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SENTIMENT ANALYSIS OF NEWS VIDEOS ABOUT ARTIFICIAL INTELLIGENCE IN TURKEY: A YOUTUBE CASE

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ABSTRACT

Introduction: Debate on the future of Artificial Intelligence (AI) has recently been polarized. Positive, negative, and neutral differences of opinion about AI have led to the need for further inquiry into this issue. In particular, establishing AI's future potential of use by identifying the feelings and opinions of countries about AI is deemed significant for developing nationwide and regional AI strategies. In this regard, this study aimed to determine the emotional states of Turks toward AI. Social media platform was accordingly exploited since it is an important data source to determine individuals' feelings and opinions. **Methodology:** User comments on the posts published by Turkish national news channels on YouTube were examined through Sentiment Analysis (SA). In the dictionary-based SA method implemented, consumer/follower comments were classified as positive, neutral, and negative according to their polarity scores. **Results:** Analyses indicated that 697 (48.6%) of user comments were positive, 380 (26.5%) were negative, and 357 (24.9%) were neutral. It was concluded that Turkish society's feelings toward AI were generally positive. **Discussion and Conclusions:** YouTube users' current emotional states, with or without knowledge of artificial intelligence, may differ in the future. It might thus be viewed as predictable that in the future, users who are more positioned in these processes will experience certain shifts in their sentiment states toward specific issues, from positive to negative, from negative to positive, or from neutral sentimental states to positive or negative.

Keywords: Social Media; Artificial Intelligence; User; Opinions; News; Sentiment Analysis; YouTube.

1. INTRODUCTION

McCarthy et al. (1955) defined the AI concept as the science and engineering of making intelligent machines. In general terms, AI is human intelligence technology created with the assistance of computer programs (Tsaih & Hsu, 2018). AI emerged between 1950-1980, machine learning between 1980-2006, and deep learning between 2006-2017. AI has different areas of use, such as systems that emulate human thought and behavior, robots, expert systems, natural language processing (NLP), image processing, and machine learning (Ercan, 2020). It is inevitable that AI, created based on the human mind, will exist in human life, for it makes life easier. However, rapid technological advancements spark debates about whether AI will pose problems for humankind in the future and whether it will act contrary to human control and independently of its system (Dilek, 2019). Negative societal opinions about AI in the literature were grouped under unemployment (Frey & Osborne, 2017; Ghotbi et al., 2022; Lohr, 2017; Cheung et al., 2017), inequality (Bryson, 2019), cybersecurity/ethical violation (Pasquale, 2015; Jobin et al., 2019), and the fear of robots controlling society (Ghotbi et al., 2022). This, in turn, complicates the evaluation of AI's potential 'benefits' and 'harms' in the future and causes controversy (Ghotbi et al., 2022).

From a societal perspective, AI is the answer to everything for some, while others consider it a significant threat (Pedersen & Johansen, 2020). For instance, some believe AI is a system that might create new lines of business (Borenstein, 2011), while others view unemployment as the biggest problem that AI might create in society (Ghotbi et al., 2022; Lohr, 2017). Additionally, scientists are divided into two opposite poles of opinions about AI's future. While distinguished scientists such as S. Hawking and E. Musk argue that AI might be dangerous in the future and doom the end of humanity, Facebook founder Mark Zuckerberg and Cem Say claim the opposite (Efe, 2021).

Different views on the development of AI in society were advocated in *The New York Times* articles titled "*Computers Learn to Listen, and Some Talk Back*" (Lohr & Markoff 2010) and "*Study to Examine Effects of Artificial Intelligence*" (Markoff, 2014). The debate on AI's future is consequently polarized. The positive and negative differences of opinion about AI have, therefore, created the need for further inquiry into this issue and recently led to more talks about the relations between AI and society (Gezgin, 2023). Studies on AI and public perception are a new research topic that has gained prominence recently (Diallo et al., 2021).

Benyon et al. (2005) claim that social structure and culture impact the acceptance of AI technology. In this regard, it is essential to understand the general public opinions to ease AI's social acceptance and positive user experience (Ju & Takayama 2011), since when evaluated in the current context, nationwide and regional AI strategies are developed worldwide. Numerous technologies that reshape individual emotions are employed, especially by algorithmically revealing human emotions (Fazzin, 2019). In addition, understanding public opinions about AI and its management is essential to creating informed policy and shaping the public's education about AI's character, benefits, and risks (Zhang & Dafoe, 2019). Sindermann et al. (2021) maintained that

AI is a global phenomenon, highlighting the significance of investigating its acceptance in various languages and cultures. However, studies on societal perspectives on AI are scarce in the literature (Riley et al., 2009; Kamppuri et al., 2006).

In a relevant study in the literature on the research topic, Bartneck et al. (2007) investigated people's attitudes toward robots, revealing that among approximately 500 participants, US people viewed robots positively, while Mexicans regarded them negatively. Ghotbi et al. (2022) examined the emotional states of 228 university students (63 Japanese and 165 non-Japanese) toward AI at an international university in Japan. SA was conducted on student texts, revealing general positive sentiments toward AI. In a study by Zhang and Dafoe (2019), a survey was administered to 2,000 adult Americans to determine their attitudes and tendencies toward AI. Results showed that anti-AI Americans outnumbered pro-AI Americans. In another study, Fast and Horvitz (2017) analyzed *The New York Times* articles published between January 1986 and June 2016 to examine how public perceptions of AI were reflected in society and how the reflected opinion changed over time. Findings indicated that articles with optimistic content about AI were outnumbered (approximately three times) those with pessimistic content over the thirty years. However, they highlighted an increase in pessimistic and optimistic news since 2009. Riley et al. (2009) collected data through a survey from India, South Africa, and the United Kingdom to determine views about biometric facial recognition systems, one of AI's fields of study. Differences in attitudes across cultures were reported. While Indian respondents viewed biometrics positively, the UK respondents held pessimistic views. Ho et al. (2023) examined the perceptions of 245 visitors to clinics and hospitals in a Japanese region to measure Japanese acceptance of emotional AI technologies -i.e., emotion detection technology. The study found that older and male patients perceived emotional AI technology more negatively. Similarly, Johansson et al. (2024) conducted a study to measure public perception toward using AI in health. The study aimed to explore Swedish women's perceptions and attitudes toward using AI in mammography. The research found that they perceived AI as a valuable tool in radiologists' decision-making processes but demanded and expected more from radiologists. In another study, Cohen et al. (2024) examined the public perception of ChatGPT, an AI technology, on Twitter (referred to as "X" since July 2023). Their study revealed specific findings on ethical concerns that might reflect ChatGPT's functional and critical aspects. In their study, Ko and Song (2024) used Q methodology to examine various perceptions of AI ethics among 30 senior students of public middle schools. The research resulted in four classifications (i.e., Privacy Guardians, AICoexistence Pursuers, AI Ethics Conservatives, and Domestic Distributive Justice Advocates), reflecting students' concerns, attitudes toward AI, and value preferences. The research also found consensus on the importance of human dignity and some disagreement on the balanced distribution of AI's economic benefits across countries. Brauner et al. (2024) investigated how 122 German participants perceived 38 statements about AI technologies in various contexts (personal, economic, industrial, social, cultural, and health). Their study indicated significant differences between perceived assessments and expectations. Moreover, since AI technologies are still, in many ways, a "black box," neither opportunities nor risks were adequately assessed. Furthermore, the study offered considerable implications for promoting AI literacy to facilitate decision-making regarding AI

technologies.

Studies by Riley et al. (2009), Bartneck et al. (2007), and Zhang and Dafoe (2019) tackled societal perspectives on AI and revealed differences of opinion among societies. Varied perspectives on AI among societies and cultures have raised the question of which view toward AI prevails in the imagination of Turkish society. Within the scope of this study, the comments on the videos published by national news channels about AI on YouTube were analyzed through SA to gain insights into Turkish society's perceptions of AI. The research is significant as it is the first study to show Turkish society's intellectual tendency toward AI, and the data are comparable with those of other regions.

1.1. Sentiment Analysis

Social media platforms such as Instagram, Facebook, Twitter, and YouTube are the most powerful communication tools that enable users to communicate worldwide (Kaur & Sharma, 2020). In today's world, these social networking sites and microblogging sites have become significant means of transmission for individuals to express their opinions about topics, movies, videos, or products online. The reason for preference of YouTube as the research sample was it allows users to share the videos they have produced with others or offers various online opportunities such as liking, disliking, commenting, and watching videos by others. Additionally, user comments made in a comfortable environment and of their own accord are important data sources for researchers. For industry managers, understanding customers' opinions about their products and services causes significant temporal and monetary losses. Therefore, user comments on social media are important data sources to provide information about user behavior, product feedback, user opinions, and emotional states. Attempts to determine people's attitudes toward a particular issue or event on social media have riveted researchers, particularly in the last decade (Nausheen & Begum, 2018; Yaşa, 2022; Soler et al., 2012). For this reason, SA has become an important research field since 2002 (Palanisamy et al., 2013). Thus, SA might be valuable for manifold issues of interest to human-computer interaction practitioners and researchers and those in sociology, marketing and advertising, psychology, economics, and political science (Hutto & Gilbert, 2014).

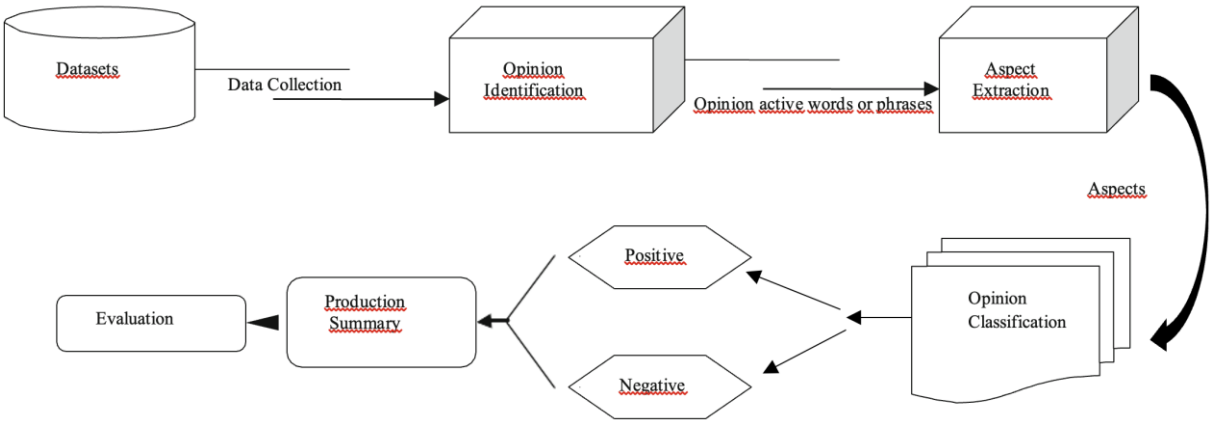
SA is a novel research field that aims to reveal people's sentiments about an entity using computer science (Medhat et al., 2014). It is also considered a field of study within the scope of text mining (Liu, 2012). In addition, it is an analysis comprised of a part of NLP. It primarily aims to analyze all the sentiments present in comments using NLP (Hemmatian & Sohrabi, 2019).

The first studies on SA (Vasileios & Janyce, 2000; Tong, 2001; Turney, 2002; Pang et al., 2002) started with sentiment classifications at the document level in the 2000s (Tan & Zhang, 2008), continued with evaluations at the sentence level (Qian et al., 2022; Nezhad & Deihimi, 2022; Li et al., 2022), and turned into evaluations at the expression level (Wilson et al., 2005; Agarwal et al., 2009). Since SA at the document level is very weak, researchers have leaned toward SA research on sentences and expressions (Hemmatian & Sohrabi, 2019).

SA comprises two steps. The objectivity or subjectivity of a sentence or expression is determined first. Its polarity (i.e., positive, negative, neutral) is then determined (Liu & Zhang, 2012; Stine, 2019; Pawar et al., 2015). The techniques used in SA are divided into two main categories: machine learning method (Riaz et al., 2017) and dictionary-based approach (Khan et al., 2017). In SA methods based on machine learning, machine learning classifiers are trained with a data set whose opinion pole is labeled, and a classification model is created to determine the opinion pole of new samples. Dictionary-based SA methods, on the other hand, exploit a dictionary containing opinion words (Onan et al., 2016; Onan & Korukoğlu, 2016). Within the scope of this study, expressions were subjected to simple SA, and the following flow chart was followed using the dictionary-based approach.

Figure 1.

Sentiment analysis process



Source: Hemmatian and Sohrabi (2019).

As shown in Figure 1, SA involves different steps. After the preprocessing steps, extracted sentiments are grouped into poles using algorithms based on the dictionary method (Hemmatian & Sohrabi, 2019). Linguistic Inquiry and Word Count (LIWC), General Inquirer (GI), and Hu-Liu04 algorithms are employed as three dictionary types in dictionary-based SA by dividing them into binary classes (i.e., positive or negative) according to their independent semantic orientations. Three other dictionary algorithms in which words are associated with valence scores related to sentimental intensity are Affective Norms for English Words (ANEW), SentiWordNet, and SenticNet (Hutto & Gilbert, 2014). Many algorithms, such as Naive Bayes and Valence Aware Dictionary for Sentiment Reasoning (VADER), are also used. Hutto and Gilbert (2014) developed VADER, a simple rule-based model for SA, and compared it with machine learning algorithms (e.g., LIWC, Naive Bayes (NB), Support Vector Machines Regression (SWM-R), Support Vector Machines Classification (SWR-C), Maximum Entropy (ME) and dictionary-based algorithms (e.g., LIWC, GI, Hu-Liu04, ANEW, SentiWordNet, and SenticNet). Their findings revealed that VADER was the best-performing algorithm in evaluating sentiments in social media texts, with a classification accuracy of 0.96 and 0.84.

2. MATERIALS AND METHOD

Using the SA, this study evaluated user comments on the videos about AI shared by national news channels in Turkey on YouTube, one of the social media platforms. This section includes the dataset, data collection, preprocessing, and SA's performance.

2.1. Instruments and Libraries

Google Colab was used as the development environment, and Python was used as the software language. Developed by Guido Van Rossum in the early 1990s, Python was preferred because of its user-friendliness and comprehensive libraries for machine learning, data analysis, and processing (Dierbach, 2012). Also known as "Colaboratory," Google Colab is a programming environment that allows Python to be written and run without requiring any configuration via the browser, with free access to GPUs and easy sharing (Google Colab, 2023). The MAXQDA qualitative data analysis program was employed to create word clouds.

The study employed libraries, including pandas, numPy, nltk, demoji, and matplotlib.

- Pandas facilitates data analysis and preprocessing. It is also a library that allows easy processing of files with .csv and .txt extensions. It was used to process and analyze the data stored in .csv files.
- The NumPy library is used to perform scientific calculations. It was exploited for sentiment values and various mathematical calculations for SA.
- Nltk is an open-source library for working with natural human language data developed in Python. It was employed to remove English stop words.
- Demoji is utilized to convert facial expressions used to express emotions (emojis) into texts. In this study, emojis in the data set were identified and removed using the demoji library.
- Matplotlib is used to visualize the analysis findings of the data set. It was employed in this study to visualize the positive, negative, and neutral emotional states after SA.

2.2. Dataset

The study included an analysis of Turkish comments on national news channels about AI on YouTube. The obtained data set was based on the user comments (excluding those between users) on YouTube on September 05, 2023, in line with the Turkish comments on AI-related videos of national news channels in Turkey.

This study included a sample of user comments on news videos about "AI" of national news channels in Turkey because the videos directly connected with the research topic and had a high number of likes, dislikes, views, and comments. Therefore, the high number of likes, dislikes, views, and comments compared to other AI news videos further expands the research's impact and increases the intensity of user interaction.

In AI news videos, only the top comments were taken as a basis because any user commenting below a top commenter can create a discussion environment by replying to the top commenter and changing the top commenter's perception and attitude toward AI technology. This situation can also affect sentiment analysis at specific points. Therefore, the study is based only on top user comments under online news videos. The national news channels forming the data set and the number of top comments by Turkish users on these channels are presented in Table 1.

Table 1.

YouTube news titles, URLs, number of comments, and news channels

News Titles and URLs	**Number of Comments**	**News Channel**
Yapay zekâ insanlığın yerini mi alacak? Ertan Özyiğit ile Kayıt Dışı - 19 Mart 2021 [*Will artificial intelligence replace humanity? Off the Record with Ertan Özyiğit - March 19, 2021*] URL: https://www.youtube.com/watch?v=Fh9w8JQd1NQ&t=5s	263	TV100
ChatGPT programı ne kadar "Zeki"? | Teke Tek Bilim - 23 Ocak 2023 [*How "Smart" is the ChatGPT program? | Head to Head Science - January 23, 2023*] URL: https://www.youtube.com/watch?v=q2f7hrelqtc&t=9s	248	Habertürk TV
Robot öfkelendi, insana müdahale etti! [*The robot got furious and responded to the human*!] URL: https://www.youtube.com/watch?v=1F90g2l-YEo	181	TV100
Abdullah Çiftçi: "Türkler yapay zekâ alanında dünyada ilk 5'te" [Abdullah Çiftçi: "*Turks are in the top 5 worldwide in artificial intelligence*."] URL: https://www.youtube.com/watch?v=sK_GQ1vEb3g	163	CNN TÜRK
Bilim Kurgu Filmlerini Aratmayan Olay: Yapay Zekâ Komutanını Öldürdü [*An Incident Like a Science Fiction Movie: Artificial Intelligence Killed Its Human Operator*] - TGRT Haber URL: https://www.youtube.com/watch?v=bgzOsgurUVw&t=6s	134	TGRT Haber TV
Yapay Zekâ Kafesinden Kaçtı | Aralarında Güç Savaşı Başlayabilir! [*Artificial Intelligence Escaped from Its Cage | A Power Struggle May Begin!]* URL: https://www.youtube.com/watch?v=ugo93hxDtAg	100	Haber Global
Google'ın Elini Ayağını Dolandıran Olay! Yapay Zekâ İddiası Gündemi Sarstı [*The Incident That Nonplussed Google! Artificial Intelligence Claims Shook the Agenda*] URL: https://www.youtube.com/watch?v=Hn2nVzRJG0Y&t=6s	69	Haber Global
Yapay zekâ kendini nasıl geliştiriyor? | Teke Tek Bilim - 5 Eylül 2021 [*How does artificial intelligence improve itself? | Head to Head Science - September 5, 2021]* URL: https://www.youtube.com/watch?v=_r6ADEVhuCs&t=1443s	66	Habertürk TV
Yapay Zekâ Tehdit Mi Fayda Mı? | Yapay Zekânın Karanlık Yüzü | 22.07.2023 Sıra Dışı Gündem [*Is Artificial Intelligence a Friend or a Foe? | The Dark Side of Artificial Intelligence | 22.07.2023 Extraordinary*	53	Haber Global

Agenda] URL: https://www.youtube.com/watch?v=TBLpwKxf4Gw&t=2s		
Ürküten Görüntüler! "Yapay Zekâ İnsanlığı Ele Geçirecek" [*Dreadful Images! "Artificial Intelligence Will Take Over Humanity"*] URL: https://www.youtube.com/watch?v=Uf5-qWlcX0s	45	Haber Global
13 yıllık yuvada '"Yapay zekâ'" çatlağı! ["*Artificial intelligence" Crack in The 13-Year-Old Home*!] URL: https://www.youtube.com/watch?v=bhO6-R_xMTU&t=9s	37	Show Ana Haber
Erdoğan'ın sesini yapay zekâ ile taklit etti [*He Imitated Erdoğan's Voice Using Artificial Intelligence*] URL: https://www.youtube.com/watch?v=p3hlz2Zt5q8	36	Show Ana Haber
Yapay Zekâ Canlandı mı? Google Ne Yapacağını Şaşırdı! [*Is Artificial Intelligence Revitalized? Google Lost Its Bearings*!] URL: https://www.youtube.com/watch?v=kuJitAxVYf0&t=4s	30	Haber Global
Yapay zekâ insan beynini hantallaştırıyor mu? | Teke Tek Bilim [*Is Artificial Intelligence Making the Human Brain Cumbersome? | Head to Head Science*] URL: https://www.youtube.com/watch?v=h0uIuNnDnjI&t=4s	30	Habertürk TV
Teke Tek Bilim'de yapay zekâ teknolojileri konuşuluyor... [*Artificial Intelligence Technologies Are Tackled in Head to Head Science...*] URL: https://www.youtube.com/watch?v=1R2XHcOXq9o	28	Habertürk TV

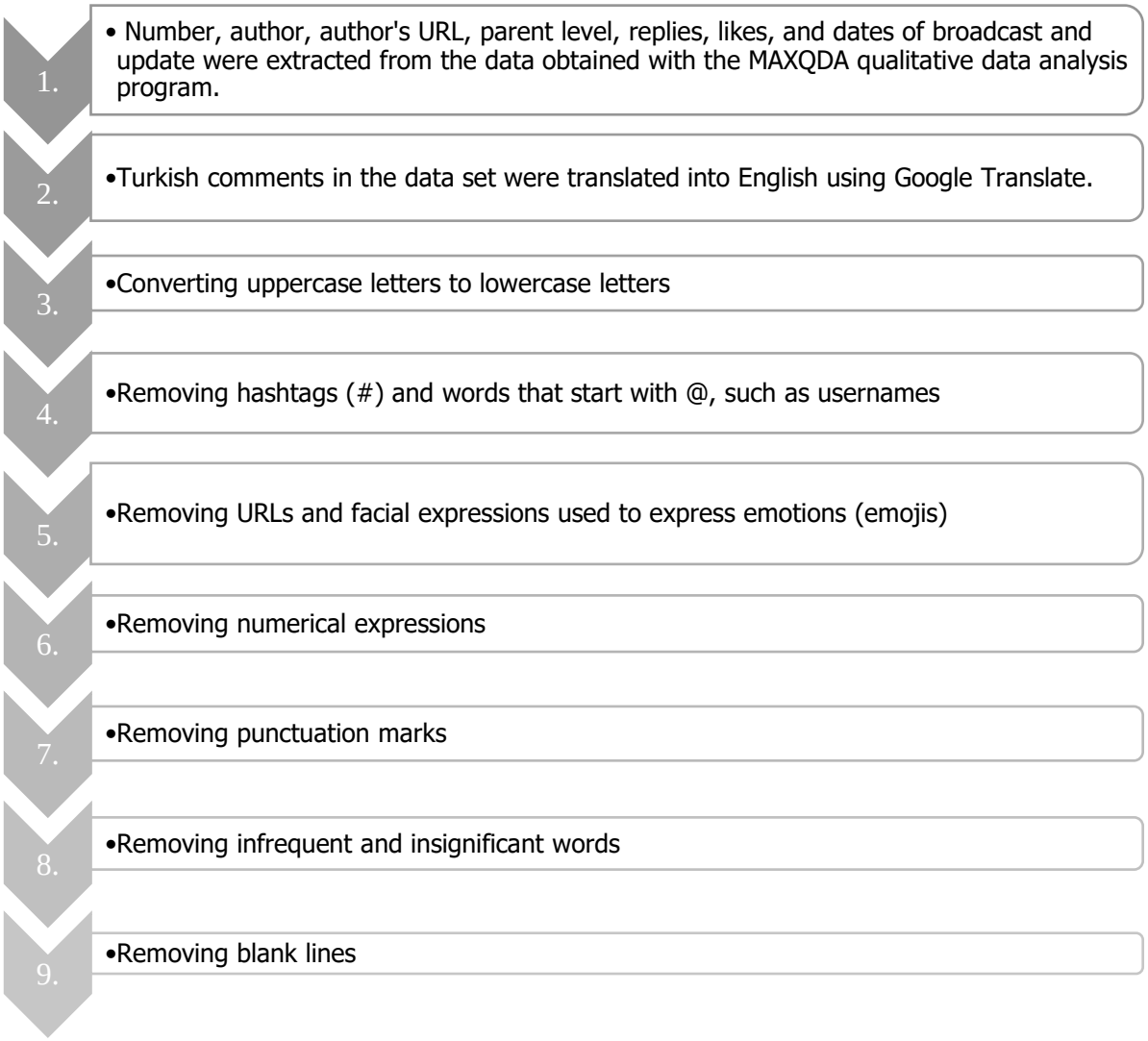
Source: Own elaboration.

2.3. Preprocessing with Text Mining

The data set on a research topic can be accessed easily and quickly through social media platforms. However, while using these environments to express views on a specific topic, spelling errors made by users and some opportunities provided by these platforms, such as emojis, mentions of other individuals, or referencing (hashtags), require some action before obtaining research findings. For the classification model utilized in the study to give accurate results, the procedures applied to all shares in the data set obtained through the MAXQDA qualitative data analysis program are presented below:

Figure 2.

Preprocessing of the data set



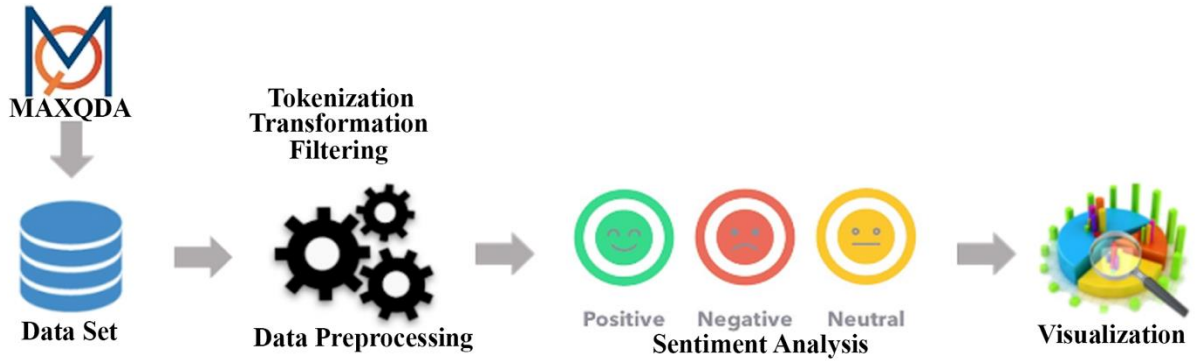
Source: Own elaboration.

2.4. Creating the Sentiment Analysis Model

The preprocessing step was primarily applied to the data set obtained through the MAXQDA program. At this stage, "tokenization" was initially applied, the texts were split into words, and specific suffixes were removed. In the subsequent "transformation" process, the Turkish data set was translated into English, and uppercase letters were converted to lowercase letters. In the third stage, "filtering," hashtags (#) and words starting with, such as usernames, URLs, facial expressions used to express emotions (emojis), numerical expressions, punctuation marks, and some words that might not impact the SA were filtered. Ultimately, following the data preprocessing step, the blank lines in the data set were removed.

Figure 3.

Sentiment Analysis Model



Source: Tarakcı (2023).

After data preprocessing, SA was conducted using language processing "Valence Aware Dictionary for Sentiment Reasoner (VADER)", one of the popular libraries of NLP. VADER was preferred because the language of the processed data is English, and it is a word and rule-based SA tool that adapts to the sentiments expressed in social media environments. It also considers word order and degree variables (Chauhan et al., 2018). Recommended specific scores were used to classify opinions through the SA instrument Vader, proposed by Hutto ve Gilbert in 2014. Predefined words were preferred for positive, negative, and neutral sentimental intensities. Words are matched with scores that express the sentimental intensity. The data's sentiment intensity is calculated by summing the scores of each word in the data. In the word list, features are assigned values between [-4, +4] that indicate sentiment polarity and intensity. In the next step, the values of each word in the dictionary are collected and adjusted according to the rules, and finally, a combined score is calculated in the [-1, +1] range. Specific threshold values used in this study to classify YouTube user comments as positive, negative, or neutral through VADER are as follows: *"Fpi = positive vs >= 0.05 / negative vs <= −0.05 / neutral* in other cases"[1] (Hutto & Gilbert, 2014; Aslan, 2023). Depending on the values, the composite value obtained following the SA is classified as positive if greater than or equal to [+.05], negative if less than or equal to [-.05], and neutral if [+.05]. and [-.05]. The results of SA are presented in the findings section.

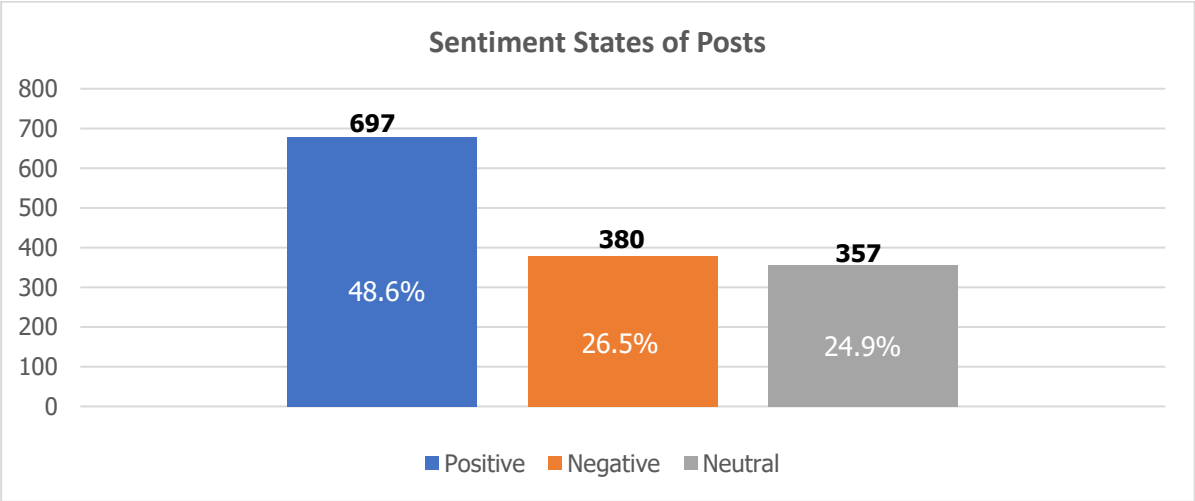
3. FINDINGS

Following the preprocessing of the data set comprising 1,483 user comments obtained from YouTube, it was determined that 1,434 comments were suitable for SA. The comments in the resulting data set were collected in three different sentiment classes: positive, negative, and neutral. The numerical and percentage distributions of the data regarding sentiment classifications are displayed in Table 1.

[1]In the value, vs represents the combined score of i. comments, while Fpi is calculated as the sentiment polarity (positive, negative, or neutral) of i. comments. Upon identifying the sentiment states of the comments in the data set, the study focused on comments with positive, negative, and neutral sentiment states.

Figure 4.

Sentiment States of Posts



Source: Own elaboration.

The SA of user comments about AI-related video posts of Turkish national news channels are shown in Figure 4. Tabular examination within the framework of the dictionary-based Vader classification revealed the following percentages: positive comments (48.6%), negative comments (26.5%), and neutral comments (24.9%). Additionally, 697 of the 1434 user comments on 15 videos about AI on national news channels were positive, 380 were negative, and 357 had neutral sentiments. Accordingly, results indicated that users' sentiment states were predominantly positive, with negative and neutral sentimental attitudes almost equal or close to each other.

Table 2.

User comment examples of news posts, scores, and labels

User Comments	SA Score	Labels
This is amazing! It gives logical answers no matter what you ask.	{'neg': 0.0, 'neu': 0.594, 'pos': 0.406, 'compound': 0.6249}	Positive
Human intelligence halted in a place. It is AI that will allow humanity to progress.	{'neg': 0.109, 'neu': 0.229, 'pos': 0.663, 'compound': 0.8658}	Positive
Robot soldiers are mandatory now. Robots will fight at the headquarters instead of young soldiers.	{'neg': 0.0, 'neu': 0.492, 'pos': 0.508, 'compound': 0.4767}	Positive
There is no problem between people and codes.	{'neg': 0.104, 'neu': 0.578, 'pos': 0.319, 'compound': 0.9756}	Positive
AI serves humanity.	{'neg': 0.0, 'neu': 0.648, 'pos': 0.352, 'compound': 0.6632}	Positive
AI will be racist. That's for sure.	{'neg': 0.396, 'neu': 0.297, 'pos': 0.307, 'compound': -0.2263}	Negative
AI is nothing but making people lazy.	{'neg': 0.677, 'neu': 0.323, 'pos': 0.0, 'compound': -0.2732}	Negative

If AI surpasses its creator, it will be humanity's doom.	{'neg': 0.396, 'neu': 0.321, 'pos': 0.283, 'compound': -0.2741}	Negative
People will be unemployed because of these robots.	{'neg': 1.0, 'neu': 0.0, 'pos': 0.0, 'compound': -0.4019}	Negative
It is a danger to both humanity and all living things. They have no compassion.	{'neg': 0.279, 'neu': 0.45, 'pos': 0.27, 'compound': -0.0258}	Negative
Here is the future for you.	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
Like human.	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
No way!	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
It is all just software.	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
This is ultrarealistic.	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral

Source: Own elaboration.

Table 2 shows user comments, SA scores, and labels of YouTube news videos about AI. Based on sample user comments, comments that do not indicate any sentiment states or mostly contain interrogative expressions were assigned a neutral label by specifying the polarity score as "0". Other scores assigned different values were created after calculating the words in positive or negative sentences.

Figure 5.

The Word Cloud of News Comments

Source: Own elaboration.

Word clouds enable the frequently used words in a research data set to be interpreted in a specific context and the themes to be visualized and presented based on the

findings (Williams et al., 2013). A visual word cloud was created based on user comments on the AI-related video posts of national channels on YouTube. As seen in Figure 5, words in user comments were visually shaped according to their size and color. While the most frequently used words in the cloud have dark and large shapes, those with light and small shapes refer to reduced frequency (Yaşa, 2022).

In this context, a figure-based interpretation indicates that the most frequent word was "intelligence," followed by "artificial, people, world, program, human, god, robot, teacher, time." The frequencies and percentages of these words are given in the table below. Based on the most frequently repeated words, user views on AI centered around three main themes: 1) AI's definition and characteristics (e.g., artificial intelligence), 2) AI's effects on individuals and society (e.g., people, world, human, and god), 3) AI's functional and technological effects (e.g., robot, program, teacher, and time). These themes indicate how individuals perceive AI and approach it from different perspectives.

Table 3.

Top 10 word frequencies and percentages in news comments

Total Word Count =17434	**Frequency**	**%**
Intelligence	311	1,78
Artificial	297	1,70
People	228	1,31
World	109	0,63
Program	105	0,60
Human	94	0,54
God	92	0,53
Robot	83	0,48
Teacher	77	0,44
Time	77	0,44

Source: Own elaboration.

The total number of words in user comments regarding the topic was 17,434. A close examination of the frequencies and percentages of the most frequent words in user comments on YouTube videos yielded the following statistics about the top 10 words: "intelligence" n=311 (1.18%), "artificial" n=297 (1.70%), "people" n=228 (1.31%), "world" n=109 (0.63%), "program" n=105 (0.60%), "human" n=94 (0.54%), "god" n=92 (0.53%), "robot" n=83 (0.48%), and "teacher" and "time" n=77 (0.44%). Since the research topic was about AI, it is expected for the most frequent word to be "intelligence," but other words also support the research topic. In addition, the fact that individuals expressed their views on AI with such words as "human" and "god" reflects a particular state of consciousness regarding AI's religious and ethical dimensions and its effects on individuals. At this point, AI's potential to be perceived as "god" by individuals or that AI has individual characteristics suggests the uncertainty of the boundaries of human-machine relations. Additionally, repetitive words such as

"robot" and "program" might emphasize individuals' perceptions of technology and their views on AI. Therefore, we can conclude that individuals expressed their opinions by considering technical information in their perceptions of AI and positive or negative social and ethical values regarding humanity.

Table 4.

Frequency and Percentages of the Top 10 Negative Words in Comments on Artificial Intelligence

Total Word Count =17434	**Frequency**	**%**
Cannot	56	0,32
Attention	27	0,15
Afraid	26	0,15
Bad	26	0,15
Wrong	21	0,12
Destroy	20	0,11
Dangerous	16	0,09
Kill	16	0,09
Fake	15	0,09
Problem	13	0,07

Source: Own elaboration.

Frequency and percentage distributions of the most frequently used negative words in user comments on YouTube videos demonstrated that "cannot" was used n=56 (0.03%) times. In contrast, the other three words (n=27 attention, n=26 afraid, n=26 bad) were equal (0.15%) in the negative word group, and the word "wrong" was used n=21 (0.12%). In addition, the word "destroy," which is in the top ten negative word groups, appeared in user opinions n=20 times (0.11%), while the other two words (dangerous, kill) appeared in the negative word group n=16 times with an equal rate (0.09%). The analysis of the other top ten negative words revealed that "fake" was used n=15 (0.15%) and "problem" n=228 (1.31%) times. The negative word group provides information that users complain about issues related to AI. Based on the words "attention," "afraid," and "bad," which occurred equally in user statements, it indicated negative feelings about AI. In addition, based on the first ten word groups and the other negative word groups, users also mentioned that various security problems might occur by pointing out that AI technologies may be wrong, destructive, and worrying in their lives in the sentences formed by these negative words. Moreover, users expressed negative opinions that some professions might disappear due to AI technologies, resulting in unemployment, threats to living things, security problems in military areas, and acquiring knowledge and skills like individuals.

4. DISCUSSION AND CONCLUSION

AI technology impacts the lives of individuals and societies in different ways. It, therefore, sparks debate on whether it will potentially make human life better or worse in the future. Differences of opinion necessitate research on AI and public perceptions.

In this context, it is essential to understand public opinion to interpret the social acceptance of AI. Considering that we conducted a SA (negative/positive/neutral) on Turkish society within the scope of the study, their sentiment states on the topic might be viewed as a true reflection of the potential for AI use in the future. The main point of the study emerges at this point. Using the purposive sampling method, this study included user comments on news or discussion programs on YouTube by Turkish national channels to determine their sentiment states toward AI technologies.

SA showed that 697 (48.6%) of user comments on video posts about AI on Turkey's national news channels were positive, 380 (26.5%) were negative, and 357 (24.9%) were neutral. Based on the findings, the proximity between negative and neutral sentiment states encourages the potential for users to have a generally positive perception of AI. "Intelligence" was the most frequent word, followed by "artificial, people, world, program, human, god, robot, teacher, time. This study revealed that the most frequently recurring words and themes in users' comments on AI might be evaluated within the scope of AI-related topics, guiding prospective researchers interested in the subject. Therefore, thanks to these words, researchers can compare their study results or expand their research based on the words. At the same time, creating specific themes in the research based on the users' most frequently repeated words will guide users who conduct research in the future. This is also the case for the emotional states of users obtained as a result of sentiment analysis. Thus, the data obtained in the context of Turkey will also provide data for inevitable comparisons at the level of different countries.

Accommodating AI technology, the output of new information and communication technologies at the global level, will not happen on the spur of the moment for individuals and societies. As can be seen from the data set, specific question marks were raised in the opinions and thoughts of YouTube users within the framework of their neutral attitude toward AI. Users with little or no information about AI might gain more knowledge by participating in such processes in the future. Current sentiment states toward a specific issue may differ from future ones. It might thus be viewed as predictable that in the future, users who are more positioned in these processes will experience certain shifts in their sentiment states toward specific issues, from positive to negative, from negative to positive, or from neutral sentimental states to positive or negative. The study results will, therefore, serve as a source for future researchers, providing significant support and opening new discussion areas for their research.

As in every research, this research was conducted within certain limitations. The study included user comments within the framework of news or discussion programs on YouTube, one of the social media environments of national channels in Turkey. Therefore, this study's main limitation was its analysis of only the YouTube platform and online user comments on fifteen popular AI videos. The research is based on the top comments on the YouTube platform on September 05, 2023. Comments made after this date were therefore excluded. Another limitation was the use of the VADER algorithm.

As a result, AI applications have become one of the significant research topics locally and globally. Exploring the perceptions and attitudes of countries about AI and its

potential for future use is crucial for developing nationwide and regional AI strategies. The acceptance of AI, a global phenomenon, might be investigated in various languages and cultures. Prospective researchers are recommended to increase the diversity and size of the data set on the same topic and conduct SA using different deep learning-based classification algorithms. In addition, the data obtained from different social media environments can be used to classify emotions comparatively. By performing content analysis on the data, new descriptive studies can be conducted within specific themes. The netnography method can provide rich data on online user perceptions and attitudes toward AI technologies in various social media environments. Moreover, relevant interactions can be discovered by conducting social network analysis using data from different social media environments.

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