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Sentiments towards Emergency Remote Teaching on Twitter: A Longitudinal Comparative Sentiment Analysis

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Abstract

This longitudinal and comparative study investigated people's sentiments toward emergency remote teaching in tweets posted in two different languages from January 10 to August 16 2021 when mass vaccinations started and continued. The results indicated that English tweets (a) included more positive sentiments towards emergency remote teaching; (b) were more supportive and motivating; and (c) focused on topics related to education, online education, and English as a second or foreign language. However, Turkish tweets (a) included more similar amounts of neutral and positive sentiments; (b) involved politics and government-related content; and (c) touched on topics related to preschool education, ministry of national education and the e-school system used during the pandemic. Lastly, compared to positive and neutral sentiments, there were fewer negative sentiments in tweets in both languages suggesting that people got used to emergency remote teaching over time. In other words, despite any ongoing issues, people's reactions to emergency remote teaching on Twitter improved and became either more neutral or positive in a year or so, which implies that increasing optimism due to vaccinations during sudden health crises may calibrate people's sentiments towards compulsory solutions such as emergency remote teaching.

Key Words

Comparative sentiment analysis • Emergency online education • Emergency remote teaching • Text mining • Topic modeling • Twitter

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Introduction

The COVID-19 pandemic has impacted human life profoundly (Lytridis et al., 2020): The United Nations Educational, Scientific, and Cultural Organization (UNESCO) (2020) predicted that countries closed schools and universities due to COVID-19, which have influenced 1.5 billion students as well as parents and teachers (e.g., Ewing & Cooper, 2021). The impact of the pandemic has been on all aspects of life including teaching and learning as well (e.g., Alan, 2021; Hodges et al., 2020; McFayden et al., 2021; Nazli et al., 2021; Sahin et al., 2021). Needless to say, schools and universities had to close suddenly and, due to various advantages including no time and place dependence (Pregowska et al., 2021), switched to what Hodges et al. (2020) call emergency remote teaching that has come up with challenges that would have decreased student satisfaction. For instance, according to some college students, lack of technological resources has made emergency online education challenging (Aristovnik et al., 2020; Gonzales et al., 2020). Unsurprisingly, then, only 19% of students have been satisfied with online learning experiences while the majority was concerned about their effects on future learning (Means et al., 2020). Accordingly, instructors modified their courses in different ways ranging from switching to a pass or fail grading regime to changing course requirements (Johnson et al., 2020). These challenges and adjustments were similar at different educational levels, including, but not limited to special education (e.g., Parmigiani et al., 2020; Sider, 2020), early childhood education (e.g., Alan, 2021; Campos & Vieira, 2020; Szente, 2020), and primary education and/or secondary education (e.g., Ayda et al., 2020; Calderón-Garrido & Gustems-Carnicer, 2020).

Students' and people's decreased levels of satisfaction would reflect into their online sentiments towards emergency remote teaching. One venue where these sentiments can be addressed is social media that (a) have already become online platforms people use to share insights into their lives (Ozturk & Ayvaz, 2018) as well as presenting their opinions and ideas (Ding et al., 2020); (b) provide quick access to information (Nazli et al., 2021); and (c) house people's comments and changes in their lives. After all, people, civil and government units, and businesses use social media very commonly thus turning them into important communication tools, which has become more common and important during the pandemic when social distancing has become a commonality (Nazli et al., 2021). To illustrate, as it should be clear to anyone who has a Twitter account, using Twitter, which is very popular and widely used (Nazli et al., 2020; Ozturk & Ayvaz, 2018), people post tweets on topics in a way that presents their opinions and emotions. Thus, given that the average number of tweets posted on Twitter daily exceeds 500 million (Crannell et al., 2016), which refers to a large global scope (Ozturk & Ayvaz, 2018), people are very likely to share their sentiments towards topics including emergency remote teaching through tweets. Analyzing these sentiments can provide unique insights into how to enhance such public services as online education during times of disruption.

Consequently, it is reasonable to investigate sentiments towards emergency teaching one year after the pandemic breakout when vaccines started to become highly available to see whether the level of emotional costs had been decreasing. To this end, this study investigates the public's sentiments towards emergency remote teaching one year after the pandemic in Turkish and English tweets to produce comparative insights by addressing the following research questions:

- What were the sentiments in Turkish and English Tweets towards emergency remote teaching when mass vaccinations became available?
- How did the sentiment scores change over time?
- How did the sentiments in Turkish tweets compare to those in English tweets?
- What were the relevant terms and main themes associated with the topics most discussed in Turkish and English tweets?

Review of Related Literature

Emergency Remote Teaching

To prevent COVID-19 from spreading, most schools moved to emergency remote education using different delivery modes (Bozkurt et al., 2020). Hodges et al. (2020) calls it emergency remote teaching and separates it from systematic online learning, and Ewing and Cooper (2021) highlighted that technology adoption promoted by the pandemic is not the same as deliberate technology integration. Specifically, the difference between emergency remote education and distance education is while the former "is about surviving in a time of crisis with all resources available, including offline and/or online", the latter "is a planned activity and its implementation is grounded in theoretical and practical knowledge which is specific to the field and its nature" (Bozkurt et al., 2020, p. 2).

Despite its possible advantages such as collaboration, training and communication (Smith, 2020) and gaining experience in using online technologies and online education itself (Robin et al., 2020), rapid move to emergency online education led to many challenges. Even though teachers regarded remote education as an opportunity to continue education (Ayda et al., 2020), they were mainly concerned about connecting with and engaging their students (Ewing & Cooper, 2021). Namely, students' level of engagement with their teachers was lower, their engagement with their peers had various levels, and emergency online education was difficult and less personalized with social isolation being a major issue (Ewing & Cooper, 2021). Besides social isolation, students faced challenges in emergency online education due to limited access to technology, lack of technology infrastructure, difficulty to focus on the course and course content, increased workload, and concerns about their future professional careers (Aristovnik et al., 2020).

Khlaif et al. (2021) reported that a wide variety of factors impacted students' online engagement during emergency online education ranging from infrastructure to digital inequality. That is, emergency online education also led to enlarged digital inequality and digital privacy issues thereby negatively impacting student engagement, and the lower quality of learning content during the pandemic decreased student engagement as well (Khalif et al., 2021). Armitage and Nellums (2020) claimed that the pandemic caused a high level of learning loss and inequality. According to Lesh (2020), we have been facing two pandemics simultaneously: "racism/inequity and COVID-19" (p. 7). Similarly, Stewart's (2021) thematic review revealed digital divide and huge inequalities are associated with emergency online education in addition to drawbacks, issues, and adjustments made to deal with the challenges of emergency online education.

According to Psacharopoulos et al. (2020), the school closures due to the pandemic may result in losing 18% of future gross domestic product globally. Compared to face-to-face education, student performance may have also deteriorated in emergency online education. For example, senior medical students learning face-to-face performed better compared to their counterparts learning through an online problembased learning tutorial in terms of participation, communication, preparation, critical thinking and group skills (Foo et al., 2021). Interestingly, even though emergency online education would be accepted by students due to the pandemic and they were comfortable with it (e.g., Cicha et al., 2021), students may approach it differently with male students having more positive sentiments (Haider & Yasmin, 2021).

Twitter Sentiment Research During the Pandemic

Eutsler et al. (2021) identified emotional reactions as one of the themes covered in tweets during the pandemic. Accordingly, online microblogging tools including Twitter have become excellent targets for sentiment analysis recently (Silahtaroglu et al., 2020) especially given that social media content including social networks include users' real-life "interests, friendships, and connections" (Mungen et al., 2020, p. 250). According to Nazli et al. (2020), Twitter's "minimalist design, a vast number of users and the consequent broad span of influence" distinguishes it from other social media tools. All these insights strongly suggest that Twitter provides a rich context in which people's sentiments can be detected and analyzed especially when such sentiments can reach a peak point during crises like the COVID-19 pandemic.

Since the official announcement of the first case on March 11, 2020 (Bostan et al., 2020), Turkey has been facing the negative effects of the pandemic too (e.g., Silahtaroglu et al., 2020), which led to analyzing Twitter data to catch trends in people's sentiments or emotions. Silahtaroglu et al. (2020), for instance, analyzed Twitter content (i.e., #Evdekal hashtag) starting in the second week after the first case and checked the following ten weeks. The authors reported an abundance of positive sentiments compared to negative ones, and anticipation and trust followed positive sentiments respectively. According to the authors, Twitter users tended to share positive and encouraging messages in which they supported each other by providing sample activities that can be done at home. The most frequently used words or phrases (i.e., athome, continue, health, lifeathome) aligned with people's tendency to show support in their tweets. However, in a content analysis of tweets posted during the first week after the official announcement of the first case in Turkey, Nazli et al. (2020) reported 13 emotional states of which the most common ones were aggression, gratitude and concern. Likewise, Silahtaroglu et al. (2020) found more negative sentiments in tweets in the 3rd and 4th weeks, which contrasts with the overall picture of the 10-week period they examined. Sahin et al. (2021) also reported that, overall, average sentiment scores of tweets decreased during the pandemic between March 14 and May 14, 2020, which features a trend towards more neutral or negative sentiment scores.

According to Silahtaroglu et al. (2020), the main reason for more negative sentiments in some weeks would be due to launching curfews and other restrictions combined with economic concerns. Likewise, Sariman and Mutaf (2020) reported more positive sentiments towards wearing masks in the first two months of the pandemic, but more negative sentiments towards other policies including lockdowns and digital educational content networks. However, Sahin et al. (2021) provided no sentiment score differences between obligatory and non-obligatory isolation periods. Overall, even though these findings do not align to some extent, they suggest that Twitter content may be sensitive to major changes in social life. In this respect, Nazli et al. (2020) yielded that most corona-related tweets were about personal thoughts on the pandemic and emotions were the fourth most common category of the tweet content analyzed. Nazli et al. (2020) further claimed that tweets conveyed both personal opinions and emotional expressions throughout the first week after the onset of the pandemic in Turkey. Specifically, the number of tweets with emotional states increased towards the end of the week, which was due to increasing concerns (Nazli et al., 2020). Sahin et al. (2021) similarly found that the period between March 14 and May 14, 2020 included more tweets with higher positive and negative sentiment scores.

Interestingly, the trend of tweeting more positive sentiments at the beginning of the pandemic in Turkey has been observed in sentiment analyses conducted in other countries too. To illustrate, Barkur et al. (2020, p. 1) reported that "positive sentiments stood out" despite "negativity, fear, disgust, and sadness" in India between March 25 and March 28, 2020. Moreover, in line with Silahtaroglu et al. (2020) above, Barkur et al. (2020) found that trust was the second most common sentiment. According to the authors, these findings imply that Indians were positive about the cautions taken. During the following lockdown between March 25 and April 14, 2020 in India, the government asked people to turn off their home lights at 9 pm for 9 minutes and to use an alternative light source such as a candle to show solidarity instead (Vibha et al., 2020). Vibha et al. (2020) examined sentiments in tweets posted during the first day of this task offered by the Indian government. The authors reported that the most common sentiments were positive and trust respectively. From a more global perspective, Roy and Ghosh (2021) reported that even though positive and negative sentiments in tweets are balanced almost perfectly, public sentiments are not related to geographical closeness, and old age and ethnicity predict public sentiments toward the pandemic.

Method

Software Tools

We used the Python programming language for creating scripts that collect and analyze data programmatically. The collected tweets were stored in a MS SQL Server database for further processing and data analysis. For sentiment analysis and data preprocessing, we utilized Natural Language Toolkit (NLTK), a widely known open source package in Python, which processes text data in multiple human languages. The NLTK package is a comprehensive library that provides access to more than 50 corpora and lexicons as well as text data preprocessing features including stemming, stopword elimination, tokenization, tagging, parsing, and sentiment analysis (Bird et al., 2009). For topic modeling analysis, Gensim, which is an open source Python library (Rehurek & Sojka, 2010) was used since Gensim's parallelized implementation of topic modeling algorithms such as word2vec and doc2vec and latent Dirichlet allocation (LDA) algorithms allow for training models using large collections of text data efficiently (Rehurek & Sojka, 2010).

Procedures

Data collection

The research dataset was obtained through Twitter Application Programming Interface (API) that allows for collecting public tweets in real-time, which makes it an ideal venue for global opinion mining. The tweets related to one of the hashtags below were collected and stored in a relational database. Data collection spanned over 218 days with an average of nearly 750 tweets per day.

Several hashtags for both languages were searched among all the public tweets from January 10, 2021 until August 16, 2021. English tweets were searched using these hashtags: “#onlinelearning”,“#remotelearning” ,“#distancelearning”, “#onlineeducation”, “#remoteteaching”, “#onlineteaching”, “#distanceeducation”, “#remoteeducation”, “#distanceteaching”, “onlineinstruction” ,“remoteinstruction” and “emergencyremoteteaching”. In total, 148,968 English tweets were collected. Eliminating the duplicate tweets, tagged with multiple hashtags, resulted in 137,695 English tweets. As for Turkish tweets, the following hashtags were searched: “#uzaktaneğitim”, “#onlineeğitim”, “#çevrimiçieğitim”, “#uzaktanöğrenme” and “#uzaktanöğretim” that are comparable to their English counterparts. A total of 13,920 Turkish tweets were retrieved. After excluding duplicate hashtags, the total number of unique tweets was 13,187 Turkish. Because the NLTK library does not fully support Turkish language, Turkish tweets were first translated to English.

Data preprocessing

The data preprocessing included handling missing values, deletion of duplicates, numbers, punctuation and links, removal of stop-words, and tokenization of text. From a text mining perspective, the sentences were treated as documents in the study. Each document in text mining was considered as a bag of words or terms. No missing values were detected in the dataset. However, there were duplicated records due to retweets and multiple use of hashtags. All duplicates were removed from the dataset and uppercase letters were converted to lowercase characters to prevent duplications. Consequently, sentences were converted to tokens and stop-words were removed from the text.

Sentiment analysis

Sentiment analysis is the process of extracting subjective opinions and sentiments from text data. Sentiments can be categorized into various groups. We classified texts as positive, neutral or negative sentiments with the goal of identifying the dominant opinion of each tweet. The total sentiment score of a tweet was computed by aggregating polarity scores of all positive and negative terms, and individual tweets were labeled based on the total sentiment score. Furthermore, sentiments of Turkish and English tweets were illustrated using visualization libraries of matplotlib and wordcloud in Python language. To verify the validity of automatically calculated sentiment scores and sentiment polarities generated by the NLTK library, a list of randomly selected tweets were manually reviewed by the authors. The programmatically determined sentiments were consistent with the manual review process.

Topic modeling

Topic Modeling is an unsupervised learning method to identify underlying groups of terms and topics in a collection of text (Silge & Robinson, 2017). Many text mining methods were developed for discovering topics in a text automatically including latent semantic analysis (LSA) (Deerwester et al., 1990), probabilistic latent semantic analysis (PLSA) (Hofmann, 1999), and latent Dirichlet allocation (LDA) (Blei et al., 2003). This study used LDA, a widely-known and efficient probabilistic topic modeling technique, for topic modeling (Blei et al., 2003). LDA determines the underlying topics based on co-occurrence of terms. In LDA, terms are considered as the basic units of topics and a group of terms are associated with latent topics in the documents. It assumes that a document can contain a collection of topics with varying degrees of relevance.

We developed the LDA models by using the Gensim library built in Python (Rehurek & Sojka, 2010). The necessary preprocessing tasks such as term tokenization, term matrix and corpus generation processes were performed on the text data before applying LDA methods. The model parameter of the number of topics was chosen as 10 in the LDA models for both languages. For the visualization of model outputs, we utilized LDAVis which is an interactive tool for displaying the latent topics and associated terms (Sievert & Shirley, 2014). For selection of relevant terms in topics, LDAVis utilizes the measures of saliency (Chuang et. al, 2012) and relevance (Sievert & Shirley, 2014). Salency is estimated by using equation 1 (Chuang et. al, 2012):

$$\text{saliency}(\text{term } w)=\text{frequency}(w) * [\, p(t \mid w) * \log(p(t \mid w) / p(t))] \quad (1)$$

t represents topics, p(t) stands for the probability of topic t, and p(t |w) denotes the conditional probability of term w occurring in the topic t (Chuang et. al, 2012). The relevance measure is calculated by using equation 2 (Sievert & Shirley, 2014):

$$\text{relevance}(\text{term } w \mid \text{topic } t) = \lambda * p(w \mid t) + (1 - \lambda) * p(w \mid t) / p(w) \quad (2)$$

Lambda λ represents weight, which takes a value between 0 and 1 assigned to the probability of the term w occurring in topic t and the term lift. Optimum lambda value may differ depending on datasets and assigning lambda to 0.6 worked well in our evaluations, which was also the case in Sievert and Shirley (2014). The expression $p(w \mid t)$ / $p(w)$ denotes lift, which measures the ratio of the conditional probability of term w occurring under topic t relative to the likelihood of w occurring in the corpus.

Results

Sentiment Analysis Results

Sentiments in Turkish tweets

Sentiment analysis of Turkish tweets revealed that the majority had neutral sentiments: 5,991 tweets were neutral (45.43%) (Figure 1). There were also 5,638 positive tweets (42.75%), and 1,558 negative tweets (11.81%).

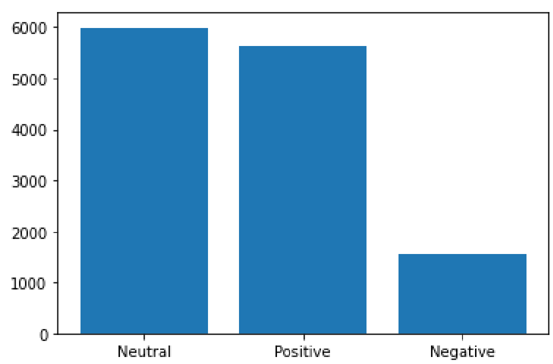

Figure 1. Sentiment Categories of Turkish Tweets

Most of the Turkish tweets were collected using hashtag "#uzaktaneğitim" followed by "#onlineeğitim". The tweets that belonged to these two hashtags collectively comprised the majority (Figure 2).

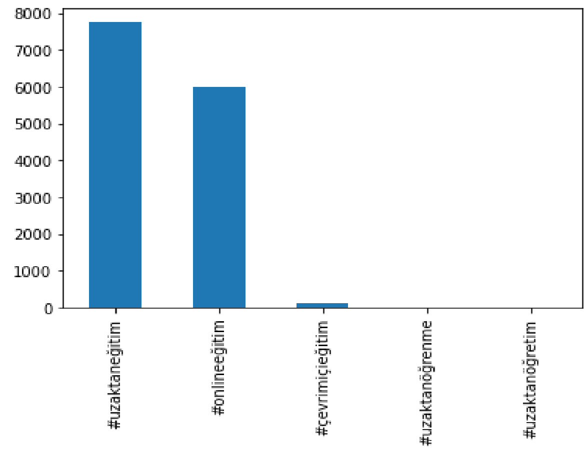

Figure 2. Number of Turkish Tweets per Hashtag

We also explored the changes in sentiments during data retrieval. Figure 3 presents the daily average sentiment scores of Turkish tweets. The highest average sentiment score per day was observed on July 20, 2021 while the lowest average sentiment score per day was observed August 10, 2021.

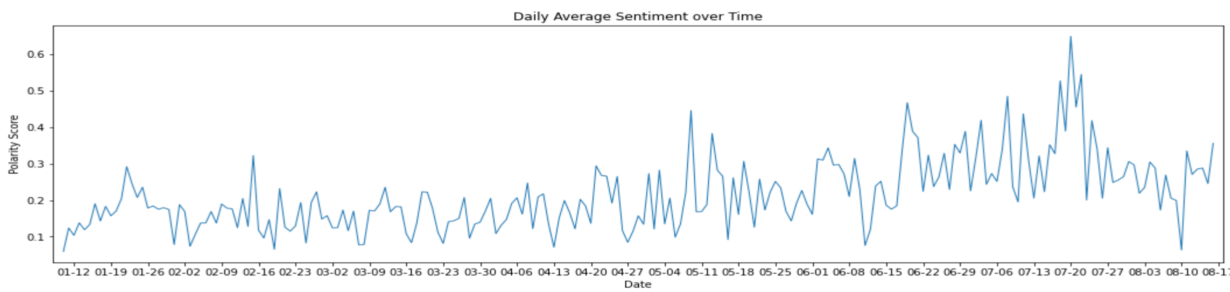

Figure 3. Daily Average Sentiment Scores of Turkish Tweets

Sentiments in English tweets

The majority of English tweets (89,807, 60.29%) turned out to be positive (Figure 4). There were also 49,400 neutral tweets (33.16%) and 9,761 negative tweets (6.55%).

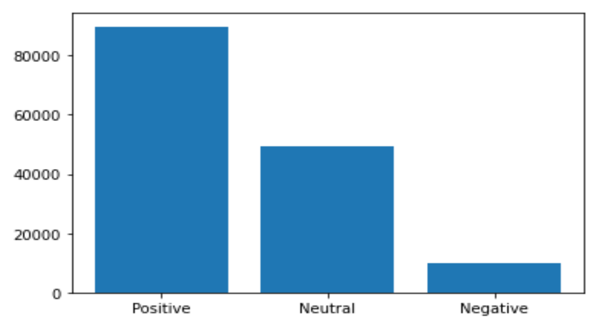

Figure 4. Sentiment Categories of English Tweets

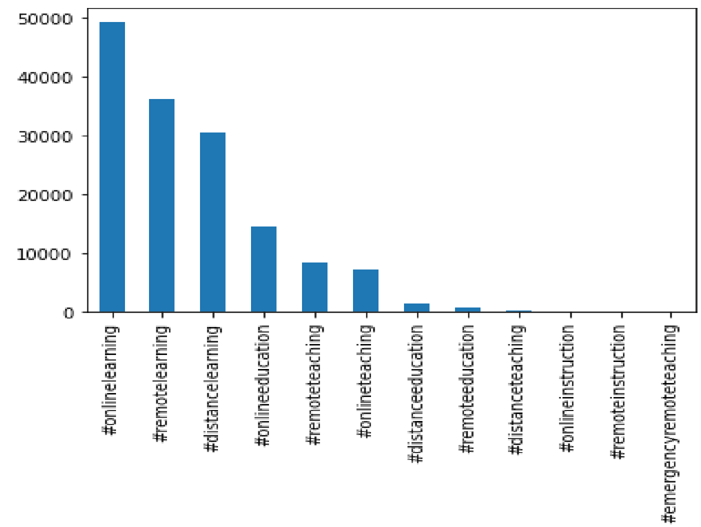

Figure 5. Number of English Tweets per Hashtag

The largest amount of the tweets were retrieved using the hashtag "#onlinelearning", followed by "#remotelearning" and "#distancelearning" (Figure 5) thereby constituting the majority. As for the daily average sentiment scores of English tweets, there was an overall decreasing trend. The lowest average sentiment score was observed on February 28, 2021 and the highest average sentiment score was noted on January 29, 2021.

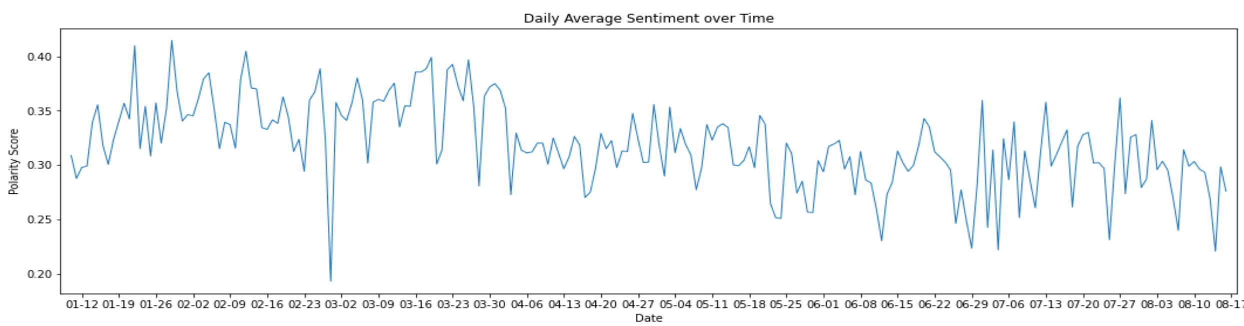

Figure 6. Daily Average Sentiment Scores of English Tweets

Word Clouds: Frequent Terms in Turkish and English Tweets

Word clouds were generated to determine the most frequent terms in Turkish and English tweets (Figure 7). In the English case, not surprisingly, the most frequent terms were "student","teacher", "school", "learn".

Figure 7. Word Cloud Representations of Frequent Terms in Tweets

Technological platforms supporting online learning such as “zoom” and “video” were among the highly frequent terms. Positive terms such as “thank”, “great”, “love”, “support”, “self-improvement”, and ”energy-efficiency” were more common in English tweets. On the other hand, frequent terms (e.g.,uzaktan eğitim, onlineeğitim, yüz yüze) observed in Turkish tweets were mostly neutral. The technologies and platforms used for emergency online education were also present in Turkish tweets (e.g., “eba”, “trt eba”, “ders eba”). Finally, Turkish tweets included opinions about politics and the government or public affairs. For instance, “ziyaselcuk”, name of the former minister of national education, and “meb”, “milli egitim”, and “milliegitim”, short names for the ministry of national education were among the frequent terms in the word cloud.

Topic Modeling Results

Topic modeling of Turkish tweets

Table 1 demonstrates primary topics discussed in Turkish tweets, and their relevant frequent terms as well as the main themes that were created manually using the frequent terms. The terms relevant to the most discussed topic were “eğitim”, “meb”, “uzaktan”, “lgs”,“onlineeğitim”, and “eba” that focused on ministry of national education, its e-school system and their connection to education and online education. The second topic included “eğitim”, “uzaktan”, “online”, “yüzyüzeğitim”, “uzaktaneğitim”, and “bilgi” that were related to learning via distance education and face-to-face education.

Table 1

Primary Topics in Turkish Tweets

Topic No	Topic Contribution of Tokens	Relevant Terms	Main Theme
1	13.7%	“eğitim”, “meb”, “uzaktan”, “lgs”,“onlineeğitim”, “eba”	Ministry of National Education and E-School System
2	12.2%	“eğitim”, “uzaktan”, “online”, “yüzyüzeğitim”,“uzaktaneğitim”, “bilgi”	Learning via Distance education and Face to face education
3	11.8%	“eğitim”, “anaokulu”, “anne”, “bebek”, “okulöncesi”, “ziyaselcuk”	Preschool Education
4	11.2%	“onlineeğitim”, “ders”, “eğitim”, “yksertelensin”,“uzaktaneğitim”, “lgs2021”	Postponing National Entrance Exams
5	10.1%	“uzaktaneğitim”, “eğitim”, “onlineeğitim”, “etkinlik”, “anaokulueğitim”, “kadın”	Preschool Education in Distance and Women
6	10%	“etkinlik”, “eğitim”, “evdekal”, “okulöncesi”, “anne”, “bebek”	Preschool education at home with respect to mothers and babies

7	8.3%	“eğitim”, “onlineeğitim”, “eba”, “uzaktaneğitim”, “sertifika” , “almanca”	Certification and Language learning in Distance education
8	8.1%	“bilgi”, “öğrenme”, “hızlıeğitim”, “uzaktaneğitim”, “kayıt” , “danışmanlık”	Fast learning techniques and Consultation
9	7.5%	“uzaktaneğitim”, “ziyaselcuk”, “onlineeğitim”, “eğitim”, “bilgi”, “etik”	Governmental affairs of distance education and ethics
10	7.2%	“eğitim”, “enstitü”, “sertifika” ,“uzaktaneğitim”, “tv”, “schools”	Certificates, Institutes and TV

Topic modeling of English tweets

Table 2 presents primary topics discussed in English tweets, the most frequent terms associated with them, and the main themes that were determined manually based on the frequent terms.The results of the topic modeling in English tweets indicated that the relevant terms to the most discussed topic were “students”, “teachers”, “school”, “learning”,“teaching”, and “education” that referred to the primary components of education. The second topic was related to terms “esl”, “efl”,”elt”, “tesol”, “tefl”, and “eal” that focused on English as a second or foreign language.

Table 2

Primary Topics in English Tweets

Topic No	Topic Contribution of Tokens	Relevant Terms	Main Theme
1	*18.9%*	*“students”, “teachers”, “school”, “learning”,“teaching”, “education”*	*Components of Education*
2	*16.6%*	*“esl”, “efl”,”elt”, “tesol”, “tefl”, “eal”*	*English as a Second or Foreign Language*
3	*16.6%*	*“education”, “online”,”elearning “onlineclass”, “onlinecourse”, “onlineeducation”*	*Education in an Online Setting*
4	*9.4%*	*“edchat”, “edtech”,”education”, “distincelearning”, “virtualreality”, “virtualteaching”*	*Virtual Education and Educational Technologies*
5	*8.1%*	*“onlinelearning”, ”languages”, “free”, “languagelearning”, “german”, “italian”*	*Language Learning Opportunities*
6	*7.6%*	*“elearning”, “onlinedegree”, ”digitalmarketing”, “business”, “university”, “career”*	*Online Degrees in higher education and its marketing*
7	*6.2%*	*“microsoft”, “teams”, ”workfromhome”, “remoteworker”, “digitalresources”,*	*Remote working, computer literacy and its digital resources*

		“computerliteracy”	
8	*5.8%*	*“affordable”, “certificates”, ”offering”, “diplomas”, “certification”, “tutoring”*	*Certification, diplomas and online tutoring*
9	*5.7%*	*“win”, “homeschool”,”learntocode”, “challenges”, homeschoolingmom”, “self”*	*Home schooling and its challenges*
10	*5.2%*	*“safety”, “productivity”, ”selfimprovement”, “energyefficiency”, “higher”, “webinar”*	*Self-improvement and productivity*

Discussion

In this study, a comparative analysis was performed to examine public sentiments on Twitter towards emergency remote teaching one year after the COVID-19 pandemic between January 10 and August 16, 2021 when mass vaccinations started and became available around the World. This time period is important to check people’s online sentiments because it is when countries became more hopeful to overcome the pandemic due to mass vaccinations and there was an increasing sense of controlling the pandemic while in the early days, the public opinions were dominated by emotions of fear and hopelessness. Such an emotional turbulence was also accompanied by the sudden need to adopt emergency remote teaching in addition to inconclusive discussions on the origins of the pandemic virus and when the pandemic would be controlled. Thus, people’s sentiments towards emergency remote teaching would not be mature enough and not reflect long-term generalizable opinions during the early period.

There were more neutral tweets than positive ones that outnumbered the negative ones in Turkish tweets, and the number of positive tweets was more than the neutral ones and far exceeded the negatives in English tweets. Namely, people’s sentiments towards emergency remote teaching were mainly neutral or positive. As the vaccination efforts continued, schools started to open in some countries across the World, which seems to have positively influenced people’s sentiments towards emergency remote teaching. However, the sentiments are not completely positive either, suggesting that especially Turkish people may have felt that there were both advantages and disadvantages of emergency remote teaching. For instance, emergency remote teaching did not have the face-to-face interaction or communication opportunity that most people would prefer; however, it provided a more secure opportunity to get involved in education. In other words, people may have understood and accepted the tradeoff between two aspects of emergency remote teaching: being less risky vs. lacking affordances of face-to-face education.

Most Turkish tweets were neutral followed by positive ones and negative ones respectively. This finding is surprising given that (a) Turkey had large-scale internet connection and/or band width issues as well as issues related to national e-school system or national education informatics network (a.k.a., EBA) (e.g., Dogan & Kocak, 2020); (b) average sentiment scores fluctuated significantly; and (c) discussions in Turkish tweets also touched on politics and government. Turkish tweets also focused on neutral terms including technologies thereby aligning with the dominance of neutrality. As for English, there were more positive tweets than neutral and negative ones.

Accordingly, despite all issues, emergency remote teaching may have continued to be regarded as a viable option in Turkey and beyond. After all, even though distance education may not replace some face-to-face affordances of in-person education, it has many advantages including accessibility that can let people learn during crises (Pregowska et al., 2021).

Both English and Turkish tweets contained more neutral and positive sentiments than negative ones, which is in contrast with such earlier findings as parents' negative perceptions of online education at the preschool level (e.g., Konca & Cakir, 2021) or teachers' concerns (e.g., Duran, 2021). Further, English tweets outnumbered Turkish ones in terms of positive content, and Turkish tweets consisted of proportionally more neutral and negative sentiments. This point further suggests that more people tweeting in Turkish chose to stay neutral and expressed their negative sentiments, and more people tweeting in English had positive sentiments towards emergency remote teaching. This insight further aligns with the finding that there were more neutral Turkish tweets than positive ones, which was the opposite for English tweets.

All these findings are also in tandem with what the word cloud analysis revealed: English tweets included a more positive content consisting of support and motivation, and people may have had a tendency to focus on technologies in both Turkish (e.g., eba, trt eba) and English (e.g., zoom, video) tweets. This last point suggests that specific technologies used may have influenced people's sentiments toward emergency remote teaching.

The lowest average sentiment scores for Turkish tweets coincided with the dates when the number of daily cases increased and national lockdowns, which is understandable given that such periods may have demotivated people. Overall, the average sentiment scores of all tweets fluctuated more starting in May 2021 and continued until August 2021. However, from January to April 2021, the average sentiment scores of English tweets fluctuated while the sentiment scores of Turkish tweets stayed more stable. In other words, people's emotional reactions to the pandemic had more ups and downs during summer 2021. Interestingly though, the average sentiment scores of English tweets were higher, and did not decrease as much as those of Turkish tweets. Those sudden increases (more positive) and decreases (more negative) in the average sentiment values of the tweets posted on a given day may have been caused by a social event, news, or any other factor that happened around that day, which is beyond the scope of the current paper. All these findings align with the earlier observation that more Turkish tweets were more neutral or negative than the English ones that were more positive content.

As for topic modeling results, the most common two topics covered in Turkish tweets focused on the ministry of national education and its e-school system as well as learning via distance education and face-to-face education using terms such as "onlineeğitim, yüzyüzeğitim, and uzaktaneğitim", which was in line with word cloud results.While the first largest topic, components of education, for English tweets was based on very similar terms (i.e., students, teachers, school, learning, and teaching) produced by the word cloud analysis, the second topic was English-as-a-second or foreign language education and it was based on different terms (e.g., esl, efl, tesol). This focus on English as a second or foreign language education suggests that English tweets were also coming from people for whom English was a second or foreign language. Namely, it seems that English tweets originated from not only English speaking countries most of which had access to COVID-19 vaccines earlier but also from non-English speaking countries, thereby increasing the generalizability of the current findings.

It is also interesting to compare the topics covered in Turkish and English tweets in terms of main themes. While the main theme of the number one topic for Turkish tweets was the ministry of national education and its e-school system, the main components of education was the overarching theme for English tweets. Given that Turkish tweets also had more political and government-related content, which is consistent with previous research showing that political tension is a common theme covered in tweets (e.g., Eutsler el al., 2020), it is no surprise that the most frequently discussed topic's main theme was related to the national education ministry that was a governmental unit. In the second topic, Turkish tweets switched to discussing distance and face-to-face education, while English tweets were mainly about English as a second or foreign language. This is also understandable given that English is the largest lingua franca in today's World and most people prefer it as a second or foreign language for different purposes. The other main themes including language learning opportunities, and higher education online degrees and its marketing also support this point. Discussing online education as a main theme was relevant to the third most common topic for English tweets that was still relevant to language learning and other associated main themes including homeschooling and its challenges, and certificates, diplomas and online tutoring.

The third main theme was preschool education for Turkish tweets and the fifth one was distance preschool education and women. Relevantly, the sixth largest topic's main theme was also about preschool education at home, mothers and babies. This finding implies that one of the educational levels where the impact of the pandemic was significant in Turkey was preschool education, which refers to concerns related to emergency remote teaching in this area. Given that students can be enrolled in preschool until the age of 5.5 years in Turkey (Goksoy, 2017), the concerns are understandable. This finding concurs with (a) the important role of distance education, technology, teacher professional development, and the cooperation between teachers and families in early childhood education (e.g., Alan, 2021); (b) the research showing that emergency online education had both advantages and disadvantages at the preschool level (e.g., Akkas-Baysal et al., 2020); and (c) the pandemic's overall impacts on preschool education in Turkey (e.g., Duran, 2021; Inan, 2020; Konca & Cakir, 2021). However, the focus on preschool education was not evident among the main themes for English tweets. Rather, English tweets' main themes were much more related to education in general, online higher education, language education, and virtual education and educational technologies.

Another big concern and the main theme of the largest topic for Turkish tweets was postponing national entrance exams for high school and university education that did not show up for English tweets. This last point implies that people in Turkey were worried about the upcoming national exams and how to handle them in emergency remote teaching, which is based on the high-stakes nature of these exams. Specifically, planning for and implementing emergency remote teaching would be much more effective when people's socio-economic and educational needs are taken into account. Ewing and Cooper (2021) highlighted that when lessons learned regarding pedagogy and instructional design keep up with technology, what we have been learning from the pandemic would be much more informative and have more long-term benefits. Consequently, solutions to sudden health crises including online education should be based on a systemic and comprehensive approach that covers the society's political, academic and socio-economic dynamics as well as pedagogy and instructional design to enhance learning and prevent learning loss.

Limitations and Recommendations for Further Research

We manually selected the target hashtags by carefully reviewing numerous potentially related hashtags and tweets to the best of their knowledge and observations. However, it is still possible that the search might have omitted some related tweets with the target hashtags. Moreover, there was a great deal of spam and irrelevant advertorial tweets marked with the target hashtags, which is common in social media. We did our best to clean the dataset by removing unrelated tweets.

In topic modeling, identifying the unique main topic of tweets is challenging as tweets might contain opinions about multiple topics and the output of LDA topic modeling can have terms related to multiple topics. For instance, the terms such as “education”, “online”, “student”, “school”,“learning”, “teaching” in English and “eğitim”, “uzaktan”, “online”, “öğrenci”, “okul”, “öğrenme”, “öğretim” in Turkish were present in multiple topics. While this makes it difficult to interpret the results, it is a general aspect of topic modeling.

Finally, this study focused on tweets collected in Turkish and English for a comparative analysis. English is a globally spoken language and Turkish is mainly spoken in a country. Therefore, English tweets are not location specific and may not reflect general sentiments about online education regarding specific countries. Specifically, the findings in the study cannot be generalized to other languages, and the sentiment analysis and topic modeling results may vary for different languages. As a result, future research may focus on tweets that are (a) marked with more hashtags determined by a larger research group; and (b) posted in more languages.

Conclusions

In this comparative sentiment analysis, both Turkish tweets and English tweets incorporated more positive than negative sentiments. Average sentiment scores of Turkish tweets was closer to zero and stable while those of English tweets decreased over time and remained mainly positive or above zero. Accordingly, English tweets were more positive, and Turkish tweets were more neutral, and tweeters largely presented neutral or positive sentiments towards emergency remote teaching when large-scale vaccinations became available. Namely, implementing large-scale vaccinations against health threats such as pandemics would motivate people and its positive impact may also hold true for people’s opinions about educational interventions employed.

Positive sentiments in English tweets included more supportive and motivating insights while Turkish tweets were more neutral, focused on educational technologies and included political content. English tweets focused on English as a second or foreign language education, online education and educational technologies. Lastly, preschool education was a very common topic covered by Turkish tweets possibly due to the fact that preschool education was greatly impacted by the pandemic and emergency remote teaching. Consequently, systemic solutions owned by all stakeholders including policy makers, teachers, parents and administrators would work better during times of disruption, which would enhance people’s sentiments towards them.

Ethic

We declare that the research was conducted in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Author Contributions

This article was written with the joint contributions of three authors.

Conflict of Interest

There is no conflict of interest in the research.

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