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# Analyzing image-based political propaganda in referendum campaigns: from elements to strategies

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**Abstract**

Due to the increasing prominence of social network services, political communication has experienced a paradigm shift. To communicate with internet users, politicians, candidates, and political organizations create fan pages. Initially, they provide text-only material on their pages; later, to increase engagement, they include photos, images, and videos. This paper investigates image-based political images in Taiwan for the first time during a nationwide referendum. Unlike an election, a referendum is a policy-based vote. We evaluate over 2000 Facebook images shared by the two most prominent political parties in order to comprehend the aspects of images and the tactics of political organizations. In addition, we examine the textual content, objects, and colors of the collected data. We find that the characteristics of propaganda materials vary between political groups. Nonetheless, the color strategies employed by both sides are equivalent, with each side utilizing its own representative colors for consolidation and the opponent's colors for attacking.

**Keywords:** Political propaganda; Social media; Election study; Referendum; Coloring strategy

## 1 Introduction

The emergence of social network services has caused a paradigm change in political communication. In order to communicate with online users on social network platforms such as Facebook and Twitter, not just politicians but also political groups create fan pages. During elections, they also use social media to spread their opinions and promote themselves. These channels allow candidates to communicate with voters who may not have access to television or newspapers. Meanwhile, numerous studies have examined the text published on Facebook and Twitter to determine how political entities disseminate propaganda on social media platforms [1, 2]. Likewise, the formats of propaganda and the platforms on which it was conducted evolve throughout time. For instance, political adverts exist not just on Twitter, but also on multimedia-rich platforms like Instagram and Tiktok [3, 4]. They often embedded images and videos in text messages to increase engagement and attract more attention. Previous research on image-based political propaganda has mainly concentrated on detecting objects, analyzing human facial expressions,

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and extracting image features [5–8]. Many scholars have also studied the use of images in propaganda during election campaigns [9, 10]. However, there are still gaps in knowledge about understanding how images are used in propaganda, such as analyzing larger social datasets to gain a more comprehensive understanding of elements and types of image-based propaganda. Additionally, there is a lack of research on investigating the differences in the use of slogans, colors, and other elements between referendum campaigns and election campaigns.

In this paper, we aim to fill these gaps by providing a deeper understanding of the elements and strategies used in online propaganda images, particularly in the context of referendum campaigns. The following are the three major research questions that have been investigated:

1. What are the elements (texts and objects) in the image-based propaganda materials during a referendum?
2. How do the government and the opposing party use color during a referendum?
3. What are the differences in images used for various propaganda purposes (e.g., attacking/consolidation) during a referendum?

To explore these questions, we examine the Facebook election campaign for Taiwan's 2021 national referendum. We choose a referendum as the target because, unlike elections, which are votes on candidates, a referendum is a vote on a proposal or a policy; hence, we are interested in determining whether the content and form of online propaganda vary by political party.

During an 8-month observation period preceding the referendum, we collected over 10,000 photographs posted by the two major parties, Democratic Progressive Party (DPP, the ruling party) and Kuomintang (KMT), on Facebook. We filtered out the top one thousand DPP and KMT photos based on the number of reaction emojis that users expressed. We performed text recognition, object extraction, and color quantification on the dataset; a detailed comparison between the two parties is made and discussed in this work.

Overall, the main findings of this work are three-fold:

1. Political propaganda in a referendum campaign typically emphasizes slogans, the voting date, and the for or against the policy. Our analysis suggests that the ruling party tends to use more infographics in their campaign materials compared to the opposition.
2. Our findings indicate that political parties often use the representative color of the opposition when attacking them, rather than the propaganda strategies commonly described in previous research.
3. The results show that political parties tend to use their representative color more frequently when consolidating their votes and the opposing party's color when attacking their opponents.

This paper is organized as follows: In section Related Works, this section introduces relevant works on political propaganda and the context of the examined referendum. In section Data & Methodology, we present the details of data collection and extraction methods for texts, objects, and colors. In section Experiment and Result, we show a comprehensive analysis of the texts, objects, and color usage in the images published by the two major parties. In section Strategic Analysis, we demonstrate an in-depth analysis of propaganda strategies. Finally, the conclusion and discussion of this work are depicted in section Conclusion and Future Works.

## 2 Related works

In 1927, Harold D. Lasswell [11] first formulated a theory of political propaganda and characterized it as "the management of collective attitudes by the manipulation of significant symbols." Since then, political propaganda has become the principal means by which political elites convey their views, plans, and ideas to the general population. In 1997, R.A. Nelson [12] described political propaganda as usually spread through the dissemination of unilaterally controlled messages. These messages attempt to influence a particular target's emotions, attitudes, beliefs, and behaviors were spread through large-scale, direct media channels. Due to the rise of the Internet, political propaganda has been redefined in the current day. Randal Marlin [13] defined propaganda as "the organized attempt, through communication, to affect belief or action or inculcate attitudes in a large audience in ways that circumvent an individual's adequately informed, rational, reflective judgment." Étienne Brown [14] considers the various means used by propagandists and categorizes three ideal types of propaganda: affective propaganda, conative propaganda, and cognitive propaganda. In 2018, Jowett and O'donnell [15] defined political propaganda as a deliberate, systematic attempt to form ideas, manipulate perceptions, and guide behavior to achieve the desired response. With the rapid growth of social network services, people's access to information has expanded beyond traditional media like newspapers and television to online platforms like Facebook and Twitter. We explain the literature on political propaganda on social media platforms and highlight the significance and relevance of our research.

### 2.1 Political propaganda on social platforms

Social media lets individuals share and receive information. Meanwhile, politicians and organizations have created fan pages to communicate with the public. However, research has shown that citizens care more about party or candidate traits than specific issues [16–18]. Based on these findings, some candidates or parties may post more photographs and favorable comments to control their image, which is propaganda. To study the impact of online propaganda, Woolley and Guilbeault [19] investigated how political parties spread their ideas through bot accounts on social media and their effects during major political events. Ferrara et al. [20] used the United States as a case study to examine the impact of online political propaganda on Twitter; they categorized bot accounts as right- or left-leaning in order to determine how political propaganda influences the presidential election.

As political elites increasingly use social platforms to connect with public, researchers have examined the information released and responded to by political entities to determine how social communication can affect the public. Brady et al. [21] studied the gauge influence of political elites on social media. They found a "moral contagion" effect, which refers to "elites' use of moral-emotional language was robustly associated with increased message diffusion." To analyze the topic and emotion of political propaganda, Miller [22] studied Russian propaganda on Twitter before, during, and after the 2016 U.S. presidential election. The results show that Russian-sponsored tweets have distinct attitudes towards different presidential candidates.

Political propaganda is a frequent method used in political communication to promote certain proposals or affect the political leanings, texts, images, and even videos of individuals. Prior to comprehending political propaganda in photographs, the majority of study relies on text mining and bot account detection [23–26]. However, using images in political propaganda has become familiar with the rise of social media.

The study of image propaganda can be divided into various categories, such as images of candidates or parties, events, or ideologies. For example, Mattes et al. [27] studied how the candidate images will affect the election results through crowdsourcing, collecting the impression netizens felt from the photos. Prior to the rise of social media, candidate posters were not a significant factor in elections. Håkansson et al. [28] examined the Swedish Election poster over a period of around a century and found several interesting phenomena such as thematic repetition of style, consistency in the use of colors and materials, and subliminal appeals. Colm A. Fox [29] investigated election posters from 1955 to 2021 and found that current posters use more complex features to demonstrate why the candidate merits voter support.

Additionally, Al-Azzawi and Saleh [30] examined the posters of four contenders in the 2020 United States presidential election and found that the visual and textual elements of the posters serve as persuasive tools to highlight the political influence. They demonstrated that the designers of the posters carefully evaluate the content and visual aids in order to persuade the audience to vote for a particular candidate. Deirdre Pretorius [31] examined three 2019 South African election posters and found that the three parties' posters differed in terms of leader size, posture, nonverbal cues, and attire.

Vliegenthart, R. [32] studied election posters in the Netherlands and found that over time, party logo and candidates appear more frequently in posters and occupy more pages, showing political personalization. Benoit, W. L. [33] studied the US presidential election posters from 1828 to 2012, and also came to similar conclusions, including praise is more common than attack, and the character of the candidate is far more than the policy.

For referendum images, O'Hagan, L. A. [34] studied Sweden's 1922 control of alcohol consumption referendum and said that the posters used during the referendum used catchy slogans, simple pictures, and bright colors to make it easy for the public to digest, using infographics to convey a rational argument. Türkmenoğlu, A.T. [35] used semiotic analysis to examine five referendum posters from the Brexit campaign to uncover the meanings conveyed by the images and text.

Regarding event detection with social media photographs, Won et al. [5] developed a visual model to recognize protesters and estimate the level of perceived violence in a snap in order to identify protest events and statistics on perceived levels of violence in various regions. Zhang and Pan [6] attempted to identify collective action events utilizing text and image data from China's most popular microblogging network, Sina Weibo. In order to detect real-world occurrences, they classified text using the long short-term memory (LSTM) model and extract visual features through convolutional neural networks (CNN).

In political party or ideological field research, Xi et al. [7] attempted to understand how politicians communicate their political ideology via social media images by studying the scene and facial expression to determine whether a politician is Democratic or Republican. Joshi and Buntain [8] analyzed comparable and ideologically associated political communication pictures by means of clustering and deep learning. They gathered photos of US congressmen via Twitter's REST API and categorized them according to their association with liberal or conservative ideology.

According to our analysis of the literature, previous research on image analysis has largely focused on object detection, facial expression recognition, and feature extraction [5–8]. However, little attention has been given to the elements, color use, and strategies of images in political propaganda. To address this, in this work, we study the text, elements,

and colors used in online propaganda images during a nationwide referendum campaign on Facebook. We aim to fill the knowledge gaps in the visual analysis of political propaganda by analyzing a large social media dataset and comparing the strategies between parties during referendum campaigns.

## 2.2 Politics in Taiwan and the 2021 National Referendum

Since the 1980s, Taiwan's politics have remained polarized for decades. In the last twenty years, the two major parties, DPP (the current ruling party) and KMT, have alternately won elections and held a majority of elected seats in the parliament [36–39]. The two parties have divergent views on China and the United States' relations, and they also disagree both online and in person regarding Taiwan's national identity [40–43]. In 2021, Taiwan held a national referendum to vote on four issues, including (1) activating the Fourth Nuclear Power Plant in Gongliao District, New Taipei City; (2) prohibiting imports of pork containing ractopamine; (3) holding referendums alongside nationwide elections; and (4) relocating a Natural Gas Terminal to protect algal reefs off Taoyuan Guanyin District. Based on the results of the vote, all four proposals are rejected. Among these proposals, the prohibition on U.S. pork imports is the most controversial and has garnered the most attention domestically and internationally. In 2020, President Tsai Ing-wen declared that the prohibition on U.S. pork products would be lifted in 2021. Concerned about food safety, KMT politicians then suggested a referendum to impose limitations on the import of pork containing ractopamine. However, the government asserts that the regulation might potentially harm relations between Taiwan and the United States, as well as Taiwan's efforts to join international trade agreements. 51.2% voted against the prohibition, while 48.8% supported it.

## 3 Data & methodology

Figure 1 depicts the overall procedure of our analysis scheme. The procedure includes five steps: (1) data collection and cleaning, (2) text recognition, (3) object extraction, (4) color quantification, and (5) visualization. We then visualize the results and conduct a thorough study of them.

### 3.1 Data collection

From April to December 2021, eight months prior to the vote, we collected our dataset on Facebook. We crawled a total of 103,845 posts whose content linked to the four referendum questions. Only 40,953 (39%) of these postings included at least one photo. To analyze the propaganda conducted by the two major parties, we assigned political labels to each post publisher. Only images published by politicians or major party affiliations are included in our database. Table 1 displays an overview of our dataset.

### 3.2 Text recognition

In order to examine the textual content of images, we utilized the Google Cloud Vision API[1] for optical character recognition. Our dataset consisted of the top 1000 images with the highest number of likes in the pan-blue and pan-green fan pages and select 10 words

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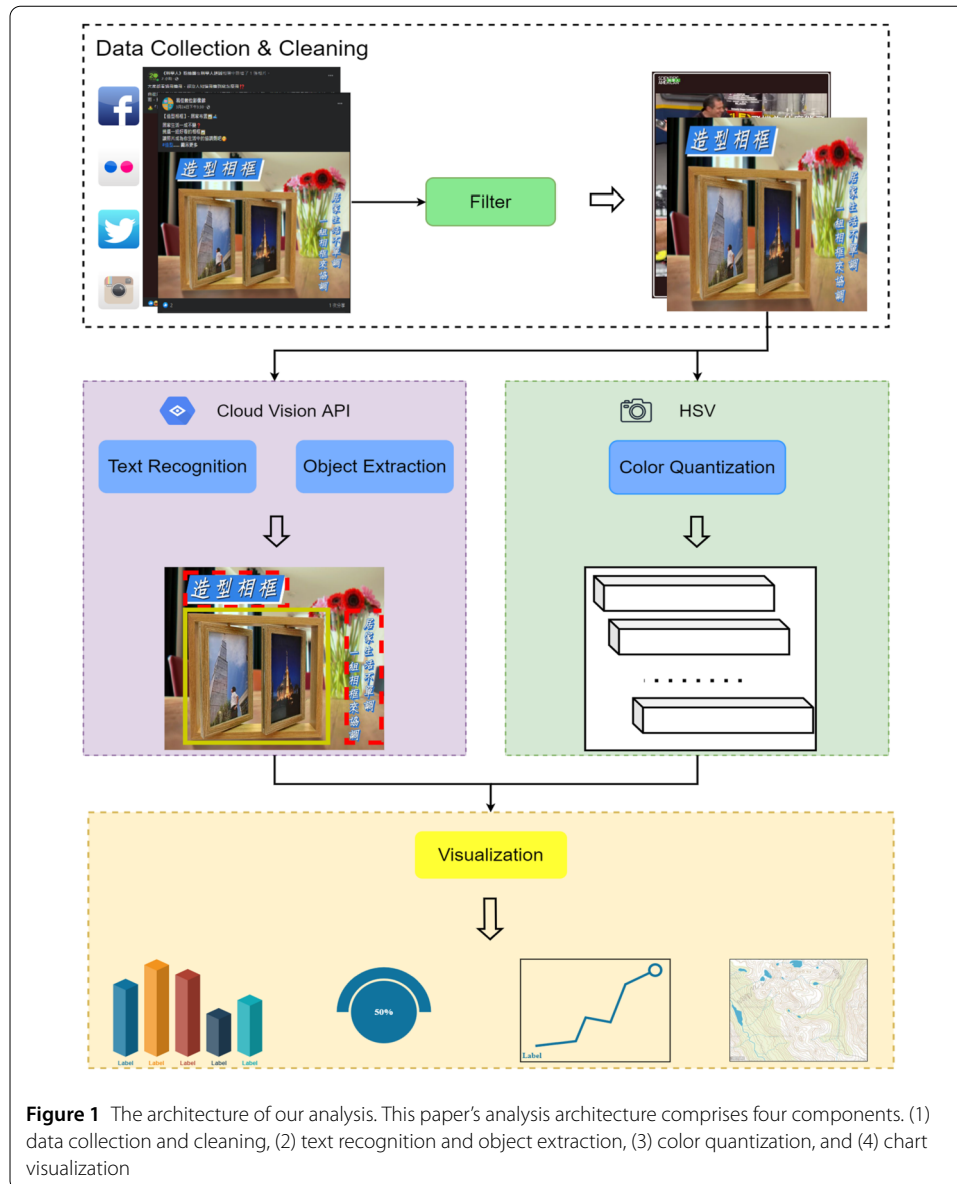
[1]https://cloud.google.com/vision.

Data Collection & Cleaning

Filter

Cloud Vision API

Text Recognition

Object Extraction

HSV

Color Quantization

Visualization

50%

Label

Label Label Label Label Label

**Figure 1** The architecture of our analysis. This paper's analysis architecture comprises four components. (1) data collection and cleaning, (2) text recognition and object extraction, (3) color quantization, and (4) chart visualization

related to the referendum for testing. We computed precision and recall scores by comparing the results of the Google Vision API with manual annotations as in Table 2. According to the results, the Google Vision API achieved a precision rate of 87.02% and a recall rate of 74.78%. Based on the results, the Vision API demonstrated well character recognition ability in our dataset (Traditional Chinese). It accurately recognized most words even in complex environments. Therefore, we will continue to use the Google Cloud Vision API as the chosen text recognition method.

### 3.3 Image categorization

We divided the data we gathered into two classes—infographic and propaganda images—in order to analyze the variations in presentations and tactics used in political propaganda. The following is a description of the categorization guide:

**Table 1** An overview of our dataset

| Item | Information |
|---|---|
| Data collection period | 2021/04/01∼2021/12/18 |
| # Fan pages | 423 |
| # Posts | 103,845 |
| # Posts about the referendum | 6,854 |
| # Images about the referendum | 9,385 |

**Table 2** Vision API text verification result.

| Text | TP | FP | FN | Precision | Recall |
|---|---|---|---|---|---|
| (a) Vision API OCR test in pan-blue images | | | | | |
| Referendum | 355 | 64 | 187 | 0.8472 | 0.6549 |
| KMT | 174 | 21 | 86 | 0.8923 | 0.6692 |
| Taiwan | 144 | 42 | 128 | 0.7741 | 0.5294 |
| 1218[1] | 132 | 57 | 41 | 0.6984 | 0.7630 |
| Vote | 111 | 21 | 32 | 0.8409 | 0.7762 |
| Disagree | 74 | 17 | 51 | 0.8131 | 0.5920 |
| Racto. pork[2] | 73 | 3 | 199 | 0.9605 | 0.2683 |
| Algal reef | 65 | 8 | 42 | 0.8904 | 0.6074 |
| Government | 63 | 16 | 10 | 0.7974 | 0.8630 |
| Health | 43 | 20 | 9 | 0.6825 | 0.8269 |
| (b) Vision API OCR test in DPP (pan-green) images | | | | | |
| Referendum | 1036 | 47 | 232 | 0.9566 | 0.8170 |
| 1218[1] | 412 | 64 | 133 | 0.8655 | 0.7559 |
| 4 disagree | 420 | 16 | 137 | 0.9633 | 0.7540 |
| Disagree | 426 | 100 | 56 | 0.8098 | 0.8838 |
| TW powerful[5] | 348 | 13 | 77 | 0.9639 | 0.8188 |
| Fourth NPP[3] | 269 | 20 | 107 | 0.9307 | 0.7154 |
| Taiwan | 231 | 145 | 16 | 0.6143 | 0.9352 |
| NGT[4] | 220 | 10 | 77 | 0.9565 | 0.7404 |
| Pork from US | 184 | 10 | 48 | 0.9484 | 0.7931 |
| Vote | 182 | 46 | 5 | 0.7982 | 0.9732 |

[1] Date of the referendum.
[2] Pork containing ractopamine.
[3] The Fourth Nuclear Power Plant.
[4] Natural Gas Terminal.
[5] Slogan: Taiwan more powerful.

- *Infographic.* An infographic is an image that is used in reports, technical publications, and signage. The formats include but are not limited to timelines, maps, data visualizations, flow charts, and statistical charts. Figure 2(a) illustrates a few instances.
- *Propaganda.* An image includes slogans without any statistical charts or data visualizations. A few samples are displayed in Fig. 2(b).

In addition to the aforementioned two categories of images, a significant component of our collection consists of photographs taken by photographers, such as photographs of large-scale outdoor campaigns with crowds.

### 3.4 Object extraction

To build upon previous research on the content analysis of political propaganda texts [44–46], we investigated various aspects of data collection. Our aim was to gain insights into how different political organizations created promotional materials to communicate their ideas and proposals. For this purpose, we utilized the Google Vision API to extract objects depicted in each photo and assessed the accuracy of the API's results through human verification.
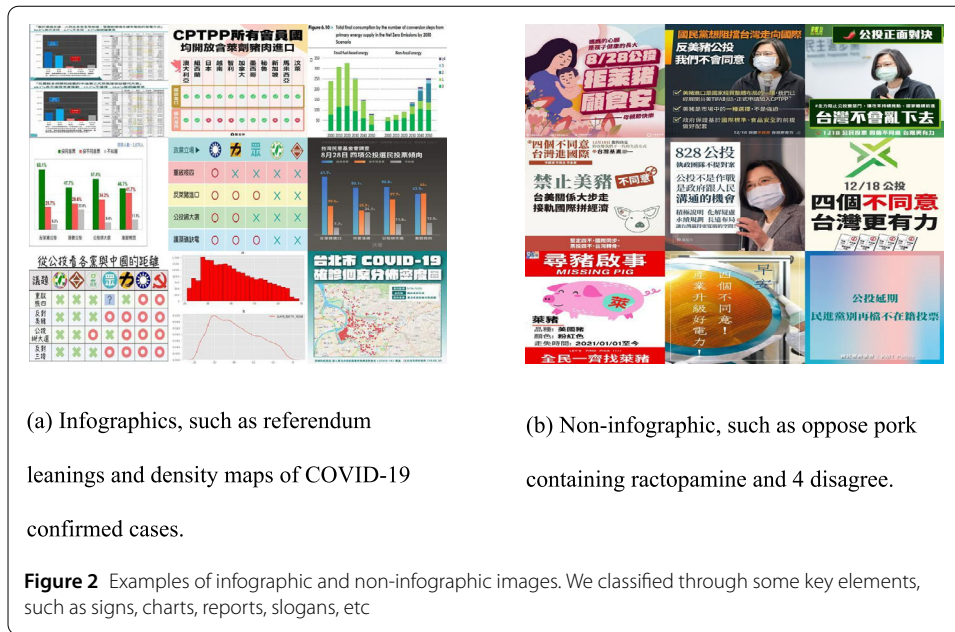
(a) Infographics, such as referendum leanings and density maps of COVID-19 confirmed cases.

(b) Non-infographic, such as oppose pork containing ractopamine and 4 disagree.

**Figure 2** Examples of infographic and non-infographic images. We classified through some key elements, such as signs, charts, reports, slogans, etc

**Table 3** Vision API object verification test result

| Text | TP | FP | FN | Precision | Recall |
|---|---|---|---|---|---|
| Suit | 321 | 51 | 235 | 0.8629 | 0.5773 |
| Eyewear | 246 | 23 | 853 | 0.9144 | 0.2238 |
| Poster | 242 | 78 | 324 | 0.7562 | 0.4275 |
| Crowd | 196 | 51 | 174 | 0.7935 | 0.5297 |
| T-shirt | 174 | 137 | 177 | 0.5594 | 0.4957 |
| Trousers | 166 | 3 | 390 | 0.9822 | 0.2985 |
| Tree | 116 | 2 | 181 | 0.9830 | 0.3905 |
| Vehicle | 132 | 51 | 87 | 0.7213 | 0.6027 |
| Hat | 118 | 79 | 130 | 0.5989 | 0.4758 |
| Building | 92 | 28 | 248 | 0.7666 | 0.2705 |
| Publication | 70 | 90 | 134 | 0.4375 | 0.3431 |
| Signage | 60 | 67 | 330 | 0.4724 | 0.1538 |
| Curtain | 54 | 8 | 64 | 0.8709 | 0.4576 |
| Community | 47 | 39 | 238 | 0.5465 | 0.1649 |
| Screenshot | 48 | 42 | 230 | 0.5333 | 0.1726 |
| Shorts | 15 | 39 | 19 | 0.2777 | 0.4411 |

In Table 3, we present the outcomes of the tagging process, indicating satisfactory precision (> 0.75) for labels such as suits, eyewear, poster, crowd, trousers, tree, building, and curtain. However, we observed that the precision of the Google Vision API was potentially inadequate for certain labels, including T-shirts, hats, shorts, signs, and publications. This discrepancy could be attributed to variations in the definitions used by human taggers compared to those employed by Google's algorithms.

For example, our human tags only considered standalone hats as hats, while excluding hooded jackets. This could potentially lead to misidentification by the Google Vision API. Despite these limitations, given the satisfactory performance across most labels, we have decided to utilize the results obtained from the Google Vision API for our research.

### 3.5 Color quantification

According to prior research, color may play a significant role in psychological effects and decision-making [47, 48]. To understand the impact of colors in image-based political communication, we quantified the color distribution of images and analyzed (1) how organizations use color to create propaganda materials? And (2) do various techniques exist for employing colors for other reasons (such as assaulting the opposition or solidifying support)?

To understand the color composition of images, we applied a color quantification approach to our dataset. We utilized k-means clustering, where $k = 5$ in our setup, to group pixels according to RGB and HSV in order to identify the prominent colors of an image.

Then, we selected the center of each cluster and computed the percentage it occupies in order to extract the five predominant colors of each image.

- *RGB (RGB Color Model).* RGB is an additive color model that uses red, green, and blue to express a color. In the system, red, green, and blue indexes are all set in range $0 \sim 255$, where $(0, 0, 0)$ represent black and $(255, 255, 255)$ represent white.
- *HSV (Hue, Saturation, and Value).* Through a cylindrical coordinate system, HSV is utilized to represent colors. Hue is a fundamental characteristic of hues like red, yellow, and green. In a cylindrical coordinate system, hue is represented as an angle in the range $0° \sim 360°$, however, in the OpenCV module for Python, it is represented as $0 \sim 180$. Saturation is the value of the purity of colors, so colors with a low saturation value will become gray. In our program, we set saturation to the range $0 \sim 255$. Value is also known as brightness. A color with a low value of brightness would become dark.

Figure 3 depicts the colors extracted by $k = 5$ and $k = 10$. Although $k = 10$ allows us to obtain a more complete description of the color distribution, $k = 5$ allows us to reserve the most dominating colors with less computational effort. We visualized and examined the color utilization for various parties, image categories, and image functions based on the results.

## 4 Experiment and result

From the data collection, we selected the top 1000 images from pan-blue and pan-green fan pages on Facebook according to the number of likes of the posts. A summary of the images is shown in Table 4. In the pan-blue subset, 109 fan pages and 496 posts were included. The number of likes of each post ranged from 904 to 113,168; in pan-green, we included 102 fan pages and 425 posts in the subset. The number of likes of each post ranged from 1917 to 95,084. We also found DPP (pan-green, the ruling party) uses more images and texts in a post than the opposition (pan-blue).

### 4.1 Text in image

We uploaded images to the Google Vision API and processed the resulting data as described previously. After the text segmentation, we tagged and used the parts of speech of words extracted from images. We then removed traditional Chinese stop words according to Table 5 and merged synonyms according to Table 6. Table 7 shows the top 10 most frequent words in pan-blue and pan-green images. We manually merged synonyms; for example, "國民黨" and "中國國民黨" are both equivalent to KMT.

**Figure 3** K values for extracting dominating colors. Example results for $k = 5$ and $k = 10$ when extracting dominating colors of images

## 4.2 Detection on image

We extracted object labels from images using the Google Vision API. There were 650 labels on 1000 pan-blue fan page images and 550 labels on 1000 pan-green fan page images. We set the threshold for reserving frequent labels at 20. Same as the text in the image, we are manually combining several overly detailed categories into one broader category. For example, we are combining eyewear, glasses, and sunglasses into the category of eyewear, and combining jeans trousers into the category of trousers. In this we will first filter those labels that are describing images, such as world, recreation, rectangle even more. Next, we manually filter some label that cannot explained in any strategy, such as table, chair or tire. Finally, we categorized labels as clothing, physical objects, and backgrounds.

## 4.3 Color quantization of images

As depicted in Fig. 4, we analyzed the color distribution of the top 1000 images from each group in this section. Figure 5 demonstrates the distribution of hue-based color usage in the HSV system using a histogram. The visualization is intended to highlight the difference in color usage between the two political groups. The figure reveals a clear polarization in using blue-tone/green tone colors between the two groups.

## 5 Strategic analysis

This section details the results of word recognition, object extraction, and color quantization performed on images published by various political groups. In addition, we analyze the strategic distinctions between the two parties' propaganda efforts. The two most important issues we research are:

**Table 4** The top 1000 images for KMT (pan-blue) and DPP (pan-green) fan page

| Information | KMT (pan-blue) | DPP (pan-green) |
|---|---|---|
| Fan pages | 109 | 102 |
| Posts | 496 | 425 |
| Max numbers of likes | 113,168 | 95,084 |
| Min numbers of likes | 904 | 1917 |
| Avg. likes/Post | 9,054 | 3,375 |
| Avg. image/Post | 2.01 | 2.35 |
| Avg. text/Image | 11.32 | 21.67 |
| Avg. object/Image | 9.76 | 9.15 |

**Table 5** Part-of-speech list for stopword removal

| Part-of-speech | Description |
|---|---|
| Auxiliary word | 啊、呀、吧(ah) |
| Coordinating conjunction | 和(and) |
| Conjunction | 等等(etc.)、的話(if) |
| Interjection | 哎呀、天呀(eh) |
| Pronoun | 你(you)、我(me)、他(he/she) |
| Preposition | 從、自(since, from) |
| Auxiliary verb | 把、將(let)、有 (have, has) |
| Adverb | 也(also)、沒有(not)、總共(total) |
| Be verb and possessive | 是(is)、的、之(of) |
| Punctuation | ,!,～,:,–,*,(,),[,] |

**Table 6** Synonym word for grouping

| Synonym words | Merged words |
|---|---|
| 中國國民黨、國民黨 | 國民黨 (KMT) |
| 民主進步黨、民進黨 | 民進黨 (DPP) |
| 台灣、臺灣 | 臺灣 (Taiwan) |
| 核四、核四廠、第四核電廠 | 核四 (Fourth NPP) |
| 中央選舉委員會、中選會 | 中選會 (CEC) |
| 公投、公民投票 | 公投 |
| 1218, Minimum of 12 and 18 | 1218 |

**Table 7** Top 10 most frequent words in pan-blue and DPP (pan-green) images

| Rank | Words | Frequency | Rank | Words | Frequency |
|---|---|---|---|---|---|
| (a) Top 10 most frequent words in pan-blue images | | | (b) Top 10 most frequent words in DPP (pan-green) images | | |
| 1 | Referendum | 419 (3.69%) | 1 | Referendum | 1083 (4.99%) |
| 2 | KMT | 195 (1.72%) | 2 | Disagree | 526 (2.42%) |
| 3 | 1218[1] | 189 (1.66%) | 3 | 1218[1] | 476 (2.19%) |
| 4 | Taiwan | 186 (1.64%) | 4 | 4 disagree | 436 (2.01%) |
| 5 | Vote | 132 (1.16%) | 5 | Taiwan | 376 (1.73%) |
| 6 | Disagree | 91 (0.80%) | 6 | TW powerful[3] | 361 (1.66%) |
| 7 | Government | 79 (0.69%) | 7 | Fourth NPP[4] | 289 (1.33%) |
| 8 | Racto. pork[2] | 76 (0.67%) | 8 | NGT[5] | 230 (1.06%) |
| 9 | Algal reef | 73 (0.64%) | 9 | Vote | 228 (1.05%) |
| 10 | DPP | 71 (0.62%) | 10 | Pork from the US | 194 (0.89%) |

[1] Date of the referendum.

[2] Pork containing ractopamine.

[3] Slogan: Taiwan more powerful.

[4] The Fourth Nuclear Power Plant.

[5] Natural Gas Terminal.

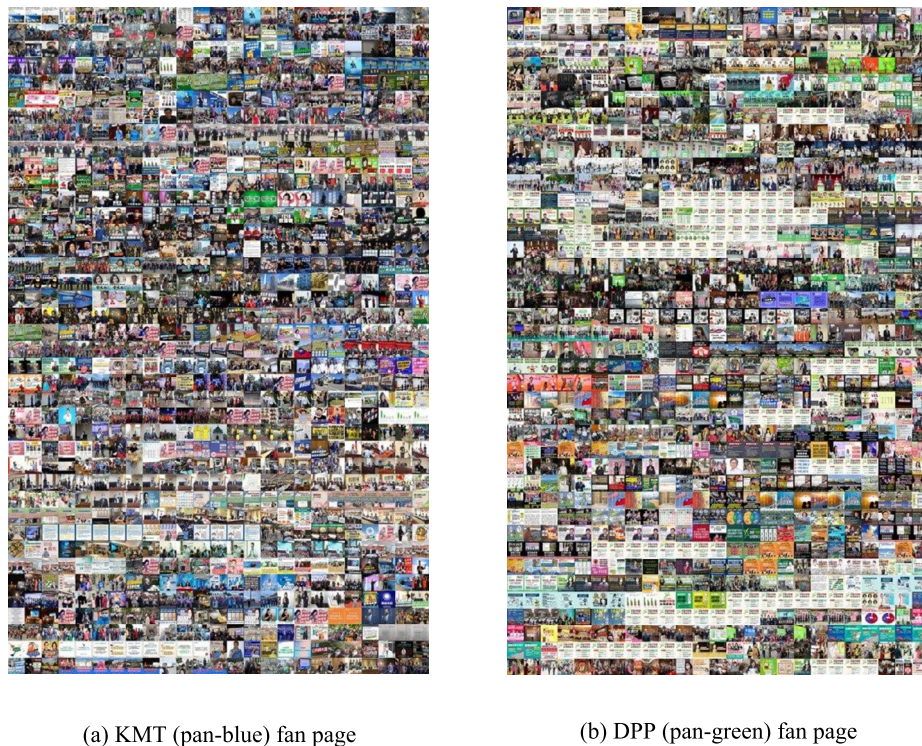(a) KMT (pan-blue) fan page                          (b) DPP (pan-green) fan page

**Figure 4** The top 1000 images from pan-blue and pan-green fan pages. To have a macro view of the dataset, we aggregate one thousand photos into one

1. Do infographic images and propaganda images vary in any way?
2. Do the images used to rally supporters and demonize the opposition vary in any way?

By responding to the two questions, we attempt to comprehend the two polarized political groups' tactics for creating propaganda materials.

To answer the aforementioned questions, we group the collected images into three categories, including infographics, propaganda, and others. The propaganda picture contains photos with linked slogans or text. The majority of the images in others were of landscapes, conferences, or people without text. We define how we classify infographics, propaganda, and other types of imagery.

- *Infographic.* An infographic is an image used for signage, reports, and technical documentation. The formats consist of but are not limited to, timelines, maps, data visualizations, flow charts, and statistic charts.
- *Propaganda images.* An image includes slogans but no statistics or data visualizations.
- *Others.* We classify images that do not belong to "Infographic" or "Propaganda images" as "Others." Our observations indicate the majority of these photographs depict various political activities.

As shown in Table 8, after manually tagging these images, the pan-blue group contains only 26 infographic images and 398 propaganda images. The pan-green group, on the other hand, creates 50 infographics and 561 propaganda images.

According to Table 8, the pan-green group produces 92% more infographic graphics than the pan-blue group (50 vs. 26). The pan-green group also uses more slogan-based
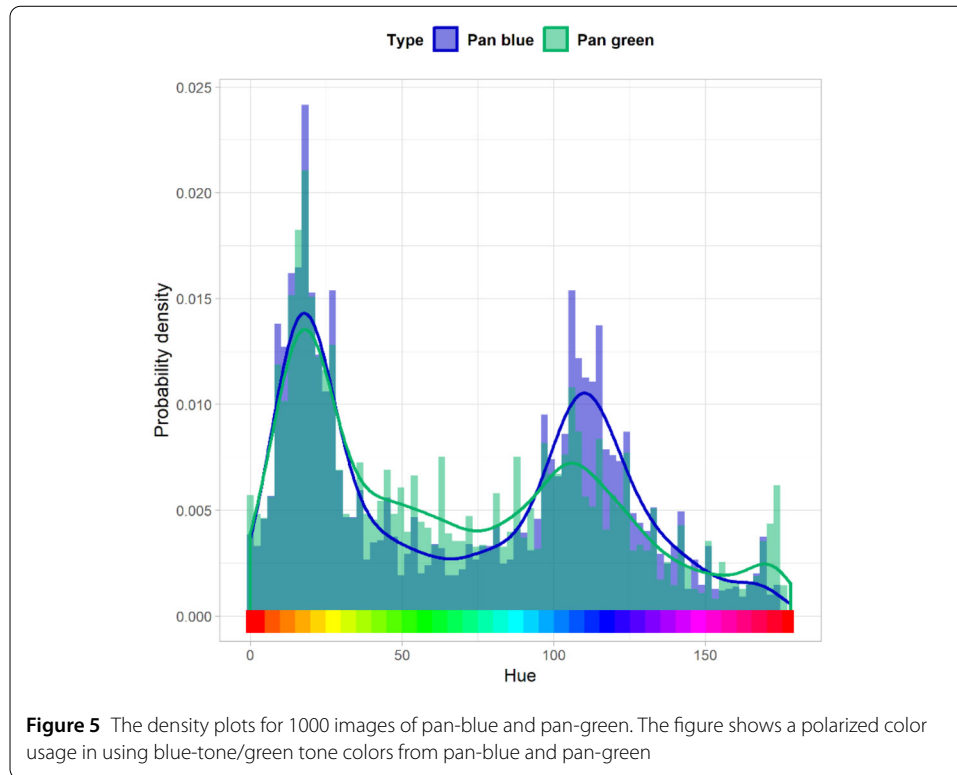
**Figure 5** The density plots for 1000 images of pan-blue and pan-green. The figure shows a polarized color usage in using blue-tone/green tone colors from pan-blue and pan-green

**Table 8** Presentation types of the top 1000 images in KMT (pan-blue) and DPP (pan-green)

| Type | Pan-blue | Pan-green |
|---|---|---|
| Infographic | 26 | 50 |
| Propaganda | 398 | 561 |
| Others | 576 | 389 |

propaganda materials than the pan-blue group. Comparatively to the pan-blue, the ruling party (pan-green) uses statistics tables and slogan visuals to justify their opposition to the referendum proposal based on the results.

### 5.1 Textual analysis

We list the ten most frequently used words retrieved from pan-blue and pan-green images, as shown in Table 7. The table demonstrates that the slogan of the ruling party's propaganda is more consistent. For example, they use "不同意(disagree)" and "四個不同意(4 disagree)" to urge citizens to vote against the referendum. From a distribution perspective, pan-green is more purposeful and organized than pan-blue by using more consistent wordings in images (the top 5 words account for 13.34% of total word usage; pan-blue: 9.87%). The results also show that the two parties are on the opposite side of the issue, such as "四個都同意(4 agree)" versus "四個不同意(4 disagree)" and "反萊豬 (oppose pork containing ractopamine)" versus "美豬(pork from the US)".

We also compare the text derived from propaganda visuals and infographics. The distinction between pan-green and pan-blue groupings is the most frequently used words in propaganda imagery. The propaganda photos on pan-green fan pages include critical terms from the referendum, such as "核四(the Fourth Nuclear Power Plant)" (1.19%),

**Table 9** Clothing, physical object, and background label proportions and p-values of $\chi^2$ tests in pan-blue and pan-green images

| Label | p-value | Pan-blue | Pan-green | Label | p-value | Pan-blue | Pan-green |
|---|---|---|---|---|---|---|---|
| (a) Clothing | | | | (b) Physical object | | | |
| Eyewear | 2.73E-05 | 16.7% | 10.2% | Vehicle | 2.81E-05 | 11.9% | 6.4% |
| T-shirt | 3.05E-03 | 18.0% | 13.1% | Poster | 3.60E-01 | 15.2% | 16.8% |
| Suit | 3.24E-06 | 14.5% | 22.7% | Curtain | 2.82E-02 | 4.0% | 2.2% |
| Trousers | 7.33E-04 | 10.6% | 6.3% | Tree | 1.95E-05 | 8.2% | 3.6% |
| Hat | 6.72E-06 | 12.9% | 6.8% | Publication | 1.17E-01 | 7.0% | 9.0% |
| Shorts | 2.14E-01 | 3.2% | 2.2% | Signage | 1 | 6.4% | 6.3% |

| | Label | p-value | Pan-blue | Pan-green |
|---|---|---|---|---|
| (c) Background | | | | |
|  | Crowd | 2.21E-01 | 13.3% | 11.4% |
|  | Building | 6.03E-07 | 8.7% | 3.3% |
|  | Community | 1 | 4.3% | 4.3% |
|  | Screenshot | 2.35E-01 | 3.9% | 5.1% |

"三接(Natural Gas Terminal)" (0.98%), and "美豬(pork from the US)" (0.90%). However, none of these words are among the most frequent words in pan-blue. The government's materials stress the slogans and questions of the referendum, whilst the opposition's materials emphasize political parties and politicians. As the referendum could be a vote of no confidence for the government, the ruling party should defend their policies rather than solicit votes for particular individuals.

## 5.2 Object extraction

Tables 9(a), 9(b), and 9(c) illustrate the proportions of clothing, physical objects, and backgrounds extracted from pan-blue and pan-blue images. In addition, we present the p-values of $\chi^2$ tests. In terms of clothing, pan-blue groups select glasses more frequently than pan-green groups; pan-green groups prefer to wear formal attire such as suits over pan-blue groups. The differences in casual wear, such as T-shirts and pants, reveal that pan-blue groups prefer T-shirts and trousers more than pan-green groups. As a party with a 100-year history that has received less support from youth in recent elections, KMT (pan-blue) politicians may attempt to create younger impressions in order to attract votes. In the physical objects, the numbers of posters appearing in the images of the two political parties appear first, indicating that posters in images are the primary means by which the parties convey their concepts. According to Table 9(c), pan-blue images contain more outdoor building scenes than pan-green images.
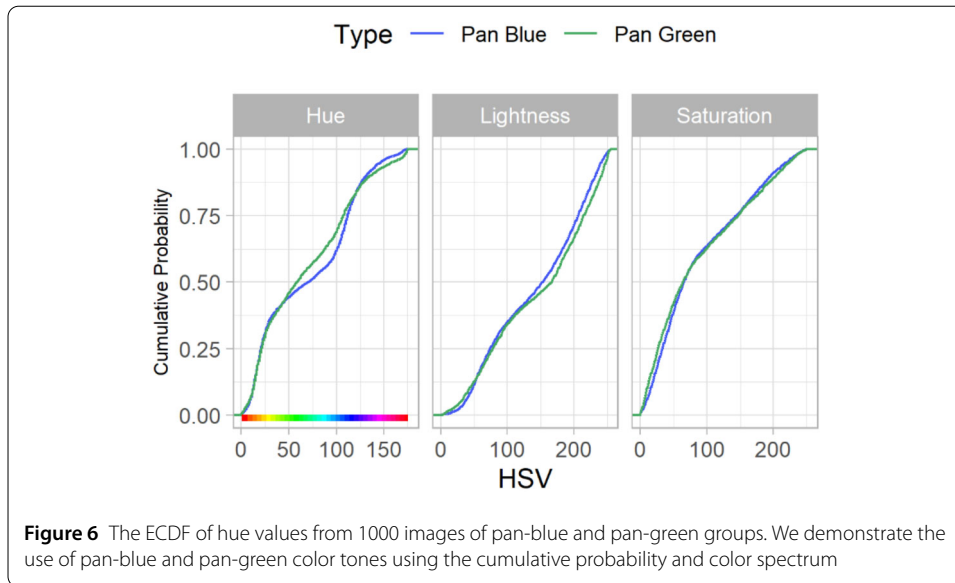
**Figure 6** The ECDF of hue values from 1000 images of pan-blue and pan-green groups. We demonstrate the use of pan-blue and pan-green color tones using the cumulative probability and color spectrum

**Table 10** Different political tendencies images are designed with different purposes

| Type | p-value | KMT (pan-blue) | DPP (pan-green) |
|------|---------|----------------|-----------------|
| Attacking | 1.26E-01 | 129 (12.9%) | 106 (10.6%) |
| Consolidating | 5.02E-12 | 306 (30.6%) | 457 (45.7%) |

## 5.3  Color quantization of images

Based on the results displayed in Fig. 5, we can discover that both pan-blue and pan-green fan pages employ hue-specific colors. As indicated in Fig. 6, based on the empirical cumulative distribution function (ECDF) results, we can deduce from Fig. 5 the specifics of the two parties' most often used hue. Through our analysis of fan pages associated with both pan-blue and pan-green political parties, we have indicated that neither party predominantly uses the color that is most closely associated with them. Instead, both parties commonly use orange-tone colors. Additionally, we found that blue-tone colors are the second most frequently used color by both parties. Such usage defies the public's view of the many political hues. We believe that this is due to the fact that the national referendum is based on policy debate rather than individual or political party campaigning.

## 5.4  Difference between attacking and consolidating images

As indicated in Table 10, we manually categorize images as either attacking or consolidating in order to comprehend how different political organizations construct their fan page graphics for various purposes. Figure 7 illustrates examples of attacking and consolidating imagery for two political organizations.

- *Attacking images.* Images depicting politicians from other parties or bearing the names of other parties. Text in photos should be satirical or accusatory. Some examples are shown in Fig. 7(a) and 7(c).
- *Consolidating images.* Images devoid of politicians from opposing parties, with the text or slogan concentrating on the issue. A few samples are shown in Fig. 7(b) and 7(d).

(a) DPP (pan-green)'s attacking images, including critiques of KMT leaders and their stance over the Fourth Nuclear Power Plant's activation.

(b) DPP (pan-green)'s consolidating images, including slogans such as 4 disagree and disapproval in relocating a Natural Gas Terminal.

(c) KMT (pan-blue)'s attacking images, including critiques of DPP's disregard for public opinion.

(d) KMT (pan-blue)'s consolidating images, including slogans such as 4 agree and saving the algal.

**Figure 7** *Attacking and consolidating images.* We present examples of attacking and consolidating images from pan-blue and pan-green groups

As illustrated in Fig. 8, after manually tagging images, we analyzed the color utilization of the two categories of images. When consolidating voters, both sides utilize their representational hue more than the opposite; for instance, pan-blue fan pages employ a bluer tone than pan-green fan pages. Intriguingly, when attacking the opposing side, both sides employ the opposing side's signature hue to build their offensive graphics. From the bottom panel of Fig. 8, we observe that pan-blue pages employ more green tones (hue value: 40–60) while assaulting DPP, whereas pan-green pages employ a blue style (hue: 100–120) when attacking. Although the positions and audiences of the two sides are polarized, the strategies for attacking and consolidating propaganda are comparable.
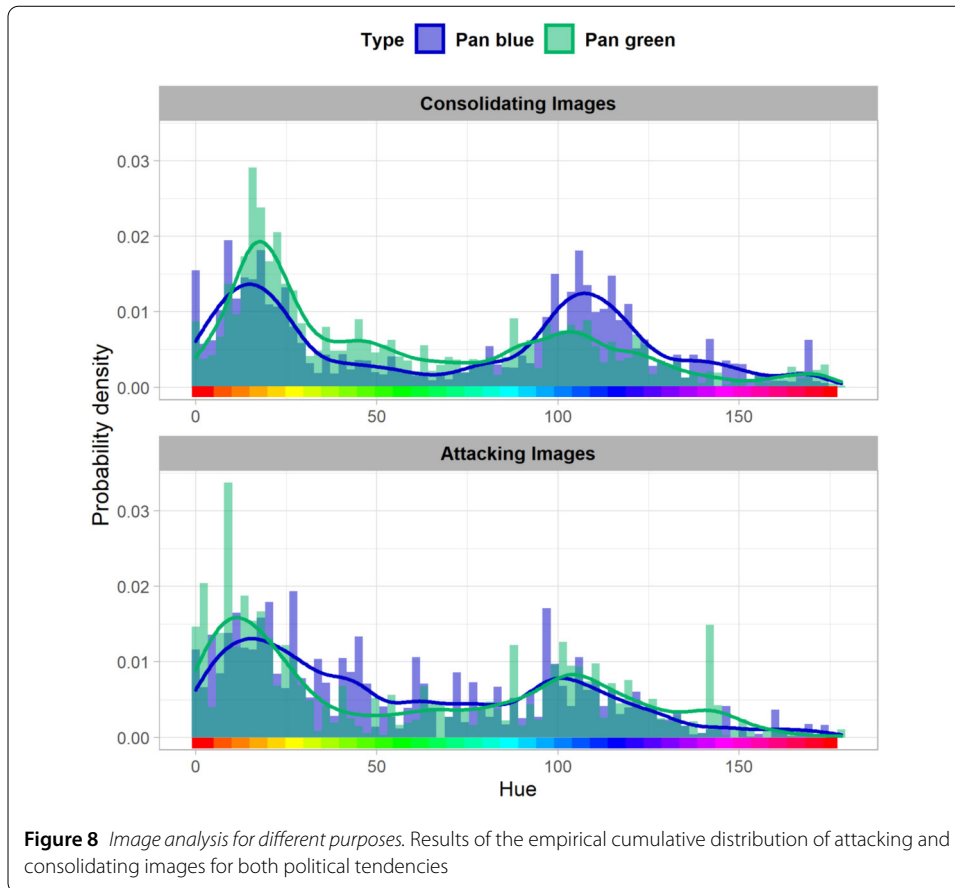
**Figure 8** *Image analysis for different purposes.* Results of the empirical cumulative distribution of attacking and consolidating images for both political tendencies

## 6 Conclusion and future works

In this paper, we present the very first study of image-based political communication during a national referendum. We studied 2000 images from the Facebook fan pages of two polarized political groups during the referendum campaign and examined them in terms of text, objects, and color. In comparison to earlier research, we presented significant findings: (1) Our analysis discovered that during a referendum campaign, political propaganda typically emphasizes slogans, the voting date, and the for or against the policy. Furthermore, we observed that the ruling party (pan-green in this case) tends to use more infographics in their campaign materials compared to the opposition. (2) By extracting objects from images, we found that the century-old party (KMT, pan-blue) preferred informal dress, but the ruling party (DPP, pan-green) chose formal attire. (3) Unlike candidate-based elections, our research indicates that political groups do not prioritize their representative colors while coloring. A plausible explanation is that the referendum is for a policy debate, not for individuals or political parties. (4) Based on images with specific purposes, i.e., attacking or consolidating, we noticed that the coloring strategies of both parties in the attacking and consolidating images are comparable, utilizing their representative color more when consolidating votes and the opposing color when assaulting.

In the subsequent phases of our research, we will broaden our examination of the propaganda differences between Taiwan's elections and referendums. We believe that further research could help us determine if our findings in this paper are applicable to candidate-based elections. In addition, we believe that a cross-cultural analysis between other coun-

tries could help us determine whether the results are applicable to other political systems. In conclusion, we list the following potential study directions:

- Integrating color psychology and political science into future research regarding the types of visuals and text content that can maximize the effectiveness of online propaganda.
- Correlating developing events or poll results to examine how political groupings respond to breaking events and poll results, such as employing radical language or representative color to consolidate support.
- Studying the similarity and differences between propaganda strategy of the referendum and election campaigns.
- Performing cross-cultural analysis between different countries to investigate if the findings in this work could be generalized to another political system.

We expect that this research will shed light on our understanding of online political communication. Moreover, we anticipate that the quantitative perspectives in this work will enable netizens and the general public to read, evaluate, and react to political propaganda from unique angles.

**Abbreviations**
DPP, Democratic Progressive Party; KMT, Kuomintang; LSTM, Long Short-Term Memory; CNN, Convolutional Neural Network; CKIP, Chinese Knowledge and Information Processing..

**Availability of data and materials**
The image dataset is currently available via https://reurl.cc/3xbe18.

## Declarations

**Competing interests**
The authors declare that they have no competing interests.

**Author contributions**
Conceptualization: MHW; Data curation: WYC, KHK; Formal analysis and Methodology: MHW, WYC; Visualization: MHW, WYC; First Draft: MHW, WYC; Revisions: MHW, WYC, KHK, KYT; Supervision: MHW, KYT. All authors read and approved the final manuscript.

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