

Modeling Hot-Topic Evolution And Public Opinion In Sports Event UGC

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User-generated content (UGC) surrounding sports events evolves rapidly as on-field incidents reshape what fans discuss, how they respond emotionally, and how attention spreads. Existing approaches often treat topic discovery, sentiment classification, and popularity forecasting as separate tasks, making it difficult to follow topic continuity, splitting, and merging across short time windows. This study proposes ETSG-Net, an event-aware temporal semantic graph network that aligns posts with match events, fuses event and text representations through cross-attention, and links window-level topic nodes using semantic, entity, keyword, and event-based evidence. Topic states, sentiment probabilities, interaction intensity, and event representations are then used jointly to classify evolutionary states and forecast short-term popularity. Experiments on the TED-S/MUNLIV sports subset, with transfer evaluation on a 2022 FIFA World Cup corpus, yielded a Topic-F1 of 0.867, a sentiment macro-F1 of 0.901, an Evolution-F1 of 0.842, and trend-prediction MAE and RMSE values of 0.071 and 0.094, respectively. Ablation, robustness, and cross-event tests indicate that event conditioning and temporal graph structure are the main sources of improvement, while sentiment and interaction features strengthen popularity forecasting. The findings show that coupling match events with dynamic topic graphs offers a practical way to trace fast-moving public opinion during sports events.

Keywords: temporal semantic graphs; sentiment classification; cross-window association; popularity forecasting; multitask learning

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1. Introduction

Large sports events concentrate public attention within a short period. Match play, refereeing decisions, player performances, and unexpected incidents prompt posts, reposts, comments, and emotional reactions across social media platforms. A public FIFA World Cup dataset contains more than 28 million tweets in 69 languages, illustrating the scale and reach of event-related UGC [1]. Posting volume and sentiment vary over the course of a match, with visible local shifts around goals [2], and domain-adapted representations improve sentiment classification on football-specific corpora [3].

Sports-event UGC differs from ordinary static com-

ments in three ways: real-world play continuously reshapes meaning across scores and match stages; topic life cycles are often measured in minutes, with discussions splitting or merging after a goal or controversial call; and popularity, sentiment, and diffusion interact rather than evolving independently. Word-frequency counts or isolated sentiment scores therefore cannot reconstruct the full trajectory of public opinion. A useful model must instead identify what is discussed, trace how topics change, explain sentiment responses, and anticipate near-term attention shifts. Event-detection research has accordingly moved from keyword statistics toward semantic, spatiotemporal, and multi-source representations. Afyouni et al. surveyed multi-feature and multi-source approaches and highlighted

noise, cross-platform adaptation, and spatiotemporal scope as recurring challenges [4]; Embed2Detect clusters word embeddings within time windows to capture short-lived events [5]; Deep-Eware couples deep feature extraction with spatial clustering for spatiotemporal event detection [6]; and Kolajo et al. combined knowledge bases and incremental clustering to improve detection in noisy social-media text [7].

More recent work models topics and sentiment jointly rather than as a rigid pipeline. Hanny and Resch combined pretrained language representations, dimensionality reduction, and clustering, producing better topic quality and more consistent within-cluster sentiment than sequential baselines [8]. This line of work supports joint and temporal modeling but does not provide a framework that aligns match events with dynamic topic structure and short-lived sentiment peaks in sports-event UGC.

To address these gaps, this paper introduces the Event-Aware Temporal Semantic Graph Network (ETSG-Net). Its contributions are threefold. First, it adds key events, match stage, score difference, and relative time to the UGC representation and uses event-text cross-attention to condition online expressions on match context. Second, it represents topics within each time window as graph nodes and builds cross-window edges from semantic similarity, entity overlap, event relevance, and keyword overlap; temporal graph attention then distinguishes emergence, continuation, splitting, merging, and disappearance. Third, it combines topic representations, sentiment probabilities and intensity, and interaction-based popularity in a trend predictor, while a joint loss constrains topic, sentiment, evolution, and popularity objectives. Experiments evaluate overall performance, evolutionary behavior, ablations, parameter sensitivity, robustness, and cross-event transfer.

2. Methods

2.1. Problem Definition and Overall Framework

Let the i UGC be $x_i = (c_i, t_i, u_i, e_i)$, where c_i is the text content, t_i is the publication time, u_i is the interaction features such as likes, replies, and shares, and e_i is the event most relevant to this UGC in time. Given consecutive windows $W_1, \dots, W_T$, the model needs to obtain the topic set, topic popularity, and sentiment distribution for each window, determine the evolutionary relationship between adjacent windows, and finally predict the popularity of the next window.

2.2. Sports Event UGC Preprocessing and Event Alignment

2.2.1. UGC Cleaning and Sports Entity Recognition

The cleaning stage preserves hashtags, emojis, team abbreviations, and player names when they carry semantic information. It removes URL parameters, repeated advertising templates, content-free reposts, and exact duplicates. Character-level normalization standardizes capitalization, repeated spaces, and common abbreviations, while emojis are mapped to tags that retain their affective direction. The named-entity recognizer uses six classes: Player, Team, Coach, Referee, Score, and Competition. An alias table links abbreviations, nicknames, and account names to the same entity, and trainable type embeddings encode entity positions. This design follows earlier work on noisy social-media terms, which preserves event-related information through semantic enrichment and ambiguity resolution [7].

2.2.2. Extraction of Key Match Events

The sequence of match events is denoted by $E = \{e_m\}_{m=1}^M$. It includes Kick-off, Goal, Card, Substitution, Penalty, VAR, and Full-time. Each event records its minute, score difference, participating teams, and match stage. Events with identical timestamps are ordered by the official time record and then assigned unique codes using event-type priority and temporal distance. The event stream contains only objective match information; it excludes sentiment labels derived from UGC, thereby preventing target leakage.

2.2.3. UGC and Event Time Alignment

An alignment window is defined from the difference between post time and event time. For UGC item i , candidate events are restricted to $[t_i - \Delta_b, t_i + \Delta_f]$. Events involving teams or players mentioned in the text receive priority. If no explicit event falls within the window, the item is assigned a Normal-play tag. The forward window is shorter than the backward window so that delayed discussion after an event remains covered. Using match progress as an external time anchor reduces the semantic drift that can arise when posts are aligned only by publication time.

2.3. Event-Aware UGC Semantic Encoding

2.3.1. UGC Context Semantic Representation

The cleaned text is passed to a pretrained Transformer encoder, and the representation of the first token is used as the contextual embedding:

$$h_i^x = \text{Encoder}(c_i; \theta_x) \quad (1)$$

Here, $h_i^x \in \mathbb{R}^d$ is the semantic vector for UGC item i , d is the latent dimension, and θ_x denotes the text-encoder

parameters. Entity labels and affective expressions are retained during training, allowing the encoder to distinguish references to players, referees, and scores.

2.3.2. Sports Event Embedding

The event representation combines four components: event type, match stage, relative time, and score difference.

$$h_i^e = E_{evt}(e_i) + E_{stage}(s_i) + E_{time}(\tau_i) + E_{score}(q_i) \quad (2)$$

In Eq. (2), E_{evt} , E_{stage} , E_{time} , and E_{score} are the embedding functions for event type, match stage, relative time, and score difference, respectively. Here, s_i denotes the match stage, τ_i is the elapsed time between the UGC item and the event, q_i is the current score difference, and $h_i^e \in \mathbb{R}^d$ is the resulting event-conditioned vector.

2.3.3. Event-Text Cross-Attention Fusion

To prevent the event vector from affecting every UGC item in the same way, the model uses cross-attention to compute a conditional semantic representation:

$$h_i^f = \text{LayerNorm} \left(h_i^x + \text{softmax} \left(\frac{Q_i K_i^\top}{\sqrt{d_k}} \right) V_i \right) \quad (3)$$

Here, $Q_i = h_i^x W_Q$, $K_i = h_i^e W_K$, and $V_i = h_i^e W_V$ are the query, key, and value vectors; W_Q , W_K , and W_V are trainable projection matrices, d_k is the key dimension, and h_i^f is the fused event-aware representation. The residual connection retains the original text semantics, while the attention weights regulate how strongly the matched event contributes to each UGC item.

2.4. Dynamic Hot Topic Discovery

2.4.1. Sliding Time Window Construction

The match timeline is divided into overlapping windows W_t . Window length governs semantic stability, while the step size determines temporal resolution. Very short windows may contain too few examples for low-frequency topics; overly long windows may combine discussions triggered by different events. Sensitivity analysis led us to use a 3-minute window with a 1-minute step. The same setting is retained in the robustness experiments so that differences are attributable to the applied perturbations.

2.4.2. Semantic Clustering and Candidate Topic Generation

Within each W_t , density-based clustering is applied to h_i^f , and outliers are removed. The candidate topic vector z_k^t is calculated as an attention-weighted mean of the cluster members, with weights reflecting semantic centrality and interaction strength. Entities and keywords are used

to label the resulting topics for visualization only; these labels are not used during supervised training. Semantic-embedding methods are better suited than pure bag-of-words representations to synonymous expressions in short texts [5, 8].

2.4.3. Comprehensive Topic Popularity Calculation

Topic popularity considers post size, interaction size, growth rate, and dissemination range simultaneously:

$$H_k^t = \alpha V_k^t + \beta E_k^t + \gamma G_k^t + \delta R_k^t, \quad \alpha + \beta + \gamma + \delta = 1 \quad (4)$$

Here, V_k^t is the normalized post count, E_k^t measures interaction volume from likes, replies, and reposts, G_k^t is the growth rate from the preceding window, and R_k^t is unique-user coverage. The coefficients α , β , γ , and δ are non-negative and sum to 1. The resulting score $H_k^t \in [0, 1]$ is the overall popularity of topic k in window t .

2.5. Topic-Evolution Modeling with a Temporal Semantic Graph

2.5.1. Dynamic Topic Graph Construction

For each time window, the model constructs graph $G_t = (V_t, E_t)$. Node $v_k^t \in V_t$ represents a candidate topic. Its attributes include z_k^t , H_k^t , the mean sentiment vector, and the event representation. Intra-window edges encode co-occurrence among topics at the same stage; cross-window edges represent possible evolutionary links. Because the graph is updated locally, the computational cost is driven mainly by the number of topics in the current window rather than by repeated clustering of the full UGC history.

2.5.2. Cross-Window Topic Association

The association score of adjacent window nodes is defined as:

$$S_{ij}^{t,t+1} = \omega_1 \cos(z_i^t, z_j^{t+1}) + \omega_2 J(A_i, A_j) + \omega_3 C_{evt}(i, j) + \omega_4 J(K_i, K_j) \quad (5)$$

Here, $\cos(\cdot)$ is cosine similarity; A_i and A_j are the entity sets of the two topics; K_i and K_j are their keyword sets; $J(\cdot)$ denotes Jaccard similarity; and $C_{evt}(i, j)$ indicates whether the topics are associated with the same event or with consecutive events. The non-negative weights ω_1 through ω_4 sum to 1. Associations above the threshold become temporal edges, and their scores serve as attention priors.

2.5.3. Temporal Graph Attention Mechanism

The propagation weight of node i to neighbor j is:

$$a_{ij}^t = \text{softmax}_j \left(\text{LeakyReLU} \left(a^\top \left[Wh_i^t \| Wh_j^t \| W_r r_{ij}^t \right] \right) \right) \quad (6)$$

Here, h_i^t and h_j^t are node states, W and W_r are trainable matrices, r_{ij}^t is the edge feature, $\|$ denotes vector concatenation, a is the attention vector, and a_{ij}^t is the normalized neighbor weight. The state update is then written as:

$$g_i^{t+1} = \text{GRU} \left(\sum_{j \in \mathcal{N}(i)} a_{ij}^t Wh_j^t, g_i^t \right) \quad (7)$$

Here, $\mathcal{N}(i)$ is the set of cross-window neighbors of node i , and g_i^t is its historical state. The GRU preserves persistent information while suppressing noise confined to a single window.

2.6. Joint Topic-Sentiment Modeling of Public Opinion

2.6.1. UGC Sentiment Classification

The sentiment head classifies the fused representation into three categories:

$$p_i^{\text{sent}} = \text{softmax} \left(W_s h_i^f + b_s \right) \quad (8)$$

Here, W_s and b_s are the classifier parameters, while $p_i^{\text{sent}} = [p_i^-, p_i^0, p_i^+]$ contains the negative, neutral, and positive probabilities. Class imbalance is handled with weighted cross-entropy; each class weight is the reciprocal of the square root of its frequency in the training set.

2.6.2. Sentiment Intensity Estimation

Polarity alone cannot distinguish a mild complaint from an intense dispute. We therefore define sentiment intensity as $I_i = p_i^+ + p_i^-$ and direction as $D_i = p_i^+ - p_i^-$. A larger I_i indicates a more decisive sentiment, while $D_i < 0$ indicates that negative sentiment dominates. At the topic-window level, sample sentiments are averaged with interaction-based weights, limiting the influence of repetitive posts with little engagement.

2.6.3. Joint Topic-Sentiment Representation

For topic k , the joint state is defined as:

$$r_k^t = [z_k^t \| \bar{p}_k^t \| H_k^t \| e_k^t] \quad (9)$$

Here, z_k^t is the topic embedding, $\bar{p}_k^t$ is the topic's mean sentiment-probability vector, H_k^t is overall popularity, e_k^t represents the dominant event in the window, and r_k^t is the joint public-opinion state. This state is passed to both the evolution classifier and the trend predictor, allowing sudden sentiment shifts and growth in interaction to influence the topic state inferred for the next time step.

2.7. Public-Opinion Popularity and Trend Forecasting

The joint states from the most recent L windows are passed to the time-series predictor to estimate popularity in the next window:

$$\hat{H}_{t+1} = f_{\text{GRU}}(r_{t-L+1}, \dots, r_t; \theta_h) \quad (10)$$

Here, r_t is the popularity-weighted global state for window t , L is the look-back length, θ_h denotes the predictor parameters, and $\hat{H}_{t+1}$ is the forecast popularity. The difference $\hat{H}_{t+1} - H_t$ is then compared with threshold ϵ to classify the trend as Rising, Stable, or Declining. Continuous popularity is evaluated with MAE and RMSE, whereas the three trend classes are evaluated with macro-F1.

2.8. Joint Loss Function and Model Training

ETSG-Net employs multi-task joint training:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{\text{topic}} + \lambda_2 \mathcal{L}_{\text{sent}} + \lambda_3 \mathcal{L}_{\text{evo}} + \lambda_4 \mathcal{L}_{\text{trend}} + \eta \| \Theta \|_2^2 \quad (11)$$

Here, $\mathcal{L}_{\text{topic}}$ is the topic-consistency contrastive loss, $\mathcal{L}_{\text{sent}}$ is sentiment cross-entropy, $\mathcal{L}_{\text{evo}}$ is the five-class evolution loss, and $\mathcal{L}_{\text{trend}}$ combines popularity regression with trend classification. The coefficients λ_1 through λ_4 weight the four tasks, η controls L_2 regularization, and Θ contains all trainable parameters. The model is optimized with AdamW and early stopping; the stopping criterion combines validation macro-F1 with trend MAE.

3. Results and discussion

3.1. Dataset and Experimental Setup

The main experiments use MUNLIV, the sports subset of the public TED-S dataset, which records the continuous Twitter stream around the 2019 Premier League match between Manchester United and Liverpool: 99,837 tweets were collected and 41,721 remain after deduplication, with sub-event and sentiment annotations provided [9]. Cross-event evaluation uses the 2022 World Cup corpus of 132,115 football-related tweets reported in [3]; reference [1] is used only to establish the scale and multilingual diversity of World Cup social media and is not part of the transfer test. Training, validation, and test windows for MUNLIV are split chronologically to prevent information leakage. Adjacent topic nodes are labeled Continuation when they share a sub-event and similar semantics, while Split, Merge, Emergence, and Disappearance follow predecessor-successor links, with two annotators reviewing borderline cases. Baselines include LDA-TFIDF, BERT-Clustering, BERTopic-style clustering, and Temporal GNN. These four baselines were selected to span the

main methodological families used for social-media topic and event analysis—lexical (LDA-TFIDF), semantic clustering without cross-window structure (BERT-Clustering, BERTopic-style), and temporal graph structure without event conditioning (Temporal GNN)—so that the contribution of each ETSG-Net component can be isolated.

Topic-F1, NMI, sentiment macro-F1, Evolution-F1, MAE, and RMSE jointly measure topic identification, cluster consistency, sentiment classification, evolution recognition, and popularity forecasting. All metrics reported in Tables 2 and 3 are averaged over five independent training runs with different random seeds; standard deviations were below 0.010 for every metric unless stated otherwise. Robustness tests keep the trained model fixed and perturb only the test inputs. Window length, step size, neighborhood size K , and the trend-loss weight were selected using the sensitivity analysis on the MUNLIV validation split only (Section 3.6) and then held fixed when transferring to the World Cup corpus, so no tuning used the transfer-test data. Table 1 summarizes the datasets and main settings.

3.2. Overall Performance Comparison of ETSG-Net

Table 2 reports performance on the common test windows. ETSG-Net achieves a Topic-F1 of 0.867, 8.6 points above BERT-Clustering, and an NMI of 0.824; its sentiment macro-F1 of 0.901 shows that event conditioning does not weaken sentiment discrimination, and its Evolution-F1 of 0.842 clearly exceeds the Temporal GNN baseline. Forecasting errors fall to an MAE of 0.071 and an RMSE of 0.094. LDA-TFIDF performs poorly on both topic and evolution tasks because short texts are lexically sparse and wording shifts quickly across windows; semantic clustering improves topic recognition but still struggles with splitting and merging without cross-window structure, a gap Temporal GNN narrows and ETSG-Net closes further through event-aware representations and the joint topic-sentiment state. In terms of computational cost, the temporal graph attention step (Section 2.5.3) scales with the number of active topic nodes and the fixed neighborhood size $K = 8$ rather than with the full UGC history, since only local cross-window edges are retained; under this setting, per-window updates and next-window forecasting complete well within the 1-minute step size used in the sliding-window construction, supporting near-real-time use during a live match.

3.3. Dynamic Evolution Analysis of Hot Topics in Sports Events

Before kick-off, discussion centers on line-ups and predicted results; once play begins, attention shifts to possession and tactics. Goals create score-related threads while

refereeing and VAR discussions develop in parallel; these later converge as score-related posts settle on the result and the VAR and refereeing threads merge into a broader controversy, before substitution talk gives way to post-match player assessments. These paths show why a single topic label cannot capture public opinion around a sports event, since one incident may generate several discussions that evolve at different rates. The temporal graph records this structure through semantic edges and node degrees, so splitting and merging can be inferred without manually tracking keywords. The first window after a key event is driven mainly by growth in popularity and negative-sentiment intensity, whereas semantic similarity and entity overlap carry more weight during ordinary play. This pattern is consistent with the event-driven nature of sports UGC, in which recurring event entities and sentiment peaks bridge short-term vocabulary shifts. Figure 1 illustrates a path from pre-match predictions through key match events to post-match evaluation.

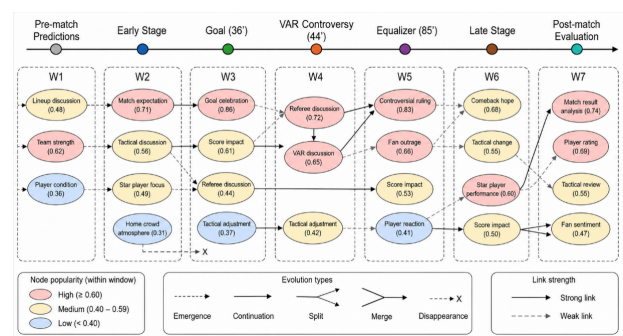


Fig. 1. Dynamic evolution of sports-event topics. Nodes represent topic clusters within each time window, node size denotes topic popularity, and edges denote cross-window semantic, entity, keyword, or event-based association linking pre-match, in-match, and post-match discussion

3.4. Event-Driven Public-Opinion Response and Trend Forecasting

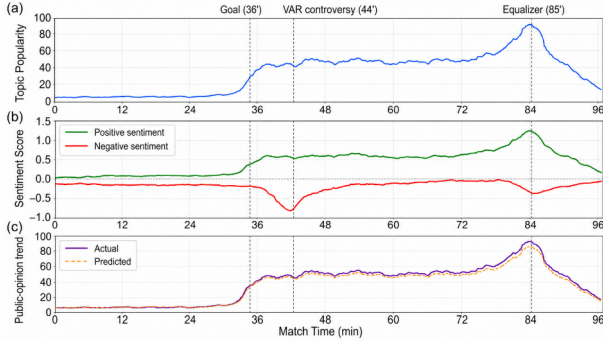
Figure 2 plots topic popularity, positive and negative sentiment, and the observed and forecast trends. Popularity rises sharply after the 36th-minute goal alongside a rise in positive sentiment; a VAR controversy near the 44th minute produces a local peak in negative sentiment, and the 85th-minute equalizer creates the match's largest popularity peak. The forecast tracks all three shifts and deviates only slightly near the peaks, because ETSG-Net conditions on the current event state rather than relying on past popularity alone, allowing it to respond earlier than a sequence model would.

Table 1. Dataset statistics and experimental settings.

Item	TED-S / MUNLIV	World Cup transfer set	Setting
UGC posts	41,721 non-duplicates	132,115	chronological split
Time scope	55 min	tournament period	event-aligned
Sentiment labels	3	3	negative / neutral / positive
Event labels	sub-event ground truth	match-event alignment	five evolution states
Window / step	3 min / 1 min	3 min / 1 min	shared
Hidden dimension	256	256	shared
Graph neighbors	8	8	shared
Optimizer	AdamW	AdamW	seed = 20260825

Table 2. Overall performance comparison. Values are means over 5 independent runs; standard deviations ≤ 0.010 for all metrics.

Model	Topic F1	NMI	Sentiment Macro-F1	Evolution F1	Trend MAE	Trend RMSE
LDA-TFIDF	0.712	0.684	0.756	0.641	0.128	0.171
BERT-Clustering	0.781	0.742	0.842	0.703	0.111	0.149
BERTopic-style	0.813	0.779	0.861	0.721	0.103	0.141
Temporal GNN	0.828	0.791	0.873	0.798	0.086	0.116
ETSG-Net	0.867	0.824	0.901	0.842	0.071	0.094

**Fig. 2.** Event-driven topic, sentiment and public-opinion evolution. Panels show (a) topic popularity, (b) positive and negative sentiment scores, and (c) actual versus predicted public-opinion trend across match time (minutes), with vertical markers at the goal, VAR controversy, and equalizer

3.5. Ablation Experiments

Table 3 isolates the contribution of each component. Removing event encoding lowers Topic-F1 from 0.867 to 0.831 and Evolution-F1 to 0.794, showing that event context supports both clustering and temporal linkage. Removing the temporal graph causes the largest decline in Evolution-F1, to 0.731, confirming that graph structure is central to recognizing Split and Merge states. Excluding sentiment fusion mainly reduces sentiment macro-F1 and raises trend MAE, indicating that sentiment intensity aids popularity forecasting; replacing cross-attention with simple event-vector

concatenation reduces Topic-F1 to 0.839, and removing interaction features raises trend MAE from 0.071 to 0.078.

3.6. Parameter Sensitivity Analysis

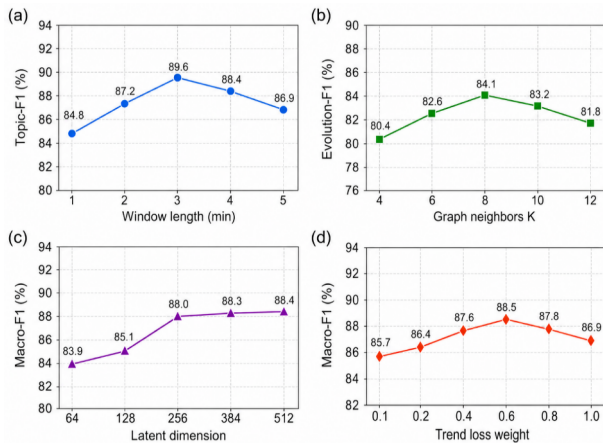
Figure 3 examines window length, graph neighborhood size, latent dimension, and the trend-loss weight. Topic-F1 improves as the window grows from 1 to 3 minutes and declines beyond that as discussions triggered by adjacent events begin to mix. Evolution-F1 peaks at $K = 8$: fewer neighbors omit plausible split or merge paths, while larger neighborhoods add weak edges. Increasing the latent dimension from 128 to 256 yields a clear gain, with little further benefit beyond that; a trend-loss weight near 0.6 gives the best overall macro-F1, as larger values overemphasize popularity regression and weaken topic separation.

4. Conclusion

This study presents ETSG-Net for tracing rapidly changing topics and public opinion in sports-event UGC by combining event-aligned text encoding, dynamic topic graphs, sentiment intensity, and interaction features within a joint learning framework. On the reported test set, ETSG-Net achieves a Topic-F1 of 0.867, a sentiment macro-F1 of 0.901, and an Evolution-F1 of 0.842, with popularity-forecasting MAE and RMSE of 0.071 and 0.094. Ablation results indicate that event context reduces ambiguity from similar wording under different match conditions, while the temporal graph is essential for identifying topic splitting and merging; the model also remains comparatively stable un-

Table 3. Ablation study of ETSG-Net. Values are means over 5 independent runs; standard deviations ≤ 0.010 for all metrics.

Variant	Topic F1	Sentiment Macro-F1	Evolution F1	Trend MAE
Full ETSG-Net	0.867	0.901	0.842	0.071
w/o Event	0.831	0.879	0.794	0.083
w/o Temporal Graph	0.824	0.894	0.731	0.087
w/o Sentiment Fusion	0.846	0.862	0.812	0.081
w/o Cross-Attention	0.839	0.884	0.801	0.084
w/o Interaction	0.851	0.895	0.819	0.078

**Fig. 3.** Parameter sensitivity analysis. Panels report Topic-F1 and Evolution-F1 on the MUNLIV validation split as window length, graph neighborhood size K, latent dimension, and trend-loss weight are varied in turn

der 20% data loss, textual perturbation, and transfer from league to World Cup data. These results should be read within the study's current scope: sentiment estimates remain vulnerable to sarcasm, irony, and multilingual writing; event alignment depends on accurate timestamps; the main MUNLIV results come from a single 2019 Premier League match, so they should be read as an in-match case study pending multi-match validation; the experiments focus on football posts from a limited number of platforms and event types, and applying the same event taxonomy to sports with different stoppage and scoring structures—such as basketball or tennis—would require redefining the event vocabulary in Section 2.2.2; and the cost of updating graphs at very large scale has not yet been fully assessed. Future work should evaluate multimodal event alignment, replicate the study on multilingual and multi-platform datasets, report annotation agreement and error cases in greater detail, and test adaptive windows and edge-pruning strategies.

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