0.000$) indicated stationarity, while KPSS suggested non-stationarity ($p = 0.012$). Arabic sentiment was consistently stationary across both tests (ADF: $p = 0.028$, KPSS: $p = 0.100$), implying more stable dynamics. Residual analysis showed autocorrelation in both series (Ljung-Box p= 0.000). Hebrew residuals were approximately normal (Shapiro-Wilk $p = 0.371$), while Arabic residuals were not ($p = 0.000$). These findings highlight differing temporal and distributional properties between the two languages.

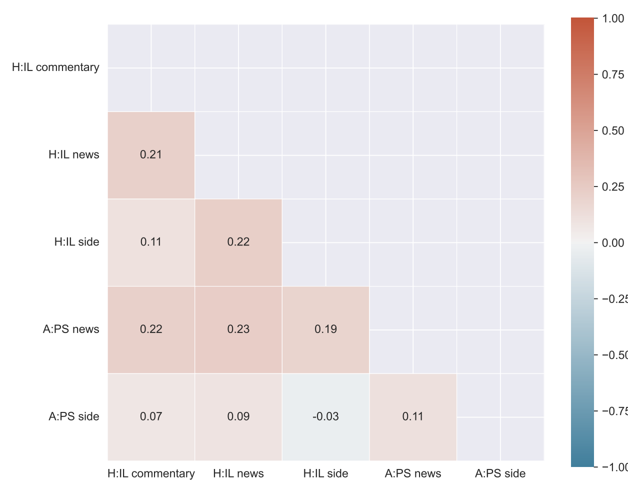

Figure 3: Correlation heatmap between Hebrew (Israeli) and Arabic (Palestinian) channel sentiment series.

Sentiment Correlation Across Languages and Channel Types. Figure 3 displays Pearson correlations among

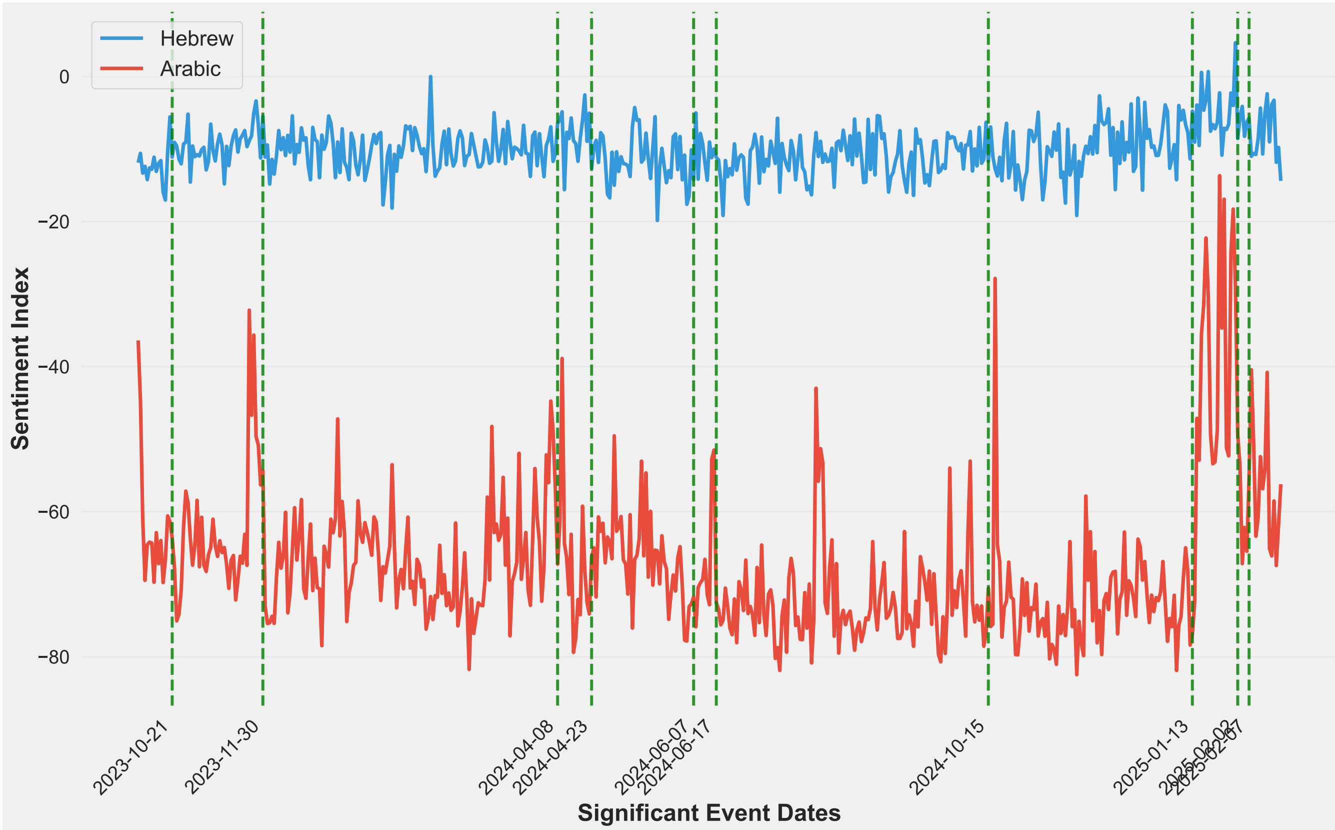

Figure 4: Daily sentiment index for Hebrew and Arabic Telegram channels, with vertical lines marking the top ten detected sentiment events.

five sentiment series, averaging 0.315 (ranged –0.034 to 1.000). Cross-language correlations peaked at 0.232 (Hebrew news–Arabic news) and reached –0.034 (Hebrew side–Arabic side), while internal correlations ranged from 0.109 to 0.222 for Hebrew and 0.113 for Arabic, indicating stronger alignment among mainstream news streams across languages and divergence among partisan "side" channels.

All series were stationary (ADF: $p < 0.05$), allowing Granger analysis ($max\_lag = 14$). Significant effects included *Arabic news → Hebrew commentary, Arabic news → Hebrew news, Hebrew side → Arabic news, and Arabic news → Hebrew side*, indicating mutual temporal influence. These results suggest that sentiment shifts in Arabic news channels may act as early signals for subsequent changes in Hebrew discourse and vice versa, reflecting cross-language narrative responsiveness.

Sentiment-detected Significant Events. Figure 4 overlays our top ten detected events on the daily Hebrew and Arabic sentiment indices. Overall, Hebrew sentiment averaged -10.10 ± 3.32 and Arabic 67.18 ± 10.23, with a moderate inter-channel sentiment correlation ($r = 0.33$) and stronger message-volume correlation ($r = 0.58$). Time-lag analysis peaked at Hebrew, leading Arabic by one day ($r = 0.28$). Table 2 in Appendix C. shows that these events coincide with pronounced pre/post shifts. For example, on `2024-10-15` Hebrew fell by 0.98 while Arabic rose by 8.96, and on `2023-11-30` both plunged (–3.66 and –24.00). These results confirm that our pipeline reliably captures robust, language-specific sentiment shifts.

Comparative Sentiment Dynamics Results. Figure 5 shows that both languages tracked the major conflict phases closely, with sharp sentiment swings at the onset of each bombardment and partial recovery during cease-fire intervals. A separate divergence analysis found an average Hebrew–Arabic gap of 55.3 ± 5.3 sentiment points, peaking during Bombardment periods (61.3) and narrowing to about 49.5 on quiet or "Other/No-event" days. Hebrew and Arabic sentiments were strongly correlated overall ($r = 0.84$, $p < 0.001$), especially during Military/Operation ($r = 0.85$) and Cease-fire/Truce phases ($r = 0.46$). Bombardment phases showed little within-period variation. Event intensity and divergence were tightly coupled ($r = 0.90$, $p < 0.001$), indicating that more severe actions produced the largest inter-community sentiment splits.

Conclusions and Future Work

Discussion. Our multilingual, time-aligned analysis shows that Arabic Telegram channels posted nearly twice as many messages as Hebrew ones and exhibited a far sharper negative tone, with Arabic sentiment spikes often

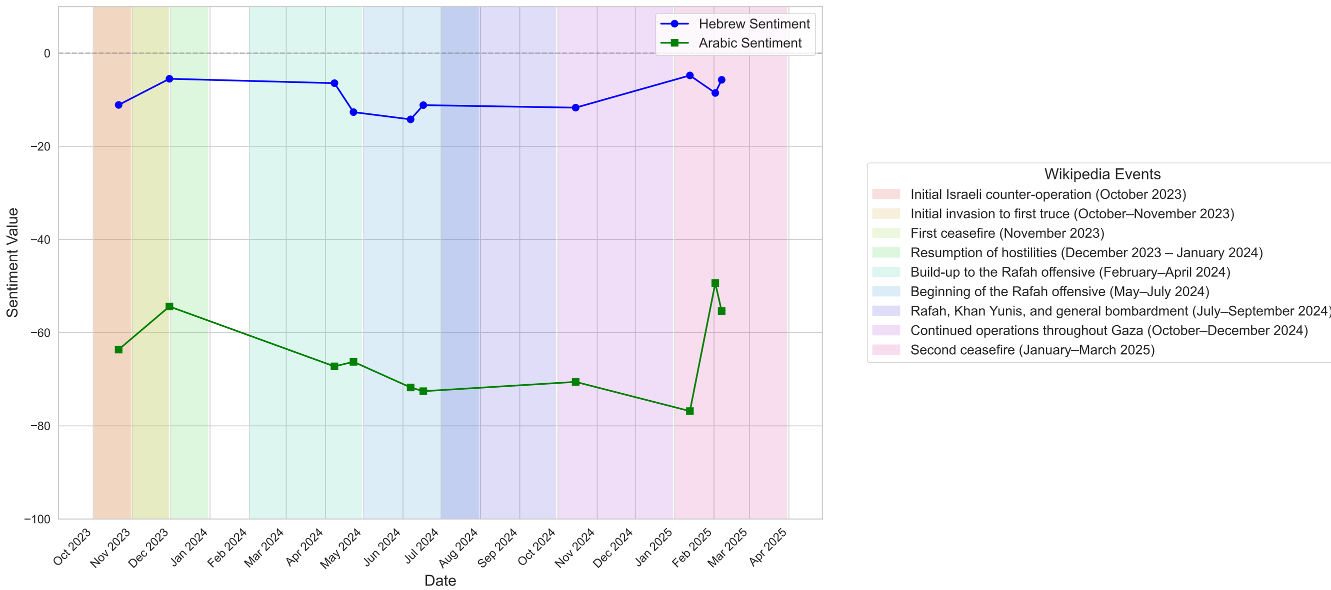

Figure 5: Sentiment values (indices) over time with Wikipedia events.

preceding similar moves in Hebrew discourse by up to two weeks—evidence that Arabic narratives can forecast Israeli-focused conversation. This lead–lag relationship offers journalists, policymakers, and OSINT analysts an early-warning signal for shifts in public mood, while the large, persistent sentiment gap underscores the need for language-specific outreach. Methodologically, combining language-tailored sentiment models with change-point and Granger tests delivered stable trends and event detection, yet the work is constrained by Telegram's selective visibility, potential classifier bias toward sarcasm or slang, and daily aggregation that mutes brief surges.

Conclusions. This study provides a multilingual, time-aligned examination of Telegram narratives surrounding the October 7, 2023 war. By fusing robust sentiment models with change-point and causality analyses, we exposed (i) systematic emotional asymmetries between Hebrew and Arabic communities, (ii) temporal influence flows in which Arabic news sentiment often foreshadowed Israeli discourse, and (iii) ten high-confidence sentiment events that co-occurred with major conflict milestones. Together, these contributions demonstrate that Telegram, despite its opacity and minimal moderation, can be mined for actionable, fine-grained insight into conflict-driven information dynamics.

Future Work. Three directions can be considered especially promising. (1) *Cross-conflict generalization.* Applying the same pipeline to wars in Ukraine, Sudan, or the South China Sea will test its portability and highlight platform-specific versus universal narrative patterns. (2) *Real-time early-warning.* Integrating the detectors into a streaming dashboard would allow journalists and humanitarian NGOs to receive hour-level alerts on emerging misinformation or escalation signals. (3) *Richer language understanding.* Fine-tuning large multilingual transformers on in-domain data and adding deception-style classifiers could capture nuanced rhetorical devices, satire, or coordinated inauthentic behavior that elude current models.

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Appendix A. Exploratory Data Analysis (EDA)

An initial assessment of data quality was performed, including examining the dataset's shape, identifying missing values, checking for duplicate messages, and generating descriptive statistics for numeric fields.

Univariate analyses were conducted to explore key distributions. We visualized the number of messages per group, the occurrence of null or empty messages, and the temporal distribution of messages over time based on the date fields.

Temporal patterns were analyzed by aggregating messages by hour of the day, day of the week, and month.

Bivariate and correlation analyses were then performed to examine relationships between numeric variables.

Categorical feature analyses included exploring the distribution of media types, forwarded messages, reply messages, and identifying the most active senders. We also analyzed basic text features, such as the presence of hashtags.

Finally, we enriched the dataset by merging external group metadata, using a predefined mapping based on the `group_name` field. This mapping, detailed in Appendix B, categorized each Telegram group by its language (Hebrew or Arabic) and ideological alignment (Israeli side, Palestinian side, Israeli commentary, Israeli news, or Palestinian news). Incorporating this metadata enabled more nuanced group categorization analyses, including comparative evaluations of message volume, engagement metrics, and narrative activity patterns across different group types and language communities.

Overall, the exploratory analysis provided a detailed overview of the Telegram dataset's structure, quality, behavioral patterns, and key engagement dynamics, forming a strong foundation for subsequent sentiment and narrative analyses.

Appendix B. Telegram Groups Mapping

To compare linguistic and narrative patterns across Telegram channels, we enriched every message with a small but carefully curated lookup table. Each record in the table is keyed by the public channel handle and supplies three descriptive attributes: (1) *Group Title* is the human-readable name that appears in the Telegram app, (2) *Language*, either Hebrew or Arabic, inferred from the channel's dominant language and verified by sampling messages, and (3) *Type*, a predefined ideological/functional class with five mutually-exclusive values: *Israeli side*, *Israeli commentary*, *Israeli news*, *Palestinian side*, or *Palestinian news*.

The above external metadata used for group categorization is shown in Table 1.

Table 1: Telegram groups metadata used for categorization by language and ideological alignment.

Group Name	Group Title	Language	Type
`idf_telegram`	IDF - The Official Channel	Hebrew	Israeli side
`ForumPressReleases`	Until the Last Hostage - The Official Page	Hebrew	Israeli side
`abualiexpress`	Abu Ali Express	Hebrew	Israeli commentary
`arabworld301news`	Arab World 301 News	Hebrew	Israeli commentary
`salehdesk1`	Abu Saleh The Arab Desk	Hebrew	Israeli commentary
`yediotnews`	News from the Field on Telegram	Hebrew	Israeli news
`Realtimesecurity1`	Real-Time News	Hebrew	Israeli news
`New_security8200`	News Channel 8200	Hebrew	Israeli news
`hamasps`	Hamas Movement	Arabic	Palestinian side
`qassambrigades`	Al-Qassam Brigades	Arabic	Palestinian side
`gazaalannet`	Gaza Now	Arabic	Palestinian news
`SerajSat`	Al-Aqsa Channel	Arabic	Palestinian news
`ShehabTelegram`	Shehab Agency	Arabic	Palestinian news

This mapping underpins every cross-group comparison reported in the main text and Appendix A, enabling us to contrast message volume, engagement, and sentiment trajectories between Hebrew- and Arabic-speaking communities and between official, news, and commentary sources on both sides of the conflict.

Appendix C. Sentiment Shifts Around Detected Events

Table 2 summarizes the sentiment changes observed one day before and after each of the top 10 significant events identified by our detection pipeline. It highlights notable shifts in both Hebrew and Arabic sentiment series, demonstrating the strength and direction of emotional responses surrounding key moments.

Appendix D. Wikipedia Parsing and Time-Period Extraction

This appendix describes the three-stage pipeline used to convert the relevant Wikipedia article into a structured timeline of conflict phases.

In the first stage, the full section hierarchy of the target article is retrieved, and each heading is recorded in a flattened sequence. These headings delineate the narrative segments of the conflict and provide the skeleton for the timeline.

Next, each heading is analyzed to infer explicit date ranges. A series of pattern-matching routines recognizes single dates (e.g. "7 October 2023"), month–year labels (e.g. "October 2023"), and multi-month intervals (e.g. "December 2023 – January 2024"). Matched date strings are converted into ISO-formatted start and end dates, and the duration of each period is calculated. The resulting intervals are then sorted chronologically to form a continuous sequence of conflict phases.

In the final stage, the article's main text is cleaned of non-content elements (navigation boxes, reference lists, tables, infoboxes) and segmented into sentences. Every occurrence of a recognized date format is located within its surrounding sentence, and that sentence is captured as a contextual annotation for the corresponding time period.

The output of this process is a single, chronologically ordered table in which each conflict phase is defined by a precise date range and accompanied by a representative text excerpt. This structured timeline underpins the alignment of detected sentiment events with documented wartime milestones.

A summary of the extracted conflict phases and their mapped date ranges is provided in Table 3.

Table 2: Sentiment changes around the top 10 detected events. Values reflect the average sentiment index one day before and after each event.

Date	Event	Hebrew Before	Hebrew After	Delta Hebrew	Arabic Before	Arabic After	Delta Arabic
2024-10-15	Event 1	-10.29	-11.27	-0.98	-74.82	-65.87	+8.96
2025-02-07	Event 2	-4.59	-8.71	-4.13	-49.31	-54.05	-4.74
2024-06-17	Event 3	-10.52	-13.82	-3.30	-64.89	-74.37	-9.48
2023-11-30	Event 4	-7.57	-11.23	-3.66	-48.39	-72.40	-24.00
2025-02-02	Event 5	-4.79	-7.37	-2.58	-32.37	-56.37	-24.00
2025-01-13	Event 6	-7.80	-4.17	+3.64	-73.26	-41.71	+31.55
2024-06-07	Event 7	-12.92	-10.23	+2.69	-71.83	-70.90	+0.93
2024-04-08	Event 8	-10.34	-8.19	+2.15	-56.93	-63.58	-6.65
2024-04-23	Event 9	-7.43	-10.55	-3.12	-71.10	-64.61	+6.50
2023-10-21	Event 10	-12.23	-9.38	+2.85	-64.62	-66.51	-1.89

Table 3: Parsed conflict phases extracted from Wikipedia section titles, each mapped to a specific date range.

Title	Period	Start Date	End Date	Duration
Initial Israeli Counter-Operation (October 2023)	October 2023	2023-10-01	2023-10-31	31
Initial Invasion To First Truce (October–November 2023)	November 2023	2023-11-01	2023-11-30	30
First Ceasefire (November 2023)	November 2023	2023-11-01	2023-11-30	30
Resumption Of Hostilities (December 2023 – January 2024)	December 2023	2023-12-01	2023-12-31	31
Build-Up To The Rafah Offensive (February–April 2024)	April 2024	2024-04-01	2024-04-30	30
Beginning Of The Rafah Offensive (May–July 2024)	July 2024	2024-07-01	2024-07-31	31
Rafah, Khan Yunis, and General Bombardment (July–September 2024)	September 2024	2024-09-01	2024-09-30	30
Continued Operations Throughout Gaza (October–December 2024)	December 2024	2024-12-01	2024-12-31	31
Second Ceasefire (January–March 2025)	March 2025	2025-03-01	2025-03-31	31
7 October Hamas-Led Attack On Israel	7 October 2023	2023-10-07	2023-10-07	1