Development of a Predictive Module Based on a Predictive Model of Self-Destructive Behavior to Implement the Concept of Second Opinion

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Abstract: Predicting the risk of self-destructive behavior is one of the important tasks in the field of psychology, psychiatry, and public health. One of the difficulties of timely diagnosis is associated with low psychological education and fears of contacting a specialist psychologist or psychiatrist. The creation of forecasting forms open in the online space will provide affordable support and reduce the stigma associated with mental health problems. The issue of creating forms that implement the concept of a second opinion to obtain a primary assessment of mental status and psychological risks becomes relevant. The proposed study describes the architecture of the module based on the Telegram platform, using a bot. The module allows you to predict the possibility of developing self-destructive behavior of the respondent based on the information entered by him, as well as assign a degree of risk. To train the model, a dataset has been created containing information about the main markers and symptoms of destructive behavior.

1 INTRODUCTION

Predicting the risk of self-destructive behavior is one of the important tasks in the field of psychology, psychiatry and public health. Self-destructive behavior includes a wide range of actions that harm a person's physical, mental and social status, including substance abuse, autoaggression (self-harm, overeating, intentional deprivation of sleep, etc.), suicidal attempts.

Self-destructive behavior is a manifestation of severe psychological stress, trauma, mental disorders. It is a destructive way to cope with experiences, which is often not even realized by the person himself. Early detection and intervention can be a decisive factor in saving life and health.

One of the difficulties of timely diagnosis of self-destructive behavior is associated with low psychological education and fears of contacting a specialist psychologist or psychiatrist. In society, such behavior is often perceived as a lack of self-control, an attempt to attract attention, and not as a symptom of underlying psychological problems. Many do not seek help because of fear, embarrassment or ignorance (Salvador, Gouveia-Pereira, Duarte, 2023). The creation of forecasting forms open in the online space will provide affordable support and reduce the stigma associated with mental health problems.

Using open forms that implement the concept of a second opinion, users experiencing psychological difficulties can receive a professional initial assessment of their mental status and the causes of distress, are redirected to qualified psychologists and receive information about support groups that can help them develop healthier coping mechanisms (Bornheimer, Czyz, King, 2022).

It is worth noting that the creation of automated diagnostic systems to analyze the risks of destructive mental symptoms is also important for the socio-economic system as a whole. People who do not seek timely treatment require large expenditures of medical resources due to a higher risk of injury associated with self-harm, suicide attempts, risky

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behavior, the consequences of overeating, non-compliance with the regime, etc. (Pan, Cheng, Sethi, 2022). Self-destructive behavior also comes with significant economic costs. Due to the need for constant symptomatic treatment, often a person cannot effectively carry out his professional activity. Predicting self-destructive behavior can help establish more effective interaction between patients and the medical system, reduce the cost of their treatment and improve physical and mental health.

It is worth noting that in the era of the Fourth Industrial Revolution (4.0), social networks became one of the most complete sources of information for the analysis of mental well-being. They provide a huge amount of personal information and allow you to predict and potentially prevent self-destructive behavior.

An important aspect is also the ability to identify social risks of self-destruction. Algorithms of social networks provide the user with potentially dangerous information that affects his perception of himself, can distort the body image, perception of social activity and success, etc. Through the analysis of groups, subscriptions, it is possible to identify and evaluate the consumed information that affects the psychological state.

The use of these social networks can also allow to adapt corrective measures to the individual needs of the user. Profile analysis can provide insight into specific triggers, stressors, and risk factors that contribute to the activation of self-destructive behavior.

Thus, we can say that the development of automated models for predicting self-destructive behavior is a very relevant topic. In this regard, we set out to develop a predictive module for the implementation of the concept of second opinion, which can be useful for personalized diagnosis, psychological education and popularization of crisis care.

2 METHODOLOGY

Predictive systems based on machine learning play an important role in healthcare, helping to predict and diagnose various medical conditions, optimize treatment processes and improve outcomes for patients. Currently, data mining methods are increasingly being used in clinical diagnostics, and they have the potential to support this area.

Here are some examples of predictive systems in healthcare:

1. Diagnosis of diseases: Machine learning methods can be used to create models that can help doctors diagnose various diseases. Based on a large amount of clinical data, models can be created that can predict the likelihood of a particular disease based on symptoms and test results. For example, the paper (Lee, Choi, Shin, 2020) shows results that demonstrated that machine learning methods can be successfully applied to predict malaria using patient information.
2. Risk forecasting: Predictive models can be used to assess the risk of developing certain diseases in patients. For example, the model can be used to assess the risk of developing cardiovascular diseases, diabetes or cancer based on risk factors such as age, gender, genetic predisposition, lifestyle and medical history of the patient. For example, a machine learning-based model has been created to predict AKI (you need to decipher it once) for all pediatric intensive care patients (Dong, Feng, Thapa-Chhetry, Cho, Shum, Inwald, Newth, Vaidya, 2021), the described model accurately predicts moderate and severe AKI 48 hours before the start of AKI.
3. Clarifying the disease prognosis: Predictive models can help in determining the prognosis for patients with various diseases. For example, the model can be used to predict the likelihood of recovery from cancer, estimate life expectancy, or determine the effectiveness of a particular treatment. So, researchers have created a GAP model (Ryerson, Vittinghoff, Ley, Lee, Mooney, Jones, Elicker, Wolters, Koth, King, Collard, 2014) that accurately predicts the risk of death in chronic ILD (you need to decipher it once). The ILD-GAP model accurately predicts mortality in the main subtypes of chronic ILD and at all stages of the disease.
4. Optimization of treatment processes: Predictive models can help optimize treatment processes, for example, by predicting the likelihood of complications after surgery or evaluating the effectiveness of various treatment methods based on historical data.
5. Resource planning: Predictive systems can help with resource planning in healthcare, such as predicting the need for blood, medicines and medical equipment based on historical data and current demand. Special services are being created that help in the

distribution of patients and the initial diagnosis (Chizhik, Egorov, 2022).

However, it should be noted that these predictive systems must be carefully designed, validated and tested to ensure their accuracy and reliability. In addition, it is important to consider ethical issues and patient data protection when working with medical data.

In psychiatry, there are several diagnosis prediction systems that use various methods and algorithms. Some of them include:

1. Structured Clinical Interview for DSM (SCID) is a structured interview that is used to diagnose mental disorders according to the Diagnostic and Statistical Manual of Mental Disorders (DSM) (Sheehan, Lecrubier, Sheehan, Amorim, Janavs, Weiller, Hergueta, Baker, Dunbar, 1998). It is based on journalization and a systematic approach to the assessment of symptoms and criteria for diagnosis.
2. Online Assessment Measures (OAM) are online tools and questionnaires that allow patients to fill out forms and questionnaires to assess their symptoms and conditions. The results can be used to predict the diagnosis or assess the severity of mental disorders.

These are just some of the diagnosis prediction systems in psychiatry. Each system has its own characteristics and approaches to predicting the diagnosis, and their use depends on the specific clinical situation and the needs of the patient. It is important to note that all these systems should be used in combination with the clinical knowledge and assessments of an experienced doctor.

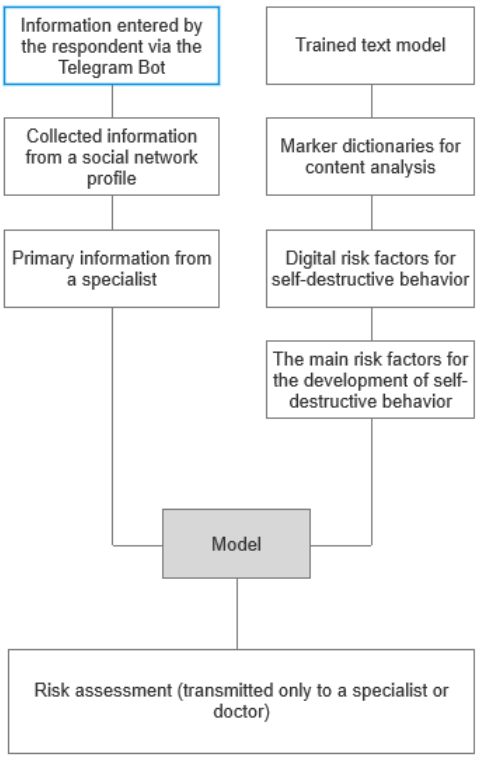
In this paper, we describe the development of a predictive module based on a predictive model of self-destructive behavior to implement the concept of second opinion, using Telegram bots and social network parsing.

To create the module, it is planned to use a model implemented in the form of a library, with the input of information through the Telegram bot and the addition of information from social networks via the API. The front part of the module in the form of a bot in Telegram will improve the user experience, since this tool is a familiar tool for users and does not cause rejection when used. During the implementation of the module, it will be possible to build a relaxed conversation with the patient through dialogue.

Telegram bots are applications that automate various tasks and offer interactive interaction with users through the Telegram messenger. They are created using the Telegram API and can perform a wide range of functions, from providing information to performing complex operations. The bot itself is connected to the model via the Telegram API (Application Programming Interface) — a set of programming instructions and agreements that allow developers to interact with the Telegram messenger and create various applications and bots. Telegram provides an API that allows developers to send and receive messages, manage user accounts, create bots, and much more. The Telegram API is based on the HTTP protocol and allows developers to create applications that can send text messages, media files, location and other types of content. It also allows you to interact with user accounts, get information about users and groups, manage chats and configure various messenger functions.

Additionally, automated parsing from the Vkontakte social network is used. If the user provides a link to his profile, the parser from our system, instantly, through the VK API, collects basic information about the user's profile, in order to identify the main interests of the respondent, based on his subscriptions and public information. Additionally, the information obtained by the survey is verified and the information that is presented in the social network profile. All the collected information is transferred to a model that evaluates the risks of destructive behavior. The general scheme of work is shown in Figure 1.

Figure 1: General architecture of the module.



The purpose of this module is to be able to collect a patient's medical history in a dialog mode and provide a preliminary diagnosis based on the collected data. To implement such a module, a trained model containing a priori knowledge about diseases and symptoms is required. However, the complexity of this approach lies in the fact that in classical medicine the symptoms are obvious ("the hand hurts", "the ear does not hear", etc.), and for the diagnosis in psychiatry such accurately describing the problem information may be missing, and the context of the patient's statements, his judgments and reasoning, therefore, an important role text analysis plays, which is implemented in our module by talking in the form of a dialog with a bot.

All collected information is anonymized and transmitted to a service implemented in the Phyton language, which provides an assessment of the risks of self-destructive behavior, based on a predictive model for predicting the risk of self-destructive behavior, on a scale from 1 to 10. Where the maximum number is the maximum risk of self–destructive behavior.

The architecture of the Telegram bot consists of the following main components:

1. Telegram Bot API: This is the official API from Telegram, which provides the ability to interact with the bot. The bot registers in Telegram and receives a token to access the API.
2. Web Server: The bot must have its own web server that will process requests from the Telegram API. The server must be configured to receive incoming messages and send responses.
3. Message Handler: This is the component that is responsible for processing incoming messages from users. Uses various approaches such as NLP and ML to understand the user's intentions and determine the appropriate response.
4. Data storage: In our case, we do not aggregate data from users, but only store depersonalized data in the form of a cache, which is cleared after the session ends.
5. External services: As noted earlier, we additionally pull up information from the Vkontakte social network, for this purpose the VK API is used.
6. Sending messages: The bot uses the Telegram API to send reply messages to users. It can send text messages, images, audio and other types of media files.

3 STRUCTURE AND CONTENT OF A PREDICTIVE MODEL FOR PREDICTING THE RISK OF SELF-DESTRUCTIVE BEHAVIOR

The predictive module is based on a previously developed structural-level predictive model of self-destructive behavior, which included the following components::

- • The main risk factors for the development of self-destructive behavior, including both clinical symptoms of emotional disorders and socio-cultural factors of the micro- and macro-environment, identified based on the analysis of the basic theories of self-destructive behavior that we described earlier (Uglova, Bogdanovskaya, Nizamutdinov, 2023);
- A text Dataset collected from social media communities where destructive content is published. The specified data set is used to train the system and search for destructive content in the response texts. As a result, during the processing of data arrays from social networks (from groups in which destructive content is published by users, self-destructive behavior is discussed), the main semantic markers of destructive behavior are identified. Additionally, the semantic core can be expanded by user queries in search engines based on Yandex information.Wordstat.
- Dictionaries of markers for content analysis, allocated on the basis of implicit ideas of modern youth about self-destructive behavior (Tropnikov, Nizomutdinov, Uglova, 2019);
- Digital risk factors of self-destructive behavior, identified on the basis of experimental study of profiles in social networks, and the value-semantic component of the user's information image.

We have developed a questionnaire that included the main risk factors for the main types of self-

destructive behavior: suicidal thoughts; depression; self-harm; alcoholism and drug addiction; excessive use of gadgets/social networks. networks; overeating/malnutrition; sleep deprivation/regime violations; risky behavior; self-criticism and self-deprecation; ignoring their diseases; provoking conflict situations; sacrificing their own interests; extreme behavior. All factors are evaluated on the Likert scale (0-7). Let's describe the basic factors:

- Biological factors (family history of diseases; hormonal disorders, imbalance in neurotransmitters, etc.);
- Personal risk factors (lack of knowledge or awareness; impulsivity; perfectionism; excessive self-confidence; willingness to seek help);
- Psychological factors (mental health problems such as depression, anxiety or eating disorders, etc.; reduced emotional state; substance use; previous suicide attempts or autoaggression);
- Social factors (pressure from relatives; pressure from a wide social circle; social isolation; bullying/mobbing; conflict situations);
- Digital factors (specialized content popularizing a certain lifestyle (fitness bloggers, coaches, marathons, etc.); culturally specific content based on certain values; aggressive entertainment content);
- Environmental risk factors (unsafe environment; access to hazardous materials; micro-community factors; financial stress or poverty);
- Situational risk factors (emergencies; fatigue; lack of time).

An open source library for natural language processing, SpaCy, was used to create NER classification models (Colic, Rinaldi, 2019). As a result, SpaCy showed the best extraction speed, maintaining comparable accuracy from 80% to 89%. The trained model of feature extraction from texts in social networks by NLP methods showed sufficient accuracy in processing unstructured text data.

The SpaCy library is a popular tool for natural language processing, including the task of recognizing named entities (NER). SpaCy provides an easy-to-use and efficient API for creating NER classification models. SpaCy offers pre-trained NER models that can be used to recognize named entities in Russian and other languages. These models are trained on large volumes of marked-up data and are able to distinguish different types of named entities.

In our system, this combination helped to identify markers associated with self-destructive behavior, which were identified earlier and described by us in the section on the structure of the model.

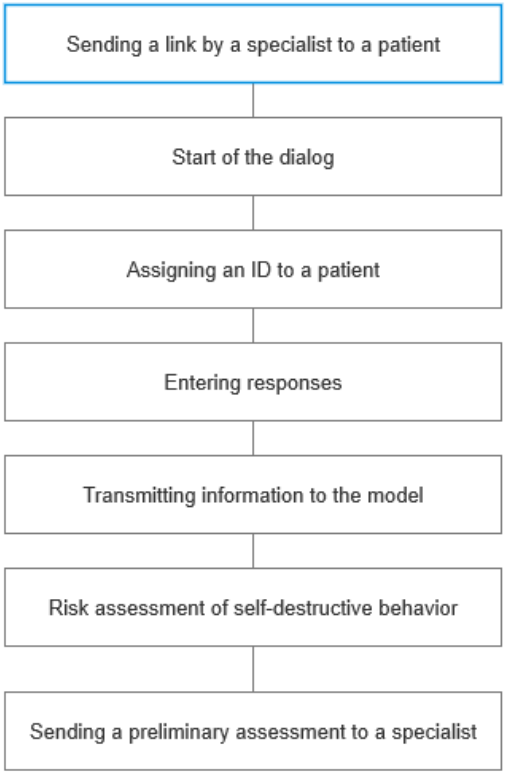


Figure 2: General model of patient interaction with the service.

The final scheme of the module is shown in Figure 2. Consider a step-by-step scenario:

1. The specialist sends the patient a link to the bot in Telegram.
2. The user, by entering a link in Telegram, begins a dialogue with the bot.
3. The bot consistently asks questions about the overall socio-demographic state of the respondent.
4. Gradually, as they communicate with the bot, the respondent is asked special psychological questions about social, biological, environmental and personal risks that require

a detailed answer or a choice of answer options.

5. As a result of the survey, the respondent is asked to leave a link to a profile on the Vkontakte social network (optional).
6. Additionally, if the link was specified, data is collected and processed from the profile in the social network, via the API. The user's subscriptions are analyzed automatically, the main topics of subscriptions are highlighted, the completed information is compared with the one specified in the profile.
7. All collected information is transmitted to the service in the form of depersonalized data.
8. The received information is processed on the server side. Based on the model of predicting the risk of self-destructive behavior, the respondent is assigned a score on a scale from 1 to 10, characterizing the risk of destructive behavior.
9. At the same time, the respondent himself does not see the conclusion, since this information is auxiliary for the specialist, and only serves as a second opinion.

4 PILOT STUDY

We conducted a pilot study involving 15 respondents who provided access to their social media profiles.

During the study, respondents were asked to fill out a questionnaire about the risks of self-destructive behavior, as well as undergo a clinical interview with a professional psychologist to assess the risk. Next, the expert psychologist was asked to assess the degree of risk of the appearance and development of various forms of self-destructive behavior (scale from 1 to 10).

The degree of consistency of the expert assessments of the psychologist and the predictive module was checked by calculating the Kendel concordance coefficient. Coeff. Of Concordance = 0.678, which indicates the consistency of expert assessments.

Here is an example of an assessment of the risk of self-harm by a specialist psychologist and a predictive module in respondents who participated in the experiment. (Figure 3).

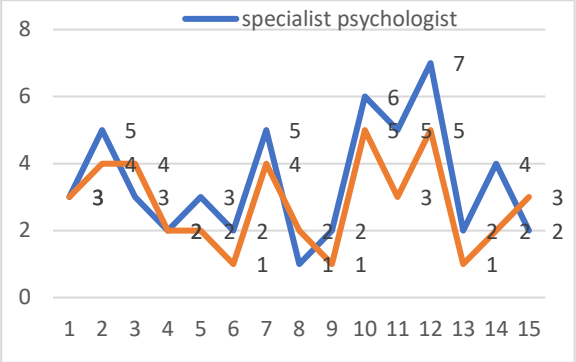


Figure 3: Assessment of the risk of self-harming behavior by a specialist and a predictive module (Likert scale 1-10).

The figure shows that the predictive module provides more cautious risk assessments of self-harming behavior, but the profile of 15 respondents shows that the dynamics of risk is assessed in accordance with the opinion of a specialist psychologist.

5 LIMITATIONS OF THE PREDICTIVE MODULE

An automated predictive module for collecting data on the risks of self-destructive behavior provides many advantages for optimizing the diagnostic process, but it is associated with a number of limitations and problems.

Automated collection using a chatbot is based on the respondents' subjective opinion about their well-being and their ability to constructively assess their condition and understand the proposed questions. Respondents with severe mental and organic disorders who are in deep clinical depression, respondents under 14 years of age, will be unable to use this module independently, which should be taken into account when diagnosing.

It is important to take into account the technical capabilities of respondents to use this module. Not all respondents may have the proper level of information literacy and experience to use a chatbot for diagnostics. Respondents may feel uncomfortable or resist automated data collection, especially if they have concerns about privacy or technological literacy.

The lack of functional compatibility of the gadget, the absence of a profile in social networks can prevent the unhindered passage of the survey and the compilation of a complete profile of the respondent. Do not forget about the human factor. The respondent

may make a mistake when filling out the questionnaire, which will lead to an incorrect interpretation of the data received.

It is also worth considering that the psychological experience of self-destructive behavior is very individual and not all risk factors can be taken into account in the model, which can lead to differences in diagnosis for certain groups. In the continuation of the study, we are going to expand the socio-demographic range of the sample to clarify gender, cultural and age markers.

First of all, our module is aimed at working with structured data (scale estimates, statistical indicators of profiles in social networks). An important stage in the development of the system will be a meaningful, qualitative analysis of data, work with the content produced by respondents, which has important clinical value for diagnosis. However, this functionality is quite expensive, which also makes it difficult to develop research in this direction.

For the introduction of such technologies, the problem of standardization of the obtained diagnostic materials also arises. In the process of testing our experimental model, we plan to cooperate with the psychological support service to clarify the poor form of data presentation for both specialists and respondents.

6 CONCLUSION

The development of a predictive module based on a predictive model of self-destructive behavior to implement the concept of second opinion is significant both for individual users and for society as a whole and the healthcare system in particular. This system can help collect statistical information, identify social groups with high risks of self-destructive behavior, identify areas with the greatest stress load and, based on the information received, transform and develop a crisis intervention service where they are most needed.

Risk forecasting is also important for prevention. It is easier for users to turn for information and diagnostics to an automated system that can raise awareness about mental health, simplify access to information about mental health services and create support groups as a safe space for open conversations about emotional problems.

In the future, we plan to expand the diagnostic sample, including respondents from various socio-demographic groups, detailing the prognostic model, as well as creating additional digital resources that implement the functions of support groups and crisis information. Also, one of the areas of work will be the testing of this predictive module in educational institutions and socio-psychological services.

The novelty of this product and research lies in the fact that an interdisciplinary approach is involved in the work, we are not limited to linear texts alone, but use a trained model, text analytics and social network parsing for a full-fledged analysis.

Separately, it is worth noting the attitude to personal data and medical secrecy. Our module does not aggregate data using impersonal information. This is done to protect privacy and respect the privacy of people whose data may be used. Depersonalization of data allows data to be used for statistical analyses, research or other purposes, but at the same time prevents the possibility of identifying individuals based on this data.

Also, the possibility of sending images is planned, which then, using computer vision, can be processed and also interpreted in the work of the model.

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