Neural Network Assessment of Post-Traumatic Risk Behavior Using Social Media Posts Analysis

Iurii Krak[1,2], Oleksandr Ovcharuk[3], Olexander Mazurets[3,*], Olena Sobko[3], Maryna Molchanova[3] and Olexander Barmak[3]

[1]Taras Shevchenko National University of Kyiv, Kyiv, 64/13, Volodymyrska str., 01601, Ukraine
[2]Glushkov Institute of Cybernetics of NAS of Ukraine, Kyiv, 40, Glushkov ave., 03187, Ukraine
[3]Khmelnytskyi National University, 11, Instytuts'ka str., Khmelnytskyi, 29016, Ukraine

Abstract
In paper the method for neural network assessment of post-traumatic risk behavior using social media post analysis is proposed, which is formed as an integrated indicator that takes into account the intensity of PTSD content, the presence of comorbid mental disorders and the emotional context of messages, and allows you to study the temporal dynamics of changes in risk patterns of each user separately. The neural network models used, which are components in the detection of risky behavior, had the following metrics: for the detection of PTSD content, was achieved Accuracy 0.934, Precision 0.948, F_1-score 0.841 and AUC 0.872; in turn, the models for the detection of concomitant mental disorders showed the following Accuracy metric values: 0.934 for anger, 0.869 for anxiety, 0.843 for depression, 0.984 for narcissistic condition and 1.0 for panic condition. The experiments conducted with the analysis of time series of risky behavior showed a close correlation with manual data analysis and the existing labels of depression symptoms in the studied dataset. This demonstrates that the model not only detects statistical patterns, but also agrees with real psychological manifestations recorded by expert labeling. Proposed approach forms a methodological basis for the development of automated emotional monitoring systems and the creation of timely intervention tools that can help reduce the risks of crisis states in society.

Keywords
post-traumatic risk behavior, PTSD, comorbidity, neural network, social media post analysis

1. Introduction

Pandemics, armed conflicts, and other social upheavals are leading to an increase in the number of people suffering from post-traumatic stress disorder (PTSD). According to the World Health Organization, approximately 3.9% of the world's population has experienced PTSD during their lifetime [1], and in Ukraine, the prevalence among the civilian population is about 25%, with almost half of the population (57%) at risk of developing the disorder [2]. A study among adolescents aged 11–17 in Donetsk and Kirovohrad regions showed that 31.7% of adolescents in Donetsk region expressed suicidal thoughts and 9.5% made suicide attempts, while in Kirovohrad region, 19.6% and 5.1%, respectively, reported similar manifestations, with a particularly high risk among girls [3]. PTSD, classified in DSM-5 as a trauma and stress disorder, is associated with an increased tendency to risky behavior according to criterion E2 [4], reflecting impulsive or dangerous actions after a traumatic experience, and is often accompanied by comorbid mental disorders, such as depression [5], anxiety disorders [6] and substance use disorders, as well as disorders of emotion regulation [7]. Based on current empirical data, it can be assumed that the combination of PTSD with comorbid disorders and manifestations of negative emotional orientation in communication increases the likelihood of risky behavior on social media.

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*Corresponding author.
yuri.krak@gmail.com (I. Krak); off4aruk@gmail.com (O. Ovcharuk); exe.chong@gmail.com (O. Mazurets); olenasobko.ua@gmail.com (O. Sobko); m.o.molchanova@gmail.com (M. Molchanova); alexander.barmak@gmail.com (O. Barmak)
0000-0002-8043-0785 (I. Krak); 0009-0008-3815-0035 (O. Ovcharuk); 0000-0002-8900-0650 (O. Mazurets); 0000-0001-5371-5788 (O. Sobko); 0000-0001-9810-936X (M. Molchanova); 0000-0003-0739-9678 (O. Barmak)

The aim of the study is the neural network assessment of post-traumatic risky behavior using the analysis of social media messages, which is formed as an integrated indicator that takes into account the intensity of PTSD content, the presence of concomitant mental disorders and its emotional context, and allows examining the temporal dynamics of changes in risk patterns of each user individually.

The contribution of the study is a new neural network approach to automated assessment of post-traumatic risk behavior based on social media texts, which integrates the detection of PTSD content, concomitant mental disorders, and the emotional context of messages. The method involves constructing individual trends of risk patterns within time windows, which allows investigating the dynamics of changes in users' behavioral risks.

2. Related works

Assessment and prediction of risk-taking behavior, particularly related to post-traumatic stress disorder, has become a subject of active scientific research in recent years. Considerable attention is paid to identifying behavioral risk indicators, among which DSM-5 criteria play an important role, in particular E2, which determines a tendency to dangerous or self-destructive actions. In modern scientific works, researchers use a wide range of approaches – from classical statistical methods [8] and psycholinguistic analysis to advanced machine learning technologies and neural network models. Special attention is paid to the analysis of social network data, which, due to the high accessibility and emotional richness of user content, are becoming a valuable source of information for determining psychological states and propensities for risky behavior. The active growth of the number of studies in this area emphasizes the relevance of creating effective automated tools for the early detection of users at increased risk based on the analysis of their online communication.

The paper [9] provides a general overview of PTSD as a serious mental condition that develops after experiencing or witnessing traumatic events. The etiology, clinical manifestations, and current treatment methods for PTSD are reviewed according to DSM-5 criteria. Particular attention is paid to psychotherapeutic and pharmacological approaches, as well as issues of accessibility and effectiveness of treatment. The authors analyze the latest research on promising therapeutic methods and emphasize the need for further study of the mechanisms of PTSD development and improvement of treatment strategies.

Studies [10] and [11] highlight the relationship between PTSD symptoms and factors related to substance use. Both studies demonstrate that increased levels of PTSD symptoms are associated with greater nicotine dependence, higher barriers to quitting smoking, more severe difficulties in quitting smoking, and increased frequency and amount of alcohol use. However, no statistically significant association was found between PTSD symptoms and cannabis use. The authors emphasize the importance of considering traumatic experiences, physical health, and substance abuse history when developing targeted prevention and treatment programs aimed at reducing the comorbidity between PTSD and addictions. Adolescence is characterized by increased vulnerability to traumatic disorders, the development of behavioral and psychoactive addictions, and risky and criminal behavior. A longitudinal study of Italian children and adolescents showed that, although there was a general decrease in symptoms of traumatic stress several years after the initial wave of the COVID-19 pandemic, a proportion of adolescents continued to experience psychological distress, with the impact of the pandemic remaining differentiated by gender and the association between physical activity and a decrease in stress symptoms being weak [12]. Restrictions during the pandemic particularly affected active children, disrupting their usual routines and potentially reducing the protective role of physical activity, consistent with the hypothesis of maladaptive emotion regulation strategies through addictions. At the same time, an analysis of the network structure of psychopathology showed that symptoms of complex PTSD, in particular affective dysregulation, play a key role in the comorbidity of PTSD and behavioral or psychoactive addictions, among which problematic Internet use is the most central manifestation [13].

A systematic review of recent studies further confirmed that PTSD symptoms in adolescents, including emotional withdrawal and externalizing manifestations, are associated with increased propensity for violence, delinquency, and overall risk-taking, with additional factors including substance abuse and family violence [14]. Overall, these findings highlight the need for early identification of modifiable risk factors and strengthening of protective mechanisms, particularly those focused on affect regulation, to support adolescent mental health and prevent risky behavior.

A study [15] of young adults suggests a strong relationship between PTSD, psychosis, and risky alcohol use. Network analysis of symptoms revealed that key nodal and bridging symptoms are «delusions of control» and risky alcohol use, while specific manifestations of psychosis, such as delusions of persecutory or grandiose delusions, form the strongest relationships in the PTSD symptom structure. The findings highlight the need to develop targeted interventions that address core symptoms to reduce the comorbid impact of PTSD, psychosis, and hazardous alcohol use among young adults.

Despite significant progress in research on PTSD, comorbid mental disorders, and risk behaviors, a number of issues remain poorly understood. In particular, there is limited research examining the interactions between PTSD-related content, comorbid mental disorders, and the emotional context of messages in digital environments, as well as the dynamics of changing risk patterns over time.

Our previous research is devoted to neural network detection of PTSD from text posts [16], as well as neural network detection of mental disorders [17]. This study is a continuation of previous ones and aims to fill these gaps by developing an integrated neural network approach to assess posttraumatic risk behavior in online communication, which takes into account PTSD content, comorbid psychiatric disorders, and the emotional context of messages, and also allows to investigate the temporal dynamics of risk patterns of each user. Such an approach can serve as the basis for further preventive and therapeutic strategies aimed at supporting mental health in different age and social groups.

3. Method design

The proposed methodology is based on the use of neural network models for multi-level text analysis, which allows not only to identify potentially traumatic content, but also to study its temporal dynamics in relation to manifestations of emotional dysregulation and concomitant mental disorders. As a result, a complex indicator of risky behavior is formed, which can serve as the basis for early identification of high-risk groups and further development of preventive strategies for supporting mental health. The scheme of the approach is shown in Figure 1.

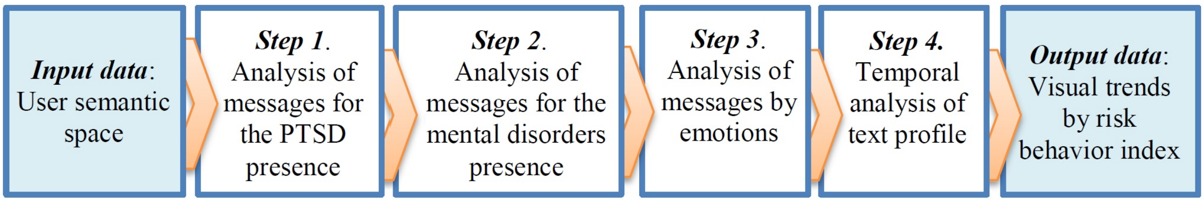

Figure 1: Approach diagram for neural network assessment of post-traumatic risk behavior.

The method starts by using the user semantic space as input, which reflects their social media activity and contains all messages for analysis with date and time:

$$P_u = \{(m_i, t_i)\}_{i=1}^{N} \tag{1}$$

where m_i – the message text, t_i – the timestamp, N – the number of user messages.

At Step 1, messages are analyzed for signs of PTSD, which allows identifying potentially traumatic content and highlighting it as a basis for further assessment. For each message m_i, the neural network model calculates the probability of the presence of signs of PTSD:

$$P_{PTSD}(m_i) \in [0, 1], \tag{2}$$

If $P_{PTSD}(m_i) > 0.5$, it is considered that the message contains signs of PTSD ($F_1 = 1$), if less than 0.5 – such manifestations are absent ($F_1 = 0$). To detect signs of PTSD in the message, a neural network of BERT-type architecture was used, which is the result of previous research [16].

In Step 2, messages are analyzed for signs of concomitant mental disorders, which provides a more comprehensive assessment of the user's mental state and allows taking into account comorbid manifestations. The study analyzes the following types of mental disorders: anger, anxiety, depression, narcissistic, panic. Accordingly, a vector is formed for each message:

$$F_2(m_i) = \big(p_1(m_i), p_2(m_i), \ldots, p_k(m_i)\big), \quad p_k(m_i) \in \{0, 1\}, \tag{3}$$

where $k = 5$, and is responsible for the corresponding mental disorder index.

To identify each of the mental disorders, neural network models of BERT-type architectures, which is the result of previous studies, were used [17].

In Step 3, messages are analyzed by emotional context, which allows us to assess the nature and tone of emotional manifestations in the texts. Within the framework of the study, it is important to identify precisely the negative tone.

$$F_3(m_i) = \begin{cases} 1, & \text{if message tone is negative,} \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

Tone determination is performed using the «roberta-base-go_emotions» neural network [18].

Step 4 performs a temporal analysis of the text profile, which allows us to study the dynamics of changes in risky behavior based on the calculated risk index and the user's emotional reactions within the specified time windows. To do this, a time stamp t_i is attached to each message, which allows us to perform a sliding analysis within a moving window of W days. For each user u, the baseline risk level is calculated as the ratio of the number of messages containing PTSD content to the total number of messages within the window:

$$R_{PTSD}(u, t) = \frac{\sum_{t_i \in |t-W,t|} F_1(m_i)}{\sum_{t_i \in |t-W,t|} 1}, \tag{5}$$

Two additional modifying factors are taken into account: Boost-comorbidity ($\delta c = 0.2$) is activated if more than 30% of PTSD messages are accompanied by other mental disorders, and Boost-negativity ($\delta n = 0.3$) is added if more than 50% of PTSD messages within the window have a negative emotional context. The integral risk index for user u at time t is calculated as:

$$R(u, t) = \min\big(1, R_{PTSD}(u, t) + \delta c + \delta n\big), \tag{6}$$

where $R(u, t) \in [0, 1]$ is a normalized indicator of risky behavior. The obtained time series $\{R(u, t)\}$ allow tracking individual trends in users' risk patterns, which provides the opportunity for early detection of high-risk groups.

For a better understanding of the interaction of the steps of the approach, below present a diagram of the method for neural network assessment of post-traumatic risk behavior using social media post analysis, which is an extended diagram of the proposed approach (Figure 2).

The processing results in the formation of output data in the form of visualization of trends over time series [19], which integrates information about PTSD content, concomitant mental disorders, and emotional context, providing a comprehensive assessment of potential risks for each user [20].

The proposed methodology provides a comprehensive approach to automated assessment of post-traumatic risky behavior based on the analysis of user texts in social networks. The integration of several neural network models allows for the simultaneous detection of PTSD content, concomitant mental disorders, and the emotional context of messages, which increases the accuracy and depth of the assessment. By constructing individual time series of the risk index, the method allows for the study of the dynamics of changes in users' behavioral patterns and the timely identification of high-risk groups.

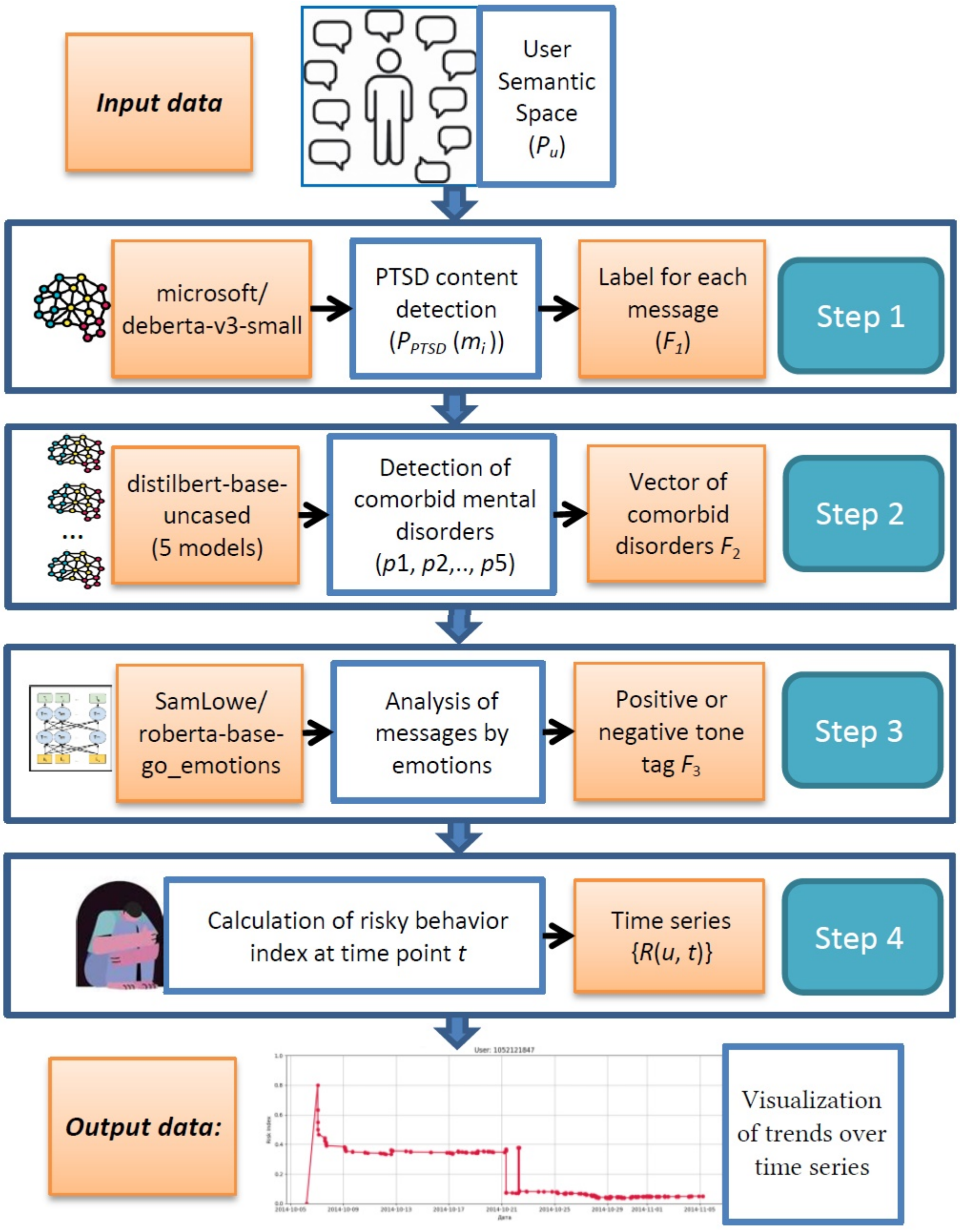

Figure 2: Scheme of the method for neural network assessment of post-traumatic risk behavior using social media post analysis.

Thus, the methodology forms the basis for the further creation of mental health support systems and the development of preventive strategies.

4. Research data and experimental software

The methodology proposed in Section 3 was tested on the dataset «Depression: Twitter Dataset + Feature Extraction», published on Kaggle [21].

The dataset contains 20,000 labeled English tweets collected for mental health analysis and representatively balanced [22]. It includes data on depressive and non-depressive statements of social media users, intended for research in the field of natural language processing and detection of mental disorders. The dataset also contains the field «post_created» and the field «user_id», which makes it suitable for temporal analysis of user semantic space [23].

Experimental studies were implemented in the Google Colaboratory environment [24], which provides an interactive space for performing Python-oriented calculations and provides access to GPU-based computing resources [25]. The software is created in the form of a Jupyter notebook, the modules used of which can be viewed here [26], which allows for a sequential organization of the research stages, starting from data loading and preprocessing to model building and analysis of results.

To process social media texts, pre-trained transformer models were used, integrated through the Transformers library [27], which provided inference in the tasks of PTSD content classification, identification of concomitant mental disorders, and emotional tone analysis. The neural network architecture was implemented based on the PyTorch framework [28], which was used as a backend for performing deep computing and optimizing the weight parameters of the models [29].

All computations were performed in a unified cloud environment, ensuring reproducibility of experiments through standardized library and runtime configuration [30]. This allowed us to systematically investigate the temporal dynamics of risky behavior by integrating data on PTSD content, comorbid mental disorders, and emotional context of messages into a single analytical platform.

5. Result and discussion

The neural network models used to detect signs of PTSD and comorbid mental disorders in texts were borrowed from our own previous research. For the model used to identify PTSD content, the following indicators were obtained during training on validation data: Accuracy – 0.934, Precision – 0.948, F_1-score – 0.841 and AUC – 0.872 [16]. For comorbid mental disorders, 5 independent models were used, which showed the following results [17]: for «Anger/Intermittent Explosive condition» – Accuracy 0.934; for «Anxiety condition» – 0.869; for «Depression» – 0.843; for «Narcissistic condition» – 0.984; and for «Panic condition» – the maximum value is 1.0.

To determine the tone label, a model [18] was used, trained on the «GoEmotions» corpus, which covers 27 categories of emotional states and a neutral class, which provides generalization ability when analyzing texts with a pronounced emotional coloring. Within the framework of this study, the obtained emotional states were grouped into generalized categories of «negative» and «non-negative», which allowed to increase the interpretability of the results and simplify further analysis.

Accordingly, after analyzing all messages in the dataset for signs of PTSD, the graph shown in Figure 3 was obtained.

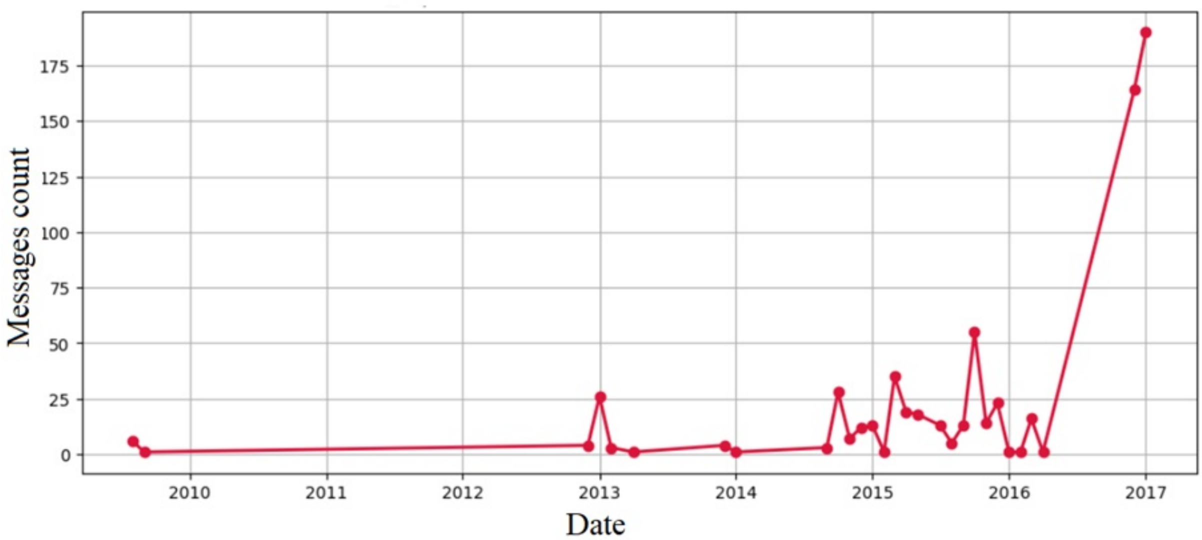

Figure 3: Graph of messages analysis regarding the presence of PTSD symptoms.

The graph shows the time dynamics of the number of messages classified as containing signs of PTSD. The abscissa axis shows the time scale covering the period from 2009 to the beginning of 2017, and the ordinate axis shows the number of corresponding messages. The visualization demonstrates that for a long time the intensity of the appearance of such posts remained minimal or almost absent. Only since 2013 have individual bursts of activity begun to be recorded, but they were episodic in nature and did not form a stable trend. Starting from 2015, the dynamics become more pronounced: a gradual increase in the number of messages is observed, which is accompanied by uneven fluctuations, which may indicate periodic exacerbations associated with PTSD symptoms. The most dramatic increase in the number of such messages was recorded at the end of the studied period – in 2016 – at the beginning of 2017, when there is a rapid jump in the frequency of detected PTSD posts. Such dynamics indicate a significant intensification of the discourse related to post-traumatic states, and can be explained both by external socio-political factors and changes in the behavior of social media users.

In the available dataset, the latest messages date back to 2017. At the same time, the recorded dynamics of the increase in the number of PTSD-related posts at the end of the study period indicates the feasibility and relevance of further scientific research in this direction, since such manifestations demonstrate a tendency to increase and require deeper analysis.

Analysis of risky behavior by users yielded the results shown in the graphs shown in Figures 4 - 6. The graph shown in Figure 4 displays the dynamics of the user's risky behavior index based on a thirty-day sliding window. Several characteristic phases are observed in the time frame: an initial sharp spike in the index values, its gradual decrease to almost minimal levels, and then a new stage of stabilization at an elevated level. Such a trajectory may indicate the presence of short-term crisis periods, which are replaced by relative remission, but over time form a repeated accumulation of risk signs.

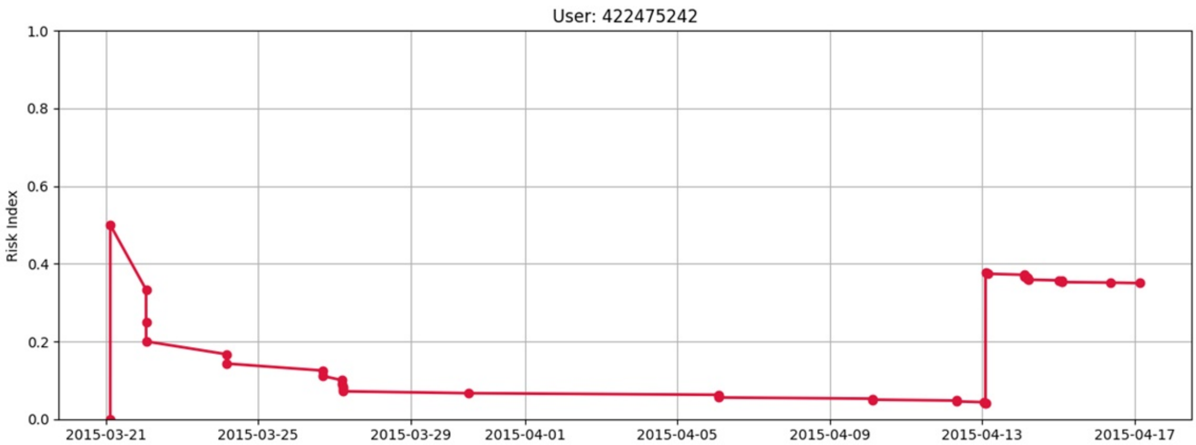

Figure 4: Time series analysis graph for possible risky behavior with spikes.

For example, the message from 21/03/2015: *«Fuck "facts". Fact: I'm a unicorn with a horn that shoots rainbow flames, pisses cake batter, and shits gumdrops.»* – is defined as containing signs of PTSD & an additional reinforcing factor of the poor man's pantry of a depressive state. The dataset used had the markup «depressive state» or «not depressive state», and the post is marked as depressive in the dataset, which correlates with the results obtained.

Also, when analyzing risky behavior, a number of graphs without spikes are observed, for example, as in Figure 5.

Analysis of the user's publications with the identifier shown in Figure 5 indicates the dominance of motivational, sports and everyday topics without systematic manifestations of negative orientation or signs of post-traumatic stress disorder. The single mention of the loss of a loved one has a context of overcoming difficulties and self-support rather than fixing long-term destructive states. This is directly consistent with the obtained graph, in which the risk index remains at a minimum level throughout the period, confirming the absence of significant fluctuations that could indicate a psychological crisis or persistent negative patterns in the user's behavior.

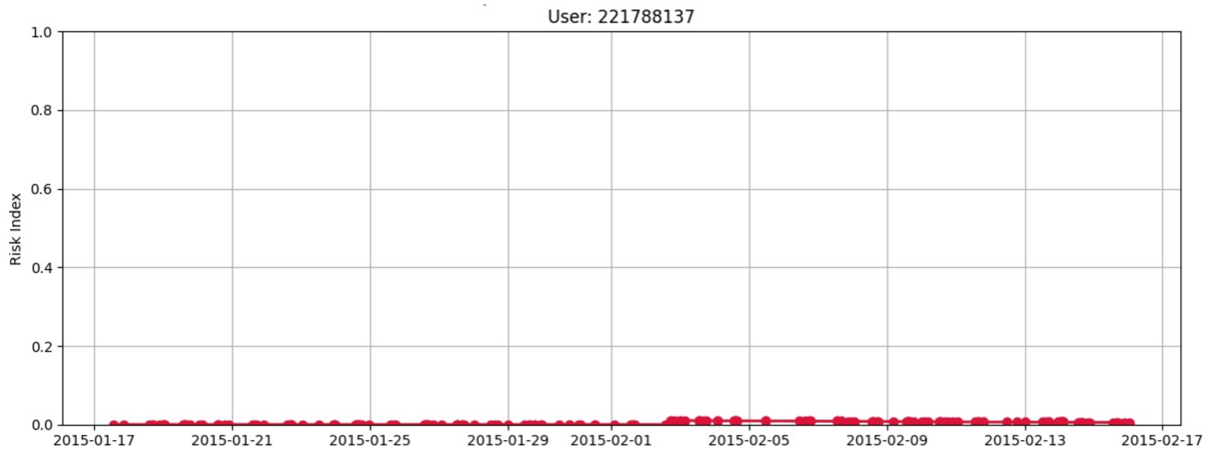

Figure 5: Time series analysis graph for possible risky behavior with no fluctuations.

However, the methodology still has limitations. For example, when analyzing the graph shown in Figure 6, most posts showed high indices of risky behavior.

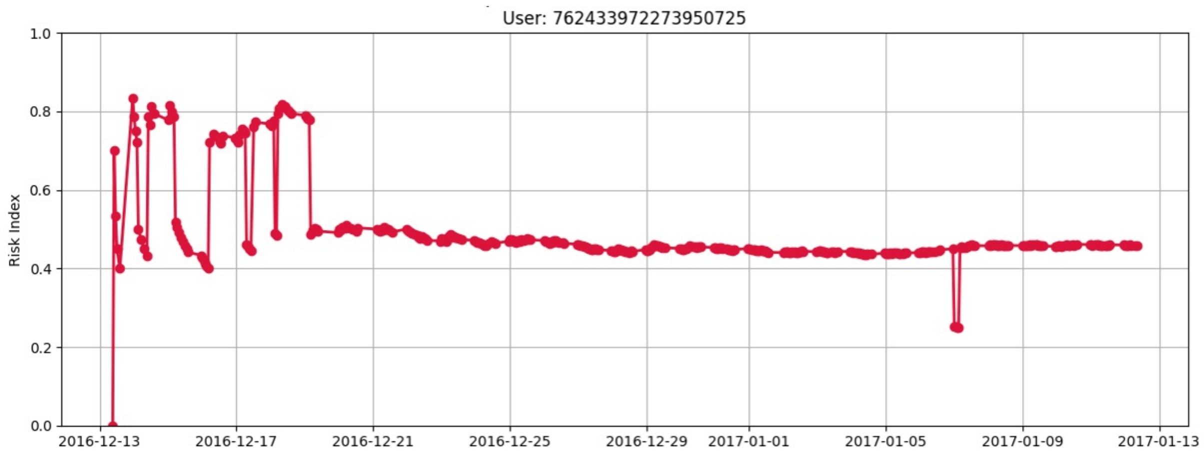

Figure 6: Time series analysis graph for possible risky behavior with high indicators.

Among the posts were: *«Oh yes, my criminal record? The only thing illegal I've done is absolutely KILLIN it on the dancefloor. Haha just kidding! I've killed a man»*, *«yeah demifiends cool but can he do this slays god and gets cursed to infinite reincarnation»*, which are clearly negative and aimed at aggressive actions. However, after a full analysis of the author's posts, including *«This imposing presence... He is no ordinary opponent. Be on your guard.»* and *«Hanged Man entered Nirvana just by being touched by Aleph.»*, it is most likely about game characters and experiences in games, and not in real life. This is due to the training sample on which the neural network was fine-tuned to detect PTSD and comorbid disorders. Therefore, to identify such posts, the neural network needs to be further trained.

The analysis shows that although the proposed approach has limitations, it is capable of identifying risk trends in user behavior, which opens up opportunities for timely response to potential exacerbations, prevention of crisis states and support for targeted interventions. It is important that the model takes into account not only the presence of PTSD, but also the concomitant comorbidity and negative emotional coloring of posts, which act as additional reinforcing factors. It is through these components that the risk index acquires greater sensitivity and reflects a complex multidimensional picture of the user's psycho-emotional state, allowing its dynamics to be interpreted not as a simple accumulation of episodes, but as a systemic indicator that combines various aspects of dysfunctional behavior.

6. Conclusion

In accordance with the goal, the method for neural network assessment of post-traumatic risk behavior using social media post analysis is proposed, which is formed as an integrated indicator that takes into account the intensity of PTSD content, the presence of comorbid mental disorders and the emotional context of messages, and allows you to study the temporal dynamics of changes in risk patterns of each user separately. The neural network models used, which are components in the detection of risky behavior, had the following metrics: for the detection of PTSD content, Accuracy was achieved – 0.934, Precision – 0.948, F_1-score – 0.841 and AUC – 0.872; in turn, the models for the detection of concomitant mental disorders showed the following results: 0.934 for anger, 0.869 for anxiety, 0.843 for depression, 0.984 for narcissistic condition and 1.0 for panic condition (according to the Accuracy metric). Such accuracy indicates the admissibility of using neural networks in the field of mental health monitoring.

The experiments conducted with the analysis of time series of risky behavior showed a close correlation with manual data analysis and the existing labels of depression symptoms in the studied dataset. This confirms the validity of the approach and demonstrates that the model not only detects statistical patterns, but also agrees with real psychological manifestations recorded by expert labeling.

Thus, the proposed approach forms a methodological basis for the development of automated emotional monitoring systems and the creation of timely intervention tools that can help reduce the risks of crisis states in society.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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