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Emotion Analysis on Youtube Comments for 2023 Turkish Presidential Elections

2023 Türkiye Cumhurbaşkanlığı Seçimleri için Youtube Yorumlarında Duygu Analizi

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Araştırma Makalesi Research Article

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ABSTRACT

The 13th Presidential election has created a wide agenda in many countries as well as in Turkey. In this election period, along with traditional media tools, social media tools were also used frequently in the execution of election campaigns. Interactions received through social media platforms once again proved the effective power of social media tools to reach large masses of all parties and party leaders. For this reason, the Open Microphone program organized by Oğuzhan Uğur, in which many politicians participated, was followed with interest not only in Turkey's agenda, but also in the world's agenda. In this context, this study aims to reveal various analysis findings with Emotion Analysis methods, especially from the comments made within the scope of this program. For this purpose, in this study, a total of 261.728 user comments, specific to 7 different politicians, were analyzed using the NRC emotion dictionary. With the NRC emotion dictionary, a broader emotional polarity was obtained, including the emotions of anger, fear, trust, anticipation, surprise, sadness, joy, and disgust, in addition to positive or negative emotion polarity. As a result of the findings, this study reveals that the emotion analysis of the masses through Youtube comments or different platforms can be a critical source of information for political campaigns.

Keywords: Emotion Analysis, Presidential Election, NRC Emotion Dictionary, Natural Language Processing, Youtube.

ÖZ

13. Cumhurbaşkanlığı seçimi Türkiye'de olduğu kadar birçok ülkede de geniş bir gündem yaratmıştır. Bu seçim sürecinde, seçim kapmanyalarının yürütülmesinde, geleneksel medya araçlarının yanı sıra sosyal medya araçları da çok sık kullanılmıştır. Sosyal medya platformları üzerinden alınan etkileşimler tüm siyasi partilere ve parti yöneticilerine, geniş kitlelere ulaşmak için sosyal medya araçlarının efektif gücünü bir kez daha kanıtlamıştır. Bu nedenle Oğuzhan Uğur'un düzenlediği ve birçok siyasetçinin katıldığı Açık Mikrofon programı sadece Türkiye gündeminde değil dünya gündeminde de ilgiyle takip edilmiştir. Bu kapsamda bu çalışma özellikle bu program kapsamında yapılan yorumlardan Duygu Analizi yöntemleri ile çeşitli analiz bulgularını ortaya koymayı amaçlamaktadır. Bu amaç ile bu çalışmada 7 farklı siyasetçi özelinde toplamda 261.728 kullanıcı yorumu, NRC duygu sözlüğü kullanılarak analiz edilmiştir. NRC duygu sözlüğü ile birlikte pozitif veya negatif duygu polaritesine ek olarak öfke, korku, güven, beklenti, sürpriz, üzüntü, neşe ve tiksinti duygularının da yer aldığı daha geniş bir duygu polaritesi elde edilmiştir. Elde edilen bulgular neticesinde bu çalışma Youtube yorumları veya farklı platformların üzerinden kitlelerin duygu analizinin siyasi kampanyalar için kritik bir bilgi kaynağı olabileceğini ortaya koymaktadır.

Anahtar Kelimeler: Duygu Analizi, Cumhurbaşkanlığı Seçimi, NRC Duygu Sözlüğü, Doğal Dil İşleme, Youtube.

Introduction

The 13th Presidential election, which was held in Turkey in the first round on May 14 and in the second round on May 28, created a wide agenda in many countries as well as in Turkey. The 1st Round elections, especially shaped by 2 candidates, were left to the 2nd Round elections with the current President of Turkey Recep Tayyip Erdoğan and Kemal Kılıçdaroğlu. As a result of the 2nd round of elections, 13th President of Türkiye Recep Tayyip Erdoğan was elected. This election period, in which social media tools have been used very frequently as well as traditional media tools, unlike all election processes to date, has once again proven the effective power of social media tools to reach large audiences for all political parties and party leaders. Social media platforms have long been the easiest and most common platforms that people around the world use to express their feelings (Chauhan et al., 2021: 2602). In addition, the rapid dissemination of information through social media platforms allows politicians to deliver their messages quickly and directly to large audiences, unlike traditional media (Baker Al Barghuthi and Said, 2020: 107). Especially for the politicians who are candidates for the presidency and for the new parties that have just joined the elections, the programs made on Youtube attracted the attention of the masses. The Open Microphone program performed by Oğuzhan Uğur under BabalaTv channel was followed with interest not only in Turkey but also in the world agenda. The program, in which 12 different political actors participated, always ranked first in the trends during the week it was broadcast, and each program was watched by 10 million people. This whole process has enabled such programs, which are carried out on social media tools, unlike traditional media tools, to reach large audiences as well as to obtain comments on the attitudes of these audiences. The use of social networks in elections, interpreted by many analysts as the secret of Barak Obama's success in national elections (Tumasjan et al., 2010), can play a more decisive role in today's elections (Chaudhry et al., 2021; Shevtsov et al., 2023). Donald J. Trump, who was clearly behind Hillary Clinton in the 2016 US presidential election polls, was able to win the election in contrast to the election polls, by using social media platforms extensively in his election campaign. For this reason, today, all political parties give more importance to the use of social media during their political campaigns and invest more for this purpose.

Thousands of comments made under each broadcast program have allowed political parties and politicians to both reach more people and have broader information, unlike the pools conducted by survey companies. The information to be obtained from these comments is of critical importance both for the current election period and for the roadmaps of individual political characters. Moreover, with the participation of many different politicians in this program organized by BabalaTv, it also allows the comments made on each program to be comparable. Because each program was conducted with the same opportunities for each politician and with questions that were especially curious about the opposition audience. Emotion or sentiment analysis (if it explores too much emotion, the term "Emotion" is often used instead of "Sentiment" in the literature), which is the subject of many studies and even more popular today, is frequently used in determining the poles of opinion. Thus, it creates a new alternative to understand user, consumer or voter orientation and therefore make smarter decisions. Emotion analysis can help with the mining of human behavior, which can help in decision making and prediction tasks, especially with data obtained from social networks (Chauhan et al., 2021: 2603). Today, political campaigns and their managers benefit from this wide array of information available on social networking platforms to learn more about voter views and thus design their campaign strategies (Budiharto and Meiliana, 2018: 4). For this purpose, this study aims to reveal various analysis findings with Emotion Analysis methods, especially from voter comments made on Open Microphone Youtube program.

One of the vital elements in an election is the election pools, which monitor the election process and provide candidates with information about the voter (Salunkhe and Deshmukh, 2017: 540). Although election pools can provide consistent information about the vote rates of candidates or parties, they cannot provide both consistent and sufficient information about voter attitudes or expectations. Moreover, while traditional pools are very costly, online information can be easily obtained, used and analyzed for free (Salunkhe and Deshmukh, 2017: 540; Budiharto and Meiliana, 2018: 3). In addition, social media analysis or emotion analysis is cheaper and faster than traditional statistical methods, as well as allowing an election campaign to be followed instantly (Ceron et al., 2015: 5; Endsuy 2021: 9). It is possible to obtain and analyze daily interest data with a emotion analysis method, which is also the subject of this study. In this way, voter attitudes regarding election campaigns and all discourses within these campaigns can be followed quickly. In addition, while faced with problems such as the shyness of individuals as a result of obtaining personal opinions in traditional pools and the limited time in which the pool is conducted, there is no such problem in comments made through social media comments. In the light of all this information, another aim of this study is to reveal that the emotion analysis findings carried out on social media platforms have a complementary effect on election pools. Rather than looking for an alternative to traditional pools methods, this study tries to reveal that approaches such as "sentiment analysis" can be a supporter of other methods in understanding public perception, especially during election periods when intensive communication activities are required. For this purpose, it has been revealed that the emotion analysis approach can be a tool that politicians can obtain useful information both during the election campaigns and in the following periods. In addition to all these, the data used within the scope of this study was collected on the internet without knowing the real personality of any user or using profile information, only taking into account their comments or shares. For this reason, we focused on data as a result of direct sharing, without focusing on individuals. Thus, unlike traditional pools methods, ethical problems are eliminated.

Literature

Although there are many studies aiming to analyze the election results through the posts shared on Twitter, most of these studies cannot provide appropriate and consistent results about the election results (Tumasjan et al., 2010; Gayo-Avello, 2013; Ramteke et al., 2016; Salunkhe and Deshmukh, 2017; Budiharto and Meiliana, 2018; Nausheen and Begum, 2018; Batra et al., 2020; Baker Al Barghuthi and Said, 2020). Moreover, as stated in Gayo-Avello (2012), it will not be possible to make an election prediction on social media unless appropriate regulations and sample selections are made. Because the sample from which the obtained data is obtained cannot fully represent all voters. In particular, characterizing these views as only positive or negative is insufficient for the prediction of the election results alone, and at the same time, it does not provide an inference about the emotions that provide positive or negative polarization. In addition, it will not be surprising that users who comment on certain hashtags or under certain topics already follow these people or channels, so they have a more positive feeling. The vague demographic characteristics of voters expressing their opinions on social media (for example, not being 18 years old) prevent such analyzes from being fully consistent and precise. However, a study on the comments of voter groups with more than one political view on an unbiased program may contain information waiting to be discovered for political authorities. As Ramteke et al. (2016) stated, although sentiment or emotion analysis models alone are not suitable for predicting election results, they can become a very important component when other analyzes and statistical models are combined. Additionally, like O'Connor et al, (2010), Sanders and van Den Bosch, (2013) revealed in their analysis on Twitter that traditional polls are more accurate as a predictor of the outcome. However, they also revealed that Twitter statistics and the resulting analyzes show a high correlation with elections and surveys. Chauhan et al., (2023) showed promising results even though the sentiment analysis results they conducted with TextBlob in the 2019 Indian elections had a higher error rate than traditional survey studies when compared to the real election results. This error rate difference, which varies between 6% and 8%, can be reduced to more satisfactory rates with machine learning supervised learning approaches, especially instead of the dictionary-based approach used. On the contrary, Tumasjan et al. (2010) revealed that the frequency of mentioning political parties does not allow the prediction of election results yet. Rita et al., (2023) revealed in their study on tweets for the 2019 British General elections that sentiment analysis cannot be used directly to predict election results. One of the main reasons for this situation is that the appropriate sample selection could not be made on these randomly selected Twitter users. However, beyond the prediction of the election results, the attitudes and feelings of the citizens towards a political figure are closely related to the campaign to be followed. For this reason, it would be a more accurate approach to carry out such an analysis, especially through the comments made specifically for a program attended by a certain politician. Thus, there will be no problem in determining the addressee of the comments made, and inferences regarding the desired audience will be obtained as a result of this program.

Since Tumasjan et al. (2010) stated in their studies that Twitter is indeed a frequently used platform for political negotiation and expression of opinion, analysis studies on election periods over social networks have increased rapidly. Boutet et al. (2012) presented the first classification study in this field by using statistical methods on Twitter for the 2010 UK elections. Sanders and van Den Bosch (2013) have shown that consistent results can be obtained with election pools, even with the frequency of mentioning political parties on Twitter alone. With all these efforts, the increasing interest in this field has been interesting for more researchers, especially with the developments in the field of sentiment analysis. Salunkhe and Deshmukh (2017), in their emotional analysis on the US presidential election based on twitter data, determined that sadness (sadness) was the dominant emotion in tweets about Hillary Clinton, and joy was the dominant emotion in tweets about Trump. Ramteke et al, (2016) revealed that the posts about Trump have more positive sentiment polarity in percentage, supporting the results of Salunkhe and Deshmukh (2017). Nausheen and Begum (2018) found that, unlike the other two studies, Hillary Clinton had a higher percentage of positive sentimental polarity. Shevtsov et al. (2023), in their study focusing on the 2020 US elections, examined both Twitter and Youtube comments instead of considering a single social networking platform. Although Donald Trump had more positive sentiment polarity in both social networking platforms, this ratio differed for both platforms. In addition, the study findings reveal the sentimental polarity connections between these two platforms. Endsuy (2021) evaluated the 2020 US elections with VADER in terms of sentiment polarization day by day in terms of time period. Study findings reveal that for both candidates, as the election gets closer, tweets with positive sentiment polarity increase and results with negative sentiment polarity decrease. However, while the candidates had the same positive sentiment polarity at the beginning, as the election approached, more tweets belonging to Joe Biden were classified as having positive sentiment polarity. This study reveals with its results how important sentiment analysis and daily analyzes from social media platforms can be during the election process. Yavari et al. (2022) discussed the 2020 US elections in terms of sentiment polarity using VADER, like Endsuy (2021). Yavari et al. (2022) compared the 2020 US elections with other sentiment analysis methods used in the literature, specifically VADER. The results obtained revealed that the VADER method is the method with the highest accuracy rate, especially within the scope of the 2020 US elections. Chaudhry et al. (2021) analyzed the 2020 US elections by comparing them with the sentiment analysis results of the previous election period for each state. As a result of the empirical findings they obtained, they revealed that there is a certain correlation between the election results and the sentiment analysis results. Although Singh and Sikka (2021) conducted a sentiment analysis on a very limited data set for the 2020 US elections, they found that YouTube comments about Joe

Biden reflected more positive sentiments, unlike the study of Shevtsov et al. (2023).

Although sentiment or emotion analysis studies on text data obtained from social media platforms such as Twitter or Facebook are very often performed, studies on comments made on YouTube are relatively few. In addition, among the sentiment or emotion analysis studies conducted on YouTube comments (Siersdorfer et al., 2010; Bhuiyan et al., 2017; Muhammad et al., 2019; Cunha et al., 2019; Singh and Tiwari, 2021), there are very few election-specific studies (Wisnubroto et al., 2022; Shevtsov et al., 2023). In addition, it should not be forgotten that the comments made specifically for YouTube consist of comments specific to the subject. Unlike YouTube, most of the posts on Twitter are for information sharing rather than comments, so it does not create a suitable infrastructure to measure voter attitudes. As mentioned above, although there are many studies on the US elections, there are also studies specific to many countries. Turkey (Uysal et al., 2017; Baker Al Barghuthi and Said, 2020), England (Rita et al., 2023), Indonesia (Budiharto and Meiliana, 2018), Netherlands (Sang and Bos, 2012; Sanders and van Den Bosch, 2013), Singapore (Choy et al., 2011), India (Sharma and Moh, 2016; Chauhan et al., 2023), Nigeria (Oyebode and Orji, 2019), Colombia (Cerón-Guzmán and León-Guzmán) are just a few of these countries.

This study is the first study to perform emotion analysis on YouTube comments and elections in Turkey. In addition, unlike other studies on Turkish elections, a broader emotional polarity was obtained in this study instead of only positive or negative emotional polarity. Considering the heavy use of social media in Turkey, such an analysis will be useful in creating an insight for all political factors about the elections. In addition, unlike other studies in the literature, this study aims to analyze voter attitudes with the comments obtained from an election-specific program, rather than the idea of creating an election predict.

Material and Method

Today, with the increase in the number and users of social media platforms and the rapid replacement of traditional shopping with online shopping, it causes users to share many thoughts that can be interpreted and open to analysis on these platforms in electronic media (Çılgın et al., 2023: 94). Sentiment or emotion analysis is frequently used by marketing and customer service teams with data obtained from social networking platforms to determine consumers' attitudes. In addition to these business applications, it can be used to identify mass opinions on financial, social and political issues and to develop policies (Çılgın et al., 2022: 1093). As a result of the increasing use of social media and the active sharing of ideas and opinions by users on this platform, this large amount of data, which is accessible to everyone online, constitutes a unique data source for analyzing political elections. Sentiment or emotion analysis, a sub-field of Natural Language Processing, can be used to explore opinions, feelings, evaluations and attitudes together with all these data sources.

Emotion analysis can often be performed with two different approaches, dictionary-based or machine learning. Due to the nature of machine learning methods, a training data is needed, therefore a manually labeled data set, while dictionary-based emotion analysis does not need a training data. In addition, while it is necessary to vectorize text data for machine learning methods, a good data preprocessing process is sufficient in dictionary-based emotion analysis. The dictionary-based approach uses an existing dictionary containing words or phrases previously labeled as positive, negative, or neutral (or with a value ranging from 1 to -1) (Khoo and Johnkhan, 2018: 495). In the dictionary-based approach, the polarity of a text or document is based on the semantic comparison of the words or phrases in the text or document with the words in the dictionary (Taboada et al. 2011: 271). In this study, a dictionary-based approach, which offers both ease of use and speed, and more emotion polarity than just positive, negative or neutral emotion polarity, was used. For this purpose, NRC Emotion Dictionary (Mohammad and Turney, 2013: 442; Mohammad and Kiritchenko, 2015: 303) was used in this study. In this dictionary, which contains 14,182 words, there is not only positive and negative emotion polarity, but also a classification of eight different emotions: anger, fear, trust, anticipation, surprise, sadness, joy, and disgust. Two classifications (positive and negative) are not sufficient to reach detailed information, especially in sentiment analysis related to political situations, which are also the subject of this study. For this reason, it may be more important to perceive with which emotion the users who are already close to a certain emotion polarity (with positive emotion polarity for this study) have a positive hold.

All the data used within this study were obtained from the programs made in the Open Microphone program performed by Oğuzhan Uğur on the BabalaTv channel on YouTube. Many political party members participated in this program within the scope of the 2023 elections. In accordance with the program format, opposition questions were asked by the audience to all participating politicians, allowing the politicians to answer the questions of the people. The program, in which 12 different political actors participated, always ranked first in the trends during the week it was broadcast, and each program was watched by 10 million people. In this context, this study deals with the comments of the 6 programs that received the highest attention according to the number of views and comments. Detailed information about the data used in the study is presented in Table 1.

As can be seen in Table 1, the program to which many politicians showed interest was followed by large masses. The comments for each program were obtained by waiting 1 month after the broadcast of the program. Thus, comments were obtained after reaching a certain number of audience and the number of comments. Only the data of the program in which Kemal Kılıçdaroğlu was present were obtained within the week following the broadcast of the program. Because after the broadcast of the program, more than 100 thousand comments were made in just 2 days. While obtaining the comments of all programs, the comments that received high interaction (likes or comments) were obtained primarily.

Figure 1

Flowchart of Analyzing The Research Paper

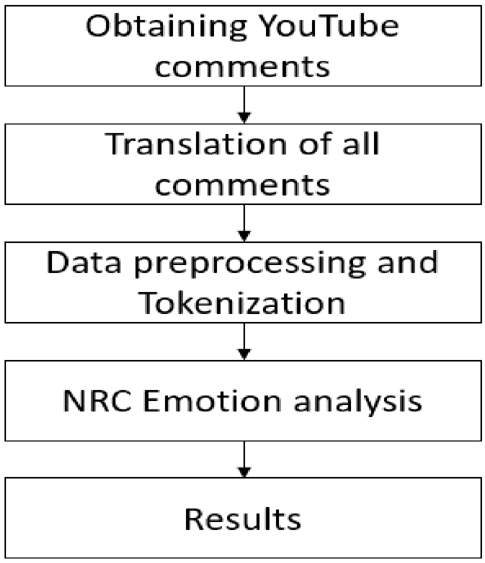


Table 1

Information on The Data Sets

Politicians	Program Date	Number of Comments Obtained	Number of View
Kemal Kılıçdaroğlu	24 May 2023	53.556	29.205.000*
Barış Atay	12 January 2023	46.435	20.981.000*
Sinan Oğan	24 April 2023	23.033	15.745.000*
Muharrem İnce	1 September 2022	58.288	13.745.642*
Ümit Özdağ	4 August 2022	18.201	10.046.000*
Metin Külünk	5 December 2022	37.932	7.750.000*
Ali Babacan	2 May 2023	24.283	5.616.000*

*Data on the number of views are current numbers and were obtained on 11.06.2023.

As shown in Figure 1, user comments for each program were obtained with the help of a web scraper developed in Python. All user comments obtained have been translated into English as the NRC dictionary is in English. In addition, the problems of finding root words and removing suffixes encountered in text analysis in Turkish, which is an agglutinative language, were thus overcome. All this translation process was carried out automatically with the "deep_translator" library in the Python programming language. Since the "deep_translator" library only supports up to 500 words in the translation phase, only comments less than 500 words were used within the scope of the study. Then, data preprocessing steps were completed by performing each of the steps of lowercase conversion, punctuation, removal of stop words and lemmatization for each text data. In addition to these actions, all URL and E-mail related words, noisy words, extra lines, extra spaces have been deleted from all comments. Then, each word of each comment was analyzed using the NRC dictionary.

Research Findings

The data sets of each program were evaluated separately using the NRC emotion dictionary. As mentioned before, the words in each comment were scored according to the emotion scores in the NRC emotion dictionary. It should also be noted that although the stopwords have been removed, not every word in these comments may have an emotion equivalent. In this study, two different reports were presented in detecting emotions. The first of these is the ratio of each emotion in the entire data set. In other words, by considering all the comments of a single politician as a single text, the ratio of certain emotions in this text was calculated. In the dual approach, the dominant emotion of each comment was determined. To be more explanatory, each comment was handled one by one, the ratios of the emotions in each comment were determined and the emotion with the highest ratio was used to represent that comment.

As can be seen in Figure 2, the distribution of sentiments on the basis of words of the comments of the program carried out with each politician is presented. As mentioned before, the ratios were calculated for each word by using all the comments of each program. As a result of the findings, the comments with the highest "Anger" emotion belong to Sinan Oğan and Kemal Kılıçdaroğlu follows immediately. The comments with the least "Anger" emotion belong to the program realized with Metin Külünk. The most "Anticipation" emotion was detected in the comments of Kemal Kılıçdaroğlun. It is quite remarkable that Sinan Ogan, who has the highest rate in the scope of many other emotions (especially positive emotions), has the lowest rate in the scope of "Anticipation" emotion. This is a finding that the program carried out by Sinan Ogan met expectations at a very high level. Although "Disgust" was determined as the least common emotion in the comments, Muharrem İnce had the highest rate of this emotion. Although "Fear" is the second emotion with the lowest rate after "Disgust", it is seen that all politicians have similar rates except for Sinan Ogan. It is seen that Sinan Ogan obviously has the lowest rate. "Joy" is one of the emotion that are higher for Sinan Ogan than other politicians. Close to Sinan Ogan, Kemal Kılıçdaroğlu has a high rate of "Joy". When we look at the "Negative" emotion rates, Metin Külünk and Ali Babacan have the lowest rates. Although Sinan Ogan had the highest rate in "Positive" emotion polarity, he had the highest rate in "Negative" emotion polarity. Among the negative emotions, Sinan Ogan is mostly represented by the emotion of "Sadness". In "Suprise" emotion, Kemal Kılıçdaroğlu and Sinan Oğan are distinguished from other politicians and have achieved higher emotional polarity. Similarly, Sinan Oğan and Kemal Kılıçdaroğlu had the highest rates for the emotion of "Trust". As a result of these findings, it is obvious that the comments made especially to the politicians who are candidates for the Presidency contain more obvious feelings. In addition, it is seen that the comments of every politician, except for "Negative" and "Positive" emotions, are mostly represented by the "Trust" emotion.

In order to obtain more robust results, as can be seen in Figure 3, the emotion ratios of the approach in which the emotions of each comment are determined one by one are presented. It should also be noted that within the scope of this approach, 8 emotions other than "Negative" and "Positive" emotions were evaluated, and "Negative" and "Positive" emotions were evaluated externally. In other words, each comment was first classified according to 8 emotions and then classified separately according to 2 emotions as "Negative" and "Positive". As can be seen in Figure 2, the emotional rates vary considerably for each comment. With this approach, Anticipation, Trust and Anger were determined as the most dominant emotions in the comments. Very low rates were obtained on the basis of comments of other emotions. As a result of the findings obtained, the comments with the highest "Anger" feeling belong to Muharrem İnce, followed by Barış Atay. A shape parallel to the previous approach, the feeling of "Anticipation" was determined in the comments of Kemal Kılıçdaroğlu. However, it is seen that the comments of Sinan Ogan are represented by more "Anticipation" emotion this time. Similarly, Kemal Kılıçdaroğlu and Sinan Ogan had the highest rates for the "Trust" emotion. However, when evaluated on the basis of comments, these rates are quite close. Contrary to the first approach, it is seen that with this approach, the emotion of "Anticipation" comes to the fore the most in the comments of politicians.

Figure 3

Emotion Ratio Distributions on The Basis of Each Comment

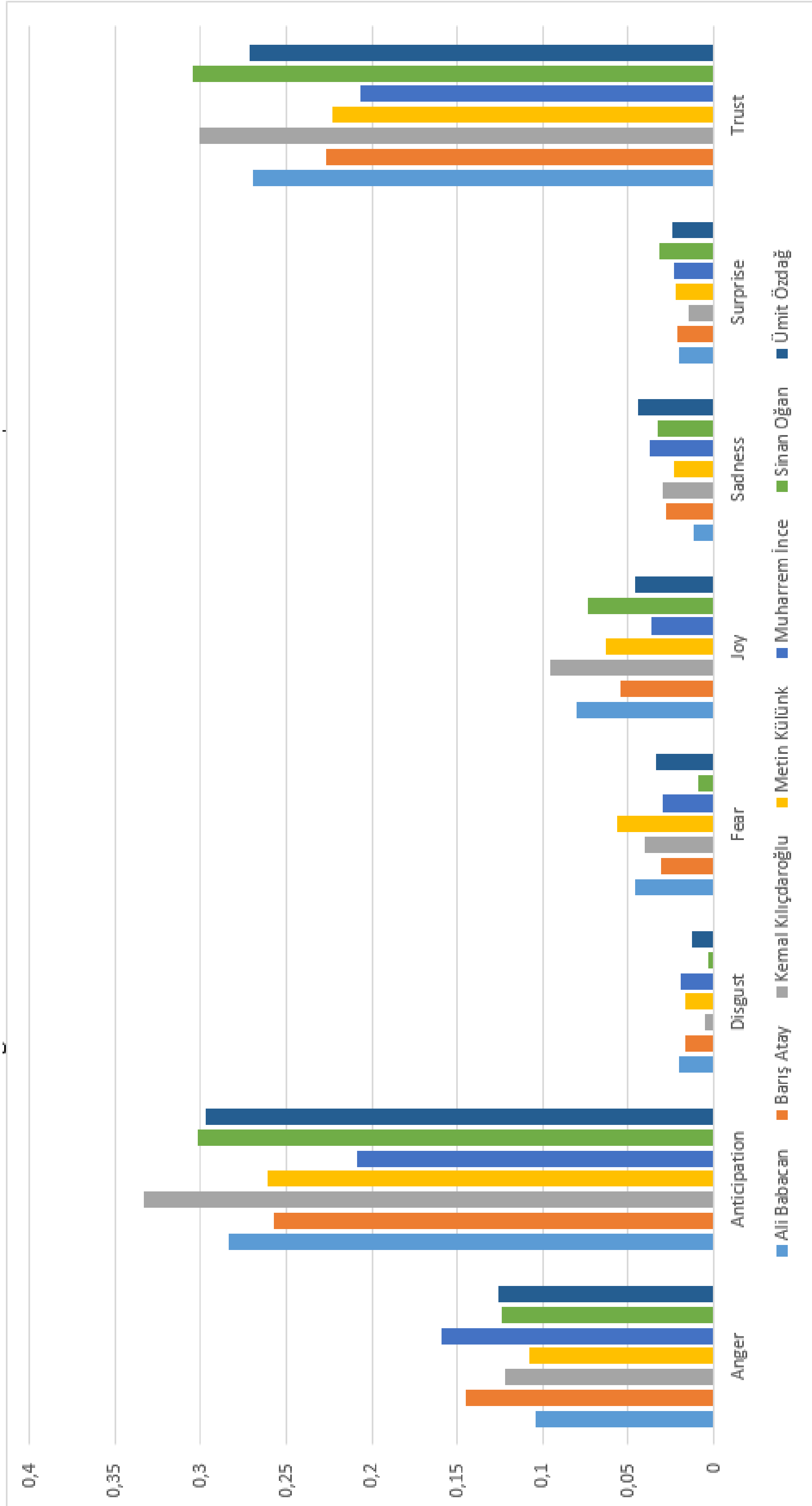
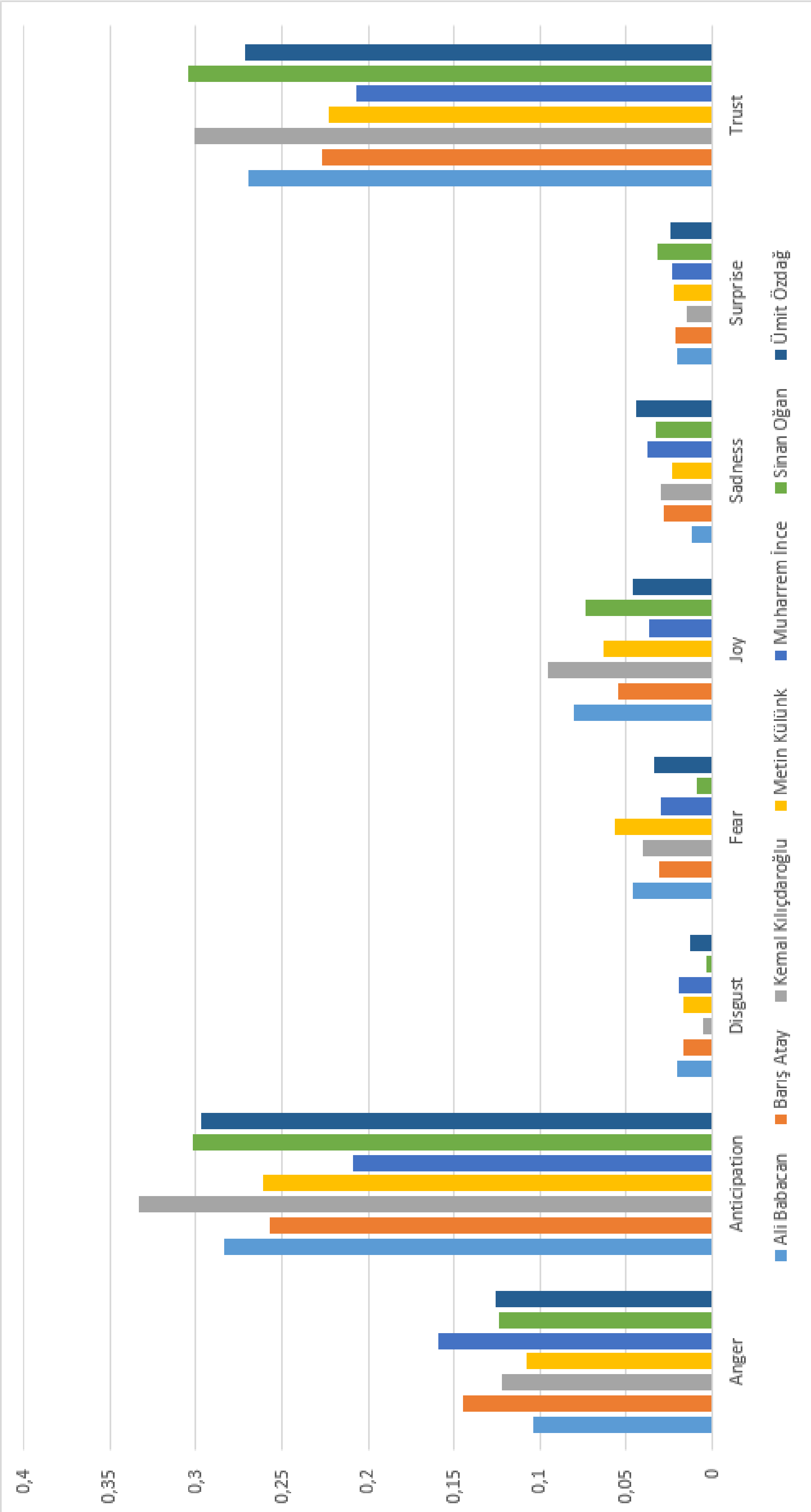


Figure 3

Emotion Ratio Distributions on The Basis of Each Comment



As mentioned before, another important aspect is the “Positive” and “Negative” emotional polarity of each comment. In this context, as can be seen in Figure 4, each comment is classified separately as only “Negative” and “Positive” (these two are available in neutral comments that do not represent emotions). As can be seen in Figure 4, the politician with the highest number of “Positive” comments was Kemal Kılıçdaroğlu with 71.8%, while Muharrem İnce had the least “Positive”comments with 48.9%. At the same time, Muharrem İnce is the politician with the highest number of “Negative” comments with 26.2%. Kemal Kılçdaroğlu, on the other hand, was the politician who received the least “Negative” comments compared to other politicians with 6.7%. “Neutral” comments, which do not express any emotion, have almost close ratios for each politician and range from 17.4% to 24.9%.

N-gram is an n-character portion of text longer than n characters. Generally, it divides the text into a series of overlapping n-grams. (Cavnar and Trenkle, 1994). The N-gram model or algorithm is one of the most preferred tools in speech and language processing, both in the preprocessing stage and in understanding the text content better (Çılgın et al., 2023). Within the scope of this study, 2 grams, 3 grams, 4 grams and 5 grams were used for each politician on a word basis. In this way, it will be possible to get an insight into the content of the comments. For this purpose, the highest five n-gram results obtained according to the degree of frequency are given in Table 2. Each n-gram result presented in Table 2 is ranked from top to bottom by frequency of use.

Figure 4

Negative and Positive Affect Ratio Distributions on The Basis of Each Comment

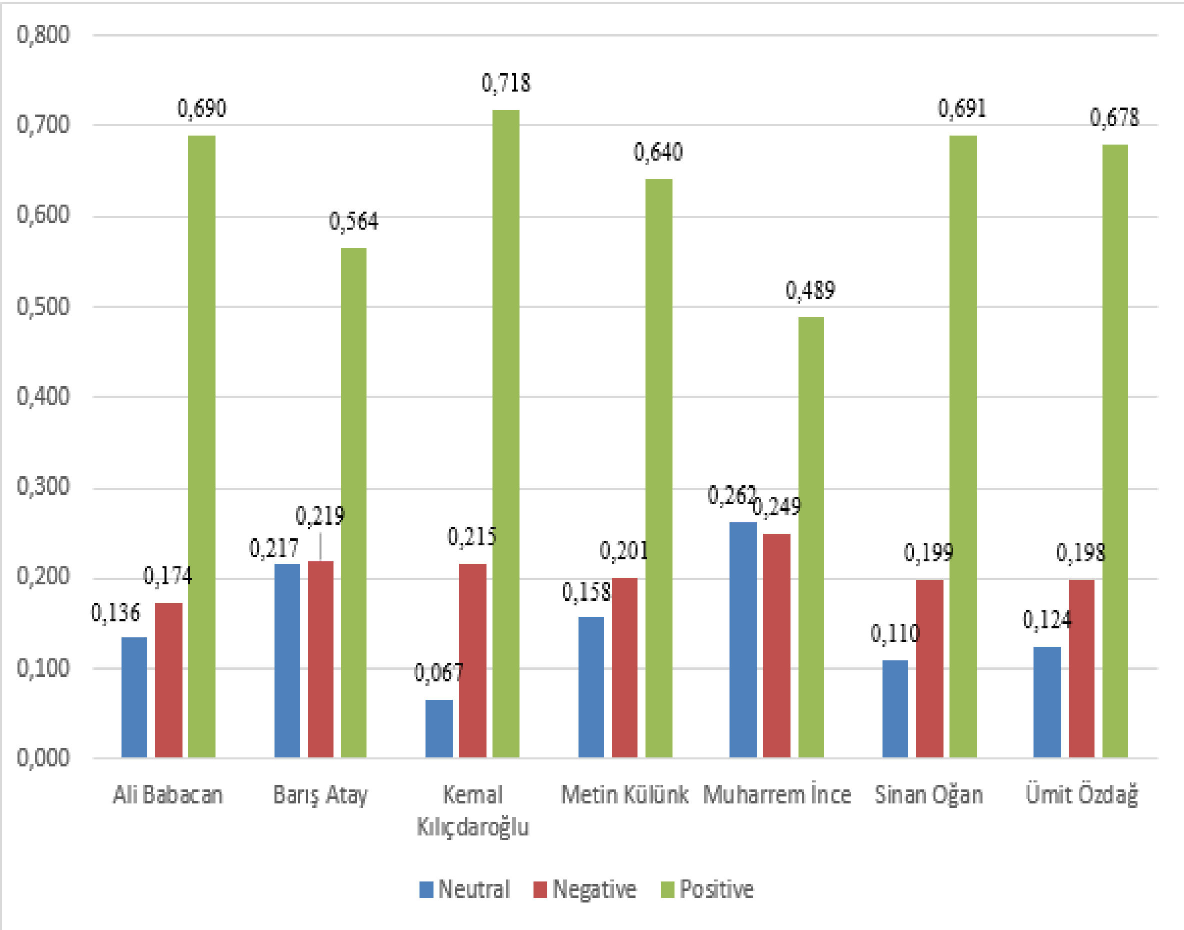


Table 2

Top Five n-grams

2-gram	3-gram	4-gram	5-gram
Ali Babacan			
ask, question	know, ask, question	Ogan, come, so called, nationalist	majority, young, people, appreciate, naive
young, people	answered, every, question	hour, without, getting, bored	economic, policy, prestige, western, world
good, luck	first, time, watched	ask, single, question, economy	student, worried, future, would, like
like, thank	so called, nationalist, person	silly, question, asked, Babacan	economy, ask, single, question, economy
country, need	man, calm, style	Turkish, politics, polarizing, destructive	politician, seemed, even, smarter, thanks
Barış Atay			
good, luck	without, getting, bored	watched, without, getting, bored	best, episode, ive, ever, watched
question, asked	answered, every, question	im, sure, many, people	admired, Atays, patience, replied, calmly
ask, question	know, ask, question	best, episode, ive, ever	calmly, style, politician, could, ever
Muharrem, İnce	gave, good, answer	may, god, give, patience	knowledge, general, problem, working, class
one, vote	wish, continued, success	Atays, patience, replied, calmly	amazing, really, best, among, section
Kemal Kılıçdaroğlu			
first, round	would, like, thank	hour, without, getting, bored	4, hour, without, getting, bored
good, luck	without, getting, bored	country, need, honest, reliable	country, need, honest, reliable, leader
first, time	vote, peace, mind	comment, eye, filled, tear	research, make, right, choice, Turkey
second, round	vote, first, round	Sinan, Ogan, first, round	apolitical, friend, also, influenced, opinion
young, people	vote, second, round	vote, second, round, watched	make, mistake, first, round, give
Metin Külünk			
answer, question	without, answering, question	Uğurs, inexplicable, bitter, smile	Uğurs, inexplicable, bitter, smile, face
young, people	clear, answer, question	giving, u, opportunity, see	without, answering, question, good, job
question, asked	answered, every, question	without, answering, question, good	first, time, feel, someone, deputy
good, luck	giving, u, opportunity	gave, clear, answer, question	get, nervous, answer, cant, get
clear, answer	saying, come, let	come, let, order, tea	opinion, answer, give, purely, escapeoriented
Muharrem İnce			
İnce, right	say, ınce, right	may, god, give, patience	looking, determined, man, run, state
ask, question	may, god, give	hold, party, like, team	republic, nation, one, way, country
good, luck	without, getting, bored	always, right, dont, choose	country, hold, party, like, team
question, asked	answer, every, question	im, leaving, 2nd, round	biggest, problem, country, hold, party
young, people	İnce, always, right	one, vote, country, one	hope, next, life, good, happy
Sinan Oğan			
good, luck	without, getting, bored	let, finish, first, round	one, vote, victory, party, one
presidential, candidate	good, luck, Oğan	million, people, chasing, wrong	speck, cause, pinnacle, unjust, cause
vote, Oğan	good, luck, president	second, round, 5, year	million, people, chasing, wrong, person
Turkish, nationalist	need, people, like	first, time, listened, politician	get, lost, among, million, people
peace, mind	need, politician, like	really, need, politician, like	may, allah, make, way, clear
Ümit Özdağ			
ask, question	friend, sitting, front	happy, one, say, Türk	people, love, romantic, politics, really
victory, party	happy, one, say	thank, everyone, contributed, program	give, answer, question, give, clear
sitting, front	good, luck, teacher	teacher, gave, good, answer	congratulate, teacher, hearty, congratulation, needed
good, luck	ask, question, impartial	friend, sitting, front, row	also, agree, much, many, thing
first, episode	give, harsh, answer	presidential, candidate, victory, party	politician, repeatedly, interrupted, asked, disrespectful

As can be seen in Table 2, although the n-grams formed for each politician differ, there are common points on some issues. “good, luck”, “ask, question” and “young, people” are all politicians available under 2-gram. Although 2-grams can be useful in discovering the most common words, it may be useful to use a higher number of n-grams in order to provide semantic integrity. For this reason, the 3-gram, 4-gram and 5-gram results differ for each politician. When the 3-gram results are examined, the results of “first, time, watched”, “vote, peace, mind”, ”clear, answer, question”, ”need, politician, like”, ”give, harsh, answer” draw attention. Among the 4-gram results, the results of “ask, single, question, economy”, ”Turkish, politics, polarizing, destructive”, ”best, episode, ive, ever”, ”country, need, honest, reliable”, ”come, let, order, tea”, ” million, people, chasing, wrong”, “teacher, gave, good, answer” draw attention. Among the 5-gram results, the findings of “student, worried, future, would, like”, ” knowledge, general, problem, working, class”, ”apolitical, friend, also, influenced, opinion”, ”opinion, answer, give, purely, escapeoriented”, “get, nervous, answer, cant, get”, ”get, lost, among, million, people”, “people, love, romantic, politics, really”, “politician, repeatedly, interrupted, asked, disrespectful” are seen as remarkable findings.

Conclusion

The 2023 Presidential elections have become an agenda that attracts the attention of not only the voters in Turkey but also the parties from many different countries. The election period, which followed with very close rates, was realized with a very intense election campaign for each politician. The 2023 Presidential elections have become an agenda that attracts the attention of not only the voters in Turkey but also the parties from many different countries. The election process, which followed with very close rates, was realized with a very intense election campaign for each politician. In this election process, especially the use of social media has become a very important issue for politicians. The Open Microphone program performed by Oğuzhan Uğur under BabalaTv channel was followed with interest not only in Turkey but also in the world agenda. The program, in which 12 different political actors participated, always ranked first in the trends during the week it was broadcast, and each program was watched by 10 million people. As can be seen as a result of these programs, the election dynamics that are about to change completely also bring different election analyzes with them. For this reason, thousands of comments made under each program or post published on social media platforms have allowed political parties and their managers to have both much more people and a broader knowledge, unlike the research done by survey companies. The information to be obtained from these comments is of critical importance both for the current election period and for the roadmaps of individual political characters. Considering the heavy use of social media in Turkey, such an analysis will be useful in creating an insight for all political factors about the elections. In this context, this study reveals various analysis findings with Emotion Analysis methods, which are among the following comments made within the scope of this program. In this study, no direct inference was made regarding the election results. As stated before, both the fact that such an inference is still not proven at the desired levels by sentiment or emotion analysis and that the comments of all presidential candidates are not included within the scope of the reviewed comments prevent such an inference. It should also be noted that although the main purpose of this study is not to compare the results of the findings with the election results, it is possible to make inferences about the election results. In particular, inferences on some emotions can be useful in providing a prediction for the election results. For example, it can be an indicator for the percentage of votes Sinan Ogan, who has the highest proportional emotion of “Surprise”, got especially in the first round of elections. In addition, the fact that Kemal Kılıçtaroğlu, who has been involved in politics for many years, has a high emotion of “Surprise”, reveals how effectively he promoted this program, but also reflects that this promotion is a late campaign. In addition, the n-gram results obtained can provide useful information in discovering the main focal points of the voters commenting within the scope of the program. It is possible to obtain these and many other inferences from the findings of this study. Therefore, this study reveals that the emotion analysis of the masses via Youtube comments or different platforms can be a critical source of information for political campaigns. Another point that is worth mentioning is that this study reveals the use of an analysis method, which has not been applied in Turkey, in the election environment, on a social media program that is unprecedented in the world, in extracting information during the election process. The findings obtained and the introduced model architecture are of data feature, especially for political and communication science experts. In this context, the findings obtained and the inferences regarding the application model architecture definitely need to be discussed by relevant scientific experts. In future studies, not only user comments, but also content analysis of the performance of the politicians examined here within the scope of the program will be useful to expand the literature in this field.

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