

Introduction

Society is greatly influenced by communication. The feelings elicited by communications are influenced by how information is expressed and its context. Thus, it is important to better understand how language usage can be optimized to maximize positivity in different contexts. General language is often used in political discussion to represent broad concepts, while specific language narrows claims, both may be appropriate in different contexts. My study used lexical hierarchies to determine how the specificity of language affects sentiment and controversy in political and non-political discussions on social media. The relationship between language specificity and sentiment can provide insight into which method of communication most effectively elicits positivity in political and non-political contexts.

Question

Communication is used to influence people, but does communicating in general or specific terms influence the feelings it elicits? Also, how does the context of communications affect this?

Background Research

- The Construal Level Theory suggests that positive political communications often involve core and consistent attitudes, strong identities, and personal morals. When communications become more specific, the discussion highlights trade-offs and real consequences. In political discussions using specific language, those details make disagreements clearer, which can increase conflict. (Luguri, J., Trope, J., Liberman, N., 2013)
- Wordnet is a lexical database that identifies words as hyponyms (specific) or hypernyms (general). (Miller, G., 2019)
- Bots on X (formerly Twitter) spread misinformation and manipulate users with posts focusing on elections and political crises. X users post about negative content 34% more than positive content. This can significantly prove a bias towards negative conversation on X. (Stillwell, D., 2024, Troupe, D., 2019)
- Most bots have less than 50 followers and 10 times as many following than followers. (Zhou, Z. and Sun, L., 2018)
- The media can shape beliefs and ideas about politics by proposing debates and highlighting issues. Hostile or negative bias on social media can further influence the viewer’s opinions. (Perloff, R., 2021)

Hypothesis

Because general language is more inclusive and specific language narrows claims, I hypothesized that, in political discussions, general language will elicit more positive sentiment and spark less controversy. In contrast, for non-political topics, I expect specific language to elicit more positive sentiment and to be less controversial.

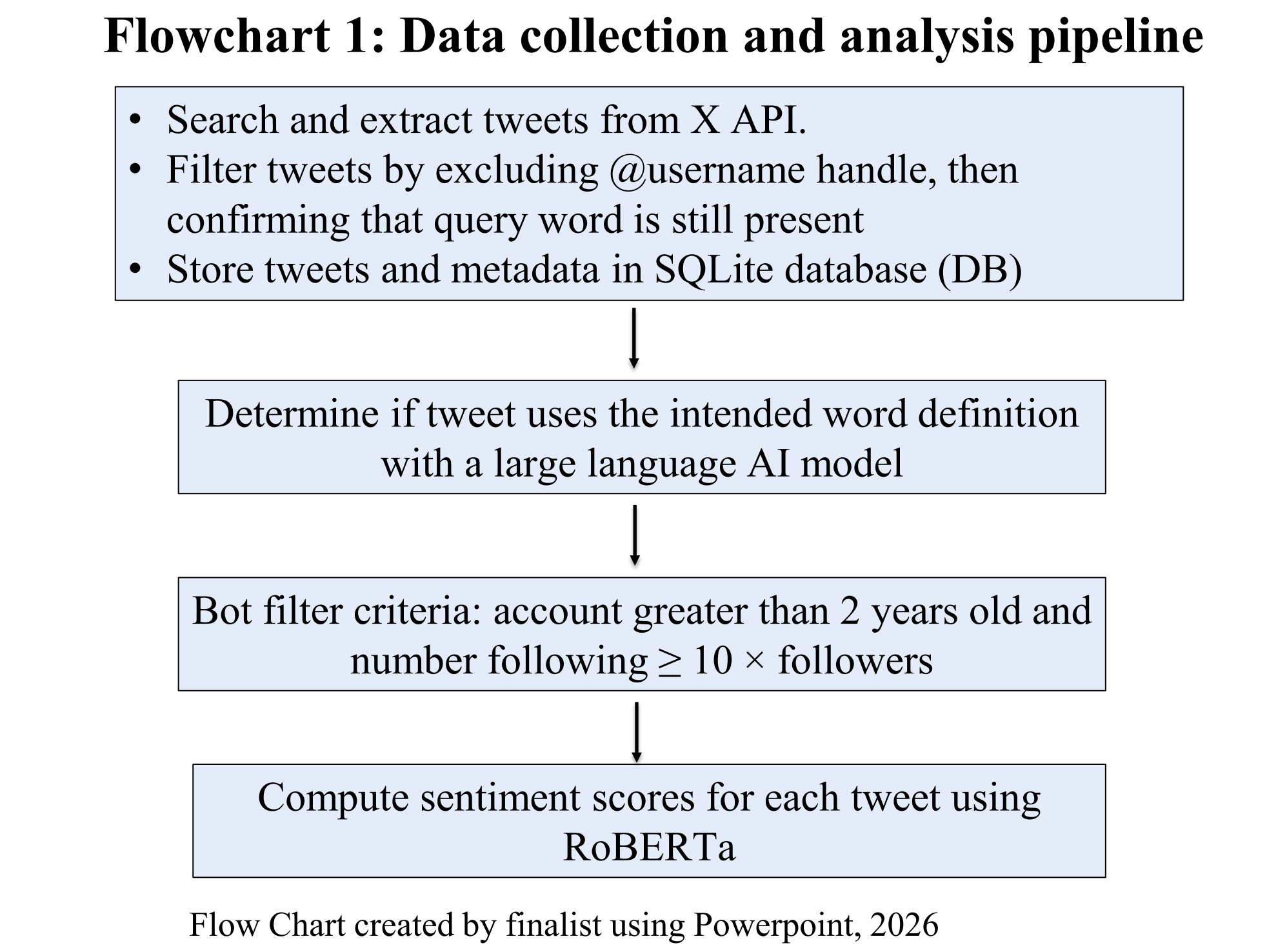
Materials

- X Developer Account with a Basic Plan
- Python
- Computer
- ChatGPT and Gemini for coding assistance
- roBERTa AI model for tweet sentiment scoring
- Excel
- WordNet version 2.1 (for lexical hierarchies)
- 10 political and non-political topics were described with 4-word lexical hierarchies (from WordNet 2.1) progressing from specific to general using 80 query words

The Role of Language Specificity in Sparking Controversy on Social Media

Procedures

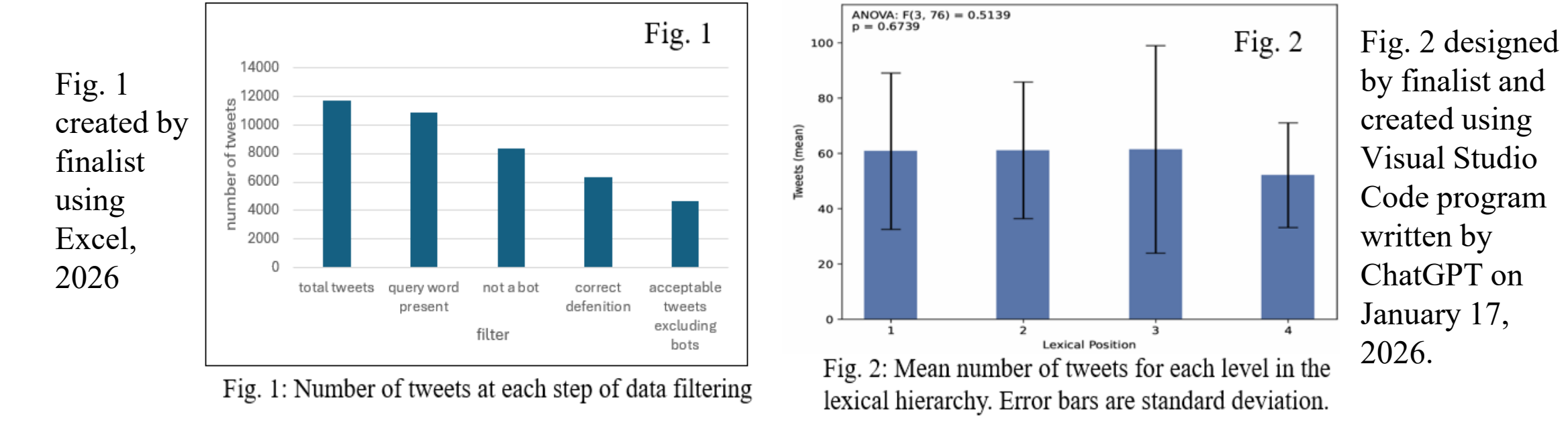
- For political and non-political topics, 10 sets of four-word lexical hierarchies were created using WordNet. I defined sub-topics (for example, means of transportation) and used the associated hypernyms (general) and hyponyms (specific) from WordNet to determine hierarchies ranging from specific to general words for each sub-topic.
- Political topics involve societal issues such as taxation, and non-political topics involve everyday concepts such as pets.
- Posts (11,725) were retrieved from X.com API using words from a lexical hierarchy as search terms using custom Python scripts.
- Data handling complied with X’s Terms of Service.
- Data processing programs were written in Python (aided by Chat-GPT and Gemini). Project design, code structure, and analysis criteria were established by the experimenter.
- Retrieved posts were cleaned for data quality and stored in an SQLite database with metadata (Flowchart 1).
- A program was written in Python to apply an AI model (Gemini) to determine the probability that each post (11,725) used its query word with the intended definition (criteria: p=1)
- Possible bot accounts were identified and removed based on user metadata (criteria from Zhou & Sun, 2018).
- A Python program was written to access the sentiment analysis AI model roBERTa (Cardiff NLP Group, 2020), which was used to quantify the sentiment of tweets (>6000 tweets) between -1 (negative) to 1 (positive).



- For each sub-topic, tweet sentiment score was predicted from the hierarchical position of the query word (specific to general) using linear regression.
- Linear regression of sentiment from word hierarchical position was performed for each topic: $\text{post_sentiment} = a \cdot (\text{word_hierarchy}) + b$. Word hierarchy range: 1-4.
- To analyze controversy for each topic, linear regression predicted the variability of post sentiment from hierarchical position: $\text{STDEV}(\text{post_sentiment}) = a \cdot (\text{word_hierarchy}) + b$.
- I compared the correlation coefficients of the regressions for each 4-word hierarchy between political and non-political topics.

Results

- A total of 11,725 tweets were collected across all search terms, and 10,848 contained the search term after removing the twitter handle. 8,348 tweets passed “not-a-bot” criteria, and 6,337 applied the correct definition and usage of the query word. After filtering, 4,633 tweets were classified as acceptable. (Fig. 1)
- The mean number of tweets collected and accepted for each level in the lexical hierarchy were similar (Fig. 2, ANOVA p=0.6739, not significantly different).



Lexical Hierarchy Predicts Sentiment

- For political topics, 6/10 hierarchies showed positive correlation coefficients, meaning positive sentiment increased as the wording became more general (Fig. 3).
- For non-political topics, 9/10 hierarchies displayed negative correlation coefficients, sentiment decreasing as the wording became more general (Fig. 4).
- For political topics, standard deviation of the sentiment score increased as wording became more general (Fig. 5). For non-political topics, standard deviation of the sentiment score decreased as wording became more general (Fig.6).

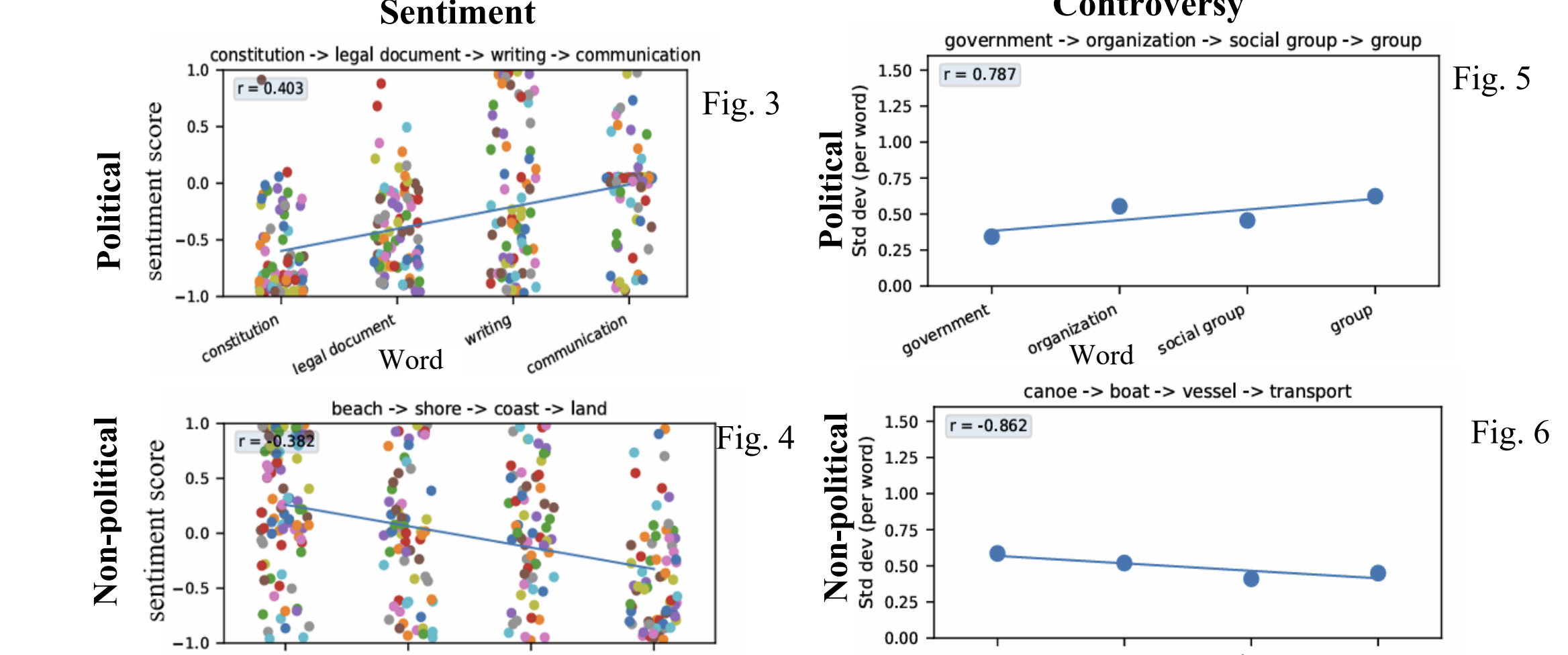


Fig. 3 & 4: Lexical hierarchy predicts sentiment score for each sub-topic. Each symbol is the sentiment score of a single tweet that used the query word. r-value magnitude: how well lexical hierarchy predicts sentiment.

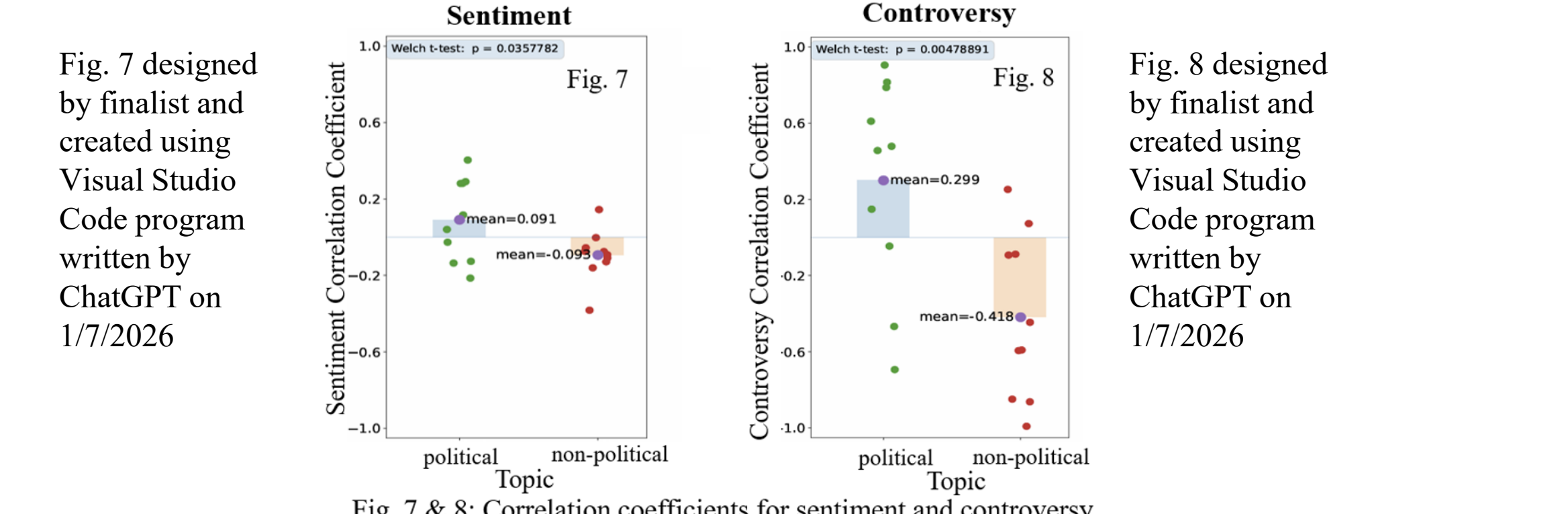
Fig. 3 & 4 designed by finalist and created using VS Code program written by ChatGPT on 1/7/2026

Fig. 5 & 6: Lexical hierarchy predicts standard deviation for each sub-topic. Each symbol is the standard deviation of sentiment in tweets that used the query word. r-value magnitude: how well lexical hierarchy predicts Std Dev.

Fig. 5 & 6 designed by finalist and created using VS Code program written by ChatGPT on 1/7/2026

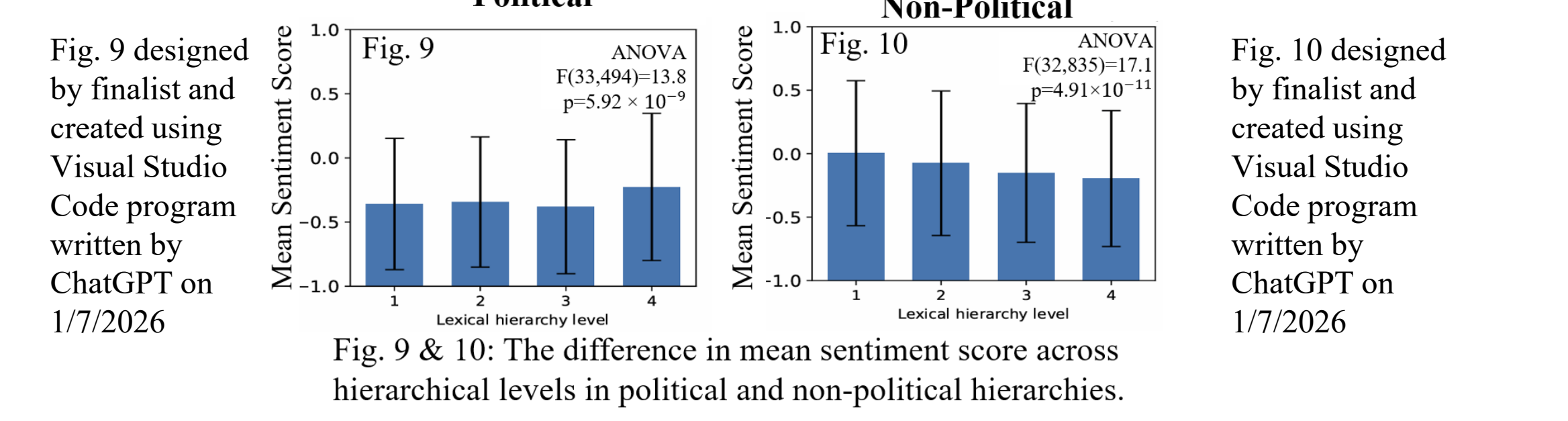
Political vs. Non-Political

- For political topics, lexical hierarchies (specific to general) showed a mean positive prediction relationship with sentiment score. Non-political lexical hierarchies showed a mean negative prediction relationship with sentiment score. (Fig. 7)
- Sentiment (Fig. 7) and controversy (Fig. 8) correlation coefficients differed significantly (p<0.05) between political and non-political hierarchies



Negativity Bias

- For both political and non-political lexical hierarchies, the average response sentiment tended to be negative or neutral. (Fig. 9 & 10)
- An average sentiment near zero reflects a range of positive to negative responses.



Discussion

- Word position in a lexical hierarchy predicts the sentiment of communications about political and non-political topics.
- Supporting my hypothesis, I found that, for political topics, communications with the highest positive sentiment used general wording. In contrast, communications about non-political topics had the highest sentiment when more specific words were used.
- Although political topics can have negative and positive implications, my findings support the use of general language in political discussions to increase positive sentiment.
- A consequence of using X to study communication is an established negativity bias (Stillwell, D., 2024). Most of my retrieved tweets communicated negative sentiment, consistent with this tendency.
- In both political and non-political hierarchies, words using the highest sentiment communications had the widest range of positive and negative responses, which indicated controversy. In contrast, words with the lowest sentiment scores had mostly negative responses, therefore less controversy.
- This challenges the part of my hypothesis stating that language with the highest sentiment score has lower controversy. However, the data is also consistent with the possibility that general language in political contexts creates more positive communications, but negativity bias is not fully overcome (i.e., “haters gonna hate”).

Conclusion

- Communicators covering political topics should focus on general language to maximize the amount of people reacting positively to their communications, despite how controversy may increase.
- These findings support the ideas of medieval political observer John Lydgate, when he stated "You can't please all of the people all of the time."
- My study identifies correlations between word specificity, sentiment, and controversy rather than causal effects. To determine a causal relationship between word use and how communications are perceived, a study would need to be conducted in political and non-political contexts, where subjects view different versions of the same message, one using specific language and one using general language. This would allow word specificity to be the only independent variable to test for a shift in sentiment and controversy.

Significance

I identified predictors of sentiment and controversy in language usage. Identifying a causal relationship between language specificity and sentiment/controversy would allow me to provide recommendations to political and non-political communicators to maximize positive reactions to their statement. For example, I recommend the use of general language by political communicators to elicit more positive reactions.