# Small-Large Model Collaboration in Public Opinion Topic Discovery: A Case Study with the Pager Bomb Attack

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## I. INTRODUCTION

ON September 12, 2024, a serious cyber operation was launched against Lebanon's paging systems. Thousands of pagers exploded simultaneously across Lebanon, causing fires, injuries, and fatalities. This event left an indelible mark on Lebanon and the world, serving as a wake-up call for the need to secure critical systems in an increasingly interconnected and vulnerable digital landscape. In the aftermath of this incident, many believe that everyday electronic devices can serve as weapons for geopolitical tensions [1], and social media can accelerate the wide spread of such kind of event [2]. The attack also highlighted the growing role of cyber warfare in modern conflicts and the dangerous potential for such operations to cause significant harm beyond traditional battlefields.

Existing research has focused on public opinion analysis of routine events such as terrorist attacks and violent protests [3]–[5]. However, few studies have empirically analyzed different public attitudes towards these changes for the form of war, especially differences in different linguistic spaces in different nations. At the same time, for such an unprecedented attack, what are the consequences in this globalization world.

In this paper, we analyzed the English and Arabic comments generated on three social media platforms, YouTube, Twitter/X, and TikTok. The Lebanon bombing generated a large number of civilian casualties, which could easily create large-scale public opinion on social media. Additionally, the Middle East has limited manufacturing capacity and often relies on imported goods. It can be assumed that the bombing raised critical concerns regarding the safety of electronic devices, leading to similar discussions across different language spaces on social media.

However, social media public comments have problems of multilingualism, semantic complexity, and noise [6]. Existing unsupervised topic discovery methods rely on the representational power of pre-trained language models [7], and semi-supervised methods are unable to continuously add supervised labels to deal with the increasing number of comment topics [8]. While Large Language Models (LLMs) have shown good potential in capturing complex semantics [9], [10], they still face challenges in handling the rapidly evolving dynamics of public opinion topics. To address these issues, integrating large and small models can effectively balance semantic stability with adaptability. Large Language Models can function as semantic anchors, capturing the dynamically changing semantics of comments through their large number of parameters and providing supervisory signals, whereas small models are capable of quickly modeling local topics. Such co-evolving hybrid architectures are rarely explored.

This study attempts to answer the following questions:

Q1: What are the public opinions towards the pager bomb event?

Q2: Are there any differences in public attitudes towards warfare changes in such cyber-physical deadly attacks in different language spaces?

Q3: How will the pager bomb event affect global electronics sales?

We propose a semi-supervised topic discovery continuous optimization methodology with large and small model


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collaboration, aiming to continuously analyze the public topics and attitude in different linguistic spaces. Furthermore, we propose a blockchain-based security governance framework that leverages Decentralized Autonomous Organizations (DAOs) to implement full lifecycle monitoring of electronic devices, in order to make sure that people can safely use these products.

The primary contributions of this study are as follows.

1) We propose a continuous optimization method for topic analysis with small and large model collaboration, which substantially improves the efficiency of topic modelling, with a single collaboration round improving accuracy by about 3%.
2) We present a data-driven analysis of multilingual opinion topics and public attitudes on the pager bomb incident, revealing common public concerns about the safety of electronic devices.
3) We propose a trustable framework to resolve the issue of ensuring the trustworthiness and security of electronic devices, which can resolve the issue of tracing every phase of the product lifecycle to provide secured manufacturing and usage.

The remainder of the paper is organized as follows. Section II reviews the research related to topic modeling and language modeling. Section III outlines the details of the events and the data situation. Section IV describes the present large and small model collaboration approach, including the collaboration mechanism, topic distribution representation, cross-clustering, and large model error correction. Section V presents the experimental results. Section VI discusses the changing form of warfare, how to manufacture trustworthy electronic devices based on DAO. Section VII summarizes the paper.

## II. RELATED WORK

### A. TOPIC MODELING APPROACH

Topic modeling has been explored for a long time. There are probabilistic models like LDA [11], Hierarchical Topic Models [12], [13], Multilingual Topic Models [14], [15], and Short Text Topic Modeling [16], [17], which are widely used. However, in the actual text corpus, there usually are certain correlations between topics, the direct application of LDA modeling often fails to produce the desired effect [18]. Neural network-based topic modeling research, like Feedforward neural networks, variational autoencoder, and recurrent neural networks has demonstrated efficiency. Among these, variable auto-encoder (VAE) performs well [19].

### B. LANGUAGE MODELLING APPROACH

The comprehension and acquisition of representations of potential linguistic features is important [20]. Language modelling can be defined as the prediction of subsequent words in a self-monitoring manner, which is known as the "pre-training" approach [21]. The range of pre-training models extends from Word2Vec [22], to BERT [23], and recently LLMs [24]. Subsequently, fine-tuning a limited number of model weights has been recognized as a more personalized and efficient technique, for example: efficient adapter-based parameter fine-tuning [25]. It is crucial to say that the LLM does not represent a total replacement for the previous deep learning models. Instead, LLMs offer novel training inference pathways and enrich the training paradigm for natural language processing tasks.

### C. HYBRID AND COLLABORATIVE MODELING APPROACHES

Recent work has explored combining different modeling paradigms to leverage their complementary strengths [26]–[29]. These approaches range from integrating neural networks with probabilistic topic models to collaborative frameworks where multiple specialized models work together for enhanced performance. However, existing hybrid approaches typically focus on static integration rather than dynamic collaboration between large and small models. The challenge of continuously adapting to rapidly evolving topics in multilingual, noisy social media environments, particularly for unprecedented events like cyber-physical attacks, remains largely unaddressed in current literature.

## III. DATA COLLECTION

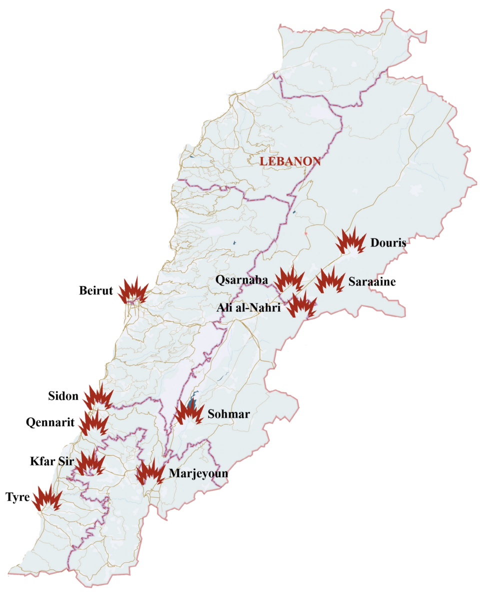


FIGURE 1: Locations of the two explosions in Lebanon

### A. EVENT DETAIL

On September 17, 2024, a communications equipment explosion in Lebanon killed nine individuals and injured approximately 2,750 others. Two days later (September 19, 2024), a secondary explosion triggered by Israel resulted in 25 fatalities and 608 injuries. These incidents occurred during the low-intensity conflict between Israel and Hezbollah in Lebanon. As illustrated in Figure 1, the explosions affected multiple locations across Lebanon. Traceability analysis identified the pagers' origins with Golden Apollo (Taiwan, China) and BAC CONSULTING KFT (Hungary). On November 10, 2024, an Israeli spokesperson confirmed Prime Minister Benjamin Netanyahu's approval of the operation against Hezbollah in Lebanon.

### B. DATASETS

To investigate public responses, we collected social media data from TikTok, YouTube, and Twitter/X between September 17 and 25, 2024. A distributed web crawler was developed to capture 13,867 TikTok comments, 4,045 YouTube comments, and 11,649 Twitter/X posts. To ensure user privacy, all data was anonymized to exclude personally identifiable information (e.g., user IDs, geolocation) and restricted to academic research use only. To reduce bots and spam comments, we removed duplicate, overly short, and emoji-only comments.

The final dataset comprised 29,561 entries. Temporal distribution of the data is summarized in Fig. 2.

In addition, to ensure the reliability of spam comment annotations, three independent annotators participated in the labeling process, with detailed agreement metrics and divergence analyses provided in Appendix A. The inter-annotator agreement reached excellent levels (Cohen$\kappa > 0.8$), with minor discrepancies primarily focusing on conversational comments, which were resolved through consensus revision.

The temporal distribution of comment volumes across TikTok, YouTube, and Twitter/X from September 17 to 25, 2024, exhibited distinct patterns. Following the initial explosion on September 17, all platforms experienced rapid growth in engagement, with TikTok and YouTube reaching peak volumes of 4,867 and 8,539 comments, respectively, within 48 hours. However, engagement on these platforms declined steadily after September 19. In contrast, Twitter demonstrated delayed responsiveness: while its comment volume remained stable until September 24, a sharp surge occurred on September 25 (6,044 comments), surpassing TikTok's peak volume by 124%. This 144-hour lag (from September 19 to 25) suggests potential linkages to user demographics or external events.

## IV. METHODOLOGY

This study proposes a collaborative framework integrating large and small models for topic analysis of social media comments. As shown in Fig. 3, the architecture consists of three components. The 14B open-source large language model generates initial topic labels through prompt engineering, serving as semantic anchors to capture overarching public opinion trends across multilingual social media comments. The semi-supervised small model encodes these labels into latent representations, enabling efficient modeling of locally evolving subtopics. Meanwhile, the stronger large model (e.g., GPT-4o) functions as an error corrector, detecting inconsistencies in topic clustering and refining the

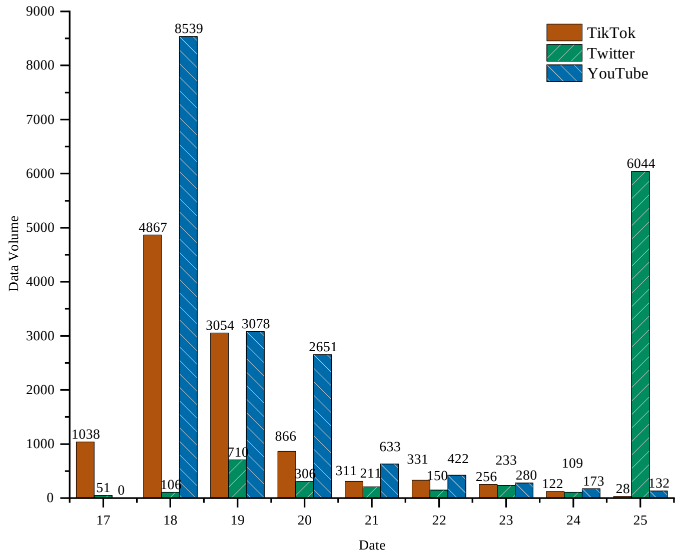


FIGURE 2: Volume of public comments captured between September 17 and 25, 2024. TikTok/YouTube surges 48h post-September 17 explosion.

clustering process to enhance accuracy. This approach leverages the large model's strength in stable semantic capture and the small model's agility in adapting to dynamic shifts in public opinion. Through iterative collaborative loops, bidirectional knowledge transfer achieves an effective balance between semantic stability and adaptability. Subsection A details the collaborative workflow, followed by component specifications in Subsections B and C. Important symbols can be found in the Table 1.

### A. COLLABORATIVE WORKFLOW

To enable bidirectional knowledge transfer between models, we design a semi-supervised pipeline where:

1) The 14B $\mathbf{LLM}$ generates initial topic labels through prompt engineering.
2) The VAE-based small model encodes labels into latent representations ($\mathbf{z} \in \mathbb{R}^d$).
3) The stronger $\mathbf{LM}$ (GPT-4o) detects inconsistencies via cross-cluster entropy analysis ($\mathcal{H}(\mathbf{R_A}, \mathbf{R_B}) > \tau$).
4) The $\mathbf{LLM}$ is fine-tuned with corrected data $\mathcal{P}'$ containing identified errors $\mathbf{IC}$.

This creates an optimization loop: $\mathbf{LLM} \Rightarrow$ VAE $\Rightarrow$ $\mathbf{LM} \Rightarrow \mathbf{LLM}$ (Algorithm 2).

In Algorithm 2, $\chi$ controls the semi-supervised batch size, $\mathbf{LLM}$ denotes the 14B-parameter generator, $\mathbf{LM}$ the error-correcting model (GPT-4o), and $\mathbf{z}$ the VAE-generated latent representations. The dataset $\mathcal{D}$ contains $N$ comments, while $\mathbf{R_A}$ (Birch) and $\mathbf{R_B}$ (GaussianMixture) represent divergent clustering results. Through $\mathbf{SFT}$ (Supervised Fine-Tuning) on corrected prompts $\mathcal{P}'$, the refined $\mathbf{LLM}'$ achieves stabilized topic modeling.

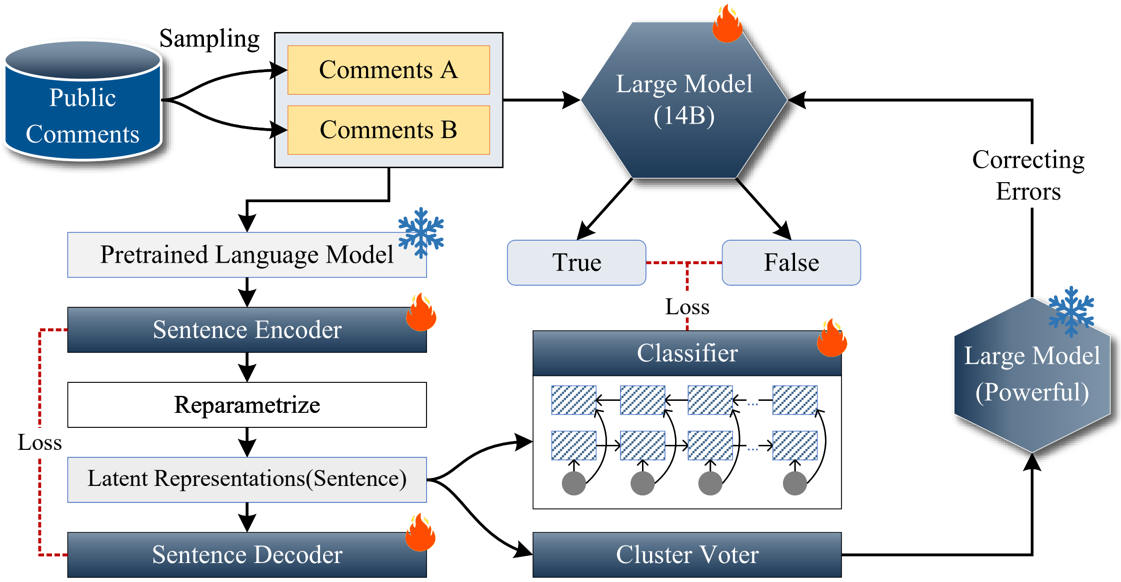


FIGURE 3: The topic analysis framework for collaboration between large and small models

**Algorithm 2** Iterative Collaboration Framework

**Require:** Social media comments $\mathcal{D} = \{\mathbf{c}_i\}_{i=1}^{N}$; Max iterations $T$; Convergence threshold $\epsilon$; Batch size $B$; Entropy threshold $\tau$

**Ensure:** Topic clusters $\mathcal{C}$; Topic summaries $\mathcal{S}$

```
Initialize 14B LLM LLM_θ and VAE encoder VAE_φ
Set iteration counter t ← 0
while t < T and ΔL ≥ ε do
    for j = 1 to χ do
        Sample (c_1, c_2) ~ D
        Generate pseudo-label y ← LLM_θ(c_1, c_2)
        Encode latent representation z ← VAE_φ([c_1; c_2; y])
    end for
    Cluster Result: R_A ← Birch({z, D})
    Cluster Result: R_B ← GaussianMixture({z, D})
    Compute cross-cluster entropy H(R_A, R_B)
    if H(R_A, R_B) > τ then
        Identify inconsistent comments IC ← LM(R_A, R_B)
    end if
    Construct fine-tuning prompts P' ← (IC, D)
    Fine-tuning LLM'_θ ← arg min_θ L_SFT(LLM_θ(P'))
    Compute loss difference ΔL ← |L(θ') − L(θ)|
    Set θ ← θ' and t ← t + 1
end while
Generate C, S ← LLM'_θ(D)
```

TABLE 1: Nomenclature Table

| Symbol | Definition |
|---|---|
| $LLM$ | Language model with 14B parameters |
| $LM$ | Better performing language models, such as GPT-4o |
| $VAE$ | The VAE-based small model |
| $P'$ | Data modified by the LM |
| $IC$ | Error data set identified by the LM |
| $\chi$ | Semi-supervised batch size |
| $c$ | Social media comments |
| $z$ | The vector representation of the comment after encoding through the language model, XLM-RoBERTa |
| $L$ | Loss Function |
| $R$ | Topic results obtained by clustering algorithm. |
| $N$ | Number of social media comments |
| $\kappa$ (Cohen's) | A metric for measuring pairwise inter-annotator agreement, accounting for chance agreement. |
| $\kappa'$ (Fleiss') | A metric for measuring overall agreement among three or more annotators. |
| $P_o$ | Observed agreement: proportion of annotations where annotators concur. |
| $P_e$ | Expected agreement: proportion of agreement expected by random chance. |
| $M$ | Total number of comments in the annotated dataset (10,241). |
| $\alpha$ | Concentration parameter of Dirichlet distribution . |
| $\alpha_0$ | Uniform prior for Dirichlet distribution ($\alpha_0$ = [1,1,...,1]). |
| $\beta(\alpha)$ | Multivariate Beta function |
| $\Gamma(\cdot)$ | Gamma function (used to compute $\beta(\alpha)$) |
| $S$ | Number of Monte Carlo samples for KL divergence estimation |

### B. TOPIC DISTRIBUTION REPRESENTATION

Topic discovery is contingent upon semantic modeling of the text. Prior research has demonstrated the efficacy of word embeddings or sentence embeddings derived from pre-trained language models as valid sequence representations.

The comments posted by users on social media are typically brief and clearly focused on a specific topic.In this study, we design a semi-supervised topic representation model based on a variational autoencoder. The model as a whole consists of three parts: an encoder, a decoder and a classifier. The latent representations obtained from encoder are input to the decoder and classifier, and the supervised labels for the classifier come from the LLM. The overall operation in two stages: cross-lingual encoding and topic-aware latent space learning.

Since the crawled comments have Arabic, we chose XLM-RoBERTa as a cross-language pre-trained language model. The comments $c_1$ and $c_2$ obtained by random sampling from the collection of comment data are passed through the same Encoder to obtain the feature vectors $E_{c1}$ and $E_{c2}$. The encoder encodes the feature vectors $E_{c1}$ and $E_{c2}$ to obtain the latent representation $z$. The Decoder uses $z$ to characterize the distribution of the original comments. The decoded reconstruction is made to converge to the original data distribution by optimizing the model parameters $\theta$, as shown in (1).

$$p_\theta(c) = \int p_\theta(c \mid z) p_\theta(z) \mathrm{d}z \tag{1}$$

In the sampling process, we extend the standard VAE by replacing the Gaussian prior with a Dirichlet distribution. Probabilistic modeling has demonstrated that the Dirichlet distribution is an effective means of capturing the distribution of topics in a document. It can also represent the probability distribution of multiple mutually exclusive events. The Dirichlet distribution is constructed from parameters extracted from the mean $\mu_s$ and $log\sigma^{2_s}$ of the latent variables, as shown in (2).

$$\mathbf{z} \sim Dirichlet(\alpha) \tag{2}$$

In this context, $\alpha$ represents a hyperparameter that reflects the distributional characteristics of comment coding in the latent space. The probability density function of the Dirichlet distribution is illustrated in (3).

$$p(\mathbf{z} \mid \alpha) = \frac{1}{\beta(\alpha)} \prod_{i=1}^{K} z_i^{\alpha_i - 1} \tag{3}$$

where $\beta(\alpha)$ represents the multivariate Beta function, defined as (4):

$$\beta(\alpha) = \frac{\prod_{i=1}^{K} \Gamma(\alpha_i)}{\Gamma\left(\sum_{i=1}^{K} \alpha_i\right)} \tag{4}$$

Here, $\Gamma(\cdot)$ denotes the Gamma function, and $K$ denotes the latent dimension, consistent with the Dirichlet distribution in (3).

The classifier is composed of a bi-directional long and short-term memory (BiLSTM) network and multiple fully connected layers, and finally the degree of approximation of the comments $c_1$ and $c_2$ is output through a Sigmoid function, which is 1 if it belongs to the same topic and 0 otherwise, as shown in (5).

$$\hat{y} = Sigmoid(FC(BiLSTM(z))) \tag{5}$$

The loss function is comprised of three components: the reconstruction loss, $L_{recon}$, the KL divergence penalty, $L_{KL}$, and the classification loss, $L_C$. These are illustrated in equations (6), (7), (8)and (9).

$$L_{\text{recon}}^k = \frac{1}{N} \sum_{i=1}^{N} \|c_i^k - \hat{c}_i^k\|_2^2 \quad (k = 1, 2) \tag{6}$$

$$\mathcal{L}_{KL} = \mathbb{E}_{q_\phi(z|\alpha)} \left[ \log \frac{q_\phi(z|\alpha)}{p_\theta(z|\alpha_0)} \right] \approx \frac{1}{S} \sum_{s=1}^{S} [\log q_\phi(z^s|\alpha) - \log p_\theta(z^s|\alpha_0)] \tag{7}$$

where $z^s$ăis theăs-th latent sample fromă$q_\phi(z|\alpha)$; $\log q_\phi(z^s|\alpha)$ăandă$\log p_\theta(z^s|\alpha_0)$ăare the log-probabilities ofă$z^s$ăunder the posterior and prior, $S$ăbalances estimation accuracy and computational cost, which validated via hyper-parameter tuning.

$$L_C = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \tag{8}$$

$$L = L_C + L_{\text{recon}}^1 + L_{\text{recon}}^2 + L_{\text{KL}}^1 + L_{\text{KL}}^2 \tag{9}$$

### C. CONSENSUS CLUSTERING AND ITERATIVE REFINEMENT

After the model training is completed, the obtained mean vector $\mu$ can effectively summarize the important features of the input data and reflect the distribution center of the input in the latent space. Therefore, the sentence-level coding vectors are used as inputs to the clustering algorithm for semantic clustering. The error correction pipeline operates in three phases: high-confidence sample identification via consensus clustering, outlier detection through divergence analysis, and iterative refinement using targeted prompts.

In order to reduce the uncertainty associated with unsupervised, we designed a consensus clustering mechanism to correct errors in the LLM to improve the robustness of iterative optimization.

Consensus clustering refers to the use of multiple algorithms for thematic clustering and then identifying high confidence samples by clustering consensus, as in (10). and detecting potential errors in non-intersecting regions, as in (11). Finally, the stronger LM (e.g., GPT-4o) detects the Irrelevant Comments (**IC**) in non-intersecting regions, as in (11). In this study, we take the intersection of the two topic clustering results obtained based on two clustering algorithms, Birch [30] and GaussianMixture [31].

$$R_I = \{c | c \in R_A \cap R_B\} \tag{10}$$

$$\mathbf{IC} = \mathbf{LM}(R_A \cup R_B \setminus R_I) \quad (11)$$

Then, we designed three Prompts to accomplish the tasks in different stages. The Prompt $A$ enables the stronger LM to find out the comments that do not match the current topic $R_I$; the Prompt $B$ is used to fine-tune the optimized LLM; and the Prompt $C$ is used to finally generate the summary description of the topic. The details of the Prompts as below.

**Prompts:** Details of three prompts.

**Input** Comments
**Output** Irrelevant Comments, Topic Summary
$PromptA$ :
Summarize the following list of comments in a topic description, and output the indices of all comments that is not related to the current topic description.
$PromptB$ :
Please decide whether the two comments in the following list entry belong to the same topic, and answer in the fixed form of [serial number: yes or no] in the order of the list.
$PromptC$ :
Summarizing the content of the topic from the given list of comments needs to include the object to which the topic is oriented, all the stances of people, the group attitudes included.

TABLE 2: Hyperparameter Settings for Large and Small Models

| Parameter Category | Parameter Name | Value |
|---|---|---|
| **Large Language Model (LLM)** | | |
| Basic Configuration | Parameter Scale | 14B |
| | Number of Iterations | 2,3,4 |
| Training Parameters | Learning Rate | 3e-4 |
| | Batch Size | 16 |
| | Learning Rate Scheduling | linear |
| | Validation Steps | 50 |
| | Weight Decay | 0.01 |
| LoRA Configuration | LoRA Rank | 8 |
| | LoRA Alpha | 32 |
| | LoRA Dropout | 0.1 |
| | LoRA Target Modules | ALL |
| **Small Model (VAE-based)** | | |
| Architecture | Embedding Dimension | 768 |
| | Hidden Size | 64 |
| | Latent Dimension | 32 |
| Training Parameters | Learning Rate | 0.003 |
| | Batch Size | 1024 |
| | Dimensionality Reduction | 2 |

TABLE 3: Results of sampling with different distributions

| Method | Origin | Collaboration |
|---|---|---|
| Gaussian | 0.72 | 0.74 |
| Dirichlet | 0.75 | 0.77 |
| Beta | 0.73 | 0.74 |

## V. DATA ANALYSIS AND EXPERIMENTS RESULTS

In this section, we have conducted a comparative analysis of the subjects in English and Arabic, respectively, with the objective of gaining a comprehensive understanding of the public's concerns regarding this bombing incident.

### A. EXPERIMENTAL DESIGN

To ensure reproducibility and clarify the experimental setup, this subsection details the key hyperparameters and configuration settings for the large and small models used in the topic analysis framework.

The parameters in Table 2 were determined through empirical tuning to balance model performance and computational efficiency. For the 14B-parameter LLM, LoRA (Low-Rank Adaptation) was applied to enable efficient fine-tuning, with target modules set to "ALL" to ensure comprehensive parameter adaptation. The small model uses a compact architecture to enable rapid encoding of comment text into latent space, supporting real-time topic clustering. All parameters were validated across multiple random seeds to ensure stability of experimental results.

### B. COMPARATIVE ANALYSIS

To validate the effectiveness of collaboration between large and small models, we randomly selected 200 to 500 commentsto construct semi-supervised test datasets. According to our methodological design, these constructed datasets do not require manual annotation to evaluate outcomes. The powerful large model generates correction signals approaching human-level accuracy during iteration. Based on these correction signals, the classifier achieves up to 75.2% accuracy without collaboration, and up to 77.2% after one collaborative optimization, with an average improvement of about 3% in accuracy for multiple sampling validations. Then, different sampling distributions are also compared. As Table 3 demonstrates, the Dirichlet prior outperforms Gaussian/Beta distributions by 2%-3% in accuracy. We performed 20 bootstrap resamples (with replacement) from the validation data to quantify uncertainty in the accuracy gain. The 95% confidence interval for the improvement was calculated as [2.3%, 3.8%], confirming that the observed improvement is stable across resampled datasets and not due to random variation.

We set the dimensionality of the text vectors after dimensionality reduction to 3 dimensions, and the effect before and after collaboration is shown in Fig. 4 and Fig. 5. The results of both GaussianMixture and Birch clustering algorithms validate that the collaboration of large and small models can help the small model to obtain a better representation of the topics, and thus a clearer distribution of topics is obtained.

In the clustering process, both algorithms obtained three

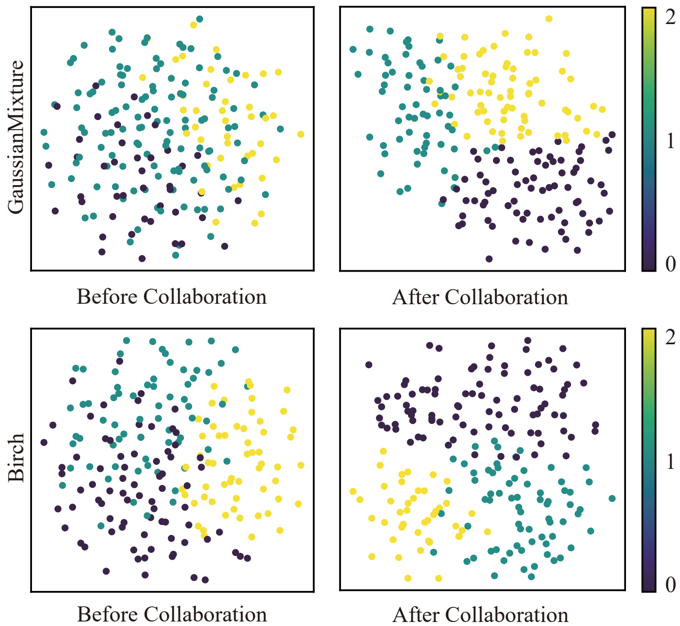


FIGURE 4: Clustering performance before and after model collaboration with 200 sample sizes. The lower the thematic overlap, the better the clustering outcome.

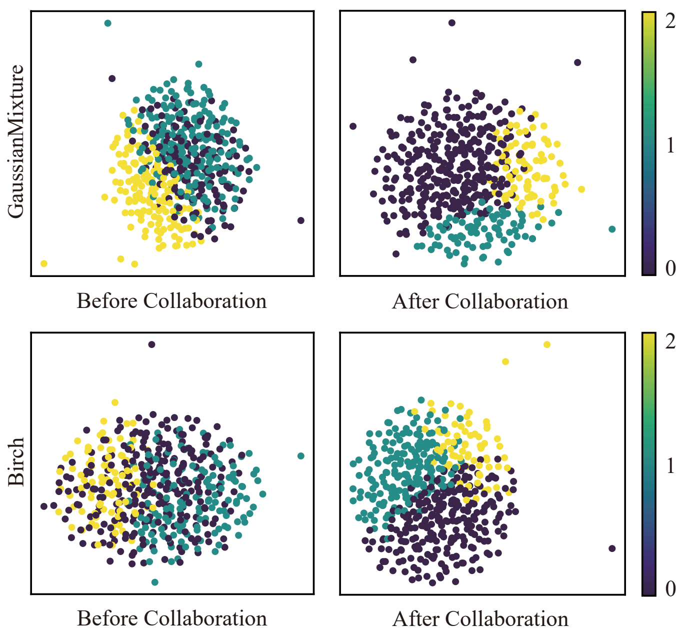


FIGURE 5: Clustering performance before and after model collaboration with 500 sample sizes. The lower the thematic overlap, the better the clustering outcome.

topics, and the intersection of the two obtained nine topic clusters. The clustering results after the collaborative optimization of the small and large models are shown in Fig. 6, where the top three graphs show the percentage of comments in the before and after topic clusters obtained from the results of the GaussianMixture algorithm for the main three topic

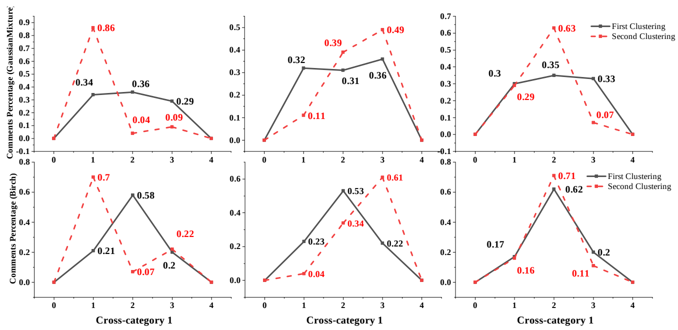


FIGURE 6: Percentage of comments in different topic clusters before and after collaboration of small and large models.

clusters, and the bottom three graphs show the crossover results based on the Birch algorithm. The results show that the topics obtained from clustering after single-round collaboration are more concentrated, and the differences obtained from different clustering algorithms are decreasing.

To further validate the effectiveness of our proposed framework, we also compared it against traditional topic analysis methods , Latent Dirichlet Allocation (LDA) and BERTopic, under the same settings. The detailed results of these comparisons can be found in Appendix B.

### C. TOPIC ANALYSIS

To find the topic words in the comment clusters, we train a neural network classifier using the comment clusters as labels for weighting the input features. The input of the classifier is the output of the last layer of the LSTM in the semantic representation model word encoder. The structure of the classifier also consists of an LSTM and a multi-layer perceptron (MLP). We use the Integrated Gradients (IG) [32] of the deep learning model to compute the weights. The contribution of each feature to the prediction result of the model can be quantified.

The top 10% of words with the highest degree of contribution to the weight of each sentence were calculated according to the attribution classifier. The statistically representative English and Arabic words and the corresponding frequency counts are presented in Table 4 (Arabic terms were professionally translated by native speakers, with back-translation validation to preserve semantic intent). The words included the subject of the incident, Israel, which launched the attack, and the battery, the carrier of the explosion. The results in English indicate that the commenters tend to equate this Israeli action with a terrorist attack and express concern about the safety of portable electronic devices with batteries, such as mobile phones. The results in Arabic indicate that most commenters made religiously related statements, expressing hope for peace and concern for the safety of their devices.

The summary of four representative topics from the category of words, is presented in Table 5. Topic 1 comprises a discussion of the Israeli attack on Lebanon and the question of whether it was supported by Western countries or

TABLE 4: Frequency Results for Words Attributed to The Top 10% of Attribution Weights

| English Words | Frequence | Arabic Words | Frequence |
|---|---|---|---|
| Israel | 333 | (God) | 51 |
| Terrorist | 203 | (Peace) | 13 |
| Phone | 133 | (Lebanon) | 5 |
| Attack | 96 | (Battery) | 4 |
| Devices | 69 | (Safe) | 3 |
| Battery | 64 | - | - |
| Safe | 49 | - | - |

TABLE 5: Representative topic results

| Topics Index | Topic Words |
|---|---|
| 1 | Israel, Terrorist, World, Western, Attack, American |
| 2 | Pager, Phone, Battery, China, Electric, Device, Safe |
| 3 | Brilliant, Thanks, Hahaha, LoL, Beautiful |
| 4 | Manufacturer, Radio, Communication, Products, Chain |

the United States. Topic 2 comprises a discussion on the safety of electronic devices, including pagers and collectors. This discussion also encompasses a comparison between the safety of Chinese products and those manufactured in other countries. Topic 3 is a spontaneous thread comprising a considerable number of commenters with negative attitudes towards Lebanon or Islam. The thread is, in essence, supportive of Israel's actions. Topic 4 is a discussion of the manufacturing industry, the industrial chain, and the ability to control communications, which is reflected in this event.

### D. TOPIC DESCRIPTION

LM GPT4o and the open-source LLM model Qwen2.5-14B were employed to assess the generation of topic summaries across diverse categories in accordance with the prescribed $Prompt\ C$. The findings are documented in Table 6. Topic 0 accentuates Israeli aggression against Lebanon and Palestine, portraying the action as a terrorist act. Topic 1 incorporated the input of manufacturers from countries such as the Taiwan region of China, which conveys a sense of skepticism regarding the reliability of Western media and technological products. Topic 2 supports the Israeli incursion into Lebanon's communication infrastructure and also expresses skepticism about Chinese-made products. Topic 3 likewise articulated discontent with Western government policies and irresponsible media conduct. Topic 4 conveys skepticism regarding the technological capabilities of Hezbollah, as well as the involvement of Chinese and American technology companies in the incident. Topic 5 maintains a stance of disapproval towards Israel and its Western allies.

The findings indicate that utilizing a comprehensive model to generate topic summaries provides significant benefits in terms of depth and readability. The large model permits the display of greater detail in the generated summaries, facilitating an expedient and intuitive comprehension of the self-organized topic clusters. Conversely, the summaries generated by these larger models are both logical and complete, and they provide a more comprehensive understanding than word lists obtained from traditional topic modelling.

TABLE 6: Summary of topics from all public comments.

| ID | Aspect | Summary |
|---|---|---|
| 1 | Objects | Israel, Hezbollah |
| | Stances | Emphasizing Israel's acts of aggression against Lebanon and Palestine and describing it as a terrorist State |
| | Attitude | Supporters recognized Hizbullah's capabilities and criticized Israeli attacks on civilians, demonstrating empathy for the victims and a thirst for truth about the conflict |
| 2 | Objects | Israel, Hezbollah, Manufacturers in Taiwan and other countries |
| | Stances | A clear tendency to criticize Israel as an evil country, while at the same time supporting Hezbollah and expressing dissatisfaction with the policies of Western countries (especially the United States). |
| | Attitude | Emotions are characterized by anger and distrust, especially towards Western media and technological products, which are perceived as playing a negative role in the conflict. Repeatedly, skepticism about Western countries and technologies is emphasized, reflecting deep concerns about the global situation and the ethics of science and technology. |
| 3 | Objects | Israel, Hezbollah, and the communication technologies associated with them (e.g., walkie-talkies and cell phones) |
| | Stances | Biased towards criticizing Israel for the threat its technology and military actions pose to civilians, while expressing distrust of Chinese-made products, especially in the context of war. |
| | Attitude | Emotions are expressed as anger and skepticism, with criticism of Israel coexisting with support for Hezbollah, which is perceived to have responded in the face of Israel but is also blamed for Israel's indiscriminate attacks. |
| 4 | Objects | Israel, Hezbollah, and related countries and organizations in international politics. |
| | Stances | Tendency to criticize Israel as an internationally recognized apartheid state and to express dissatisfaction with the role of the United States in global affairs. |
| | Attitude | Sentiment is expressed as anger and cynicism, especially toward Western governments and media, which are seen as spreading misinformation. Criticism of technology and social media is also mentioned, reflecting disillusionment and alarm with modern society. |
| 5 | Objects | Israel, Hezbollah, the Ukrainian government, and international technology companies (e.g., Apple). |
| | Stances | Biased towards criticizing Israel for the high number of civilian casualties in the conflict, while also questioning Hezbollah's technological limitations. |
| | Attitude | Emotions show helplessness and anger towards the war, especially sympathy for the harm done to ordinary people. In addition, references to skepticism about Chinese and American technology companies suggest that they may have played a complex role in the conflict. Overall, the text conveys a deep concern about the war and its aftermath, while reflecting a concern for geopolitical dynamics. |
| 6 | Objects | Israel, Hezbollah, ISIS, the CIA, and international technology companies |
| | Stances | Criticizes Israel and its allies as culpable for their actions and questions the role and intentions of the West in the conflict. |
| | Attitude | Emotions show a strong aversion to terrorism and a belief that Israel has caused suffering in other countries while protecting its own interests. It also reflects trust in China and Russia, asserting that these countries may be more reliable options. The overall mood is one of anger and frustration, emphasizing a boycott of Western products, which are perceived as potentially insidious threats |

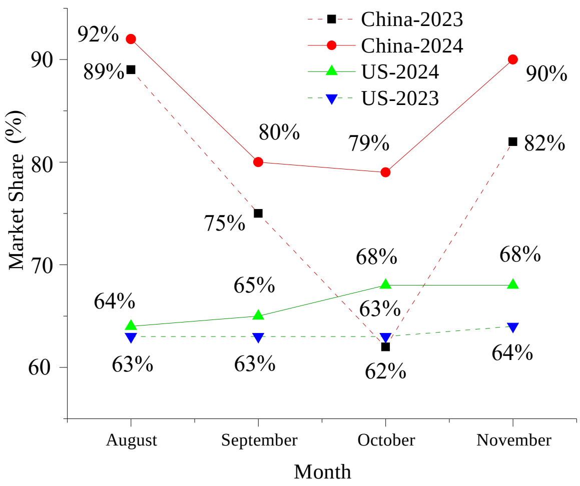


FIGURE 7: Smartphone market share held by Chinese and US brands in their respective countries.

However, it was also observed that the large model has the potential to generate an overall, generalized summary, which results in each topic exhibiting similar sentiments and attitudes. It is evident that the large model is unable to represent certain commentators and attitudes that are clearly pro-Israeli, which ultimately results in a certain degree of objectivity being lost.

## VI. DISCUSSION

In this section, we focus on discussing the cognitive warfare and the implications of the pager bomb incident for electronic device security, aiming to explore potential research directions for scholars rather than presenting experimentally verifiable conclusions.

### A. COGNITIVE WARFARE

It is our contention that the pager bomb event was distinct from conventional military operations, which constituted a combination of mosaic warfare and cognitive warfare. In terms of operational purpose, the attack not only weakened Hezbollah's communication capability, but also undermined people's trust in electronic devices and systems through the application of psychological deterrence.

From an operational standpoint, this approach aligns with the concept of mosaic warfare, as proposed by the United States, which entails a strategy of dispersed strikes designed to weaken the enemy's overall defensive capabilities. Israel exhibited the adaptability of a modest combat unit by simultaneously detonating civilian communications equipment in multiple locations through the utilization of sophisticated technology. The explosions required significant pre-preparation costs but demonstrated lower lethality accuracy. However, on the other hand, the sudden, widespread and untraceable explosion has the effect of creating a horrific psychological deterrent and achieving a deeper cognitive warfare effect. As a direct consequence, there was a shift in perceptions of electronic devices and communication systems, with a subsequent increase in distrust directed towards all similar devices and supply chains. The risk of further crises that could impact on Lebanon's social stability and economic resilience is heightened.

The combination of cognitive and mosaic warfare may evolve into a prospective form of future warfare, representing a conjunction of terrorism and weaponry in the context of the contemporary international situation. Technological penetration, information manipulation and other forms of warfare have introduced novel risks and crises to the globalized industrial and supply chains. The enhancement of public confidence in electronic equipment has emerged as a social and technical challenge confronting countries across the globe.

### B. SECURING ELECTRONIC DEVICES WITH TRUSTED TECHNOLOGY

We collected data on the smartphone market shares of China and the United States in 2023 and 2024 to observe the potential impact of the bombing event on countries with smart phone production capacity, as shown in Fig. 7. According to Canalys[1], Apple's smartphone market share in mainland China declined from 27% in Q4 of 2023 to 13% in Q4 of 2024.

Notably, this correlation does not imply direct causality. We have incorporated analyses of confounding factors that may influence market dynamics, including seasonal sales fluctuations, policy adjustments, and brand-specific strategies. We found that the event amplified existing consumer concerns about device safety, rather than acting as a sole driver, thereby indirectly shaping purchasing preferences for national brands perceived as more trustworthy. This nuanced relationship reflects how public anxiety, triggered by the pager bomb incident, interacted with other market forces to influence observed share shifts.

To enhance civilian safety in electronic device usage, we propose a framework employing technical measures to ensure the security of global supply chains. For instance, all nodes of cell assembly and all links of international transportation may be incorporated into untrustworthy operations by individuals or organizations regarding lithium battery equipment. The following parts will be demonstrated from both theoretical and technical architectural perspectives.

**Theoretical Foundation:** The Decentralized Autonomous Organization (DAO) [33] is a recently and rapidly developing theoretical architecture that has its origins in the rapid growth of the crypto economy. Although there are numerous operational definitions of the DAO concept, most of these definitions describe it as a mobile organization or loosely structured community that is self-directed and governed through smart contracts without a central authority or management structure [34]. The decentralized nature of the production, assembly and transportation of electronic devices makes the

[1] https://canalys.com/newsroom/china-smartphone-market-q4-2024

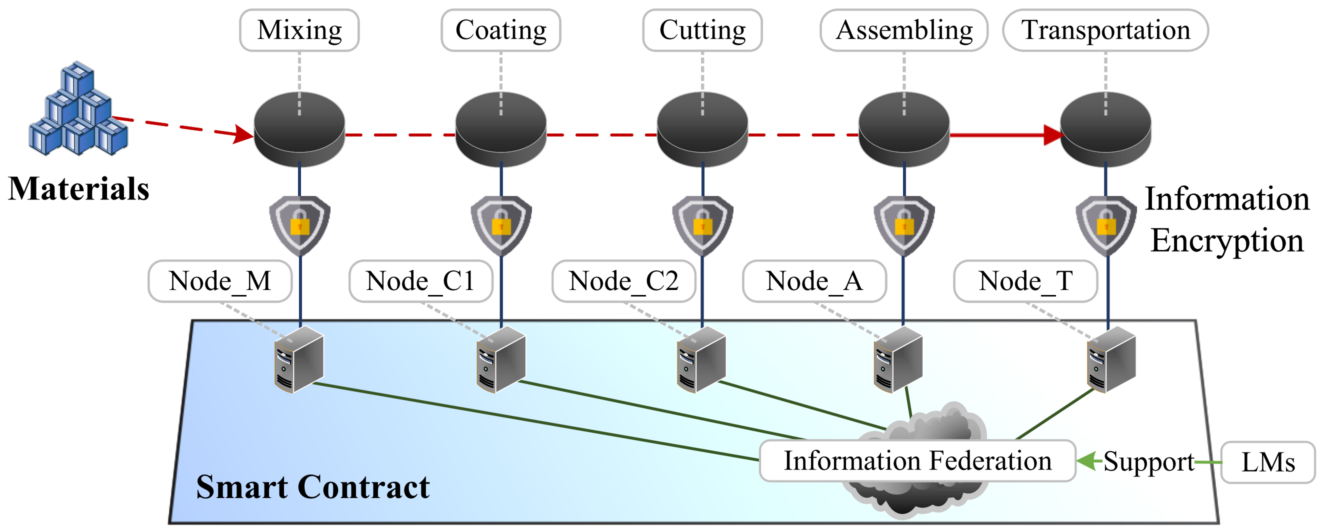


FIGURE 8: DAO-based electronic device trust framework, using lithium batteries as an example. Mixing, Coating, Cutting represents the production process of lithium battery, Assembling represents the assembly of electronic devices of lithium battery equipment, and Transportation represents the trade and transportation process of electronic devices. LMS represents large models, like GPT-5.

use of DAOs to manage these processes an optimal method of enhancing the trustworthiness of the devices.

**Technical Support:** A system based on the DAO [35], which incorporates blockchain, federated learning, cryptographic algorithms and other trusted technologies, can provide a transparent and tamper-proof information system for the production and transportation of electronic devices. We design a trusted DAO-based framework for lithium batteries as an example, as shown in Fig. 8. The information of each link is recorded as a non-tamperable information node through the blockchain and follows a smart contract. Then, cryptographic algorithms are provided to encrypt the information to protect the intellectual property rights and business interests of all parties if necessary. Finally, a distributed computing method of federated learning is provided to achieve joint data mining and decision-making optimization of all parties without the data going out of the domain.

The information security and reliability of the trust framework are fundamental: in component traceability and in manufacturing evidence preservation, NFC chips assign unique identifiers to each part. Lightweight encryption is applied to key data, like raw material purity and other production parameters, prior to blockchain storage. Consensus mechanisms ensure data immutability, aligned with multi-node collaboration scenarios in electronic device supply chains. During manufacturing, commercial privacy is protected by leveraging zero-knowledge proof (ZKP) technology: this guarantees compliance with quality inspection without disclosing any specific process parameters involved in information security. Besides, Large Models (LMs) are integrated into the framework in a supportive role: it dynamically generate smart contract triggering conditions based on the historical risk data previously stored on the blockchain while analysing information in the supply chain logs to give precise risk warning recommendations to DAO nodes.

## VII. CONCLUSION

We analyzed the attitudes of social media users and the pager bomb event's impact on the manufacturing and use of electronic devices. By comparing the topics of English and Arabic users, we found that people in different language spaces share common concerns regarding electronic devices. By analyzing smartphone market share trends in China and the United States, we found a correlation between the pager bomb event and people purchasing national brand phones.

Past research has demonstrated that topic analysis requires expert-curated annotation to guide the model. The generalized capabilities of large language models enable initial labeling jobs. However, there is a paucity of literature on the collaboration of large and small models for topic analysis. We propose a semi-supervised topic analysis method and establish a continuous optimization approach from a large model to a small model to a large model. In a crawled collection of social comments, we validate that large and small model collaboration can continuously improve topic discovery performance.

Currently, armed conflict has become an ever-present element of people's daily lives, while cognitive attacks are proliferating through social media platforms. These attacks manifest as distributed and self-organized topic communities, shaping public opinion. A proposed solution to this issue is the implementation of the DAO-based transparent and democratic electronic device production framework, which aims to enhance individuals' psychological security expectations.

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## APPENDIX A ANNOTATOR AGREEMENT DETAILS

### A. ANNOTATION CONTEXT AND DATASET

The annotation was conducted on a subset of comments primarily sourced from the TikTok platform, with a total of 10,241 comments included. After initial screening, the dataset comprised 1,912 spam comments and 8,329 non-spam comments. Three annotators with expertise in social media content analysis labeled each comment as “spam” or “non-spam” based on a predefined guideline. The guideline defined spam as content including but not limited to: irrelevant advertisements, repetitive gibberish, automated bot-generated text, and off-topic rants. Non-spam included user opinions, contextual discussions, and conversational replies.

### B. EVALUATION METRICS

To quantify inter-annotator consistency, two metrics were used:

#### 1) Cohen’s $\kappa$

For pairwise agreement between two annotators, Cohen’s $\kappa$ was calculated to measure agreement beyond random chance. Let the confusion matrix be Table 7.

TABLE 7: Confusion Matrix Definition.

| | Annotator 2 | |
|---|---|---|
| Annotator 1 | Non-spam | Spam |
| Non-spam | $a$ | $b$ |
| Spam | $c$ | $d$ |

where total number of comments $M = a + b + c + d = 10,241$.

The observed agreement $P_o$ represents the proportion of comments where both annotators agreed, as shown in (12).

$$P_o = \frac{a+d}{M} \tag{12}$$

The expected agreement by chance is calculated from the marginal probabilities, as shown in (13).

$$P_e = \frac{(a+b)\times(a+c)}{M^2} + \frac{(c+d)\times(b+d)}{M^2} \tag{13}$$

where $(a+b)/M$ and $(a+c)/M$ are the proportions of non-spam labels by each annotator, and $(c+d)/M$ and $(b+d)/M$ are the proportions of spam labels.

Cohen’s $\kappa$ is then calculated as (14):

$$\kappa = \frac{P_o - P_e}{1 - P_e} \tag{14}$$

#### 2) Fleiss’ $\kappa$

For measuring agreement across all three annotators, Fleiss’ $\kappa$ was computed to account for multi-annotator consistency:

$$\kappa = \frac{P - P_e}{1 - P_e} \tag{15}$$

where $P$ is the mean proportion of agreement across all comments, and $P_e$ is the mean probability of random agreement across the two label categories (spam/non-spam).

### C. ANNOTATION CONSISTENCY AND RESOLUTION OF DISCREPANCIES

The inter-annotator agreement was excellent: pairwise Cohen’să$\kappa$ăranged from 0.81 to 0.87 (average = 0.84), and the overall Fleiss’ă$\kappa'$ăfor the three annotators was 0.82, confirming high consistency.

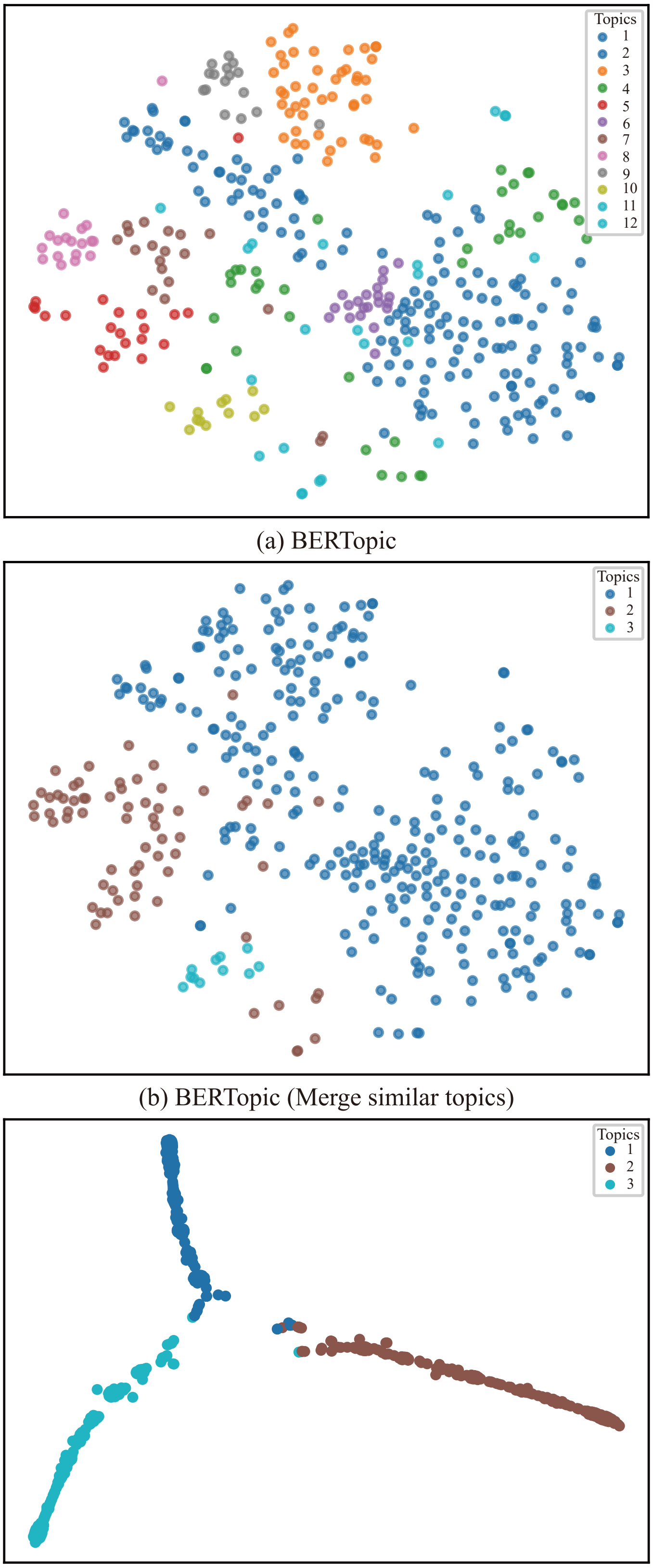
The primary source of divergence involved "conversational comments", e.g., thread replies, like "Thank you for sharing information" or short social exchanges, like "Yes sir". Disagreements stemmed from two ambiguities: (1) contextual relevance, whether short replies meaningful only in dialogue chains qualify as non-spam) and (2) informational value, whether trivial phrases like "Same here" count as genuine interaction). To maintain the integrity of follow-up topic analysis, we have retained these ambiguous comments as non-spam comments. These annotated files can be found at https://github.com/UpcNlp/PagerBomb.

This Cohen’s $\kappa$ validates the reliability of annotations for the TikTok dataset (1,912 spam; 8,329 non-spam). Resolved discrepancies reflect real-world nuances in social media dialogue, with the iterative process ensuring alignment with analytical needs.

## APPENDIX B TRADITIONAL TOPIC MODEL RESULTS

To enable an intuitive comparison between our framework and classic topic-discovery baselines, we conducted controlled experiments on two representative methods: Latent Dirichlet Allocation (LDA) and BERTopic, using 500 stratified samples and the same embedding model as our large-small model framework. The BERTopic results as shown in Fig. 9 (a), the initial clustering process yielded 12 distinct clusters. A total of 377 out of 500 samples were allocated to these clusters, while 123 samples were identified as outliers. Following the merging of semantically similar topics, as shown in Fig. 9 (b), the total number of clusters was reduced to 3. Cluster 1 comprised 286 samples and was found to be associated with the following core keywords: “israel_hezbollah_terrorists”, The second cluster contains 67 samples, the core keywords of which are “phones_battery_explosives”. The third cluster contains 11 samples, the core keywords of which are “motorola_owned_pagers_wrong”, and the remaining 136 samples are outliers. The LDA clustering result, as shown in Fig. 9 (c), visualised via t-SNE dimensionality reduction, manifests as three distinct clusters. While these clusters appear well-separated in the 2D space, closer inspection reveals certain limitations. The elongated shape of the clusters suggests that LDA struggles to capture fine-grained semantic nuances, instead relying on broad probabilistic distributions.

The limitations of the two baselines are clearly highlighted. BERTopic tends to over-cluster by dividing comments into as many categories as possible. Even after merging semantically similar topics, the number of outliers remains as high as 136, reflecting its sufficient robustness to noise in this event. LDA, on the other hand, struggles to capture the relevance between comments in complex contexts. Although its clustering results show three clearly separated clusters in t-SNE visualization, it cannot reflect the fuzzy correlations between topics, leading to insufficient semantic coherence.




(a) BERTopic

(b) BERTopic (Merge similar topics)

(c) LDA

FIGURE 9: t-SNE Visualization of Topic Clustering Results for BERTopic (Initial), BERTopic (After Merging Similar Topics), and LDA

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