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Methods for Assessing the Psychological Tension of Social Network Users during the Coronavirus Pandemic and Its Uses for Predictive Analysis

Aida Khakimova [1,*], Oleg Zolotarev [1], Bhisham Sharma [2], Shweta Agrawal [3,*] and Sanjiv Kumar Jain [4]

1 Institute of Information Systems and Engineering Computer Technologies, Russian New University, Radio St. 22, Moscow 105005, Russia; ol-zolot@yandex.ru
2 Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura 140401, Punjab, India; bhisham.pec@gmail.com
3 Institute of Advance Computing, Sage University, Indore 452001, Madhya Pradesh, India
4 Department of Electrical Engineering, Medi-Caps University, Indore 452001, Madhya Pradesh, India; sanjivkumar.jain@medicaps.ac.in
* Correspondence: aida_khatif@mail.ru (A.K.); shweta.sagecse@gmail.com (S.A.); Tel.: +7-905-372-96-15 (A.K.)

Abstract: This article address approaches to the development of methods for assessing the psychological state of social network members during the coronavirus pandemic through sentiment analysis of messages. The purpose of the work is to determine the psychological tension index by using a previously developed thematically ranked dictionary. Researchers have investigated methods to evaluate psychological tension among social network users and to forecast the psychological distress. The approach is novel in the sense that it ranks emojis by mood, considering both the emotional tone of tweets and the emoji's dictionary meanings. A novel method is proposed to assess the dynamics of the psychological state of social network users as an indicator of their subjective well-being, and develop targeted interventions for help. Based on the ranking of the Emotional Vocabulary Index (EVI) and Subjective Well-being Index (SWI), a scheme is developed to predict the development of psychological tension. The significance lies in the efficient assessment of the fluctuations in the mental wellness of network users as an indication of their emotions and a prerequisite for further predictive analysis. The findings gave a computed value of EVI of 306.15 for April 2022. The prediction accuracy of 88.75% was achieved.

Keywords: sentiment analysis; n-gram; Twitter; emoji; social networks; COVID-19

check for updates

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1. Introduction

The outbreak of COVID-19 was accompanied by an "infodemic"—an over-abundance of information about the outbreak [1]. There has been both a surge in scientific publications [2] and an increase in the number of discussions on social networks. The Twitter dataset provides a wide range of relevant information related to user behavior, emotions, and opinions about world events [3]. Researchers have explored methods to assess the psychological tension of social network users and predict psychological distress during the pandemic [4].

Machine learning [5] is widely being used to predict psychological distress among social network users. A study by Ahmed et al. [6] analyzed Facebook posts to predict anxiety and depression among users during the pandemic. Researchers have also used sentiment analysis to examine the psychological tension of social network users. Hossain et al. [7] examined the sentiment of tweets related to COVID-19 and found that negative sentiment was associated with higher psychological distress among users.

Text analysis of a tweet corpus is complicated by the fact that tweets are very short messages, often combined with images, videos, and emoticons, and text analysis is not as obvious as on other corpus types [8].

Twitter sentiment analysis starts from scanning the tweets for hashtags to collect all related data. The next step is to pre-process and clean up the tweets. Then, the tweets are analyzed depending on the specific purpose. Sentiment analysis uses a list of words associated with strongly positive or negative sentiment [9]. Budiharto and Meiliana [10] used polarity as the difference among the list of positive and negative words in every text separated by the total number of sentiment words when predicting presidential elections.

The simplest tone dictionary is a list of words with a sentiment value for each word [11]. The Russian language is rarely used for tonal analysis research [12,13]. However, a method for extracting Russian vocabulary [14] was designed for grammatically correct media texts and not for Internet content. To determine public opinion in Russian texts, a Tone Dictionary was developed [15].

Previous studies have suggested that NLP (Natural Language Processing), machine learning [16], and sentiment analysis [17] are effective methods for assessing psychological tension of social network users during the coronavirus pandemic. These methods can provide insights into the emotional state and language use of individuals on social networks during the pandemic. This can be used in predictive analysis to identify individuals or groups at higher risk of psychological distress and develop targeted interventions to help.

Despite the promising results, there are limitations to these methods. For instance, NLP may not capture the nuance of human language, and machine learning algorithms may suffer from over fitting or bias problems. Therefore, it is crucial to develop reliable and validated methods for assessing psychological tension of social network users during the pandemic.

In view of the mentioned limitations, this research is aimed at creating methods for determining “emotional charge” of user-generated Internet content, as well as creating predictive models for assessing the psychological and social well-being of the population in the context of the coronavirus pandemic.

The research here proposes to examine the interaction between emoji and text. Additionally, based on the previous studies, the following three hypothesis were formed.

The first hypothesis is that emoticons affect their accompanying texts depending on the valency. Positive emojis make the message more positive, while negative emojis make it more negative [18,19].

Looking at the valency of emoticons used, Derks et al. [20] reported that the valence of emoji corresponded to the valence of the context, suggesting that emojis reflect the valence of the context, and serve to clarify the valence of the message (second hypothesis).

The third hypothesis is that the repetition of emojis enhances the emotional valence of the message. Based on this hypothesis, this article proposes a method for calculating the IPTt (Index of Psychological Tension for tweet) indicator.

The approach proposed in this article has the following features:

- A five-rank scale is used to assess the emotional charge of terms and emojis;
- Emojis are considered, with a multiplying factor used when using multiple identical emojis;
- Parameters can be applied both at the level of a tweet and at the level of an array of tweets.

The objectives of this research work are as follows:

i. Analysis of collections of tweets using proprietary software for highlighting tonal words about socio-psychological accounting;
ii. Creation of a tonal dictionary of terms (with assignment of a rank and type of tonality);
iii. Development of methods for assessing the psychological state of social network users based on sentiment analysis of messages;
iv. Creation of methods for assessing the dynamics of the psychological state of network users as a reflection of their subjective result;
v. Creating a methodology for analyzing the predictive accounting for psychological heightened severity, with the mood of tweets and pandemic indicators.

The proposed dictionaries contain not only ranked terms, but also ranked emojis and text emoticons. The dictionaries contain all detected word forms with a common root, including abbreviations, intentional change in the spelling of words.

2. Related Work

Article [21] shows that English is the dominant language used in sentiment analysis studies. Most authors have studied texts in English. The text of bilingual documents (in English and other languages) was translated into English to extract the useful information.

A study by Chen et al. [22] analyzed over 100 million tweets related to COVID-19 and found that the dominant sentiments were negative, with fear being the most prevalent emotion. The study also found that there was a significant increase in negative sentiments during the early stages of the pandemic. Similarly, a study by Almishal et al. [23] analyzed over 60,000 tweets related to COVID-19 and found that the dominant sentiment was anxiety, followed by sadness and anger. The study also found that there was a significant increase in negative sentiments as the number of COVID-19 cases increased.

Study by Abdel-Basset et al. [24] analyzed over 400,000 tweets related to COVID-19 and found that the dominant sentiment was negative, with fear being the most prevalent emotion.

Cao et al. [25] used sentiment analysis to evaluate the emotional state of social network users during COVID-19. The study analyzed over 6 million Weibo posts related to COVID-19 and found that negative emotions such as anxiety and anger were prevalent among social network users.

Li et al. [26] used topic modeling to identify the key topics discussed by social network users during COVID-19. The study analyzed over 2 million Weibo posts related to COVID-19 and found that topics related to health, the economy, and government policies were prevalent. The study also found that the level of discussion of these topics was associated with the psychological tension of social network users.

A study by Liao et al. [27] used network analysis to examine the social network structure of Twitter users during COVID-19. The study analyzed over 1.6 million tweets related to COVID-19 and found that users who were more connected to others in their network reported lower levels of psychological tension. Gao et al. (2021) analyzed tweets to identify the emotional state of social media users during the pandemic [28].

Samuel et al. [29] analyzed the text of tweets in the United States during the COVID-19 peak to track the evolution of the fear–panic–despair triad associated with COVID-19. Bhat et al. [30] examined the positive, neutral, and negative sentiments of tweets related to the spread of COVID-19. Lwin et al. [31] studied global Twitter emotional trends in relation to the pandemic by applying a lexical approach and the Crystal-Feel algorithm to four emotions (fear, anger, sadness, and joy).

An exploratory study and sentiment analysis on a big dataset about the COVID-19 pandemic focusing on the Omicron variant was proposed by Thakur N. et al. [32]. The role of Twitter during the COVID-19 pandemic in spreading information and misinformation was presented through sentiment analysis [33].

The researchers proposed various indices to measure the sentiment of tweets. For example, the Sentiment Index represents the proportion of the difference of positive emotions and negative emotions to the totality of positive emotions, negative emotions, and neutral emotions of users [34,35].

Gann et al. [36] chose 6799 tokens based on Twitter data, and each token was assigned a sentiment score, specifically the *TSI* (Total Sentiment Index), indicating whether it is a positive or negative token:

$$TSI = \frac{p - \frac{tp}{tn} \times n}{p + \frac{tp}{tn} \times n} \tag{1}$$

where p is the number of occurrences of a token in positive tweets and n is the number of occurrences of a token in negative tweets. Furthermore, tp/tn is the ratio of total positive tweets to total negative tweets.

The Sentiment Index was used to analyze and forecast customer changes and feelings over time [37]:

$$SI = \frac{P - N}{P + N + N^t} \quad (2)$$

where P denotes the number of positive tweets, N the number of negative tweets, and N^t the number of neutral tweets.

Sentiment Score assesses a good or negative statement in a text or document [38]. Ratings can be given on a scale of 0 to 10, with 0 indicating a negative score, 4 indicating neutral, and 7 indicating a good score. In general, the sentiment score is defined as the weighted average of the document's sentiment score [39].

Panchenko [40] evaluated Russian-language texts on Facebook using various methods. The Word Sentiment Index is a measure of the proportion of positive to negative terms in all texts (posts and comments). The Text Sentiment Index (*TSI*) is a ratio of positive to negative texts in a corpus. The Word Emotion Index is a ratio of emotional (positive or negative) words in the corpus of texts. The Text Emotion Index is a ratio of positive and negative texts in the corpus. Two approaches concentrate on emotive terms, while the other two concentrate on text classification.

During the coronavirus pandemic, researchers analyzed public opinion, emotions, and sentiment in social media posts. Twitter is one of the best social networks for gathering news [41]. To analyze sentiment in India [42], visualization methods were used—a word cloud and a graphical representation of emotions. Rustam et al. extracted tweets related to COVID-19 and visualized people's moods by dividing tweets into positive, neutral, and negative [43]. Naseem et al. when analyzing opinions about COVID-19, each tweet is marked as positive, negative, or neutral [44].

Zhang et al. [45] suggested a sentiment classification system that organizes opinion terms in the WordNet lexical method dataset to categorizing text at the sentence level rather than the document level.

Sanders et al. examined one million tweets to gauge public opinion on the usage of masks as a preventive approach during the COVID-19 epidemic [46]. Based on Twitter data, NLP was utilized to analyze the increase in the frequency of positive tweets, as well as perform topic clustering and visualization.

Jalil et al. [47] conducted a statistical analysis of keyword trends in the corpus of tweets about the coronavirus disease pandemic and analyzed the sentiment of the collected tweets using various feature sets and classifiers.

3. Materials and Methods

A technique for sentiment analysis of tweets based on English-language tweets is proposed. The technique is based on ranking of emotional words and emojis. To determine the tone of tweets, experts created dictionaries of ranked words and emojis (emotional components, elements). A five-point system (-2, -1, 0, +1 or +2) was chosen to determine the degree of emotional charge of dictionary elements, and each element of the dictionary was assigned a degree of emotional charge.

Tweets were collected in Excel format, using the Vicinitas API, while marking up the texts of tweets by words and by the tweets themselves. Next, the text processing system was used to extract terms from tweets, and the addresses of occurrences of terms were saved. After that, the terms were normalized; a separate list of normalized terms was created, including the address of the term in its original form.

The list of stop-words was used to filter the list of selected words. A large number of stop-words have been created. The biggest challenge in extracting keywords from tweets using the standard set of python stop-words (the standard set comprises only conjunctions, interjections, etc., which were eliminated from consideration) was similar to “noise”, namely, many words that are unrelated to the explored topic. Categories of stop-words were added based on expert analysis (place names, dates, days of the week, names of months, proper names, names of institutions, positions, and so on). New stop-words were added to the collection on a regular basis.

Then, the list of terms was processed by an expert with the assignment of ranks according to the emotional scale. The list of terms in the database includes the following elements: term, its rank, synonyms, abbreviations, derivatives, informal spellings. This makes it possible to compare the different representations of the same term with its main meaning and eliminate errors in determining the frequency of use of the term in messages.

Tweets often use informal notations for common words. After analyzing the tweets, following categories of spelling errors are identified.

Internet memes (Lol), slang (kinda, wonna, outta), informal abbreviations (government as gov’t, gvnt; children as cdns; kid as kd; years as yrs; season as szn; month as mths; COVID as cvd), informal spellings (because as cuz, bc, bec; you as u; no as *n*;), repeating letters in a word (dieeeeee, knowwww), hiding informal vocabulary (fwcked, fkg, fking), informal exclamations (ummmm, ew).

These distortions were considered when extracting terms from tweets by comparing them with the correct form of the words. Some categories of word distortion were used to add emotion to the text of tweets, such as letter repetition, informal vocabulary, and informal exclamations. This was considered when assessing the emotionality of a tweet.

In addition, the emotionality of tweets is enhanced using emojis. A list of emojis was compiled and ranked on a five-digit emotional scale. When assessing the emotionality of a tweet, ranks of the words (in various spellings) and emojis were considered. Then, an additive evaluation of the “emotional charge” of each tweet was performed and the average value of the evaluation for the collection of tweets was calculated. An Index of Psychological Tension (IPT) is proposed. IPT is calculated as the sum of the ranks of emotionally charged words and emojis for each tweet:

$$IPT_t = \frac{\sum r_t + \sum (e_t \times k)}{n_w} \tag{3}$$

where, IPT_{t}—Index of Psychological Tension for the tweet, r_t—ranks of the emotional words in tweet, e_t—ranks of emojis in tweet, k—enhancing coefficient:

$$k = r + (m_e - 1) \times 1.25 \times r) \tag{4}$$

m_e—number of emoji repeats.

For the collection of tweets, the proposed equation to evaluate the average (IPT_{av}) is:

$$IPT_{av} = \frac{\sum IPT_t}{n_t} \tag{5}$$

where, IPT_{av} is Index of Psychological Tension for collection of tweets, n_t—number of tweets in the collection.

Data for research (Results, Section 1) were downloaded from Twitter from 22 April 2022 to 30 April 2022). Data for research (Results, Section 2) were downloaded from Twitter from 1 January 2021 to 31 January 2023). Data for research (Results, Section 3) were downloaded from Twitter from 20 November 2021 to 8 December 2021). These time periods were chosen such that they were comparable to the average incidence rate (excluding periods of sharp spikes in incidence) (Results, Sections 1 and 3). The period of pandemic development was chosen (excluding the initial period of the pandemic development and the end period) (Results, Section 2). The upload was carried out using the analytical mechanisms of Twitter (https://www.vicinitas.io/) (accessed on 22 March 2023). This allows for uploading the Tweet Id, Tweet Type, hashtags, User Id, Name, location. Vicinitas is an effective way to import tweets using Twitter's streaming API. Vicinitas allows us to search and display up to 2000 tweets for free. The results have been integrated into Microsoft Excel to remove duplicate content [45]. The whole procedure took place in real time. This research contains 7830 English tweets (including retweets) (Section 1), 4771 English original tweets (Section 2), and 4024 Russia original tweets (Section 3).

For the automated calculation of the IPT, a set of programs in the python language was developed, which implemented the following functions:

- Building a corpus of tweets based on the created database structure in sqlite3, including the tweet body, author, geographic label, creation date, tweet type;
- Extracting of terms from tweets, the address of the occurrence of the term in the tweet is simultaneously fixed for navigation through terms to analyze their context;
- Expert assessment of the degree of emotional charge of terms with the setting of ranks on a scale of "−2, −1, 0, +1, +2" (from strongly negative to strongly positive) and the assignment of expert ranks to terms in the database;
- Calculation of IPT based on the calculation of the additive rank of the terms in tweets, considering their frequency, and outputting the results to an excel table.

The predictive analysis method assumed that, in tweets discussing the coronavirus, the main emotions are related to the coronavirus disease. The emotional background of people was undoubtedly influenced by reports of morbidity and mortality during the pandemic, illness, and death among the social circle. From the published indicators of the coronavirus pandemic, the considered indicators were: (1) the average mortality per week (for the period of publication of the tweets of the collection); (2) the average incidence per day (over the period of publication of the collection); (3) average increase in incidence (thousand people) for 4 months prior the period of publication of tweets. Then, a search was made for the correlation of these indicators with the results of sentiment analysis of tweets. The predictive analysis technique was tested on Russian-language messages related to the coronavirus from Twitter for the periods March–April, July–August, and November–December 2021.

Collections of user messages from the tweets were prepared for different periods of time (Table 1).

Table 1. Characteristics of collections of Russian-language tweets for different periods of time.

Period	Collection 1	Collection 2	Collection 3
	From 28 March 2021 to 26 April 2021	**From 30 June 2021 to 31 August 2021**	**From 20 November 2021 to 8 December 2021**
Number of tweets	17,869	12,481	6245
Number of original tweets	14,223	6958	3755
Number of Russian-language tweets (after the removal of other Cyrillic languages)	12,604	6513	3495
Number of tweets (after the removal of pandemic updates and news)	3947	2714	2480
Number of tweets after filtering (removing incoherent answers)	1741	1182	1101

A method of predictive analysis of the growth of psychological tension was created, based on the rankings of the IPT. The predictive analysis technique included the following sequence of steps: (1) Preparation of collections of tweets for different periods of time; (2) Expert compilation of dictionaries of both negatively and positively colored vocabulary, selected from the collections; (3) Machine calculation of the modification of the IPT coefficient into the Emotional Vocabulary Index (EVI) as the ratio of negative to positive vocabulary for each array, per 1000 messages; (4) Graphical representation of the calculation results; (5) Choice of an indicator characterizing the pandemic, which correlates with the EVI; (6) EVI forecast.

To assess the dynamics of the psychological state of social network users as a reflection of their subjective well-being, this article proposes to define the value of the Subjective Well-being Index (*SWI*) of messages for a certain period (year, month, and week).

The *SWI* was calculated using the formula:

$$SWI = \frac{N_{negative}}{N_{positive}} \times \frac{100}{n}, \tag{6}$$

where, $N_{negative}$ is the number of negative tweets, $N_{positive}$ is the number of positive tweets, n is the total number of tweets. Negative and positive tweets were ranked by IPT.

The Emotional Vocabulary Index (*EVI*) was calculated for a collection of tweets. It is equal to the ratio of negative to positive vocabulary (including emojis) per thousand tweets:

$$EVI = \frac{\sum m_{negative}}{\sum m_{positive}} \times \frac{1000}{n}, \tag{7}$$

where, *EVI* is Emotional Vocabulary Index, $m_{negative}$ is the number of negative words in collection of tweets including emojis, $m_{positive}$ is the number of positive words in collection of tweets, including emojis, and n is the number of tweets.

4. Results

4.1. Index of Psychological Tension

To test the method of automatic calculation of the *IPT* indicator, words, and expressions on the topics "Reproductive health and coronavirus (COVID)" and "Reproductive health and vaccine" were included in the dictionary of terms (first dictionary) (Table 2) and the dictionary of emojis (emoji dictionary) (Table 3). All these words and emojis were extracted from a collection of tweets containing the keywords (hashtags): "COVID, fertility", "COVID, infertility", "Coronavirus, fertility", "COVID, sterility", "Vaccine COVID Fertility".

Table 2. Examples of ranked terms and phrases from tweets discussing infertility and corona virus.

Rank	−2	−1	+1	+2
1	Brain fog	affected by the SARS-Cov-2	brag	Amazing
2	Bitch	Affecting	boom	Best
3	Apocalyptic	affects	better	Does not
4	Abnormally shaped sperm	Affect sperm quality	avoid	Enjoy
5	Affected	aggravated	adequate	Excellent
6	Alarm	Bad	alright	Good reason
7	Annihilation	Adverse reaction	amusing	Great
8	Cancer	Affect	Have babies	Hope

Table 2. *Cont.*

Rank	−2	−1	+1	+2
9	Catastrophic	Affect fertility	having a baby	Love
10	Chaos	Affect fertility	effective	Luck
11	Clot	Affect of	excites	Safe
12	Control of the population	abortion	Good	Safely
13	Crap	Alter	gratitude	Safety
14	Crisis	autism	care	Save
15	Decreased motility	anti-fertility	insight	Saving lives
16	Decreased sperm	bump	inspiration	
17	Deformed sperm	Came down	interesting	No evidence
18	Dead	Can cause	Ironic	No indication
19	Death	Can impact	irony	No link
20	Decimating	Can lead	help	Recover
21	Culprit	Can mess	How ironic	Stay alive
22	Damage	Being sick	improved	Survivor
23	Destruction	Birth defect	increased	Thanks
24	Die	catch COVID	mitigation	Truth

Table 3. Examples of ranked emojis from tweets discussing infertility and coronavirus (adapted from https://www.emojiall.com/ru/search_results?keywords= (accessed on 27 March 2023)).

Rank	−2	−1	+1	+2
1	feces	surprise	new moon, self-irony	glows with happiness
2	monster	confused	relieved	laughing to tears
3	skull and bones	don't care	crystal ball, divination, wealth	rolling with laughter
4	in a cold sweat	bored	winking	smiling face with hearts
5	censorship	grimace	shows tongue and winks	laughs with closed eyes
6	angry	without emotion	laughing nervously	I love you
7	speechless, no words, irritation	I don't see anything	prayer, remembrance	stars in the eyes, admiration, enthusiasm
8	speechless	shrugs	smiles pretty	sunshine, positive attitude
9	tears flowing	disappointment	raised fist, strength, power	at a party
10	horrified	thinking	slightly smiling	scarlet heart, love
11	brain explosion	blushing	full moon smiles, self-irony	orange heart, vitality
12	vomiting	confused	grinning	sparkling heart, love
13	crying	a little sad	everything is fine	loving face
14	shocked	silence and disappointment	delicious	thumb sup
15	biohazard	grinning	in a cowboy hat, freedom, fun	laughing

For a collection of 1380 original tweets (excluding retweets) on the topic "Reproductive Health and Coronavirus", IPT = −0.172 (Equation (5)). At the same time, for 4610 tweets (including retweets), IPT = −0.183 (Equation (5)). A comparison of these values suggests that tweets with negative content are often re-tweeted.

For the collection of tweets on the topic "Reproductive Health and Vaccine", for 990 original tweets IPT = −0.12. For 3220 tweets (including retweets), the IPT = −0.07. Consequently, positive tweets (often messages about vaccine safety) are circulated as retweets.

Negative IPT values indicate that discussions about coronavirus and fertility are dominated by negative assessments that accompany judgments that coronavirus causes infertility. The differences between IPT values calculated from original tweets and those calculated from retweets can help to identify trends in the spread of judgments of a particular tone.

4.2. Index of Subjective Well-Being

The Twitter user @e****** (Ottawa, ON, Canada) was randomly selected. The user's 4771 tweets were downloaded for the period from January 2021 to January 2023. A lot of tweets were divided into arrays for each month (Tables 4 and 5). SWI values were calculated per each month (Equation (6)). The SWI values were compared with the incidence during the COVID-19 pandemic and the monkey pox outbreak 2022 (the calculation was performed based on the data of [47–49]). The results are presented in Figure 1.

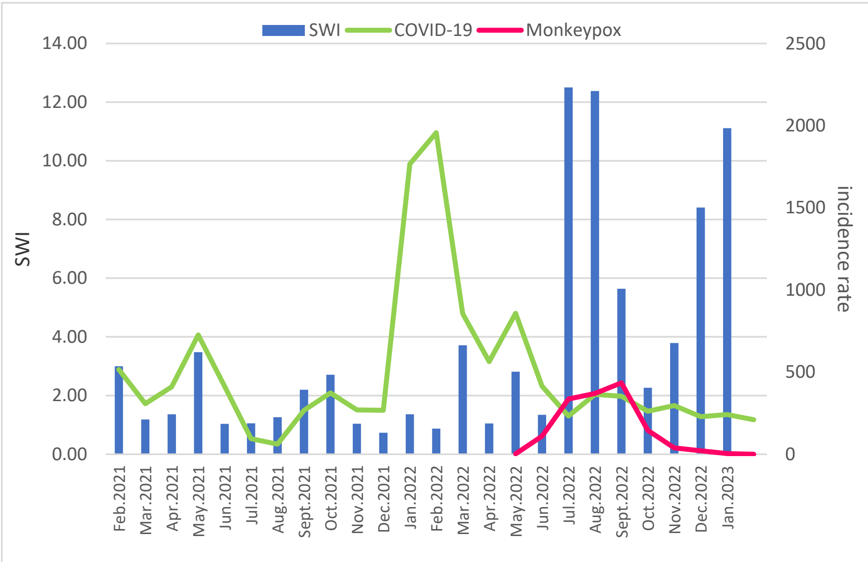

Figure 1. SWI results from Twitter user @e****** (Canada) for the period from January 2021 to January 2023 compared to cases of COVID-19 (average weekly incidence of COVID per month, one tenth) and monkey pox (cases per month) in Canada.

Over the entire observation period, positive tweets only prevailed over negative ones in July 2021. In February, May, September, and October 2021, there is a similar level of negativism in tweets with the incidence of COVID. For example, a surge of negative sentiment in May 2021 was due to the following facts: the death of residents of two nursing homes in Ontario, who were badly affected by the corona virus, dehydration, and neglect [47] (terms—terrible, died due to dehydration); deaths of colleagues and friends [48,49] (terms—we lost a colleague, my anger goes to a govt, tragically, miss).

In January–February 2022 surges of negativity are due to the Freedom Convoy, protests in Canada that began with a protest of truck drivers against vaccine passports. In July–August 2022 the negativity is associated with health problems in Canada and the outbreak of COVID (terms—depressing, COVID19′s Omicron 'tsunami', staffing crisis, ER crisis, impossible workloads). The mention of an outbreak of monkey pox is in June. In December 2022–January 2023, the negativity was associated with the COVID crisis in children's hospitals (terms—child will never grow up, children's hospital crisis, the poorest health and well-being outcomes for children and youth), and the oppression of women in Afghanistan (terms—Suicidal, indefensible, Afghan women will die, imprisoned at home).

Table 4. Examples of negative/positive words and collocations of tweets from Twitter user @e****** (Canada) for the period from January 2021 to December 2021.

Month	Negative Words and Collocations (1)	Positive Words and Collocations (2)	Number of (1)	Number of (2)	Number of Tweets
January	Deaths, heartbreaking, died, humanitarian crisis, killed, desperately, heavy damage, 💔	Hope, Proud, happy, amazing folks, Vaccines are powerful, thankful	33	17	55
February	Enemy, dies with corona virus, death, racial inequality, Shocking, unfair, killed, wrong direction, very scary	Brave, great, loved, Hope, save lives, brilliant	33	10	110
March	Death, "alarming rates", scandal, deeply saddened, extreme stress, Heartbreaking, dies of COVID-19	Amazing, positive impact of vaccines, hope, 🙏	61	28	184
April	😢, will die, much worse, dies of #COVID19, so much alarm, very bad, policy failure tsunamis, desperate time, disaster, 😯, shocking	Hope, hopefully, helpful, beautiful tribute, 🎉, very good vaccine	104	32	239
May	Terrible, died due to dehydration, lost a colleague to #COVID19, 💔, have died, tragically burned down, broken-hearted	Hoping, terrific work, great picture, braving, 😃	81	17	137
June	Horror, sadness, shock, All dead, life too fragile, COVID crisis, bad idea, very frustrating, deaths	Great progress, Grateful, great news, Amazing, highly effective, good day, ❤️	56	40	135
July	Dangerous, epidemiological stupidity, victims, unfortunately, 😷, 😕, insane, One of the scariest things, Shocking	Brave, love, Beautifully, super nice, wonderful story, help keep everyone safe, help save lives	23	27	81
August	Deaths, 💩, anxiety, crying, sadness, died, suffer, dangerous, troubling, died of #COVID19, hell	Helping, ❤️, safety, save lives 🙏, amazing	48	32	119
September	stressed, burnt out, disbelief, saddened, dangerous, deaths, tragic, disheartening, terrifying, 🤬	Help, wonderful, kindness, safety	96	28	156
October	die alone, scary, crisis, horrifying inequity, died, Saddened, COVID-19 deaths, tragic loss	Hope, help, enjoying, beautiful, excellent	39	18	80
November	Death, killed, 🤦 ♀, shocking, dead, died from COVID, 😕, Disappointing, serious risk	helped save people, Help, fabulous, grateful, Hope	66	36	176
December	Died, vaccine inequity, dangerous, stress, deeply troubling, worrisome, maddening, unacceptable	Incredible, wonderful, hoping, help, careful	110	51	295

Table 5. Examples of negative/positive words and collocations of tweets from Twitter user @e****** (Canada) for the period from January 2022 to January 2023.

Month	Negative Words and Collocations (1)	Positive Words and Collocations (2)	Number of (1)	Number of (2)	Number of Tweets
January	get worse, painful, staffing crisis, died, deaths, pandemic chaos, distress, burden, tragic	Wonderful, Hooray for community, encouraging, terrific, incredible support	178	54	242
February	furious mob, disheartening, distress, occupation, utter lawlessness, harassed	🙏, 👏, Hope, great step, proud, victory	163	40	467
March	Devastating, terrible, death, society's cracks, heartbreak, deaths from COVID, evil, 😷, Confusing time	unsung heroes, amazed, Grateful, ❤️, save lives	59	10	159
April	risk of dying because of COVID, suffering, damaged, died of COVID-19, 👀, terrible organ damage	Success, great, astonishing, 😁, proud	33	22	143
May	Deaths, occupation, feel unsafe, awful, Sad, pandemic tragedy, humiliation	Great, helped, fabulous, godsend	39	11	126
June	huge loss, lonely, worse nightmare, 😒, brunt of anger, deaths	Excellent, victory, congratulate, successful, hope	38	18	157
July	staffing crisis, furious, vandal, Omicron 'tsunami', shocking, 😔, getting angrier, depressing as hell	good people, good protection, beautifully, 🙏, won	25	4	50
August	Kill, pandemic worsens, harassed, aggressive attacks, threats, and intimidation, shocking, getting worse, very troubling	Help, Amazing, very well done	26	3	70
September	Crisis, harass, death, killed, dangerous, killer of humans, Terrifying, 🙄	positive step forward, hope, help, 🙏, great victory	23	6	68
October	Deaths, the worst, disturbing, chaos, crisis, harassment	Successful, saves lives, victory, Bravo	33	14	104
November	Devastating, deaths, Unfortunately, chaotic, chaos, crisis, anxious, panic, anger, ❤️	Helping, Friendly, magic, good thing	44	9	129
December	children's hospital crisis, suicidal, die, deaths, very sad	most enthusiastic, good wishes, saved lives	29	5	69
January 2023	dangerous, false, exhausting pandemic journey, health care crisis, 👀	Dreaming, save, be safe, fun events	15	3	45

4.3. Methods of Predictive Analysis of the Growth of Psychological Tension

Dictionaries of negatively and positively colored Russian vocabulary and emojis selected from the collections were compiled (examples are given in Tables 6 and 7). At the same time, strongly emotionally colored terms and emojis with a rank of −2 (negative) and +2 (positive) are highlighted. For example, references to death (death, mortality, die, die out, kill, etc.), horror (horror, 😱), and evil (malice, sinister, 😠) were classified as negative vocabulary. Positive vocabulary included references to love (love, beloved, 🥰), victory (victory, win), and hope.

Table 6. Examples of negative emotional Russian vocabulary (translated to English) and negative emojis used in tweets discussing the coronavirus.

Period	From 28 March 2021 to 26 April 2021	From 30 June 2021 to 31 August 2021	From 20 November 2021 to 8 December 2021
Number of tweets	1741	1182	1101
Coronavirus references	1848	1247	1205
Aggression, aggressive	2	3	5
Hell, infernal	6	1	2
Anti vaxxer, anti vaccinator	-	1	22
Apocalypse, apocalyptic	1	1	1
Trouble, poor, poverty	12	5	6
Demon, infuriate, demonism, piss off	5	5	3
Bio weapon, biological weapon	5	23	5
Afraid	10	10	6
Blame, guilty, culprit	11	12	15
Bastard, filth	4	4	0
Evil, anger, spiteful, malice, angry	9	5	13
Death, mortality, lethal	43	34	27
Funeral, bury, burial	2	2	1
Kill, killer	39	24	26
😭	35	39	13
😫	1	1	
😠	-	9	5
🤬	-	2	1
😱	2	1	2
🤮	-	9	-
🤢	2	2	3
😡	61	8	4
🤡	8	9	4

Table 7. Examples of positive Russian vocabulary (translated to English) and positive emojis used in tweets discussing the corona virus.

Period	From 28 March 2021 to 26 April 2021	From 30 June 2021 to 31 August 2021	From 20 November 2021 to 8 December 2021
Thank you, give thanks	4	8	13
Great, greatness	1	2	3
Splendid, splendor	1	2	1
Believe, faith, believer	6	12	12
Be proud, proud	1	3	-
Kindness	18	18	10
The best	25	20	24
Love, beloved	16	17	14
Hope	8	3	11
Win	95	101	69
Laugh, funny	16	8	2
🤣	26	7	28
😜	4	1	2
🥰	9	5	2
😂	31	24	9
🙂	11	6	5
😊	5	3	6
❤️	7	2	-

A variant of machine calculation of the modified IPT coefficient is proposed and named as Emotional Vocabulary Index (EVI) (Equation (7)). The Emotional Vocabulary Index was calculated for a collection of tweets, not for each tweet. It is equal to the ratio of negative to positive vocabulary (including emojis) per thousand tweets.

For each collection of tweets, the total frequency of negative and positive vocabulary was calculated and then recalculated for 1000 tweets (Figure 2). Graphical representations of the Emotional Vocabulary Index (EVI) values are shown in Figure 2 (red columns).

Among the indicators characterizing the pandemic in the Russian Federation, the following were considered: (1) The average mortality per week (for the period of publication of the tweets of the collection); (2) The average incidence per day (over the period of publication of the collection); (3) Average increase in incidence (thousand people) for 4 months preceding the period of publication of tweets (Figure 3). The indicators were calculated according to coronavirus monitor information [50].

As an indicator characterizing the pandemic, the average monthly increase in the incidence of coronavirus in the Russian Federation for four months preceding the period of collecting tweets (AMI-4) was chosen, since a correlation was found between the EVI and this indicator, R = 0.518.

Considering the trend equation, the EVI value for April 2022 was predicted (Figure 4):

The predicted value was 271.57. A check was made on the collection of tweets for April 2022. The calculated value of EVI is 306.15 (Figure 5). Therefore, the prediction accuracy is 88.75%.

The accuracy was calculated as the ratio of the calculated value to the empirical value, expressed as a percentage.

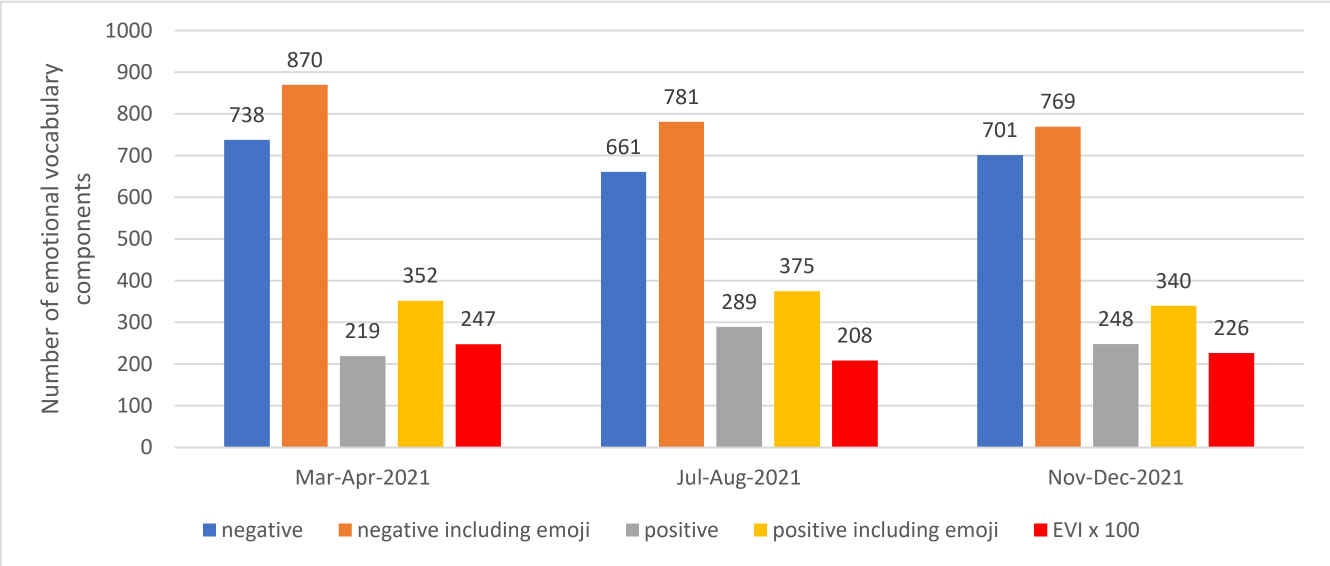

Figure 2. Emotional Vocabulary Index (EVI), and the frequency of emotionally charged terms and emojis (emotional vocabulary components) used in tweets discussing the corona virus, per 1000 tweets.

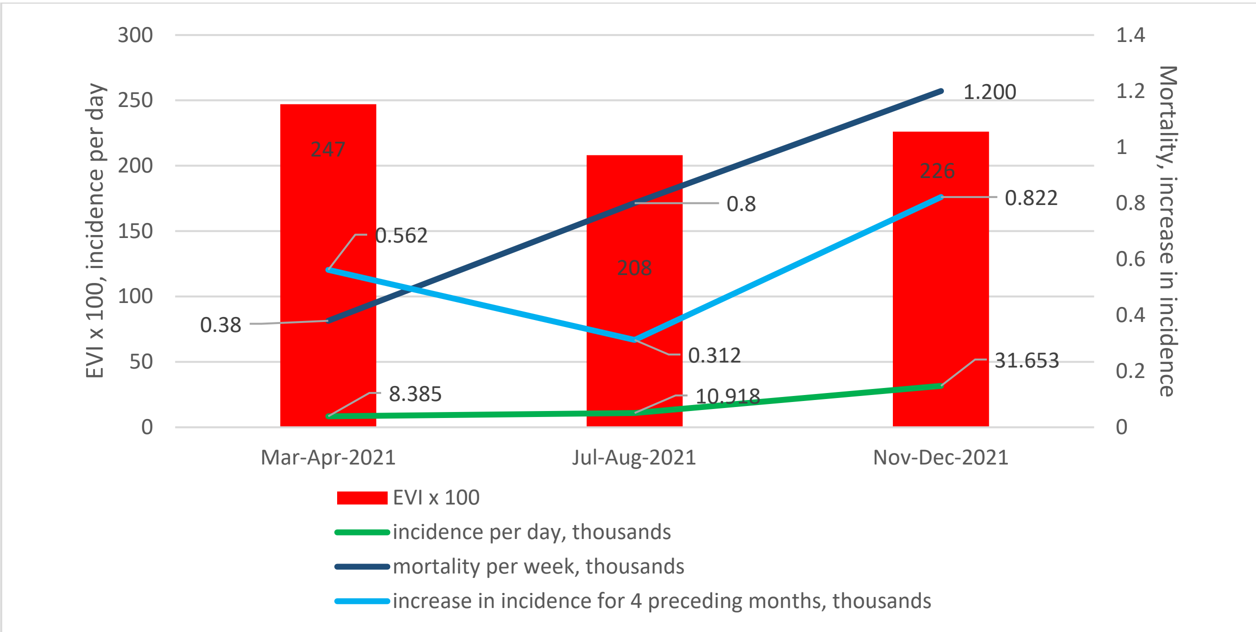

Figure 3. Emotional Vocabulary Index (EVI) with indicators that characterize the pandemic.

$$y = 0.0348x + 207.71$$
$$x = 1835,\ y = 0.0348 \times 1835 + 207.71 = 271.568$$

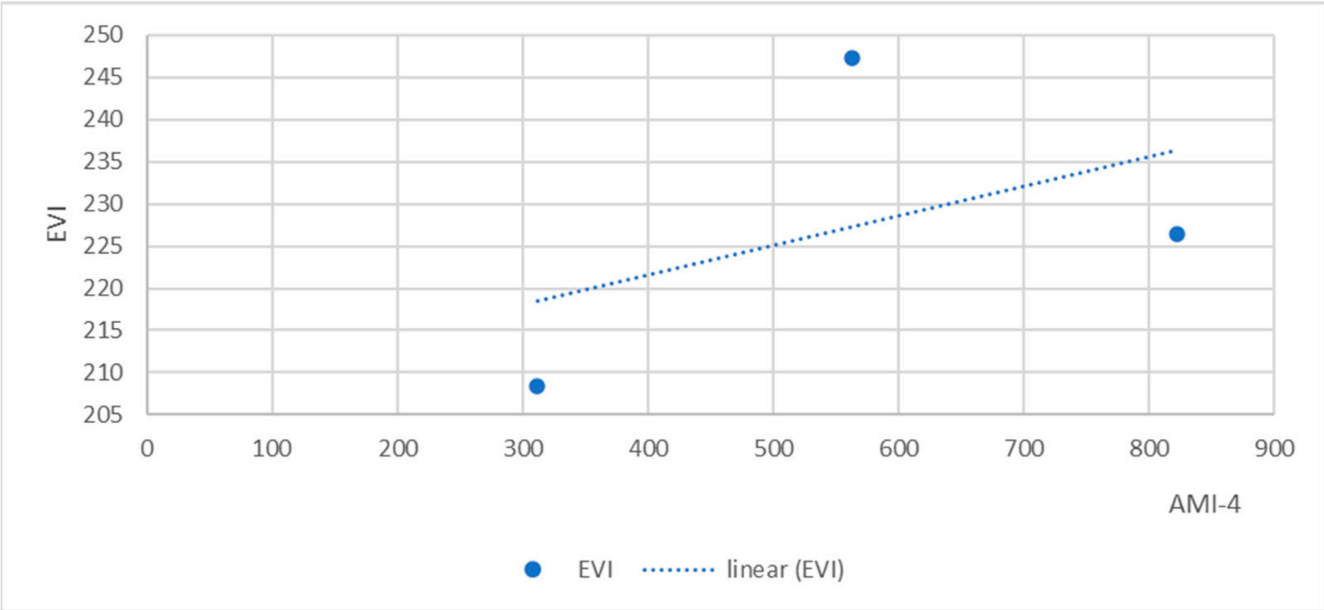

Figure 4. Correlation–regression analysis of the relationship between EVI and AMI-4. EVI—Emotional Vocabulary Index. AMI-4—average monthly increase in the incidence of coronavirusin the Russian Federation for 4 months preceding the period of collecting tweets.

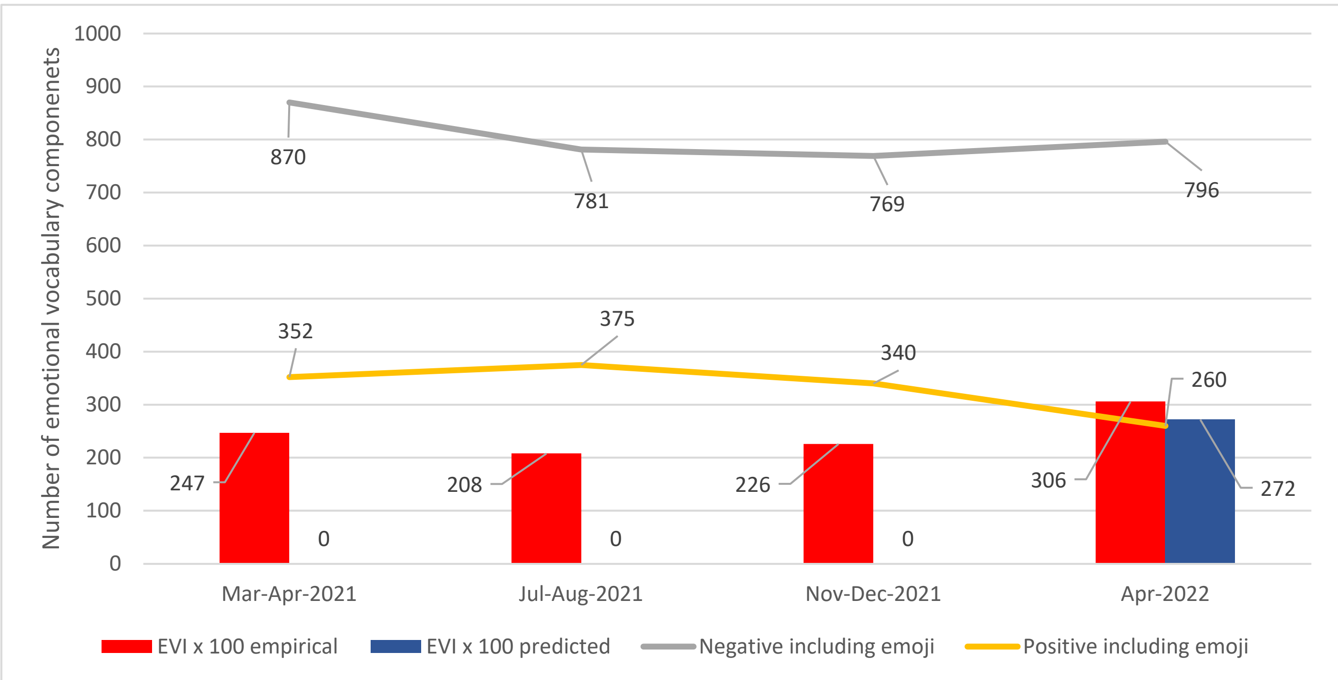

Figure 5. Emotional Vocabulary Index (EVI) (empirical and predicted) and the frequency of emotionally charged terms and emojis (emotional vocabulary components) used in tweets discussing the coronavirus, per 1000 tweets.

5. Discussion

A model for ranking the degree of emotional coloring (tonality) of tweets using statistical approaches is developed. Methods for calculating special coefficients (index of psychological tension, index of subjective well-being) are proposed.

The proposed compiled socio-psychological dictionaries for vocabulary and emojis differ from the existing ones in the following ways:

This dictionary contains ranked terms and emojis based on five ranks (-2, -1, 0, +1, +2), where rank "-2" corresponds to strongly negative emotions, rank "-1" to moderately negative emotions, rank "0" to neutral emotional coloring, rank "+1" to moderately positive emotions, and rank "+2" to strongly positive emotions. In existing works, as a rule, a smaller number of ranks are used. The ranks "-1, 0, +1" are used to create a lexicon of emoticon moods in [51]. The same ranks were used to assign values to emoticons based on the mood of the tweets [52].

The novelty of the proposed approach is to rank emojis by mood, considering both the mood of tweets and the dictionary meanings of emojis. A novel method for involuntary calculation of the IPT index based on a sentiment analysis of tweets and on previously developed thematic ranked dictionaries has been proposed. Words, expressions, and emojis in the tweets are assigned ranking values taken from dictionaries. The index of psychological tension is proposed to be calculated as the total value of the ranks of emotionally charged words and emojis for each tweet. The author's program for the automated calculation of the IPT is developed.

Additionally, a novel method was developed to assess the dynamics of the psychological state of social network users as a reflection of their subjective well-being, which is proposed to be defined as the average value of the subjective well-being index (SWI) of a particular user's messages for a certain period, as the individual IPT.

The study was limited by: (1) geographical limitations for predictive analysis; (2) time constraints (selected periods of time); (3) only tweets in Russian and English were considered; and (4) a subjective approach when assigning ranks to terms and emojis within the framework of sentiment analysis.

Further research will focus on extracting new knowledge on infectious diseases from scientific publications and social networks.

6. Conclusions

This paper analyzes approaches to determining the emotional state of Twitter users because of the coronavirus pandemic and proposes methods for assessing their psychological state. The assessment of the user's emotional intensity is based on the use of word and emoji dictionaries ranked by the degree of emotional intensity. An Index of Psychological Tension (IPT) has been proposed. It is calculated as the sum of the ranks of emotionally charged words and emojis for each tweet, which shows the emotional coloring of the tweet, considering the emojis used and informal spellings of words. At the same time, it is proposed to consider the repetition of emojis as enhancement of the emotional charge of the message and the total number of words in a tweet. For the collected tweets, the average IPT is evaluated.

A method for predictive analysis of the growth of psychological tension based on the ranking of the Emotional Vocabulary Index (EVI) has been created.

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