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A MULTIMODAL SENTIMENT ANALYSIS OF INTERNET MEMES IN THE COURSE OF PHILIPPINE ELECTIONS

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ABSTRACT
As internet memes increasingly dominate political communication, concerns about their role in reinforcing biases, fostering polarization, and oversimplifying complex political issues have intensified. Employing Natural Language Processing (NLP) in the context of Sentiment Analysis, the Darth Sentiment Analyzer – a dedicated web-based software based on Valence Aware Dictionary and sEntiment Reasoner (VADER) – was utilized to examine the sentiments (positive, negative, neutral) expressed in a dataset of over 20,000 memes, revealing that neutral sentiment is the most prevalent, followed by positive and negative tones. The study applies Halliday's Systemic Functional Linguistics and Kress and Van Leeuwen's Grammar of Visual Design to analyze both the textual and visual elements of memes, providing deeper insights into how these components collaboratively influence public sentiment. Key findings demonstrate significant variation in sentiment across political affiliations, with liberalism being the most prominent ideology, while fascism and green ideologies are underrepresented. The study also identifies the ideological appeals that shape political engagement in online spaces, with implications for educational practices. The research contributes to the growing body of research on the intersection of technology, politics, and education, emphasizing the need for responsible digital citizenship in an era of widespread online influence.

KEYWORDS: *Education, Applied linguistics, Internet memes, natural language processing, sentiment analysis, Filipino voters, Philippines*

INTRODUCTION

Political memes, as defined, are humorous or satirical images, videos, or text-based content circulated on social media platforms with a primary focus on the political sphere (De Leon & Ballesteros-Lintao, 2021). Internet political memes serve as a popular medium for expressing opinions and critiquing politics. However, political memes serve as propaganda rather than ways for developing critical thinking (McClure, 2016) which would reinforce beliefs and biases that later would create echo chamber effect that delimits every exposure to different perspectives (Candor, 2022), fostering polarization (Galipeau, 2022), oversimplifying meme content that leads viewers to misinterpretation (Al-Rawi, 2021), and disseminate unedited racist and prejudiced content (Yoon, 2016) especially the minority group (Gal & Kampf, 2016).

In Russia, it was discovered that the 2016 election was fraught with memes (Wardle & Derakhshan, 2017) and Twitter accounts spreading false information with the intention of dividing the nation (Weise, 2018). In addition, memes in China are used to spread propaganda and pit other nations against itself (Gaff, 2018; Kao & Li, 2020). In fact, there is a common practice of using memes to spread misinformation to create instability and unrest (Weitz, 2018). For instance, in Hong Kong, several students promptly circulated political memes related to COVID-19, incorporating hashtags that placed blame on China, with the objective of perpetuating entrenched anti-Chinese sentiments in the region (McMinn, 2022).

In the Philippines, Ong et al. (2022) reported a transformation in the content generated by Marcos supporters. They utilized memes as propaganda targeting experts and questioning historical facts, to develop a coherent and unified narrative that replaced the EDSA storyline. Furthermore, Bernal (2022) detailed former Vice President Leni Robredo's well-executed campaign adhered to conventional advertising standards, with professional designs and a carefully crafted slogan. The public relations strategy aimed to portray her as a composed and trustworthy figure. However, a surprise meme, "Hadouken," featuring imaginary energy blasts on social issues was intended to inject humor and creatively address pressing issues, appealing particularly to a young demographic, which drew criticism for being off-brand and inconsistent with her image.Moreover, despite considerable efforts in the field, there remains a gap in studies utilizing approaches to understand internet political memes, such as employing Natural language Processing (NLP) in the parlance of Sentiment Analysis (SA) to explore the emotional tones within political memes amid the 2016 and 2022 Philippine elections. To address this gap, this study utilized a multimodal sentiment analysis approach, analyzing multiple modes of communication and triangulating the data to help better understand how Filipino voters respond to political discourse and how traditional media influences their views.

PURPOSE OF THE STUDY

This research study utilized Natural Language Processing to delve into the realm of multimodal sentiment analysis, focusing on political memes related to the 2016 and 2022 Philippine elections. This primary objective is to unravel the underlying sentiments embedded within these internet memes.

RESEARCH QUESTIONS

1. What are the predominant multimodal sentiments expressed in Philippine internet memes related to elections?
2. How are these memes linguistically and visually organized in contributing to the overall expression of these sentiments?
3. How do sentiments in memes vary across different political affiliations?
4. What types of ideological appeals are depicted in these memes?

METHODS

This study is a qualitative research employing Natural Language Processing (NLP), sentiment analysis, and multimodal analysis to examine the linguistic and visual features of political memes from the 2016 and 2022 Philippine elections. Bhandari (2020) defines qualitative research as the systematic collection and analysis of non-numeric data, including written, visual, or auditory information, with the aim of understanding abstract concepts, subjective viewpoints, or personal experiences. In the context of this study, qualitative research is utilized to analyze the nuanced linguistic and visual elements of political memes, allowing for a deeper understanding of their meaning, sentiment, and impact on public discourse.

Filonova (2022) describes the concept of Natural Langauge Processing as a sub-field of computer science in Artificial Inteligence. It enables computers to comprehend and manipulate human language and extract valuable insights from language data, implementing them into numerous applications. There is evidence suggesting that Natural Language Processing (NLP) can serve as a valuable tool in qualitative research. Given the challenges associated with qualitative methods, NLP has the potential to alleviate some of these difficulties and enhance qualitative data analysis. Crowston, et al. (2012) explored NLP's capacity to partially automate qualitative data analysis by comparing a rule-based coding method—requiring manual development of coding rules—to a machine-learning-based automatic coding approach in analyzing software discussion forum posts.

In the context of this study, NLP was employed to analyze the linguistic elements of political memes, aiding in the extraction and interpretation of sentiments conveyed in the text. By integrating NLP with multimodal sentiment analysis, the study investigates how language and visuals collaborate to express political sentiments, particularly in the context of the 2016 and 2022 Philippine elections. The use of NLP enhances the analysis by automating the sentiment detection process, making it more efficient and systematic in categorizing and comparing the sentiments across different political affiliations and ideologies.

RESESARCH MATERIAL

The research materials for this study consist of internet memes specifically targeting the Philippine elections of 2016 and 2022. The selection of materials follows Baurecht's (2020) classification of memes, which includes image macro memes, panel memes, description memes, screenshot memes, crossover memes, and meta memes. Additionally, only memes posted during the official campaign period were included, excluding those shared after the election results.

Originally, the dataset comprised 50,000 memes. However, for the final analysis, only 20,000 memes were utilized, while the remaining 30,000 were allocated for machine training. The memes were retrieved using Scrape.py, ensuring systematic data collection. Memes that contained only images without any accompanying text were excluded to focus on linguistic and multimodal analysis.

DATA ANALYSIS

The following steps were followed based on Pimpalkar et al. (2022): Data Collection, Text Extraction, Image Captioning, Modelling and Analysis, and Data Visualization.

The first step was data collection. The researcher utilized Scrape.py in fetching the 50,000 dataset of internet memes. To address the first two research questions, which pertain to sentiment analysis, the 20,000-meme dataset was employed. This required three rounds of training to achieve a satisfactory level of accuracy in sentiment classification. Meanwhile, to answer the third and fourth research questions regarding political affiliations and ideological tendencies, a subset of 10,000 memes was used. The machine underwent two rounds of training to refine its accuracy in categorizing political affiliations and ideologies. During the trainings of the machine, text extraction and image captioning were performed to enable the machine to assign each type of sentiment and its overall expression. This process allows the machine to classify the sentiment category to which a particular meme belongs.

After completing all the training sessions administered to the machine, the researcher compiled a final dataset consisting of 20,000 internet memes. To classify its sentiments, text extraction and image captioning were performed. In text extraction, the texts from the meme were extracted using Optical Character Recognition in the parlance of easyOCR – free and open-source software that pulls out text from images. In this step, data preprocessing was performed. EasyOCR used a Convolutional Neural Network (CNN) to locate regions in the image likely to contain text. It also utilized the CRAFT (Character Region Awareness for Text Detection) model for precise text area detection. After detecting text regions, EasyOCR passed them to a Sequential Model (often a combination of CNNs and RNNs) for text recognition. This model predicted character sequences from the cropped text areas. Finally, EasyOCR incorporated language-specific rules and dictionaries to improve accuracy for supported languages.
To determine the overall expression of the sentiment, image captioning was conducted. The image caption generated by the BLIP model underwent the same process of sentiment evaluation. Both the translated text and the generated caption were individually analyzed, yielding separate sentiment scores

and labels for each. These scores were then combined to produce an overall sentiment for the image. The combination process involved summing the compound scores of the translated text and the caption, determining if the overall sentiment leaned towards positive, neutral, or negative based on predefined thresholds.

After that was modeling and analysis. The app.py script was executed in a systematic, multi-step process to evaluate the sentiment of both text extracted from images and captions generated by the model. First, the script used EasyOCR to extract text from the image. If the text (or sentence) was detected as Filipino/Tagalog, the script translated the text into English using Google Translate via API to ensure uniformity and compatibility with the sentiment analysis model, as the sentiment analysis model only accepted English. This translated text was then passed to Darth Sentiment Analyzer in the parlance of VADER (Valence Aware Dictionary and sEntiment Reasoner), a pre-trained rule-based sentiment analysis tool. VADER assigned scores to the text for positive, negative, and neutral sentiments, as well as an overall compound score representing the sentiment's intensity and direction. Moreover, to classify memes according to their respective political affiliations, the classification was based on recognizable characteristics, such as key phrases, symbols, slogans, and themes associated with each political party. For example, in the case of PDP-Laban, commonly used phrases and slogans such as *Tapang at Malasakit, Build, Build, Build,* and *DDS (Duterte Diehard Supporters)* were linguistic features utilized during training to categorize memes based on their political affiliation. Additionally, visual indicators, such as images of political figures associated with the party, as well as the party logo and color scheme (red, yellow, and blue), were also used. Furthermore, The Darth Sentiment Analyzer classifies political ideologies in memes by analyzing linguistic patterns and contextual cues associated with different ideological themes. For instance, socialism-related content often includes discussions on wealth redistribution, workers' rights, and government intervention, while green ideology focuses on environmental concerns, climate change activism, and sustainability. When processing a meme, the model first extracts the text and translates it if necessary. Next, the Darth Sentiment Analyzer evaluates the extracted text and captioned image classifying it under the most relevant political ideology. The classified results, including the extracted text, sentiment analysis, and ideology classification, are then stored in an Excel file with relevant metadata.

The last step was data visualization. The visualization of sentiment analysis results in the app.py script was achieved through the generation of bar graphs representing the distribution of sentiments across the analyzed images. After processing the images, the script saved the results, including extracted text, translated text, captions, and sentiment scores, into an Excel file for organized storage. openpyxl (often referred to as pyxl) played a crucial role in managing data storage and organization within the Excel file, which served as the foundation for visualizing sentiment analysis results. The bar graph visualization was generated using the Bargraph_Generator.py script, which read the Excel file and computed the count of each sentiment category (Positive, Neutral, and Negative). With the help of Matplotlib, the data was transformed into a clear, visually appealing bar graph. Each bar represented a sentiment category, and the graph was complemented by a summary box displaying the exact count of each sentiment type for better interpretability. This visualization provided an intuitive way to assess the overall sentiment trends in the dataset.

RESULTS AND DISCUSSION

Predominant Multimodal Sentiments Expressed in Philippine Internet Memes Related to Elections

In order to determine the predominant multimodal sentiments of Filipinos during the 2016 and 2022 Philippine elections, three types of sentiments were considered: Neutral, Negative, and Positive. To unravel the types of sentiments, memes found on Facebook, X (Twitter), and Reddit during the 2016 and 2022 Philippine elections were gathered using Scrape.py. There were 20, 000 memes used that were made sure translated into English. Those written in Filipino and Cebuano were translated for the software to analyze them. When all of the corpora were assured to be relevant to the study, they were run in Darth Sentiment Analyzer in the parlance of VADER, in accordance with the perspectives of the Appraisal Theory of Scherer (2001), to determine the dominant sentiments of the Filipinos.

As presented in Table 1 below, the predominant sentiments of the Filipinos during the 2016 and 2022 elections is neutral with a number of 7, 738 memes having an equivalent percentage of 38.69. The data above signifies that despite some political violence and political abuse happening in the Philippines --- during the elections, Filipinos remained to have neutral sentiments. Thus, the memes during the Philippine elections are more stating their expressions of their views on current political problems or issues, or from mentioning the names of candidates whom they support.

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Table 1.
Multimodal Sentiments in Philippine Election Memes

<table>
<tr><th>Type of Sentiment</th><th>Number of Memes</th><th>Sample Memes</th></tr>
<tr><td>Neutral</td><td>7, 738</td><td>

(Image_01148)</td></tr>
<tr><td>Positive</td><td>6, 964</td><td>

(Image_15579)</td></tr>
<tr><td>Negative</td><td>5, 298</td><td>

(Image_01525)</td></tr>
<tr><td>Total number of Memes</td><td>20, 000</td><td></td></tr>
</table>

The data presented above suggests that the three types of sentiments expressed by Filipinos during the 2016 and 2022 Philippine elections reveal a wide range of emotional responses, with neutral, positive, and negative sentiments each playing a significant role in public discourse. Neutral sentiments were the most common, with many memes offering observational commentary on political figures, issues, and narratives without strong opinions. Positive sentiments, while slightly less frequent, featured motivational messages that encouraged hard work and perseverance amidst the challenges of navigating political dynamics. Negative sentiments, on the other hand, reflected critical perceptions, often highlighting concerns or skepticism about certain political figures or actions, and fostering caution and awareness among viewers. Overall, these memes capture the complexities of Filipino political engagement, blending humor, motivation, and critique to express public sentiments.

The findings align with Villasor (2023), who analyzed Filipino sentiment during crisis situations and found that neutral

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sentiment was predominant, with positive and negative sentiments closely following. This suggests that Filipinos, even during politically charged periods, often express their views in measured, non-confrontational ways. This is particularly relevant in the context of election memes, where neutrality allows individuals to engage in discourse without openly expressing political allegiance or risking social backlash.

Linguistic and Visual Organization in the Overall Expression of Sentiments

As revealed in the previous section, the dominant sentiment of Filipinos during the 2016 and 2022 Philippine elections was neutral, followed by positive and negative sentiments, respectively. To achieve the overall expression of these sentiments, VADER (Valence Aware Dictionary and sEntiment Reasoner) analyzed the user's text data by comparing it with the VADER lexicon. It determined the polarity indices using the Polarity Score function which classifies the compound scores as negative, positive, and neutral. The compound score is calculated by summing all lexicon ratings and normalizing the result to a range between -1 and +1. A score of +1 represents the most extreme positive sentiment, while -1 represents the most extreme negative sentiment. The threshold values for compound scores are defined by Rao et al. (2020) as follows:

Positive Sentiment: Compound Score range from 0.5 to 1
Neutral Sentiment: Compound Score range from -0.5 to 0.5
Negative Sentiment: Compound Score range from -1 to -0.5

Table 2.
Overall Neutral Sentiment Expression

NEUTRAL SENTIMENT (7738 memes)					
Sample Meme	**Text Translation**	**C-Score**	**Image Caption**	**C-Score**	**Overall C-Score**
 (Image_00027)	You can't sit with us!	0.00	A cafeteria scene with four people sitting at a table. Their faces appear to be replaced with faces of individuals from another context. Another person, standing and holding a tray, is positioned as if they are being addressed by the group.	0.00	0.00
 (Image_00308)	Juicecolored!!! Please give them a brain they can use.	0.00	A woman wearing glasses, raising her arms dramatically with a facial expression of exasperation or disbelief, speaking at a formal setting like a podium or hearing.	0.00	0.00

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 (Image_00317)	Garlic Boy Hammer Onion Boy Pedal Boy Fall Boy Traffic Boy Show-off Boy	0.00	A collage of six images depicting a man performing various activities, including holding garlic, hammering wood, carrying onions, riding a bike with passengers, and seemingly involved in road-related activities.	0.00	0.00
 (Image_14904)	You are just the king's child! I am the show-off king!	0.00	A man wearing a white shirt pointing with his finger.	0.00	0.00
 (Image_17967)	That Binay is an animal! Small in stature, but big in stealing!!	0.00	Two men are seated closely, appearing to be engaged in a serious conversation.	0.00	0.00

Linguistic and Visual Features Found in Neutral Sentiment Memes

To deepen the analysis, internet memes were examined using Halliday's (1975) theory of Systemic Functional Linguistics. The study analyzed the translated text embedded in the memes through the lens of the three metafunctions: ideational, interpersonal, and textual. Furthermore, analyzing the visual features of internet memes is essential to understanding the overall sentiment they convey. Therefore, the researcher applied Kress and Van Leeuwen's (2006) Grammar of Visual Design.

Since neutral sentiment is predominant, the tables below present the results of analyzing the text translation of neutral memes, which serve as representations of other types of sentiments, using Halliday's Systemic Functional Linguistics and Kress and Van Leeuwen's Grammar of Visual Design.

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Table 2.1
Linguistic Features Found in Neutral Sentiment Memes

You **Carrier**	*can't*	*sit* **Process: Material**	*with us!* **Circumstance**			
Juicecolored!!! **Carrier: Implied actor**	*please*	*give* **Process: Material**	*them a brain they can* **Intensive Attribute**	*use* **Process: Relational**		
Garlic Boy **Carrier**	*Hammer* **Carrier**	*Onion Boy* **Carrier**	*Pedal Boy* **Carrier**	*Fall Boy* **Carrier**	*Traffic Boy* **Carrier**	*Show-Off Boy* **Carrier**
You **Carrier**	*are* **Process: Relational**	*just*	*the king's child!* **Attribute**			
I **Carrier**	*am* **Process: Relational**	*the show-off king!* **Attribute**				
That Binay **Carrier**	*is* **Process: Relational**	*an animal/Small in stature, but big in stealing!!* **Attribute**				

The analysis of internet memes using Halliday's (1975) Systemic Functional Linguistics and Kress and Van Leeuwen's (2006) Grammar of Visual Design revealed distinct patterns in both textual and visual elements that shape the conveyed sentiment. The ideational metafunction identified how social exclusion, implied authority, and hierarchical positioning were constructed through material processes like "sit" and relational processes such as "are" and "give," highlighting subtle yet impactful judgments. The interpersonal metafunction showed that imperative moods, as seen in "please give them a brain they can use," softened the request through politeness while declarative forms like "You are just the king's child!" established identity and social hierarchy without overt emotional charge. The textual metafunction organized these elements cohesively, ensuring that even phrases like "Small in stature, but big in stealing!!" maintained a clear structure that juxtaposed contrasting traits while framing the commentary as factual rather than subjective. Visual analysis reinforced this neutrality, with salience and composition guiding the viewer's attention without inserting emotional intensity. Thus, the study found that the memes employed strategic linguistic and visual devices to sustain an appearance of objectivity while subtly embedding evaluative meanings.

Table 2.2
Patterns of Interaction Found in Neutral Sentiment Memes

Sample meme	Gaze	Social Distance	Horizontal Angle	Vertical Angle
Image_00027	Demand	Close social distance	Frontal view	Neutral angle (eye level)
Image_00308	Demand	Far social distance	Frontal view	High angle
Image_00317	Offer	Close personal distance	Side view (right)	Neutral angle (eye level)
Image_14904	Demand	Close social distance	Frontal view	Low angle
Image_17967	Offer	Close social distance	Side view (left)	High angle

The visual analysis of neutral sentiment memes revealed distinct patterns of interaction, where "demand" gazes frequently combined with frontal views and vertical angles that shifted between neutrality, authority, and subtle intimacy. For example, close social distances with neutral eye-level angles suggested inclusivity, while high or low angles introduced mild evaluative nuances without overt emotional intensity. In contrast, "offer" gazes tended to align with side views and either neutral or high angles, creating a more detached and observational dynamic. This interplay of gaze, distance, and angle reinforced the balanced, non-confrontational tone of the memes, subtly engaging viewers while maintaining an appearance of objectivity.

Table 2.3
Patterns of Composition Found in Neutral Sentiment Memes

Meme Code	Framing	Information Value	Salience
Image_00027	Wide shot emphasizing group dynamics and separation between the individual and group.	Central focus on the seated group, with the standing figure placed on the periphery to emphasize exclusion.	Bright colors and contrasting positioning of the standing individual make them visually prominent.
Image_00308	Close-up shot highlighting the subject's dramatic expression and gesture.	Text and gesture align to convey an emotional plea or exasperation.	The subject's upward gaze and dramatic gesture dominate attention.
Image_00317	Collage-style framing showing multiple personas and narratives in separate panels.	Each panel highlights different aspects of the narrative, with the central panel being the most salient.	The central panel's size and vibrant colors draw the most focus.
Image_14904	Close-up focusing on the subject's facial expression and confrontational gesture.	Text at the top establishes context, while the pointing gesture emphasizes the subject's statement.	The intense facial expression and pointing gesture dominate the composition.
Image_17967	Medium shot capturing conversational dynamics between two individuals.	Left-to-right structure leads the viewer from one speaker to the next, emphasizing the dialogue.	The whispering gesture and serious expressions emphasize the tension in the conversation.

Visually, Kress and Van Leeuwen's patterns of interaction and composition reinforce neutrality. The use of close or medium social distances provides a balance between intimacy and detachment, allowing the viewer to interpret the memes without feeling overly involved or excluded. Patterns like eye-level perspectives and frontal angles establish equality and objectivity in representation, ensuring the subject is neither elevated nor diminished. Additionally, the composition focuses on structured framing and salience through minimal yet deliberate use of color and spatial positioning, emphasizing clarity and organization over dramatic or emotional appeal. Together, these linguistic and visual strategies create a neutral sentiment by presenting the message and visuals as straightforward, balanced, and devoid of strong affective cues.

Variation of Sentiments across Different Political Affiliations

As discussed in the preceding section, the prevailing sentiment of Filipinos during the 2016 and 2022 Philippine elections was predominantly neutral, followed by positive and negative sentiments, respectively. To examine potential variations in sentiment across the ten political affiliations, the dataset for each affiliation was analyzed using the Darth Sentiment Analyzer, guided by the principles of Scherer's (2001) Appraisal Theory, to identify the dominant sentiments expressed by Filipinos.

By integrating the principles of Appraisal Theory with the analysis of the ten identified Philippine political affiliations, the researcher conducted a thorough examination of the public sentiments of Filipinos. This analysis considered both political affiliations and the inherent positive, negative, or neutral associations of the language used. This approach provided a more nuance understanding of individual expression across different contexts, offering valuable insights into communication patterns and the cultural factors that influence language use.

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Table 3.
Variation of Sentiments across Different Political Affiliations

Political Affiliation	Type of Sentiment	Number of Memes	Percentage	Sample Meme
PDP-Laban (Partido Demokratiko Pilipino-Lakas ng Bayan)	Neutral	568	38.53%	 Neutral (Image_06526)
	Positive	538	36.5%	 Positive (image_10846)
	Negative	368	24.97%	 Negative (Image_04482)
Lakas–CMD (Lakas–Christian Muslim Democrats)	Neutral	249	39.97%	 Neutral (Image_07550)

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<table>
<tr><td></td><td>Positive</td><td>252</td><td>40.45%</td><td>Positive (Image_14956)</td></tr>
<tr><td></td><td>Negative</td><td>122</td><td>19.58%</td><td>Negative (Image_11888)</td></tr>
<tr><td>Liberal Party (Partido Liberal ng Pilipinas)</td><td>Neutral</td><td>1,962</td><td>33.51%</td><td>Neutral (image_07714)</td></tr>
<tr><td></td><td>Positive</td><td>1,969</td><td>33.63%</td><td>Positive (Image_02629)</td></tr>
</table>

<table>
<tr><td></td><td>Negative</td><td>1,924</td><td>32.86%</td><td>

Negative (Image_06784)</td></tr>
<tr><td rowspan="3">Nacionalista Party (Partido Nacionalista)</td><td>Neutral</td><td>598</td><td>40.51%</td><td>

Neutral (Image_02766)</td></tr>
<tr><td>Positive</td><td>507</td><td>34.35%</td><td>

Positive (Image_06768)</td></tr>
<tr><td>Negative</td><td>371</td><td>25.14%</td><td>

Negative (Image_18159)</td></tr>
</table>

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	Neutral	261	38.21%	 Neutral (Image_17902)
Nationalist People's Coalition (NPC)	Positive	202	29.58%	 Positive (Image_00978)
	Negative	220	32.21%	 Negative (Image_01044)
United Nationalist Alliance (UNA)	Neutral	22	40.74%	 (Image_02680)

	Positive	25	46.3%	 Positive (Image_03725)
	Negative	7	12.96%	 Negative (Image_04804)
Aksyon Demokratiko	Neutral	1,508	34.92%	 Neutral (Image_04921)
	Positive	1,759	40.74%	 Positive (Image_02359)

	Negative	1,051	24.34%	 Negative (Image_07312)
PFP (Partido Federal ng Pilipinas)	Neutral	960	37.44%	 Neutral (Image_18773)
	Positive	964	37.6%	 Positive (Image_09720)
	Negative	640	24.96%	 Negative (Image_08552)

	Neutral	865	54.51%	 Neutral (Image_18818)
Bagumbayan–VNP (Bagumbayan–Volunteers for a New Philippines)	Positive	429	27.03%	 Positive (Image_11937)
	Negative	293	18.46%	 Negative (Image_15166)

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	Neutral	745	54.54%	 Neutral (Image_19275)
PRP (Philippine Reform Party)	Positive	319	23.35%	 Positive (Image_01894)
	Negative	302	22.11%	 Negative (Image_05571)
Total Number of Memes		**20,000**	**100%**	

As shown in Table 3, there is noticeable variation in sentiment across different political affiliations. Most political parties exhibit a balanced mix of neutral, positive, and negative tones, but with specific trends. For instance, PDP-Laban has a predominantly neutral tone (38.53%), closely followed by positive sentiments (36.5%) while engative sentiments are slightly lower at 24.97%. Similarly, Lakas CMD shows a dominant positive sentiment (40.45%), followed by neutral (39.97%), reflecting the polarized views of the public. In contrast, other affiliations such as the Nationalist Party exhibit a dominant neutral sentiment (40.51%), followed by positive sentiments ate 34.35%, and negative sentiments at 25.14%. The Nationalist People's Coalition (NPC) also shows neutrality as the dominant sentiment (38.21%), with positive sentiments at 29.85% and negative sentiments at 32.21%. Meanwhile, Aksyon Demokratiko and the United Nationalist Alliance (UNA) exhibit high positive sentiment percentages at 40.74% and 46.3%, respectively, suggesting a generally favored public opinion.

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To further determine if there exists a variation of sentiments on the public voice of Filipinos during the 2016 and 2022 Philippine elections, the data were further subjected to additional analysis through ANOVA.

Table 4.
Significant Difference of Sentiments across Different Political Affiliations

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9697852.000	9	1077539.111	31.008	.000
Within Groups	695000.667	20	34750.033		
Total	10392852.667	29			

The table above demonstrates a statistically significant difference in sentiments across different political affiliations, as indicated by the F-value of 31.008 and a significance level (Sig.) of 0.000, which is below the commonly accepted alpha level of 0.05. The large F-value suggests that the variation in sentiments between the groups is substantially greater than the variation within the groups. The mean square for "Between Groups" (1,077,539.111) is significantly higher than the mean square for "Within Groups" (34,750.033), further supporting this conclusion. These results indicate that political affiliation is a significant factor in shaping sentiments, and the differences are unlikely due to random chance.

Additionally, to confirm the result contained in Table 5.2, the data was subjected to Multiple Comparison using Tukey HSD. In here, the distribution of types of sentiments — negative, positive, and neutral — of the Filipinos during the 2016 and 2022 Philippine elections for each political affiliation were considered as values in order to see if there are variations.

Table 5.
Variation of Sentiments Across Political Affiliations

(I) Political Affiliation	(J) Political Affiliation	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
PDP-Laban	Lakas-CMD	283.667	152.206	.691	-255.31	822.64
	Liberal Party	-1460.333*	152.206	.000	-1999.31	-921.36
	Nacionalista Party	-.667	152.206	1.000	-539.64	538.31
	NPC	263.667	152.206	.766	-275.31	802.64
	UNA	473.333	152.206	.116	-65.64	1012.31
	Aksyon Demokratiko	-948.000*	152.206	.000	-1486.98	-409.02
	PFP	-363.333	152.206	.382	-902.31	175.64
	Bagumbayan-VNP	-37.667	152.206	1.000	-576.64	501.31
	PRP	36.000	152.206	1.000	-502.98	574.98
Lakas-CMD	PDP-Laban	-283.667	152.206	.691	-822.64	255.31
	Liberal Party	-1744.000*	152.206	.000	-2282.98	-1205.02
	Nacionalista Party	-284.333	152.206	.688	-823.31	254.64
	NPC	-20.000	152.206	1.000	-558.98	518.98
	UNA	189.667	152.206	.955	-349.31	728.64
	Aksyon Demokratiko	-1231.667*	152.206	.000	-1770.64	-692.69
	PFP	-647.000*	152.206	.011	-1185.98	-108.02
	Bagumbayan-VNP	-321.333	152.206	.540	-860.31	217.64
	PRP	-247.667	152.206	.820	-786.64	291.31
Liberal Party	PDP-Laban	1460.333*	152.206	.000	921.36	1999.31
	Lakas-CMD	1744.000*	152.206	.000	1205.02	2282.98
	Nacionalista Party	1459.667*	152.206	.000	920.69	1998.64
	NPC	1724.000*	152.206	.000	1185.02	2262.98
	UNA	1933.667*	152.206	.000	1394.69	2472.64

	Aksyon Demokratiko	512.333	152.206	.071	-26.64	1051.31
	PFP	1097.000*	152.206	.000	558.02	1635.98
	Bagumbayan-VNP	1422.667*	152.206	.000	883.69	1961.64
	PRP	1496.333*	152.206	.000	957.36	2035.31
Nacionalista Party	PDP-Laban	.667	152.206	1.000	-538.31	539.64
	Lakas-CMD	284.333	152.206	.688	-254.64	823.31
	Liberal Party	-1459.667*	152.206	.000	-1998.64	-920.69
	NPC	264.333	152.206	.764	-274.64	803.31
	UNA	474.000	152.206	.115	-64.98	1012.98
	Aksyon Demokratiko	-947.333*	152.206	.000	-1486.31	-408.36
	PFP	-362.667	152.206	.384	-901.64	176.31
	Bagumbayan-VNP	-37.000	152.206	1.000	-575.98	501.98
	PRP	36.667	152.206	1.000	-502.31	575.64
NPC	PDP-Laban	-263.667	152.206	.766	-802.64	275.31
	Lakas-CMD	20.000	152.206	1.000	-518.98	558.98
	Liberal Party	-1724.000*	152.206	.000	-2262.98	-1185.02
	Nacionalista Party	-264.333	152.206	.764	-803.31	274.64
	UNA	209.667	152.206	.921	-329.31	748.64
	Aksyon Demokratiko	-1211.667*	152.206	.000	-1750.64	-672.69
	PFP	-627.000*	152.206	.015	-1165.98	-88.02
	Bagumbayan-VNP	-301.333	152.206	.621	-840.31	237.64
	PRP	-227.667	152.206	.879	-766.64	311.31
UNA	PDP-Laban	-473.333	152.206	.116	-1012.31	65.64
	Lakas-CMD	-189.667	152.206	.955	-728.64	349.31
	Liberal Party	-1933.667*	152.206	.000	-2472.64	-1394.69
	Nacionalista Party	-474.000	152.206	.115	-1012.98	64.98
	NPC	-209.667	152.206	.921	-748.64	329.31
	Aksyon Demokratiko	-1421.333*	152.206	.000	-1960.31	-882.36
	PFP	-836.667*	152.206	.001	-1375.64	-297.69
	Bagumbayan-VNP	-511.000	152.206	.072	-1049.98	27.98
	PRP	-437.333	152.206	.178	-976.31	101.64
Aksyon Demokratiko	PDP-Laban	948.000*	152.206	.000	409.02	1486.98
	Lakas-CMD	1231.667*	152.206	.000	692.69	1770.64
	Liberal Party	-512.333	152.206	.071	-1051.31	26.64
	Nacionalista Party	947.333*	152.206	.000	408.36	1486.31
	NPC	1211.667*	152.206	.000	672.69	1750.64
	UNA	1421.333*	152.206	.000	882.36	1960.31
	PFP	584.667*	152.206	.027	45.69	1123.64
	Bagumbayan-VNP	910.333*	152.206	.000	371.36	1449.31
	PRP	984.000*	152.206	.000	445.02	1522.98
PFP	PDP-Laban	363.333	152.206	.382	-175.64	902.31
	Lakas-CMD	647.000*	152.206	.011	108.02	1185.98
	Liberal Party	-1097.000*	152.206	.000	-1635.98	-558.02
	Nacionalista Party	362.667	152.206	.384	-176.31	901.64
	NPC	627.000*	152.206	.015	88.02	1165.98
	UNA	836.667*	152.206	.001	297.69	1375.64
	Aksyon Demokratiko	-584.667*	152.206	.027	-1123.64	-45.69

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	Bagumbayan-VNP	325.667	152.206	.523	-213.31	864.64
	PRP	399.333	152.206	.269	-139.64	938.31
Bagumbayan-VNP	PDP-Laban	37.667	152.206	1.000	-501.31	576.64
	Lakas-CMD	321.333	152.206	.540	-217.64	860.31
	Liberal Party	-1422.667*	152.206	.000	-1961.64	-883.69
	Nacionalista Party	37.000	152.206	1.000	-501.98	575.98
	NPC	301.333	152.206	.621	-237.64	840.31
	UNA	511.000	152.206	.072	-27.98	1049.98
	Aksyon Demokratiko	-910.333*	152.206	.000	-1449.31	-371.36
	PFP	-325.667	152.206	.523	-864.64	213.31
	PRP	73.667	152.206	1.000	-465.31	612.64
PRP	PDP-Laban	-36.000	152.206	1.000	-574.98	502.98
	Lakas-CMD	247.667	152.206	.820	-291.31	786.64
	Liberal Party	-1496.333*	152.206	.000	-2035.31	-957.36
	Nacionalista Party	-36.667	152.206	1.000	-575.64	502.31
	NPC	227.667	152.206	.879	-311.31	766.64
	UNA	437.333	152.206	.178	-101.64	976.31
	Aksyon Demokratiko	-984.000*	152.206	.000	-1522.98	-445.02
	PFP	-399.333	152.206	.269	-938.31	139.64
	Bagumbayan-VNP	-73.667	152.206	1.000	-612.64	465.31

The Tukey HSD results show significant mean differences in political sentiments between certain political affiliations, suggesting that people's sentiments in memes may vary widely based on their political alignment. For instance, the Liberal Party shows significant differences when compared to the PDP-Laban (mean difference of 1744.000), Lakas-CMD (mean difference of 1460.333), and others, indicating that memes related to the Liberal Party reflect much stronger positive or negative sentiments compared to other groups. The significant p-values (below 0.05) and confidence intervals that do not include zero confirm these differences as statistically significant. This pattern is particularly noticeable with Lakas-CMD, where the sentiment difference of 283.667 was significant in comparison with the Liberal Party and other affiliations, highlighting that the perceptions around this group in memes could be polarized.

The dominance of neutrality in political memes reflects a broader trend in political discourse, where strategic ambiguity allows for engagement without outright endorsement or opposition. Goje and Patil (2024) found that neutral sentiment is prevalent in Indian political discussions, as it captures a mix of public opinion rather than a clear stance. Similarly, Song et al. (2024) noted that neutrality in political messaging is often employed to appeal to a wider voter base, minimizing the risk of alienating potential supporters. This approach is evident in Philippine political memes, such as a PDP-Laban post that contrasted two figures, calling one "The Plague of the Nation" and the other "The Answer to the Plague."

Types of Ideological Appeals Depicted in Memes

Building on the previous discussion, Table 6 reveals significant variations in sentiments across different political affiliations. While most most political parties show a balanced distribution of neutral, positive, and negative tones, distinct trends are apparent.

To identify the ideological appeals depicted in the memes, the training process involved the researcher sorting the memes. The fine-tuned transformer model, highly based on BERT, RoBERTa, or another pre-trained NLP model, generates raw prediction scores, known as logits, for each political ideology. These logits are then processed through a softmax function, which converts them into probability scores, indicating the model's confidence in each ideology. The highest probability score determines the predicted ideology.

Based on the table 5 below, the distribution of ideologies depicted in the data highlights the varying prominence of political and social beliefs in digital memes. Liberalism emerges as the most frequently represented ideology, while fascism and green ideology are less frequently discussed. The memes selected for each ideology offer insight into how these ideas are humorously critiqued, celebrated, or questioned in online discourse.

The analysis of ideological representations in internet memes reveals distinct patterns of public sentiment, with liberalism emerging as the most frequently depicted ideology, often framed satirically to critique perceived indecisiveness and weak governance. In contrast, conservatism's nostalgic appeal for traditional values and stability is reflected in its portrayal of an idealized past, while socialism's emphasis on equity and redistribution surfaces through critiques of political power and calls for accountability. Anarchism, focusing on rebellion and opposition to authority, consistently emphasizes grassroots-led change, whereas nationalism's pride and loyalty narratives highlight collective progress and prioritization of national interests. The significantly lower representation of fascism, largely engaged with through digital criticism, signals its marginal and controversial position. Feminism and Green ideology, though less prevalent, maintain strong thematic consistency in challenging patriarchal norms and promoting environmental consciousness. Finally, Islamism's focus on religious unity and cultural identity is underscored by images of community engagement, reflecting its emphasis on solidarity. The study thus reveals how different ideological appeals in memes navigate between critique, nostalgia, advocacy, and humor, shaping public discourse in subtle yet powerful ways.

This finding aligns with the claim by Khosravinik (2017) that memes systematically depict societal critiques and convey messages aligned with collective welfare. Furthermore, this supports the observation by Du et al. (2020) that political memes often communicate relevant themes, shaping public discourse through relatable and impactful content.

Table 6.
Ideological Appeals Depicted in Memes

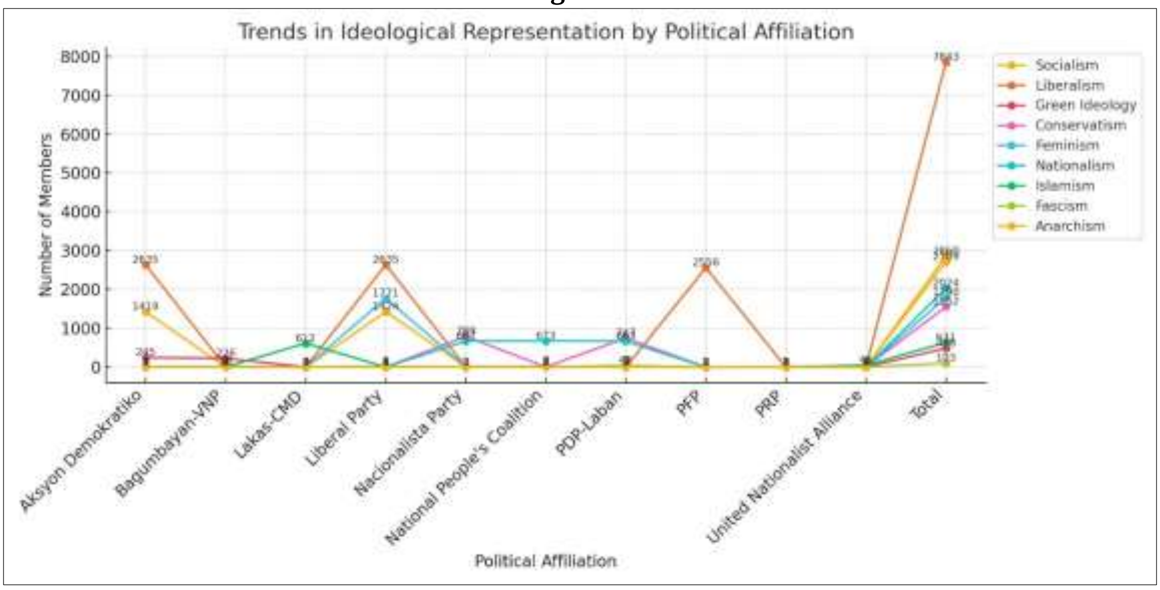
Political Ideology	Number of Memes	Sample Meme
Liberalism	7,843	 (Image_04922)
Conservatism	1,552	 (Image_16738)
Socialism	2,860	 (Image_05610)

Anarchism	2,709	 (Image_03465)
Nationalism	2,024	 (Image_00212)
Fascism	103	 (Image_05384)
Feminism	1,790	 (Image_10452)

Green ideology	488	 (Image_03510)
Islamism	631	 (Image_12646)

To further this analysis, the graph below provides a detailed breakdown of the ideological alignment across various political parties, offering insight into the ideological diversity within the political landscape. By categorizing political affiliations under the different frameworks, the data highlights the extent of alignment or membership within these ideologies for each party. This quantitative approach enables researchers and analysts to explore trends, compare ideological leanings, and assess the distribution of support across different ideological groups.

Figure 1.



The graph provides an analysis of the ideological alignments across political affiliations, highlighting how each political party embodies various ideologies. Liberalism, with a total of 7,843, is the most dominant ideology, significantly represented in the Liberal party and Aksyon Demokrtaiko, each contributing 2,635 members. This alignment reflects the progressive stance of these parties, prioritizing reforms and individual freedoms. The PFP also shows a strong liberal alignment, contributing 2,556 members, demonstrating its ideological focus on personal liberties and market-driven policies.

To evaluate the performance of the LSTM model in this study, various metrics were used to assess its effectiveness in detecting sentiment types in internet memes. The results provide insights into the model's accuracy and reliability in sentiment classification.

Table 7.
Performance Evaluation of VADER

Model	*Accuracy*	*Precision*	*Recall*	*F1 Score*
VADER	**0.9574**	**0.9493**	**0.9574**	**0.9533**

The table above presents the performance evaluation of the VADER model using four key metrics: accuracy, precision, recall, and F1 score. With an accuracy of 0.9574, the model demonstrates its ability to correctly classify approximately 95.74% of the cases, indicating a strong overall performance. Precision, measured at 0.9493, highlights that among all positive predictions made by the model, 94.93% were correct. This suggests that the model is quite reliable in predicting positive cases, minimizing false positives.

Recall, at 0.9574, shows that the VADER model is effective in identifying the true positive cases out of all the actual positive instances. This high recall value emphasizes the model's ability to detect the majority of relevant cases. The F1 score, which balances precision and recall, stands at 0.9533, providing a comprehensive measure of the model's performance. The F1 score indicates that the model has a well-rounded capability, ensuring both a low false positive rate and a high detection rate. Overall, the VADER model shows strong performance across all metrics, suggesting its effectiveness in the given application.

CONCLUDING REMARKS

Delving into the multimodal sentiment analysis of internet memes during the 2016 and 2022 Philippine elections, this study has navigated the complexities of uncovering linguistic and visual sentiments embedded in these digital artifacts. This research marks a pioneering effort in examining how memes reflect political ideologies and public opinion in the Philippine context. The study contributes a foundational exploration of how multimodal communication influences the socio-political landscape, offering insights that enrich the understanding of digital media's role in elections.

The journey was not without its challenges. Identifying and analyzing the intricate interplay of textual and visual elements in memes required methodological rigor and technological integration. Early hurdles included familiarizing with advanced Natural Language Processing tools and adapting them to the unique characteristics of memes. These obstacles were overcome through collaboration with experts, strategic planning, and continuous refinement of analytical frameworks. Each step in this process fostered resilience, critical thinking, and a deeper appreciation for the intersection of technology and political discourse.

Despite these challenges, the study establishes a foundation for future research in multimodal sentiment analysis and digital political communication. It provides an initial framework for understanding how memes shape public opinion and influence political engagement. This research not only fills a gap in academic literature but also serves as a call to future scholars to expand upon these findings. By continuing to investigate the dynamic interplay of language, visuals, and public sentiment, researchers can contribute to a more nuanced understanding of digital media's impact on democratic processes.

REFERENCES

1. *Al-Rawi, A. (2021). Political memes and fake news discourses on Instagram. Media and Communication, 9(1), 276–290.https:// doi.org/10.17645/mac.v9i1.3533*
2. *Bernal, R. (2022). "The Meme-fication of the 2022 Presidential Election (Part 1)". Institute for Nationalist Studies.*
3. *Bhandari, P. (2020). What Is Qualitative Research? | Methods & Examples. Scribbr.https://www.scribbr.com/methodology/qualitative-research/*
4. *De Leon, F. M. G., & Ballesteros-Lintao, R. (2021). The Rise of Meme Culture: Internet Political Memes as Tools for Analysing Philippine Propaganda. Journal of Critical Studies in Language and Literature, 2(4), 1-13 DOI: https://doi.org/10.46809/jcsll.v2i4.70*
5. *Filnova, E. (2022). Evaluation of Natural Language Processing and Machine Learning Tools for the Automation of the Customer Service Task. https://uu.diva-portal.org/smash/get/diva2:1693311/FULLTEXT01.pdf*
6. *6. Gal, N., Shifman, L., & Kampf, Z. (2016). "It gets better": Internet memes and the construction of collective identity. New Media & Society, 18, 1698–1714. [Crossref] [ISI]*
7. *Galipeau, T. (2023). The Impact of Political Memes: a Longitudinal Field Experiment. Journal of Information Technology & Politics, 20(4), 437–453. https://doi.org/10.1080/19331681.2022.2150737*
8. *Goje, S., & Patil, D. (2024). Sentiment analysis of political parties on social media: A machine learning and lexicon-based approach. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10, 233–246. https://doi.org/10.32628/CSEIT24105103*
9. *9.. Ong, J.C., Fallorina, R., Lanuza, J.M.H., Sanchez, F., and Curato, N. (2022). "Parallel Public Spheres: Influence Operations in the 2022 Philippine Elections". The Media Manipulation Case Book. Internews and Harvard Kennedy School Shorenstein Center. https://mediamanipulation.org/research/unmasking-influence-operations- in-the-philippines]*
10. *Scherer, K. R., Schorr, A., & Johnstone, T. (Eds.). (2001). Appraisal processes in emotion: Theory, methods, research. Oxford University Press.https://doi.org/10.1093/oso/9780195130072.001.0001*
11. *Song, C., Chen, S., Cai, X., & Chen, H. (2024). Sentiment analysis of Spanish political party tweets using pre-trained language models. Unpublished manuscript, Fudan University, Shanghai, China, and Beijing Institute of Technology, Beijing, China.*
12. *Villasor, H. (2023). Natural language processing employing sentiment analysis on the public voice of Filipinos during crisis situations. Vol. 10 Issue. 1 (January 2024) EPRA International Journal of Multidisciplinary Research (IJMR). https://doi.org/10.36713/epra15407*
13. *Yoon, I. (2016). Why is it not just a joke? Analysis of Internet memes associated with racism and hidden ideology of colorblindness. Journal of Cultural Research in Art Education, 33, 92–123.*