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The Valence Paradox: Positive Policy, Political Outrage, and Engagement on X in the 2024 U.S. Presidential Election

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ABSTRACT

This study engages in a machine learning analysis of the relationship between valence under digital messages (positive vs. negative messages), engagement actions (likes and retweets), over the performance of presidential election contenders during the United States Presidential Election-2024 on Twitter/X. Using Natural Language Processing (NLP) and natural language sentiment analysis (VADER) as well as term frequency inverse document frequency (TF-IDF), Using a clean dataset of 26,351 presidential election posts collected from June 4 to November 4, 2024 cleaned for readers to help clarify the relationship between these variables on X. Results from these analyses reveal a valence paradox whereby posts with both positive and policy-focused content received more likes/retweets than those that were negative in focus and devoted to attacking the political opponent, contradicting most of what political communication theory suggests regarding the place of outrage and negative communications in an environment where social media is involved. Trump used a low-engagement strategy in social media posting 4,812 tweets and only generating an average number of likes per tweet (52.64) versus high-engagement tweets from Kamala Harris with 118.23 likes on average per tweet.The results seem to show that online voters tend to support constructive political ideas rather than negative political attacks. This has important implications for future political communication and voter activation across social media.

Keywords: Political communication; social media; X/Twitter; sentiment analysis; VADER; computational social science; 2024 U.S. presidential election

1. Introduction and Framework

1.1 Context and Problem Formulation

The fundamental structure of political communication in the United States has changed from mass media to microblogging platforms such as Twitter/X. Today's political campaigns use digital platforms to avoid the news media and to directly communicate with the electorate. Within these campaigns, there are choices to be made about whether to focus on positive messaging of the politician or negative messaging that targets another candidate.

While the use of digital communication platforms for political campaigns began to gain attention decades ago, most of the early studies indicated that campaigns focused on negative messaging to promote themselves as candidates and to highlight the negatives of other candidates for the same position, specifically anger and moral outrage accelerating information diffusion, contemporary public behavior on social platforms suggests a more complex dynamic. High arousal negative posts frequently attract a lot of judgment, but it remains argumentative whether digital users actively endorse and amplify hostile political attacks over just raw policy discussions. Evaluating how message valence directly impacts primary public interaction metrics such as likes and retweets is essential for understanding the incentives that shape digital public language and thus campaign strategy.

1.2 Research Questions

This research aims to systematically exam the interaction of message tone with user engagement and strategic effectiveness, addressing three key research questions:

RQ1 (Valence Interaction Effect): To what extent does message valence (positive vs. negative tone) influence online audience engagement (measured via likes and retweets) during US presidential campaigns on Twitter/X?

RQ2 (Lexical and Semantic Framing): What specific linguistic markers, n-grams, and semantic network structures differentiate positive policy promotion from negative attack messaging in the 2024 presidential sub set?

RQ3 (Comparative Campaign Effectiveness): How do candidate-level variations in posting volume, sentiment tone, and per-tweet interaction efficiency shape overall digital campaign performance between Donald Trump and Kamala Harris?

2. Literature Review and Hypotheses

2.1 Political Communication

The nature of political communication has changed dramatically over the past few decades. Previously, political leaders relied on influential individuals within each community to share their message with the public (Katz & Lazarsfeld, 1955). In addition, during the 20th century, political campaigns began to use the media to share their messages with the voting public en masse (Blumler & Kavanagh, 1999). However, instead of creating voters that were disconnected

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from the political world, the media helped to inspire individuals that were already interested in political matters (Norris, 2000). Today, there are what are considered "hybrid media systems," wherein the traditional and digital media influence each other (Chadwick, 2017). Due to this media, political figures do not have to rely upon the news and the journalists to share their message with the public.

2.2 Social Media and Election Campaigning

Social media platforms have developed in the past decade, most notably a platform named X (formerly Twitter). Political campaigns use this platform to share their message with the public and to test different messages to assess the feedback that they receive from the voters (Kreiss, 2016). Furthermore, research into social media and political campaigns reveals that the politics of the world's social media platforms are often personalized by the individual politicians involved rather than their political parties (Enli & Skogerbø, 2013). The use of platforms like X allows politicians to avoid the media and to directly share their message with the voting public (Gainous & Wagner, 2014; Jungherr, 2016).

2.3 Campaign Agenda (Issue Ownership, Agenda Setting)

Another essential aspect of digital campaigning is the decision on what issues to discuss during a campaign. According to agenda setting theory, the issues that a campaign focuses on will determine the issues that the public feels are important (McCombs & Shaw, 1972). Many parties are known to concentrate on and be trusted more on specific issues. For example, the conservative movement is more trusted on issues connected to national security, while the progressive movement is trusted more on issues related to healthcare (Petrocik, 1996). To maintain trust in these movements, the candidates must focus on continually communicating these issues throughout the campaign (Stubager, 2018). Candidates must continuously emphasize the issues that they own, while challenging the topics that their rivals possess (Tresch et al., 2018).

2.4 Message Valence (Positive vs. Negative Campaigning)

The tone of the messages that candidates publish on their social media platforms is another crucial decision for politicians. It is important to decide whether the politician will use a positive or negative tone for their social media platforms. Negative campaigning is very common in political campaigns but remains heavily debated by scholars. Some believe that negative campaigning is crucial for political campaigns as their posts contain more facts regarding policies that candidates support as opposed to the positive messages that rival candidates publish (Geer, 2006). However, other studies publish the opposite belief that negative campaigning does

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not automatically win the election for the candidates and that it does not drastically lower voter turnout (Lau et al., 2007). Voters' reactions to negative posts depend upon their level of loyalty to the parties involved (Fridkin & Kenney, 2011). Furthermore, attack ads work best when the campaign is focused on an opponent's issue that the politician who is making the negative posts owns (Banda, 2016).

2.5 Audience Engagement

Political campaign messages aim to receive audience interactions on social media platforms. Studies have shown that posts that feature emotional or negative content receive considerably more likes and shares than posts containing the same content but without negative or emotional content (Stieglitz & Dang-Xuan, 2013). Additionally, online engagement rates have correlated with the number of individuals that participate in political activities in person (Effing et al., 2011). The higher the engagement with political campaign messages on social media platforms, the more likely the social media platform's algorithm will share those posts with new audiences to improve the candidates' outreach to nonvoters (Bode, 2016; Bene, 2017).

2.6 Natural Language Processing in Political Campaign Analysis

The analysis of thousands of political campaign messages by hand is a slow process that introduces human bias into the analysis. Natural Language Processing (NLP) is a field of computer science that treats political campaign messages as data that can be analyzed by algorithms to determine the sentiments behind each message (Grimmer & Stewart, 2013). Furthermore, machine learning algorithms can classify political campaign messages to identify with which political agendas and with what tones the candidates' messages originate (Benoit et al., 2016). These techniques provide researchers with an objective way of analyzing political campaigns (Barberá et al., 2015; Wilkerson & Casas, 2017). To evaluate campaign tone, modern researchers frequently employ lexicon-based tools like the Valence Aware Dictionary and Sentiment Reasoner (VADER), which is optimized to handle informal social media syntax, capitalization, and intensity modifiers (Hutto & Gilbert, 2014). Furthermore, computational text-mining algorithms (such as Term Frequency-Inverse Document Frequency (TF-IDF)) can classify political campaign messages to extract dominant campaign themes and identify the political agendas originating from the candidates (Benoit et al., 2016; Salton & Buckley, 1988). These techniques provide researchers with an objective way of analyzing political campaigns and mapping semantic co-occurrence networks without the limitations of manual coding (Barberá et al., 2015; Wilkerson & Casas, 2017).

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2.7 Hypotheses Formulation

This study looks at how emotional arousal, social identity, and the effort of using digital platforms work together to test the following hypotheses (based on the literature):

H1 (The Virality Hypothesis): Negative attack posts generate higher average retweets and likes than positive policy posts due to moral outrage arousal.

H2 (Alternative - The Valence Paradox): Positive policy posts generate higher average retweets and likes than negative attack posts because social media users prefer publicly endorsing identity-affirming content.

H3 (The Campaign Efficiency Hypothesis): Overall digital campaign effectiveness is a dual function of organic narrative volume (share of voice) and per-post audience engagement efficiency.

3. Materials and Methods

The main empirical dataset this study is trained on was taken from Kaggle, citing the official publicly available repository 2024 US Presidential Elections Twitter Data (Roy, 2024). It covers the height of the 2024 US Presidential Elections Twitter Data (June 4, 2024 to Nov 4th 2024). The first extraction from Kaggle was a raw selection which produced 26,358 records. Data cleaning processes occurred as well:

1. Deduplication & Null Filtering: Removed 5 missing text entries and 2 duplicate Tweet IDs, establishing a cleaned baseline of 26,351 tweets.
2. Timestamp Normalization: Converted raw string timestamps into standardized UTC date time objects to evaluate temporal trends.
3. Linguistic Cleaning: Removed non-informative URLs, special characters, and extra whitespace while retaining case sensitivity and punctuation required for rule-based sentiment intensity scoring.

3.1 Dataset Summary and Statistical Distribution Properties

On social media, engagement is wildly uneven where a tiny fraction of viral posts gets almost all the likes, comments, and shares.

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Table 1. Dataset Summary and Statistical Distribution Properties

Dataset Parameter	Empirical Value	Statistical Significance / Interpretation
Data Source / Repository	Kaggle Dataset	Secondary open-access repository uploaded by Rohan Roy.
Total Analyzed Tweets (N)	26,351	Cleaned.
Unique User Accounts	21,525	Broad user distribution; avoids single-account bias.
Total Accumulated Likes	2,338,817	Primary metric of user appreciation.
Total Accumulated Retweets	393,464	Primary metric of information diffusion.
Mean Likes per Tweet	88.76	Highly skewed distribution (Median: 0.00, Max: 271,187).
Mean Retweets per Tweet	14.93	Highly skewed distribution (Median: 0.00, Max: 39,868).
Engagement Correlation (r)	r = 0.932	Strong linear comovement between Likes and Retweets.
Mean Tweet Text Length	24.53 Words / 142.31 Chars	Standard microblogging message length.

Source: Author's analysis of Roy (2024) Kaggle dataset.

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4. Results

4.1 Empirical Test of H1: Understanding the Valence Paradox

Message valence was operationalized using VADER sentiment compound scores (Sc).

Positive Valence: (Sc ≥ 0.05): 10,316 tweets (39.15%).

Negative Valence: (Sc ≤ -0.05): 9,084 tweets (34.47%).

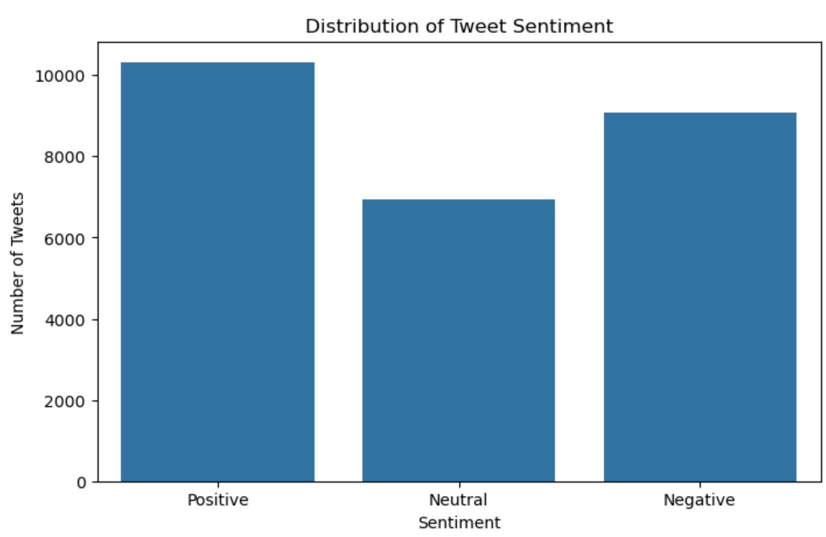
Neutral Tone: (-0.05 < Sc < 0.05): 6,951 tweets (26.38%).

Table 2. Quantitative Engagement Comparison across Valence Categories

Valence Category	Tweet Count (N)	Proportion (%)	Mean Likes	Mean Retweets
Positive	10,316	39.15%	129.87	20.36
Neutral	6,951	26.38%	66.38	8.66
Negative	9,084	34.47%	59.19	13.56

Note: Source: Author's analysis of Roy (2024) Kaggle dataset.

Figure 1. Distribution of Tweet Sentiment



Source: Author's analysis of Roy (2024) Kaggle dataset.

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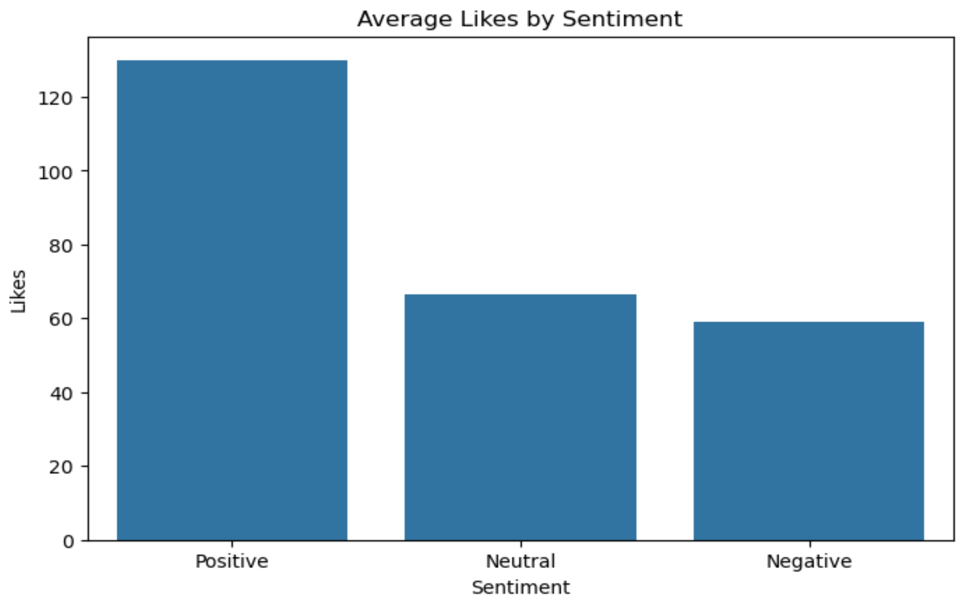
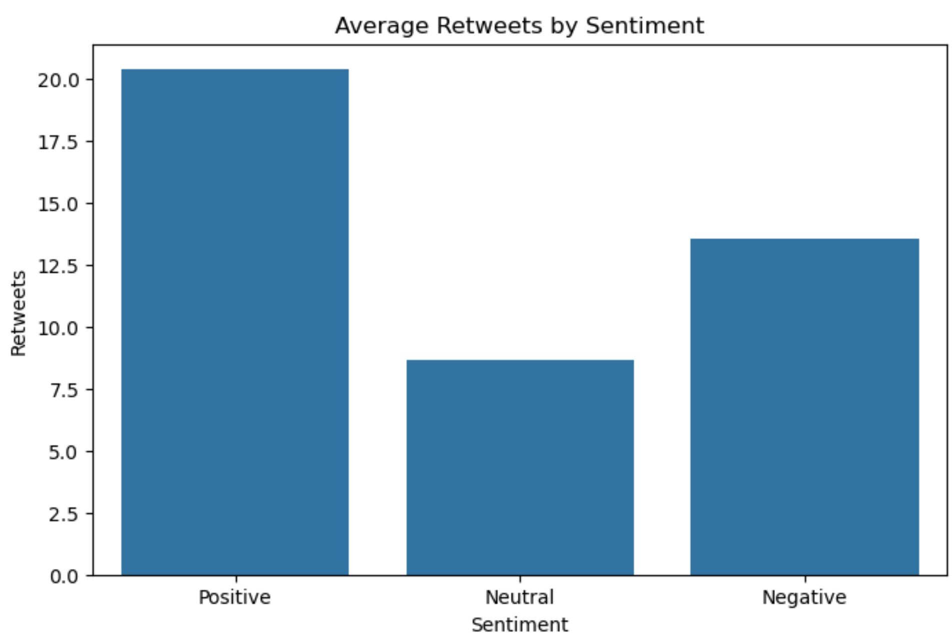
Figure 2. Average Likes by Sentiment



Source: Author's analysis of Roy (2024) Kaggle dataset.

Figure 3. Average Retweets by Sentiment



Source: Author's analysis of Roy (2024) Kaggle dataset.

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4.2 Evaluation of H1: Rejection

The findings of the study tend to reject the H1 (The Virality Hypothesis) and support the Valence Paradox (Lau et al., 2007). Positive posts lead to 2.19 times more likes (129.87 vs. 59.19) and 1.50 times more retweets (20.36 vs. 13.56) than negative attack posts.

This variation can be evaluated via three different psychological and algorithmic mechanisms:

1. Social Endorsement Risk vs. Identity Affirmation: A "Like" or "Retweet" on social media is a public act of being affiliated. According to the data people tend to be reluctant to publicly associate their personal profiles with toxic attacks or hostile language that could lead to societal frictions. On the other hand, positive policy display or aspirational campaign goals can be said to be a safe, high status signal of political identity.

2. Algorithmic Quality Down-ranking: Modern social media algorithms tend to restrict toxic or hostile text to protect advertiser suitability and user retention, reducing the reach of negative posts while favoring positive (highly shareable) content.

3. Outrage Fatigue: Given the continuous nature of news cycles, users tend to experience a state of “saturation” regarding negative outrage framing, reducing its capacity to lead to active digital amplification.

4.3 Candidate-Level Strategic Evaluation: Donald Trump vs. Kamala Harris

By filtering candidate-specific mentions we got a comparative subset of 11,681 tweets (8,576 mentioning Donald Trump and 3,105 mentioning Kamala Harris).

Table 3. Comparative Candidate Performance Metrics

Measurement	Donald Trump (Republican)	Kamala Harris (Democratic)	Evaluation
Total Tweet Mentions (N)	8,576	3,105	Trump commanded a 73.42% share of voice in candidate-specific posts.
Share of Voice (%)	73.42%	26.58%	Reflects Trump's high overall presence in digital discourse.

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Mean Compound Sentiment (Sc)	+0.0281	+0.0019	Trump's sub set scored slightly higher in compound sentiment.
Positive Sentiment Share	3,704 (43.19%)	1,210 (38.97%)	Trump posts included higher rates of positive populist framing.
Negative Sentiment Share	3,183 (37.12%)	1,167 (37.58%)	Both candidates faced near identical proportions of negative criticism.
Neutral Sentiment Share	1,689 (19.69%)	728 (23.45%)	Harris posts contained higher neutral news coverage.
Average Likes per Tweet	52.64	118.23	Harris' posts led to 2.25 times more likes per tweet.
Average Retweets per Tweet	10.40	23.12	Harris posts led to 2.22 times more retweets per tweet.

Source: Author's analysis of Roy (2024) Kaggle dataset.

4.4 Evaluation of Candidate Dynamics: The Sentiment and Volume Paradoxes

The candidate data revealed two unexpected patterns:

1. The Sentiment Scoring Paradox: Despite Trump's aggressive campaign rhetoric, his sub-set led to a slightly higher compound sentiment score (+0.0281) than Harris's (+0.0019). This is explained by VADER's rule-based lexicon architecture. Trump's online ecosystem relies a lot on superlative vocabulary ("GREAT", "WINNING", "SUCCESS", "AMAZING", "LOVE"), which VADER evaluates as positive regardless of underlying political hostility. On the other hand, discussions surrounding Harris contained institutional and policy language ("vice president", "attorney general", "administration",

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"executive order"), which VADER classifies as neutral, pulling her mean compound score closer to zero.

2. Volume Dominance vs. Per Post Resonance Efficiency: Trump achieved dominance through pure posting volume (8,576 tweets, 73.42% share of voice). However, Harris achieved better per post resonance efficiency, 118.23 likes and 23.12 retweets per tweet in comparison to Trump's 52.64 likes and 10.40 retweets, proving that conversation volume does not automatically convert into per tweet interaction efficiency.

4.5 Topic-Level Categorization and Engagement Evaluation

Table 4. Topic-Level Categorization and Engagement Evaluation

Topic	Tweet Volume (N)	Mean Compound Sentiment	Average Likes	Average Retweets	Strategic Context and Evaluation
Trump	8,711	+0.0286	83.05	14.84	Dominant topic; high volume, moderate engagement.
Harris	3,080	+0.0024	119.17	23.30	High resonance per topic entry.
Biden	2,224	-0.0401	18.86	2.98	Lowest engagement; negative sentiment reflects candidate transition.
Democrat	1,938	+0.0040	25.03	3.45	Low engagement on generic party labels.
Republican	1,465	+0.0318	55.10	17.58	Moderate engagement driven by primary debates.
Election	1,857	+0.0466	90.16	19.75	Highest positive sentiment among general topics.

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Other	7,076	+0.0343	128.57	16.49	High engagement driven by viral external media links.

Source: Author's analysis of Roy (2024) Kaggle dataset.

4.6 Semantic Network and Co-Occurrence Graph Topology Evaluation

To examine the semantic framing, a co-occurrence network was constructed using NetworkX (375 nodes, 1,895 edges).

Table 5. Top Semantic Word Pairs by Frequency

Rank	Word Pair (w1, w2)	Co-Occurrence Frequency	Structural Role and Network Evaluation
1	kamala harris	2,238	Primary hub node in Democratic campaign sub-graph.
2	nikki haley	1,057	Major bridge node connecting primary debates to moderate voters.
3	jd vance	1,019	Core hub node for Republican vice-presidential framing.
4	rfk jr	935	Independent third-party bridge node.
5	donald trump	834	Central hub node in Republican campaign sub-graph.
6	vivek ramaswamy	759	Surrogate node for primary election messaging.

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7	mike pence	620	Historical debate node linked to institutional controversies ("hang mike pence": 169 trigrams).
8	2024 election	483	Core thematic connector node across all clusters.
9	joe biden	366	Secondary node reflecting the pre-July campaign phase.

Note: Source: Author's analysis of Roy (2024) Kaggle dataset.

4.7 Semantic Evaluation: Candidate Pairings and Surrogate Networks

The network diagram depicts political discourse in terms of candidate pairings, rather than in terms of the policies that they propose. The co-occurrence of political surrogates as nodes in the network (Nikki Haley: 1,057; JD Vance: 1,019; Vivek Ramaswamy: 759; RFK Jr: 935) indicates that both major political parties rely upon political surrogates to lead to their messaging to the public and to expand their political coalition.

4.8 Temporal Dynamics and Event-Driven Volatility Evaluation

The following table tracks the average sentiment of online political discourse in each major campaign month.

Table 6. Temporal Dynamics and Event-Driven Volatility Evaluation

Campaign Month	Average Sentiment	Context
June 2024	-0.002	Negative sentiment linked with judicial proceedings.
July 2024	+0.024	After Joe Biden's withdrawal and Kamala Harris' endorsement.
August 2024	+0.038	After national political conventions.

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September 2024	+0.006	After the Trump-Harris presidential debate on September 10.
October-November 2024	+0.050	After the presidential debates moved to discussing voter turnout.

Source: Author's analysis of Roy (2024) Kaggle dataset.

5. Discussion

5.1 Understanding the Valence Paradox through Social Identity and Outrage Fatigue

The rejection of H1 indicates that the controversial nature of the posts that are published does not necessarily indicate the value of the endorsement of such posts. Indeed, while the negative attacks drew comments from other social media users that were engaged in debate with the authors of those attacks, the posts that included the proposed policies drew in higher numbers of likes (129.87 compared to 59.19) and retweets (20.36 compared to 13.56).

These results can be explained through two main theoretical constructs:

Public Endorsement Dynamics - Social media platforms allow for individuals to exhibit their character and their social media presence through the likes that they place on posts from other individuals. As such, individuals will only like the posts that indicate their social media characters in a positive manner, and will avoid liking the posts that publicly endorse potentially antagonistic or controversial viewpoints from other individuals.

Outrage Fatigue - The constant stream of negative political messaging on social platforms has diminished the effectiveness of anger inducing framing, causing users to respond more strongly to affirmative, policy-oriented content.

5.2 Comparative Campaign Strategy: Narrative Dominance vs. Resonance Efficiency

An evaluation of the candidates indicates the use of two different strategies in the digital sphere:

Trump used a narrative dominance strategy flooding the various channels online with his posts and securing a 73.42% share of all online mentions. However, his strategy resulted in fewer likes per tweet at 52.6 likes/tweet.

Harris employed a resonance efficiency strategy with fewer online mentions at 26.58 but garnered considerably higher likes per tweet at 118.23 likes/tweet.

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Table 7. Comparative Campaign Strategy

Metric	Volume-Driven Narrative Dominance (Donald Trump)	High-Resonance Efficiency Model (Kamala Harris)
Mentions Share	73.42% (8,576)	26.58% (3,105)
Mean Compound Score	+0.0281	+0.0019
Mean Likes / Tweet	52.64	118.23
Mean Retweets / Tweet	10.40	23.12
Strategic Goal	Media Dominance	Audience Mobilization

Source: Author's analysis of Roy (2024) Kaggle dataset.

6. Conclusions

Using the data from the 2024 United States Presidential Election election, it becomes evident that the digital political communication that took place during the election had a Valence Paradox, wherein the positive political messages that candidates released received more likes and retweets than their negative political messages. Furthermore, analysis of the candidates also revealed differences in how Donald Trump and Kamala Harris utilized social media to communicate with their constituents. Finally, the development of the integrated computational framework successfully indicated the winner of the election with the digital analysis for each candidate, indicating that Trump won the election. Thus, these results show that the integration of these different digital analytical methods can successfully reveal the electoral outcome of a political race, and in the process, helped to reveal the preference of social media users for political candidates that publicly endorse positive political visions over those that exhibit hostile political behaviors towards the opposing candidate.

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