Studying Emotional and Trust-building Effects of Symbolic Communication on YouTube

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Abstract. This study investigates the influence of social, cultural, and political (SCP) symbols in YouTube videos during Taiwan's 2024 presidential election. We examined how symbolic visuals in videos affected viewer engagement, emotional reactions, and trust levels. Our approach combined advanced techniques for identifying meaningful frames and LLM-based models for symbol detection and analyzing viewer comments. Findings reveal that videos with cultural symbols drew the strongest emotional responses, particularly disgust and anger, and significantly boosted user engagement and trust compared to videos without symbolic content. Statistical tests confirmed these effects were driven by symbolic content itself, not merely by channel popularity or posting frequency. Our results extend theories like symbolic interactionism, highlighting symbolism's critical role in shaping digital political discourse. Understanding this dynamic offers valuable insights for content creators, communicators, and platforms aiming to foster effective and meaningful online civic participation.

Keywords: YouTube · Large Language Models · Disinformation · Semiotics · Social · Cultural · Political

1 Introduction

YouTube plays a major role in shaping political conversations today, especially during elections. Its mix of video, audio, and text allows creators to share messages in dynamic ways that influence how people think, feel, and engage. This study focuses on how social, cultural, and political (SCP) symbols in YouTube videos affected user engagement, emotional reactions, and trust during the 2024 Taiwan presidential election.

Symbols help people communicate meaning and build connections, both offline and online. Semiotics—the study of signs—explains how we interpret symbols based on culture and context, with meanings evolving over time [1]. On YouTube, symbols like emojis, hashtags, and visual cues act as a modern language that builds community and expresses shared identity [2]. These aren't just surface-level decorations; they shape how viewers emotionally respond to content and whether they trust the source [3][4].

Researchers have tied symbolic communication to theories like Media Richness Theory, which highlights how certain media better convey complex information [5], and Social Presence Theory, which explains how symbols increase emotional connection and perceived authenticity in digital spaces [6]. While these ideas have been applied broadly, their role in algorithm-driven platforms like YouTube is less explored. Our study addresses this gap.

In the 2024 Taiwan election, symbolic content—ranging from political imagery to cultural references—was common. YouTube's recommendation algorithm and user interactions often amplified these symbols, influencing how political narratives spread across different audiences and cultural backgrounds [7][8][9].

We also explore how large language models (LLMs) like GPT-4 are advancing the annotation of video and text content. GPT-4 Vision has shown success in identifying symbolic traits in images with no prior examples [10], and it performs well on social media text annotation, though still slightly behind models trained with human-labeled data [11]. This research addresses three questions: First, **RQ1**: How do SCP symbols affect engagement, and which types generate the most interaction? Second, **RQ2**: Which SCP symbols trigger the strongest emotional responses in viewer comments? Third, **RQ3**: How do SCP symbols influence trust, and which symbols help build or reduce it?

By answering these, we aim to better understand how symbolic communication influences digital political discourse, offering insights for content creators, communicators, and platforms.

2 Methodology

In this section, first we discuss data collection, then symbol detection from video frames, and trust and emotion analysis from comment text.

2.1 Background and Data Collection

This study explores how symbols were used in digital political communication during the 2024 presidential election in Taiwan, with a focus on YouTube discourse. We used a set of keywords and hashtags to guide our data collection, some examples include: 'SpeakOutDontFight', 'taiwanelection2024', 台灣總統大選2024 (Taiwan Presidential Election 2024), 賴清德 (Lai Ching-te), 選前之夜 (Election Night).

Taiwan's 2024 presidential election featured three main candidates: Lai Ching-te (DPP), focusing on autonomy; Hou Yu-ih (KMT), promoting cross-strait ties; and Ko Wen-je (TPP), advocating domestic reform. Citizens actively fought misinformation through digital literacy and fact-checking efforts. Our study examined how symbolic content shaped political narratives on YouTube during this time. Using evolving keywords based on media reports [12], we collected 1,973 posts and 342,486 comments from January 13–27, 2024, via the YouTube API. This became the core dataset for our analysis.

Fig. 1. Symbol detection results using gpt-4o-2024-08-06

2.2 Symbol Detection on Video Frames

Before detecting symbols, we first identify meaningful moments in the videos using the PRISM framework [13]. Instead of relying on static thumbnails or the first frame, PRISM detects key frames marked by significant visual changes—moments that are more likely to carry symbolic meaning. This approach offers a dynamic and efficient alternative to analyzing every frame.

Once the key frames are extracted, we classify any symbolic content into four categories: social, cultural, political, or “No Symbol”. Social symbols reflect community norms and identities, cultural ones relate to traditions and heritage, and political symbols represent ideologies or affiliations. For this, we used the USED dataset for social symbols, for cultural symbols, datasets featuring religious imagery, pilgrimage sites, and Indian temples were used. And the political party dataset for political symbols.

Table 1. Model Performance on Symbol Detection

Symbols	Dataset	gpt-4o-2024-08-06	gemini-1.5-Pro-001
Social	USED[14]	**96.36%**	67.56%
Cultural	Religious[15], Pilgrim[16], Temples[17]	**99.06%**	98.54%
Political	Political Parties[18]	**97.30%**	94.59%

Among the models tested, gpt-4o-2024-08-06 (GPT-4o) delivered the strongest performance overall (see Table 1), achieving 96% accuracy for social symbols and 99% for cultural ones. The gemini-1.5-Pro-001 (Gemini-1.5) also performed well on cultural (98.54%) and political (94.59%) symbols but showed weaker results on social symbols, with only 67.56% accuracy.

Based on these results, we selected GPT-4o as our primary model for detecting SCP symbols. We enhanced its performance using prompt engineering, testing both system and user prompts (see Figure 1). GPT-4o's ability to return clean, structured JSON outputs made the results easy to interpret and integrate.

To illustrate its effectiveness, we provide a few examples. In one instance, a WSJ Explains frame showing a map of China, a military emblem, and a soldier was correctly classified as political Social: 0, Political: 1, Cultural: 0. Another frame, showing traditional Chinese architecture with no visible social or political cues, was labeled cultural Social: 0, Political: 0, Cultural: 1.

The model consistently recognized symbols such as flags, gestures, crowds, buildings, and on-screen text—and correctly returned Social: 0, Political: 0, Cultural: 0 for frames without symbolic content.

2.3 Trust and Emotion Analysis in Comment

Table 2. Model Performance on Trust, Emotional Intensity, and Emotion Distribution Tasks

Task	**Dataset**	**Model**	**Relative-Accuracy**
Trust/ Emotional Intensity $(1 - \text{RMSE/Range}) \times 100\%$	Anime (English)[19] Range: 1–10	gpt-4o-2024-08-06	89.76%
		gemini-1.5-pro-001	**90.97%**
	ASAP (Chinese)[20] Range: 1–5	**gpt-4o-2024-08-06**	**85.62%**
		gemini-1.5-pro-001	84.66%
Emotion Distribution $(1 - \text{JSD}) \times 100\%$	GoEmotions [21], ISEAR[22] SemEval (English)[23]	gpt-4o-2024-08-06	75.40%
		gemini-1.5-pro-001	53.10%
		ft:gpt-4o-mini2024-07-18	**79.52%**
	Emotion Corpus[24], Chinese Weibo (Chinese)[25]	gpt-4o-2024-08-06	75.26%
		gemini-1.5-pro-001	58.29%
		ft:gpt-4o-mini2024-07-18	**80.81%**

We used the MyAnimeList dataset (19,211 comments, rated 1–10) for English and the ASAP dataset (4,940 Chinese restaurant reviews, rated 1–5) for Chinese. Building on our symbol detection approach, we extended the analysis to include trust and emotional intensity, using these two open-source datasets to evaluate model performance across languages (see Table 2). Gemini slightly outperformed GPT-4o in English (90.97% vs. 89.76%), while GPT-4o performed better in Chinese (85.62%). Due to the dominance of Chinese content in our data, GPT-4o was selected as the primary model. While its English accuracy was slightly lower, it showed stronger results overall—especially in symbol detection and trust/emotion estimation for Chinese text.

Table 3. Prompt and Output

	Prompt	**Example**	**Output**
Trust	Analyze the following YouTube comments and determine the percentage of trust expressed. Provide the output in JSON format as {"Trust": int}.	The Legislative Yuan that I am most looking forward to is here. This is the Legislative Yuan I want. This will definitely be exciting.	{Trust : 85}
Emotion	Analyze YouTube comments to determine emotional content (0–1 scale). Provide the distribution of emotions (Anger, Sadness, Joy, Disgust, Fear), ensuring they sum to 100%. Output format: {"Emotion": float, "Anger": int, "Sadness": int, "Joy": int, "Disgust": int, "Fear": int}.		{"Emotion": 0.83, "Anger": 0, "Sadness": 0, "Joy": 90, "Disgust": 0, "Fear": 10}

For Emotion distribution, to improve performance beyond zero-shot, we fine-tuned a lightweight model, gpt-4o-mini-2024-07-18 the models using a merged dataset of 6,599 samples from three English and two Chinese emotion datasets as described in Table 2, with a 70/30 train-validation split. The model was trained for 15 epochs with a 0.01 learning rate, stopping before overfitting as loss plateaued. We evaluated performance using relative accuracy and Jensen-Shannon Divergence (JSD) to compare predicted and actual emotion distributions [26]. Fine-tuned models outperformed zero-shot baselines, with accuracies of 79.52% (English) and 80.81% (Chinese). We selected the fine-tuned 'ft:gpt-4o-mini-2024-07-18' for further use.

As shown in Table 3 (Trust), the model was prompted to assign a trust score to each comment using a simple format like Trust: int. For instance, a comment expressing strong enthusiasm for the Legislative Yuan received a high trust score of 85%, supported by optimistic phrases such as "most looking forward to" and "this will definitely be exciting."

The same comment was also evaluated for emotion intensity as described in Table 3 (Emotion), receiving a score of 0.83, indicating a strong emotional tone. The emotion distribution suggests a predominantly joyful sentiment with slight anticipation and no negative emotion and each emotion is multiplied with emotional intesity. Together, the high trust and emotional positivity reflect strong support and enthusiasm in the comment.

3 Result & Discussion

This study examined standout frames from YouTube political videos during Taiwan's 2024 election to see how symbolic content influenced viewers.

3.1 User Engagement Evaluation (RQ1)

As shown in Figure 2, cultural symbols received the highest engagement, averaging around 1,000 likes, over 300 comments, and nearly 90,000 views. Social and political symbols followed with slightly lower but still substantial numbers. Videos without any symbols had much lower engagement across all metrics. Interestingly, the differences between symbol types were smaller for standout frames, suggesting that once viewers start watching, all types of symbols help keep them engaged. Overall, the findings show that symbolic visuals—especially cultural ones—play a key role in driving likes, comments, and views during political events.

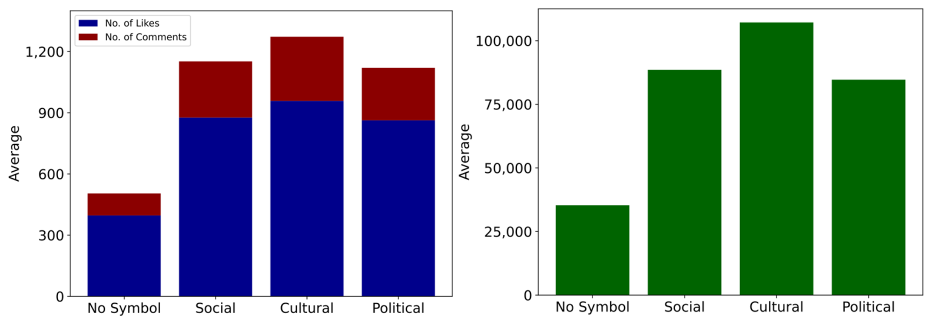

Fig. 2. Result of Engagement Analysis (Likes, Comments (Left), and Views (Right))

3.2 Analysis of Emotion (RQ2) and Trust (RQ3)

To answer RQ2, the analysis of standout frames showed that symbolic content significantly influenced the emotions expressed in YouTube comments during Taiwan's 2024 presidential election.

As shown in Figure 3 (Left), cultural symbols triggered the strongest emotional reactions, with disgust being the most frequently expressed emotion. Social and political symbols also evoked high levels of disgust and anger, reflecting viewers' strong reactions—often in response to disinformation. In contrast, videos without any symbols generated noticeably fewer emotional responses. Interestingly, the emotional intensity was relatively consistent across symbol types, suggesting that all forms of symbolic content contribute to shaping the tone of political discussions.

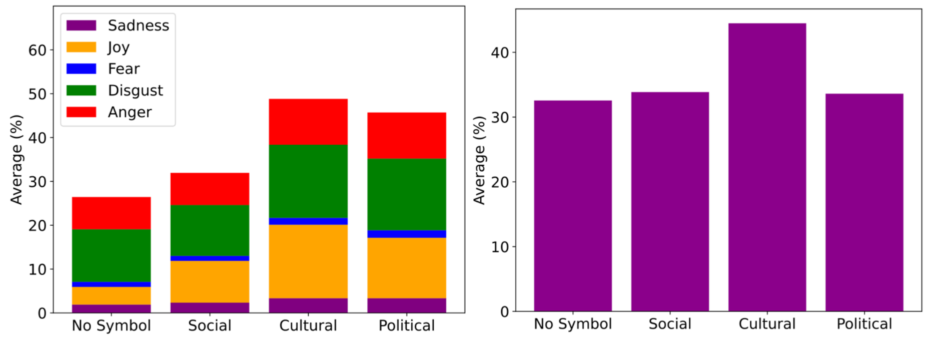

Fig. 3. Result of Emotion (Left) and Trust (Right) Analysis

For answering RQ3, our analysis of standout frames shows that symbolic content also plays an important role in shaping public trust.

As seen in Figure 3 (Right), cultural symbols had the strongest effect, with about 41% of comments expressing trust. Political and social symbols followed at around 35% and 33%, while videos without symbols had noticeably lower trust levels. This suggests that cultural symbols help convey credibility and legitimacy. Combined with earlier findings on engagement and emotion, this reinforces their consistent impact during political events.

These insights also build on established theories. They support symbolic interactionism by showing how people actively make meaning through engagement with SCP symbols [27]. They also align with the idea that digital platforms blur boundaries between public discourse and political figures [28].

The strong effect of cultural symbols across all dimensions—engagement, emotion, and trust—echoes the encoding/decoding model [29], where culturally relevant visuals help messages resonate more clearly. Their role in building trust also reflects the idea of participatory culture, where shared symbols create a sense of community during major democratic moments [3].

Overall, our findings not only support these theories but extend them, showing how symbolic content actively shapes political engagement and trust in the digital age.

3.3 Testing for External Factors and Statistical Validation

To ensure our results weren't just due to how often content was posted or how big the channels were, we also looked at post frequency and average subscriber counts across different symbol types. As shown in Figure 4 (Left), political symbols appeared most often, followed by social and cultural ones, while no-symbol videos were posted the least. In terms of followers (Figure 4, Right), channels using political and social symbols had the largest followings—over 1.6 million on average—compared to about 1.4 million for no-symbol channels. Still, despite having a wider reach, no-symbol videos consistently showed the lowest

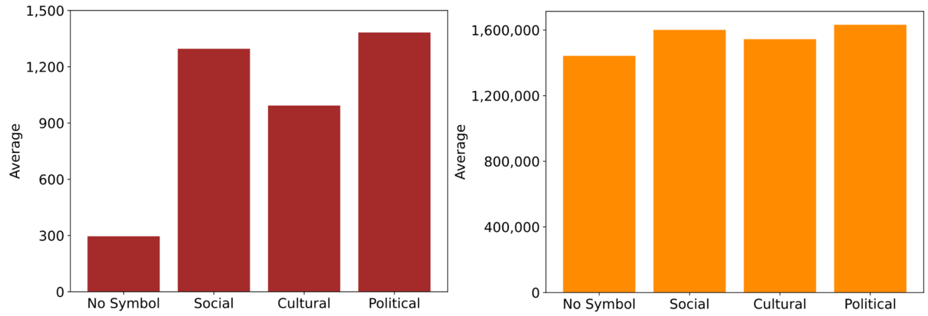

Fig. 4. Number of Post (Left) and Number of Subscribers (Right) Analysis

engagement, emotion, and trust. This suggests that it's the symbolic content itself—not just visibility—that drives how people respond.

To back up these findings, we ran statistical tests using the Kruskal-Wallis method, since our data wasn't normally distributed. The results showed clear differences across symbol types. For instance, likes and comments had extremely low p-values (3.23×10^{-24} and 1.4×10^{-14}), confirming a strong effect of symbols on engagement. Similar significance appeared for emotion (2.34×10^{-15}) and trust (3.41×10^{-33}). These results make it clear: symbolic content plays a powerful role in shaping how people interact with political videos online.

4 Conclusion

Our research highlights the strong influence of SCP symbols on user engagement, emotional response, and trust during Taiwan's 2024 election on YouTube. Among these, cultural symbols stood out—they generated the most interaction, triggered the strongest emotions, and were most effective in building trust. Overall, videos containing symbolic content consistently outperformed others, underscoring the importance of symbolism in digital political communication.

These results align with theories like Symbolic Interactionism, supporting the idea that people create meaning through their engagement with symbols. Still, the study has some limitations. It relies heavily on pre-trained vision-language models, especially GPT-4o, which may carry biases from their training data.

In future, we plan to examine additional symbol types beyond SCP such as those tied to branding or environmental causes. We also aim to develop more specialized vision-language models for symbol detection and expand our analysis to other political campaigns and platforms. Through these efforts, we hope to better understand how symbolic content shapes online political discourse and contributes to broader conversations about civic participation in the digital age.

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