Emotion Classification and Analysis of Political Communication on Twitter

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Abstract

This study analyzes emotions and topics in Turkish political tweets using transformer-based natural language processing models. We collected and cleaned a large dataset of tweets from verified political accounts, then applied two main classification tasks: topic classification and emotion classification. Topic classification was performed with a zero-shot multilingual model, assigning tweets to political and social themes such as economy, migration and health. For emotion detection, we fine-tuned a Turkish BERT model to classify tweets into six emotion categories. Statistical and visual analyses reveal how different political parties and sides express emotions across topics and over time. Temporal trends in emotions such as fear, anger, and happiness highlight how public sentiment responds to political events. The results show that transformer architectures are effective for both topic and emotion classification in Turkish political text, and they offer valuable insights for political communication research and social media monitoring.

Keywords: Emotion Classification, Topic Classification, Turkish Political Tweets, Transformer Models, Natural Language Processing, Sentiment Analysis, Social Media Analytics, Temporal Emotion Trends, BERT

1 Introduction

Social media, especially Twitter, plays a major role in political communication in Turkey. Politicians and supporters share opinions that often carry strong emotions and focus on key political topics. Understanding these emotions and topics can reveal how political messages are shaped and how the public responds.

While advanced natural language processing (NLP) methods, such as transformer-based models, have been widely used for emotion and topic analysis in English, research on Turkish political discourse remains limited. This study addresses that gap by analyzing a large dataset of Turkish political tweets. Using topic classification and emotion classification, we examine differences between parties and political sides, explore topic-specific emotional patterns, and track changes in emotions over time. The results contribute both to NLP applications in Turkish and to the study of political communication on social media.

2 Research question

This study focuses on three main questions about emotions in Turkish political communication on Twitter. First, it looks at which emotions are most common in tweets by political actors and how these emotions differ between political parties. Second, it examines how emotions change depending on the topic, such as economy, migration, justice, or education. Third, it studies how emotions shift over time and how these changes relate to important political events and changes in the public agenda. Together, these questions aim to give a clear picture of how emotions influence and reflect political discussion on social media.

3 Methodology

3.1 Data Collection

We collected tweets using a custom Python script with the `Twikit` library. The dataset covers 28 verified politicians from Turkey's seven main political parties, with four politicians selected from each party. For each politician, up to 1,000 tweets were gathered. All collected tweets were saved in CSV format.

- Retweets and replies were removed to capture only original political messages.
- Only tweets posted on or after January 1, 2021 were included.

3.2 Data Processing

After collecting the tweets, all CSV files were combined into a single dataset. Metadata such as tweet ID, politician name, party, political side, date were kept.

The tweet text was cleaned to keep only meaningful content:

- Removed retweet indicators (e.g., "RT") and user mentions, emojis, special symbols, extra spaces, and unnecessary punctuation.
- Deleted URLs and links.
- Excluded very short or single-word tweets.

3.3 Fine-tuning BERT Model

In this study, various pre-trained language models were compared for Turkish topic classification. The experiments included **'dbmdz/bert-base-turkish-uncased'** and **'savasy/bert-base-turkish-sentiment-cased'**, which are monolingual Turkish models, as well as the multilingual models **'FacebookAI/xlm-roberta-base'** and **'FacebookAI/xlm-roberta-large'**. Each model was fine-tuned on the same dataset using identical training parameters, and their performances were evaluated in terms of accuracy, and F1-score. This allowed for a direct comparison between monolingual and multilingual architectures in the context of Turkish topic classification.

All in all ,we used a Turkish BERT model (`dbmdz/bert-base-turkish-cased`) to classify emotions in tweets. The model was fine-tuned on an emotion-labeled dataset for multi-class emotion detection.

3.3.1 Dataset for fine tuning process

I also tried translating the **GoEmotions** dataset into Turkish and fine-tuning models on it, but I did not get good results, so I abandoned that approach. I used Turkish emotion dataset. English version while in fine tune stage these text are in Turkish.

- **id, text, emotion**
- 1, Every new day is a joy, Happy
- 2, I am very scared when walking through empty streets at night, Fear
- 5, I am disgusted by people's self-interest, Disgust

3.3.2 Evaluation and Results

After 4.34 epochs, the model achieved a training loss of 0.2685 and evaluation loss of 0.2567. It reached a micro F1-score of 93.49 and the same accuracy.

Emotion	**Precision**	**Recall**	**F1-score**
Anger	0.95	0.93	0.94
Disgust	0.95	0.95	0.95
Fear	0.94	0.94	0.94
Happy	0.95	0.95	0.95
Sadness	0.91	0.94	0.92
Surprise	0.91	0.88	0.90
Overall Accuracy		0.9349	

3.4 Topic Classification

We performed topic classification on a large set of Turkish tweets using a zero-shot learning approach based on the model whixh is `MoritzLaurer/mDeBERTa-v3-base-xnli-multilingual-nli-2mil7`.

3.4.1 Topic Labels and Mapping

We defined a set of Turkish topic labels relevant to political and social discourse and mapped each label to its English equivalent to facilitate downstream processing. The mapping is shown in Table 1.

Turkish Label	English Equivalent
göç	migration
ekonomi	economy
eğitim	education
sağlık	health
adalet	justice
dış politika	foreign_policy
enerji	energy
yerel yönetim	local_government
taziye	condolence
tebrik	congratulation
kültür	culture
spor	sports
afet	disaster
genel	general

Table 1 Mapping of Turkish topic labels to their English equivalents.

3.5 Emotion Classification

After topic classification, we applied emotion classification to the same dataset using our previously fine-tuned Turkish BERT emotion model.

3.5.1 Prediction Procedure

We predicted emotions for all tweets as follows:

- Tokenized each tweet.
- Converted model outputs to probabilities with softmax.
- Chose the emotion with the highest probability as the main label.
- Recorded all emotions with confidence above 70 percent for multi-label cases.

3.6 Emotional and Topic Analysis

The emotional and topic analysis phase was performed on the dataset with predicted emotions and topics per tweet. The process included:

- **Emotion Percentages by Party:** Tweets were grouped by political party and predicted emotions to calculate the percentage distribution. The top 3 emotions per party were identified and visualized using bar plots.
- **Emotion Percentages by Topic and Party:** Emotion distributions were further analyzed within specific political topics across parties. The most frequent emotions per party–topic intersection were presented in detailed visualizations, including plots.
- **Time Series Analysis of Selected Emotions:** For selected key emotions such as *Fear*, *Anger*, temporal trends were analyzed by grouping tweets by month or date. Line plots illustrated fluctuations in emotional expression over time.

4 Results

4.1 Emotion Distribution by Party

Description: This analysis shows the distribution of predicted emotions across different political parties. Condolances and congratulations tweets were removed before analyses. The top emotions per party are visualized in Figure 1.

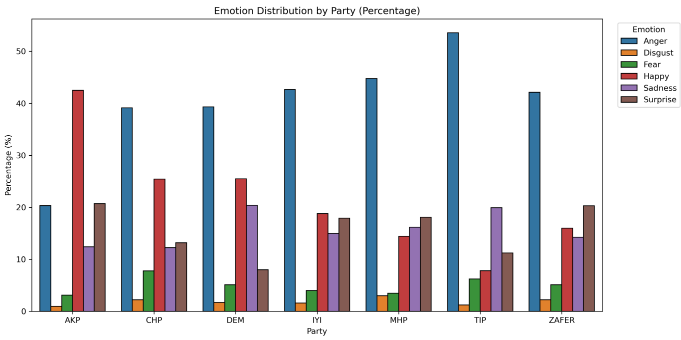

Fig. 1 Bar plot of emotion distribution by political party.

Interpretation: Since the AKP is the main party in power, their high ”Happy” percentage (42%) could be a way to show they are successful and that things are going well. The CHP, as the main party against the government, uses a lot of ”Anger” (around 39%). This is probably because they are criticizing the government and its problems. For the nationalist parties MHP and ZAFER, their strong use of ”Anger” and ”Surprise” might be because they are fighting for national values or reacting strongly to things they see as threats to the country. In short, each party uses different feelings to show what they care about and to talk to the people who support them.

4.2 Emotion Distribution by Topic and Party

4.2.1 Topic: Economy

Description: Figures 2 show the emotional reactions of different party supporters to the topic of the economy.

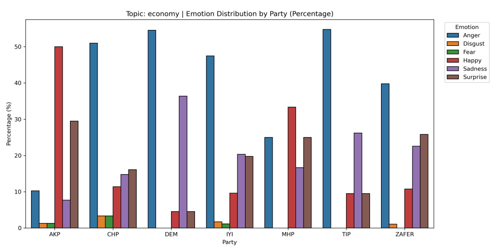

Fig. 2 Emotion distribution for the topic ”Economy” by political party.

Interpretation: The AKP, which is the party in power, talks about the economy with a lot of "Happy" emotions (over 50%). This is probably because they want to show that they are doing a good job with the economy and that it is a success. On the other hand, the main opposition party CHP uses a very high amount of "Anger" (over 50%) when talking about the economy. This shows that they are very critical of the government's economic plans and likely focus on problems like prices or inflation. Almost all the other opposition parties (DEM, İYİ, TİP, and ZAFER) also use a lot of "Anger" when they talk about the economy. This tells us that the economy is a big point of criticism for parties that are not in power.

4.2.2 Topic: Migration

Description: Figures 3 show the emotional reactions of different party supporters to the topic of migration.

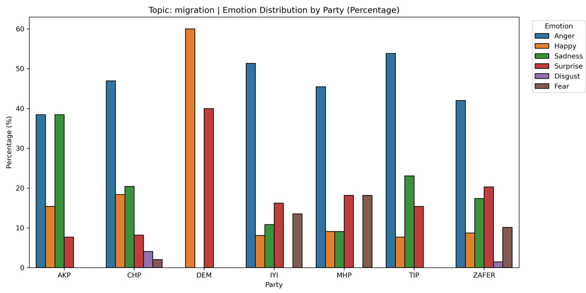

Fig. 3 Emotion distribution for the topic "Economy" by political party.

Interpretation: The parties with a nationalist focus, like MHP, ZAFER, and İYİ, use a lot of "Anger" (over 40-50%) when they tweet about migration. This shows they are very much against the current situation or government policies on this topic.

The ruling party, AKP, has a very different profile, using a mix of "Sadness" and "Happy" feelings. This might be because they are sad about the migrants' situation but happy about the help they are giving them.

The DEM party has a very high "Happy" percentage (almost 60%). This likely means they focus on a more positive, welcoming, and humanitarian view of migration. Overall, the chart clearly shows that while nationalist parties use a lot of anger on this topic, others have very different feelings.

4.2.3 Topic: Health

Description: Figures 4 show the emotional reactions of different party supporters to the topic of Health system.

Interpretation: The ruling party, AKP, has a very high "Happy" percentage (over 40%) when talking about health. This is similar to their overall tone and likely shows they are proud of their work in this area. Interestingly, the CHP's "Happy" percentage on health is almost as high as its "Anger" percentage. This is different from

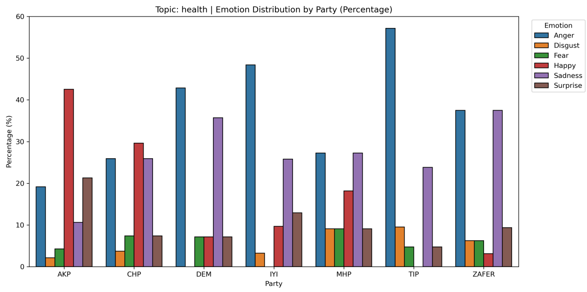

Fig. 4 Emotion distribution for the topic "Economy" by political party.

their general profile, where anger is dominant, and might show they talk about health with a mix of criticism and positive suggestions. Also, parties like DEM and ZAFER have a very high level of "Sadness" when talking about health, which suggests they are focusing on the difficulties and human problems related to healthcare.

4.3 Overall Emotional Distribution of Tweets on the Topics

Description: Figure 5 presents the overall emotional distribution of tweets on the topic of the economy , migration , health.

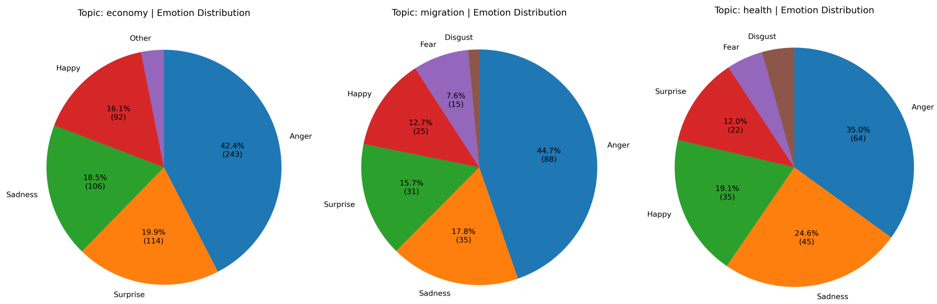

Fig. 5 Overall emotional distribution of tweets on different topics per political side.

Interpretation: For both the left and the right sides, "Anger" is the most common emotion. This tells us that political talk in general is often critical and confrontational.

However, there are some clear differences. The right side has more "Happy" feelings than the left. This suggests a more positive or confident tone. On the other hand, the left side has a higher percentage of "Sadness" and "Fear," which could point to a focus on social problems or concerns about the future.

In short, while anger is a main part of the conversation for both sides, the left's feelings are also heavily mixed with sadness, while the right's are more balanced with happiness.

4.4 Time Series Analysis of Selected Emotions

Description: The temporal trends of selected emotions (*Fear*, *Anger*) were analyzed over the data collection period. Figure 6 shows monthly tweet counts for these emotions.

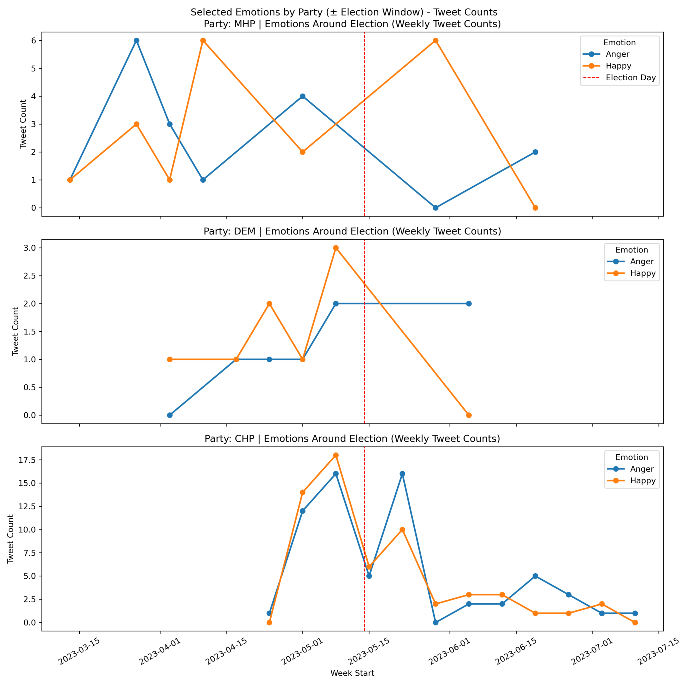

Fig. 6 Temporal trends of selected emotions.

Interpretation: Before the election, MHP's anger and happiness fluctuated, with happiness peaking during election week and anger staying low, suggesting optimism among supporters; afterward, happiness dropped sharply while anger rose slightly, possibly reflecting disappointment or shifting focus. DEM started with low anger, which rose during election week, while happiness gradually increased to its peak before falling to zero, hinting at unmet expectations. CHP saw sharp rises in both emotions about two weeks before the election, likely due to campaign intensity; anger peaked again just after the election, indicating dissatisfaction with the results, before both emotions declined as public interest waned.

5 Concluding Remarks

This study successfully used advanced NLP models to analyze Turkish political communication on Twitter. We found that these models are very effective for classifying both topics and emotions.

Our analysis showed clear emotional differences between political parties. Opposition parties like the ZAFER party often expressed anger and sadness, while the ruling AKP and MHP parties showed more happiness. On specific topics, like migration and justice, anger was the most common emotion, but discussions about education had a more mixed emotional profile, including a lot of happiness.

These findings help us understand how emotions influence political talk online. Future studies could use even bigger datasets and look at other types of media, like images and videos.

References