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 NLP models. We collected a dataset of tweets from verified political accounts, cleaned it, and applied two classification tasks: topic and emotion detection. Topic classification was performed with a zero-shot multilingual model, assigning tweets to themes such as economy, migration, and health. For emotion detection, we fine-tuned a Turkish BERT model to classify tweets into six categories. The analysis reveals how parties and political sides express emotions across topics and over time. Temporal trends in emotions like fear, anger, and happiness show how public sentiment responds to political events. Results indicate that transformer architectures are effective for both tasks in Turkish political text and provide 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

Twitter has become a key arena for political communication in Turkey, where politicians and supporters express emotionally charged views on major issues. Transformer-based NLP models, such as BERT and RoBERTa, have advanced sentiment and emotion detection. While widely used in English political discourse , applications to Turkish remain scarce [**?**]. This study analyzes a large dataset of Turkish political tweets through zero-shot topic classification and fine-tuned emotion detection.

We examine party-based differences, topic-specific emotional patterns, and temporal shifts. Findings highlight how emotions are strategically deployed in political discourse and how they mirror public reactions to political events, contributing both to NLP research in low-resource languages and to the study of political communication.

2 Methodology

2.1 Data Collection & Processing

Tweets were gathered with the `Twikit` library from 28 verified politicians representing seven major parties (1,000 tweets per politician). All CSV files were merged into a single dataset containing metadata (tweet ID, politician, party, side, date). Non-textual elements such as URLs and emojis were removed.

2.2 Fine-tuning BERT Model

We compared several pre-trained Turkish and multilingual models (`dbmdz/bert-base-turkish-uncased`, `savasy/bert-base-turkish-sentiment-cased`, `xlm-roberta-base`, `xlm-roberta-large`). The best-performing Turkish BERT (`dbmdz/bert-base-turkish-cased`) was fine-tuned for six-way emotion classification.

2.2.1 Dataset for fine tuning process

We experimented with a translated version of GoEmotions, but performance was unsatisfactory; therefore, it was not included in the final model.

- **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

2.2.2 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	

2.3 Topic Classification & Emotion Classification

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

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

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

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.

2.4 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.

3 Results

3.1 Emotion Distribution by Party

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

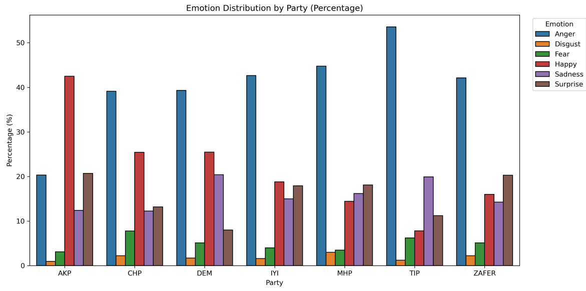

Fig. 1 Bar plot of emotion distribution by political party.

Interpretation: The AKP's high "Happy" percentage (42%) reflects their effort to present success and stability as the ruling party. The CHP, with a strong use of "Anger" (about 39%), focuses on criticizing the government. Nationalist parties like MHP and ZAFER emphasize "Anger" and "Surprise," highlighting their defense of national values and sharp reactions to perceived threats. In short, each party uses emotions differently to show their priorities and connect with their supporters.

3.2 Emotion Distribution by Topic and Party

3.2.1 Topic: Economy

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

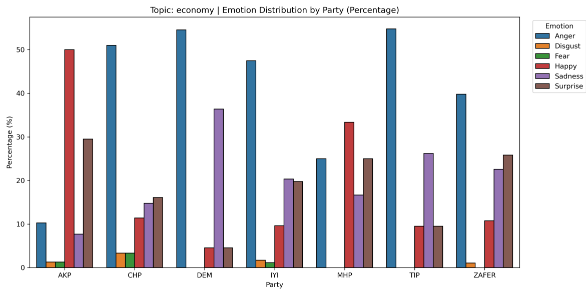

Fig. 2 Emotion distribution for the topic "Economy" by political party.

Interpretation: The AKP, as the ruling party, talks about the economy with a high level of “Happy” emotions (over 50%), likely to show success and good performance. In contrast, the main opposition party CHP uses over 50% “Anger,” reflecting strong criticism of the government’s economic policies, especially issues like prices and inflation. Other opposition parties (DEM, İYİ, TİP, ZAFER) also rely heavily on “Anger,” showing that the economy is a central point of criticism for parties outside power.

3.2.2 Topic: Migration

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

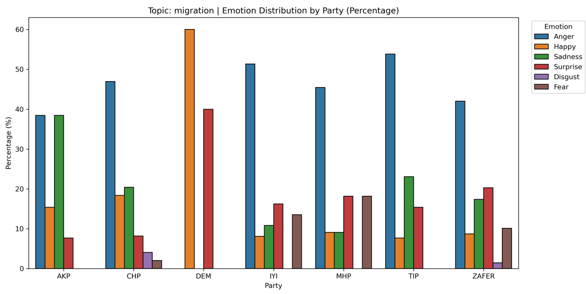

Fig. 3 Emotion distribution for the topic ”Migration” by political party.

Interpretation: Nationalist parties like MHP, ZAFER, and İYİ use a high level of “Anger” (40–50%) when tweeting about migration, showing strong opposition to current policies. The ruling AKP has a different profile, combining “Sadness” and “Happy,” likely reflecting both concern for migrants and pride in providing support. DEM, with nearly 60% “Happy,” takes a more positive and humanitarian stance. Overall, nationalist parties emphasize anger, while others express very different emotions on migration.

3.2.3 Topic: Health

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

Interpretation: The ruling AKP shows a high “Happy” percentage (over 40%) on health, reflecting pride in their work and consistent with their overall tone. CHP, however, shows almost equal levels of “Happy” and “Anger,” unlike their usual anger-dominated profile, suggesting a mix of criticism and positive proposals. DEM and ZAFER stand out with high “Sadness,” indicating a focus on healthcare difficulties and human challenges.

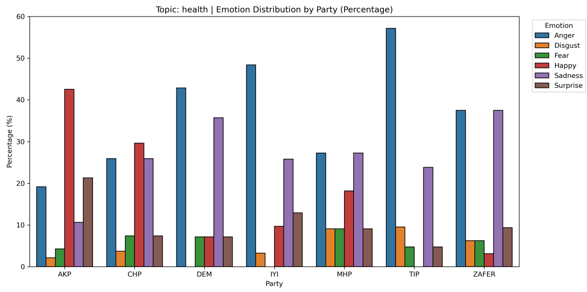

Fig. 4 Emotion distribution for the topic "Health" by political party.

3.3 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.

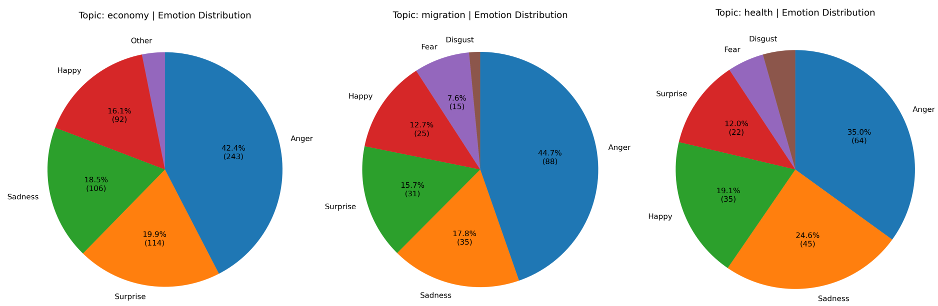

Fig. 5 Overall emotional distribution of tweets on different topics per political side.

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.

3.4 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.

Interpretation: Before the election, MHP's anger and happiness fluctuated, with happiness peaking during election week and anger staying low, suggesting optimism

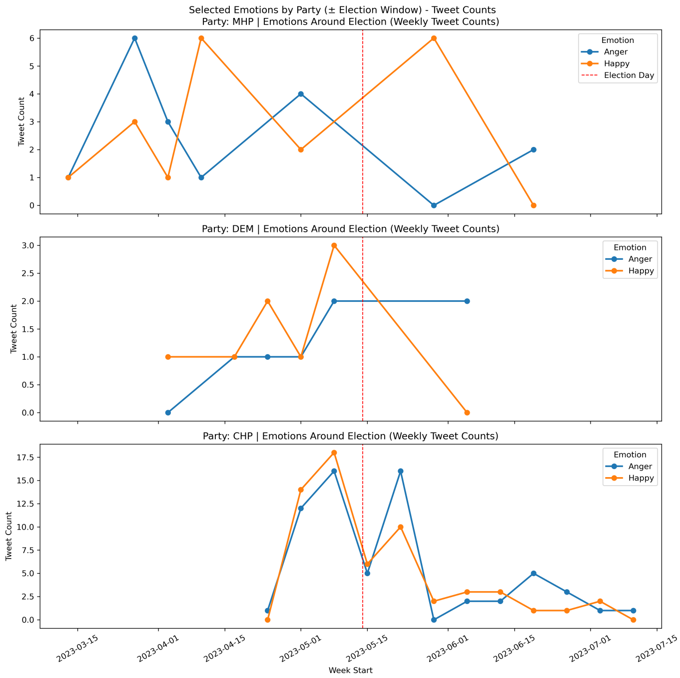

Fig. 6 Temporal trends of selected emotions.

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.

3.5 Model Explainability with SHAP

To better understand how the fine-tuned Turkish BERT model makes its predictions, we applied the (SHAP) framework. SHAP provides token-level contribution scores, highlighting which words in a tweet influenced the model's decision towards a particular emotion class.

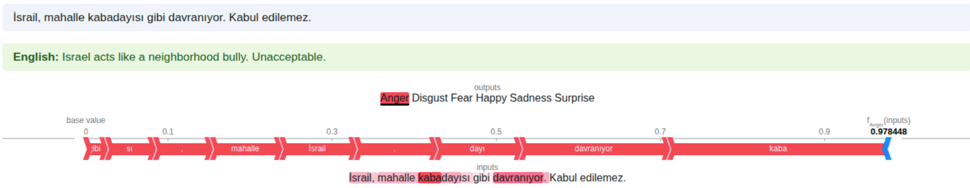

Fig. 7 SHAP explanation for a tweet classified as *Anger*.

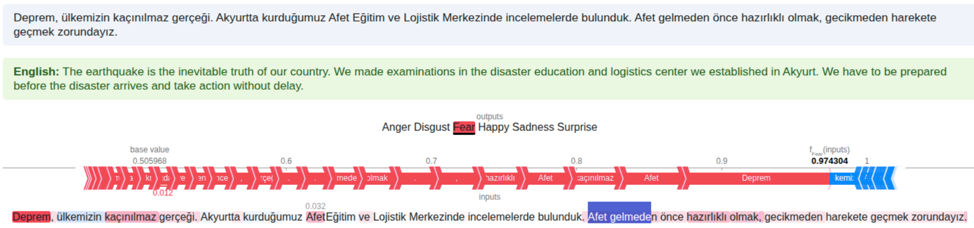

Fig. 8 SHAP explanation for a tweet classified as *Fear*.

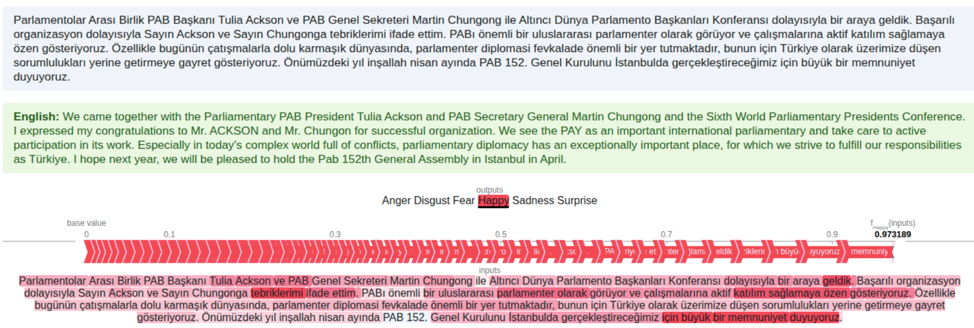

Fig. 9 SHAP explanation for a tweet classified as *Happiness*.

Fig. 10 SHAP explanation for a tweet classified as *Sadness*.

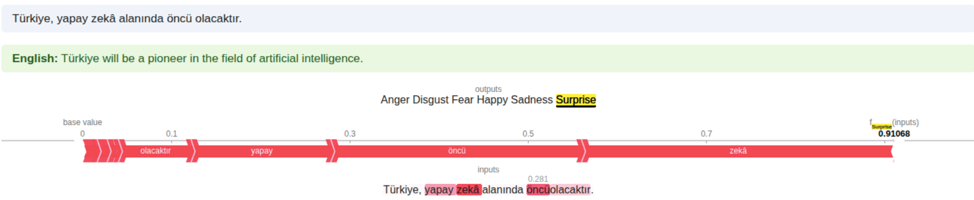

Fig. 11 SHAP explanation for a tweet classified as *Surprise*.

4 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.