Psychiatria Danubina, 2025; Vol. 37, Suppl. 1, pp 213-223

Conference paper
Research article

EMPLOYING COMPUTATIONAL LINGUISTIC TECHNOLOGIES AND OCULOGRAPHY TO DEVELOP DIAGNOSTIC TOOL FOR DETECTING AUTOAGGRESSIVE TENDENCIES IN YOUNG PEOPLE: A RIVETED GAZE INTO "GET RID OF THE SHACKLES OF THIS WORLD"

Anna Khomenko[1,2], Lala Kasimova[3], Evgeniy Sychugov[3], Marina Svyatogor[1], Anastasiya Komratova[1], Polina Domozhirova[1], Alina Aisina[1], Danil Trofimov[4], Kseniya Bikbaeva[5], Elena Sloeva[5] & Daria Smirnova[2,5]

[1]*Center for Language and Brain & Laboratory of Theory and Practice of Decision-Making Support Systems, HSE University, Nizhny Novgorod, Russia*
[2]*Institute of Mental Health, University "Reaviz", Saint Petersburg, Russia*
[3]*Department of Psychiatry, Privolzhsky Research Medical University, Nizhny Novgorod, Russia*
[4]*Department of Digital Data Processing Technologies, MIREA – Russian Technological University, Moscow, Russia*
[5]*Samara Institute of Mental Health, Medical University "Reaviz", Samara, Russia*

SUMMARY

Background: *Early recognition of autoaggressive tendencies in young people is essential for diagnostic screening and reducing suicidality risks. This can be achieved through psycholinguistic approaches such as corpus analysis and eye-tracking studies. Corpus research helps to develop generalized speech patterns of those at risk of suicide, while oculographic methods examine perceptual cues linked to suicidal tendencies.*

Methods: *We formulated an algorithmic framework for constructing verbal, visual, and multimodal material to identify autoaggressive tendencies among youth. The stimuli material was created following the idiolect paradigm of forensic authorship attribution. The first stage involved analyzing corpus data including materials from social networks and social media, the Rusentiment database, and a text collection from the Privolzhsky Research Medical University.*

Python's NLTK and SpaCy libraries for automated text processing were used to extract corpus statistics, n-grams, keywords, and collocations for identifying linguistic markers of autoaggression. Keywords were statistically ranked using Log-likelihood, T-score, and mutual information, while collocations were derived via T-score analysis. Sentiment analysis for the Dostoevsky Python library and stylistic indices (lexical diversity, readability) were also applied. The total analyzed material comprised more than 100 million tokens. We next integrated , stimulus and filler materials into an eye-tracking application (developed by LLC Lad IT Group) using standard laptop video cameras. Oculographic data quantified gaze delay differences via a percentage excess formula to pinpoint the most diagnostically relevant stimuli. In two iterations of the pilot experiment, 66 youths from the control group and 29 from the target group participated in the oculographic experiments.

Results: *In multimodal texts, most stimuli derived from corpus statistics were relevant, and all individuals in the target group showed a prolonged gaze delay; visual stimuli (pseudo-self-portraits, anime/game characters) elicited 26-36% longer gaze delay in the target group. Verbal stimuli analysis revealed prolonged gaze fixations on self-referential pronouns (12-25%) and metaphorical death expressions, although direct terms, like "suicide" showed the gaze avoidance (-11.9 to -129% deviation). We then developed a system of weighted coefficients for an automated diagnostic model. The algorithm showed 72 % accuracy in identifying autoaggression, presenting a promising tool for early diagnostic screening of this phenomenon.*

Conclusions: *The present methodology focuses on creating and employing a novel selective dataset consisting of visual, linguistic, and multimodal text stimuli integrated into the oculographic examination protocol. The oculographic detection of eye movement perceptual cues in response to exposure to the stimuli dataset may identify objective markers for evidence-based diagnostics of mental disorders (e.g., depression) and fundamental psychopathological phenomena (e.g., suicidality), including at-risk states (e.g., autoaggression). Furthermore, this approach may contribute to the enhancement of suicide prevention programs, particularly targeted interventions for the vulnerable population of young people who experience autoaggressive tendencies (i.e., self-aggression).*

Key words: *anomic suicide - autoaggression - computational linguistics - diagnostic tool - eye-movement analysis - eye-tracking – information processing - language corpus - oculography - self-aggression - suicidality - suicide screening - sociocultural context - young people*

Abbreviations: *CL – computational linguistics; NLTK - the Natural Language Toolkit*

* * * * *

INTRODUCTION

According to the World Health Organization, "every year more than 720,000 people die as a result of suicide," and "there are indications that for each person who dies by suicide, there are likely to be more than 20 others who attempt suicide"; suicide is fourth leading cause of death among young people aged 15-29 (Baydili et al. 2025, WHO 2024). Suicidality is a complex phenomenon that includes "invisible to the eye" symptoms of (i) suicidal ideation (e.g., rumination, reflection, brooding, planning), (ii) suicide-associated decline in volitional processes (i.e., intentions), and observable behavior, such as (iii) language patterns (e.g., speech content about death, increased use of personal pronouns), (iv) suicide attempts (e.g., drug overdose), (v) completed suicides, as well as (vi) parasuicidal self-harm patterns (e.g., cutting the skin to create scars). Any prior pattern of suicidality that appears over an individual's lifetime - such as suicidal thoughts, suicide attempts, or self-injurious actions - increases the risk of suicide for that person in the future; we call this the "learned suicidality phenomenon" (Heesen et al. 2024, Le et al. 2025, Syunyakov et al. 2022). Not only history of depression, suicidal, or self-harm behavior, but also different socio-demographic factors such as younger age are risk factors for suicide, especially in the context of severe social distress, as demonstrated in a global perspective by the recent COVID-19 pandemic and its associated lockdown (bringing social isolation and disconnection from the community) (Banerjee et al. 2021, Fountoulakis et al. 2022a, 2022b, Vrublevska et al. 2021). In Russia, suicidality increased to 21-29% among the general population in response to the pandemic, with young people representing one of the most vulnerable groups (Syunyakov et al. 2022).

Sociocultural changes have led to the psychological fragility of young people, i.e. millennials (Generation Y), zoomers (Generation Z, digital natives), and Generation Alpha, amidst high social pressure and the impact of rapidly developing internet technologies. Today's young people are born and raised in an era of active social media use, characterized by excessive integration along with "too much regulation", emotional disconnection as a change in communication style, communication breakdown with reality, and disturbed identity (theories of "inequality, power, and suicide" and of destructive perfectionism), disrupted belongingness and connectedness (community patterns of rejection and aggression), facilitated "suicide diffusion," and "suicide contagion" phenomena (Abrutyn et al. 2019, Kholmogorova et al. 2019, 2022, Kholmogorova & Garanyan 2004, Niveau et al. 2019, Mueller et al. 2021, Tsatsulin & Kholmogorova 2024, Turner 2015). There has been an increase in anomic types of suicides (according to Emile Durkheim's theory) among young people who currently fail to meet social standards, resulting in the experience of "purposelessness" and loss of direction in life (sense of "directedlessness") (Kar & Singh 2023). This state of affairs calls for sensitive and up-to-date diagnostic tools for the early detection of suicidality, including self-harm patterns, and for suicide prevention among young people (Sharma et al. 2024, Syunyakov et al. 2024).

Suicidality manifests as a form of autoaggression, or self-aggression, which is a fundamental underlying psychopathological phenomenon that describes emotional and behavioral disturbances of the self-preservation/survival instinct. Autoaggression harms the individual "from within" at both mental (e.g., self-deprecating thoughts, self-criticism, obsessive self-guilt ideation) and physical/somatic levels. This could manifest as self-harm behaviors such as obsessive/involuntary excoriations or skin picking disorder, as described in the field of psychodermatology, or volitional self-injury/skin cutting in an impulsive or demonstrative manner, suicide attempts, and completed suicides (Grant & Collins 2024, Jenssen et al. 2025). The phenomenon of autoaggression is somewhat opposite to aggression, which is directed "outward" and observed in interpersonal communication, as can occur in cases of borderline personality disorder or antisocial personality disorder (Barra et al. 2025, Martin et al. 2025). The term "autoaggression" is used in the Russian school of clinical psychopathology (particularly in children and adolescent psychiatry), whereas "self-aggression" or "self-injury" is favored in English-speaking schools of psychiatry (i.e., Anglo-Saxon), and in the German psychiatry school (Hames et al. 2018, Krylova et al. 2023, Malinina et al. 2023, McCloskey et al. 2012, Otte et al. 2019). However, both terms are present in the international professional literature; autoaggression (i.e. self-destruction) is described as a basic defense mechanism (i) in classical and modern psychoanalytic theory, (ii) suicide research focusing on personality traits and temperament factor, and (iii) relational theories of trauma-based studies (Frankel 2001, Giegling et al. 2018, Kernberg 2009, Kirsch et al. 2022, Pöldinger 1989). This defense mechanism represents a variation on the death drive versus life drive (Freud's Thanatos versus Eros) relating to broader representations in a person's life such as neglecting physical needs or self-care (Dal Molin et al. 2023, Kli 2018, Kirsch et al. 2022). This is not merely psychologization, but rather constitutes evidence that autoaggression manifests through various behavioral decline patterns (e.g., skin-picking). These can start with poor nutrition, substance use (alcohol or drugs) to ease "psychache" or emotional pain, lack of sleep, or avoidance of medical care for somatic illnesses, which in some cases may culminate in full-blown suicidality. This reflects the trajectory of suicidality development, where the aggregation of suicidal behavioral patterns over time leads to completed suicides at some later date. Among people living with self-harm behaviors and suicide attempts, only about 10% ultimately complete suicide, according to epidemiological data (Bellman & Namdev 2022, Le et al. 2025). The keystone message arising from those findings is that predicting behavioral patterns (representing autoaggression during person's experience) must be diagnosed promptly to prevent their potentially fatal long-term consequences.

Autoaggression is a transdiagnostic phenomenon, often observed in young people during the adolescent period in relation to various mental disorders (e.g., depression, anxiety, autism spectrum disorders) (Malinina et al. 2023, Posar & Visconti 2021). It has strong interrelationships with suicidality, despite the presence of psychotic symptoms (e.g., schizophrenia spectrum disorders) or somatic comorbidities (e.g., obsessive-compulsive spectrum disorders / skin picking disorder) (Cooper et al. 2025, Krylova et al. 2023, Onat et al. 2025). Furthermore, autoaggressive tendencies may serve as predictors of suicide, and can thus be utilized for screening purposes to evaluate suicidality risks in vulnerable populations (Barsznica et al. 2024). The objective markers of autoaggressive tendencies need to be clarified to create novel or improve existing diagnostic screening tools. This can be achieved, for example, through psycholinguistic experiments (language patterns), oculographic approaches (i.e., eye-tracking), and facial emotion recognition studies (multimodal/convolutional neural network research that includes comprehensive facial mimic analysis) (Barsznica et al. 2021, Li et al. 2023, Niveau et al. 2019, Zhu et al. 2024). Written speech patterns accurately pr d edict depression and suicidality risks via analysis of medical records, suicide notes, diary notes, linguistic corpus-based and social media post studies (Eichstaedt et al. 2018, Smith et al. 2017). Topics related to emotions (e.g., cry), interpersonal relationships such as loneliness (e.g., miss), and hostility (e.g., hate), as well as cognitive issues like self-preoccupation (e.g., first person pronouns use), figurative language use (e.g., metaphors), and lexico-stylistic changes like repetitive content (e.g., ruminations) have been related to depression. On the other hand, somatic complaints (e.g., headache, insomnia, sick) and medical references (e.g., hospital, doctor, blood), in addition to terms related low mood (e.g., sad, hurt, tears) and negative content (e.g. don't, can't, ain't, verbal emoji "lol" use with sarcastic connotation) have also been related to a history of suicide attempts or increased risks of suicidality in English and Russian language speakers (Mowery et al. 2017, Smirnova et al. 2018). Deep-learning algorithms demonstrated high accuracy in identifying language markers of suicidal tendencies in Turkish language (Baydili et al. 2025). In particular, suicide attempters demonstrated keywords, hashtags and pinned messages content distinctions compared to non-suicidal Korean language social media users (e.g., tokens "_want to die, _don't want to live, _want to cut, _like cutter knife, _like suicide impulse, _even attempt suicide, _arm warmer, _do self-harm terribly") (Kim et al. 2022). A prior corpus study of suicidal behavior in Russian-language material indicated generalized speech profiles among individuals prone to suicide (Litvinova et al. 2017).

Eye-tracking research reflects emotional and cognitive processing, and is able to identify those with risk of suicidal attempts as opposed to those experiencing non-suicidal depression across vulnerable populations of young and elder people (Barsznica et al. 2021, Carvalho et al. 2015, Ferrari et al. 2016, Xu et al. 2023, Zhu et al. 2024). Depressed patients exhibiting suicidal behavior spent more time gazing at emotional face parts (eyes and mouth) associated with negative emotions such as disgust and fear, and *neutral emotions*, compared to their non-suicidal counterparts, whereas fixation time did not differ for negative emotions such as anger and sadness or for happy emotions between the suicidal/ non-suicidal groups (Barsznica et al. 2021). Another line of research identified differences in emotional vs. cognitive information processing in depression and related suicidality, particularly in suicide attempters vs. non-suicidal depressive participants (Cramer et al. 2019, Li et al. 2023). *Need for affect (emotional) avoidance* acted as a strong predictor of suicide or elevated suicidal risk, but the need for cognitive insight (intellectual explanation) was related to a decreased risk of suicide among young adults (Cramer et al. 2019).

Taken into account the findings presented above, we suggest that objective markers, i.e. language and eye-tracking patterns, should contribute to the accuracy of screening autoaggressive tendencies as suicide predictors, rather than direct complaints expressing suicidal ideation obtained via clinical interview. We proposed to develop a diagnostic tool using psycholinguistic methods based on indirect observation and experiments focusing on linguistic corpus research and eye-tracking (oculographic) measurements of verbal and visual stimuli perception in a vulnerable population. The aim of our present study was thus to create an algorithm for constructing verbal, visual, and multimodal material suitable for diagnosing autoaggressive tendencies among young people as a part of future promising AI-driven suicidality risk assessment tool.

MATERIAL AND METHODS

To create materials that could serve as stimuli in oculographic studies, we first developed a linguistic corpus of Russian speakers. The subcorpus of individuals exhibiting autoaggression was derived from the Twitter Presuicidal Signals dataset, Rusentiment, and the Privolzhsky Research Medical University dataset. This compiled database includes digitized and electronic texts across the following categories: (i) Written, audio, and video content, as well as graphic material (i.e., pictures and symbols) produced by individuals known to exhibit autoaggression; (ii) Content that elicits reactions from individuals with autoaggression, such as reposts of texts on social media, text comments, emoticons (or other forms of ideography), and "like/dislike" reactions (dataset 1).

At this stage, we analyzed approximately 100 million tokens. This analysis was necessary to identify key elements such as verbal, pictorial, iconic, syntactic structures, clauses, patterns, and text structures that appear in the communications of these social groups and elicit emotional responses. By extracting these elements, we constructed generalized speech profiles of individuals prone to autoaggression based on their idiolect, and created stimulus materials that mimic the speech of the target groups, specifically those exhibiting autoaggression. To create filler material, we also conducted analysis of texts provided by individuals from a normal control group. Datasets here included texts from open sources (Dataset 1) consisting of more than one million tokens, broadly representing the speech of contemporary young Russian speakers. We studied this speech as a normative control for comparison with the target group, aiming to identify fundamental group differences in the frequency of verbal, pictorial, iconic, and syntactic elements.

The texts were automatically processed using Python programming libraries (NLTK – Dataset 2, - and SpaCy ru_core_news_sm model – Dataset 3) for extraction of N-grams, keywords, and collocations. An N-gram is a contiguous sequence of N tokens extracted from a text or speech corpus, where a token represents the smallest meaningful unit of analysis, being as a rule a set of symbols, sounds, syllables, or letters. In clinical and psychological research, N-grams can help to identify linguistic markers of mental states by analyzing recurrent word patterns. We highlighted keywords using various metrics such as Log-likelihood, T-score, Mutual Information (MI), Dice-Sørensen coefficient, and frequency ratio. These metrics identified the most significant and frequently occurring words in the texts of each group. Collocations – statistically stable phrases – were identified for the top 20 extracted keywords according to the T-score metric, which served to identify collocations making it possible to find the most frequent and significant combinations of words that are central to the speech structure of both groups. These elements are characteristics of the idiolect of the control and target groups (Litvinova, 2019), and are used in forensic authorship attribution as the parameters of social identification (Rubtsova et al. 2007:105; Coulthard 2004; McMenamin 2002). This set of characteristics is considered as the least controlled by the speaker during the production of any form of speech. There datasets have been used for managing our language corpus, i.e.:

- **Dataset 1.** Social network chat VKontakte (In Rus). (Accessed: 05.07.2025) URL: https://vk.com/blog_27325, Mel podcasts and blogs (In Rus). (Accessed: 05.07.2025) URL: https://mel.fm/, Social network Tumblr / Trending topics on Tumblr (In Rus). (Accessed: 05.07.2025). URL:https://www.tumblr.com/explore/trending?source=homepage_explore
- **Dataset 2.** NLTK (the Natural Language Toolkit /open source Python modules, datasets, and tutorials supporting research and development in Natural Language Processing (In Rus). NLTK requires Python version 3.8, 3.9, 3.10, 3.11 or 3.12. (Accessed: 05.07.2025). URL: https://github.com/ nltk/nltk
- **Dataset 3.** Russian – spaCY Models Documentation / free open-source library for Natural Language Processing in Python. (Accessed: 05.07.2025). URL: https://spacy.io/models/ru#ru_core_news_sm

To create filler material, we also analyzed texts provided by individuals from a normal control group. The datasets included texts from open sources, consisting of more than one million tokens, broadly representing the speech of contemporary young Russian speakers. We studied this speech as a normative control for comparison with the target group, aiming to identify fundamental group differences in the frequency of verbal, pictorial, iconic, and syntactic elements.

We also performed a sentiment analysis with neutral, positive, and negative categories using the Dostoevsky Python library. This analysis employed the type-token ratio (an index of lexical diversity), as well as the Flesch-Kincaid readability test and Gunning Fog index (indices of readability). These indices are traditional in forensic authorship examination. In most cases, the results confirmed previous studies (i.e., Litvinova & Litvinova 2017), but we also discovered new speech characteristics of individuals prone to autoaggression: autoaggressively-minded young people avoided directly naming death and paid greater attention to words related to tactile contact.

Based on corpus statistics, we created stimulus and filler material. This material was implemented in an application with an eye-tracking function to capture the perceptual responses of both the control and target groups. We utilized oculographic technology produced by LLC Lad, involving a standard laptop camera (video adapter: integrated Intel Iris Xe Graphics, Nvidia GeForce RTX 3070 Ti Laptop GPU; Camera: 720p, 30 Hz), aiming for ease of use. The data collected through the eye tracker were presented as key-value pairs, where the keys are stimulus and filler elements, and the values are the time of gaze delay in seconds. In the first iteration, 40 people were examined, and in the second iteration, 50. To include a person into control or target group, we made a comprehensive assessment based on a clinical interview, an analysis of the patient's history report (if any), as well as a tests battery application consisting of the Beck Depression Inventory (the BDI-IA version validated in Russia), Suicide Behaviors Questionnaire-Revised (SBQ-R), and Buss-Perry Aggression Questionnaire – 24 (BPAQ-24). Upon psychiatric examination, 66 people (females: n=35, males: n=31; average age of 21.5 years; n=29 in the first iteration, and n=37 in the second iteration) were assigned to the control group and 24 (females: n=14, males: n=10; average age of 19.2 years; n=11 in the first iteration: n=11, and n=13 in the second iteration) to the target group (Figure 1).

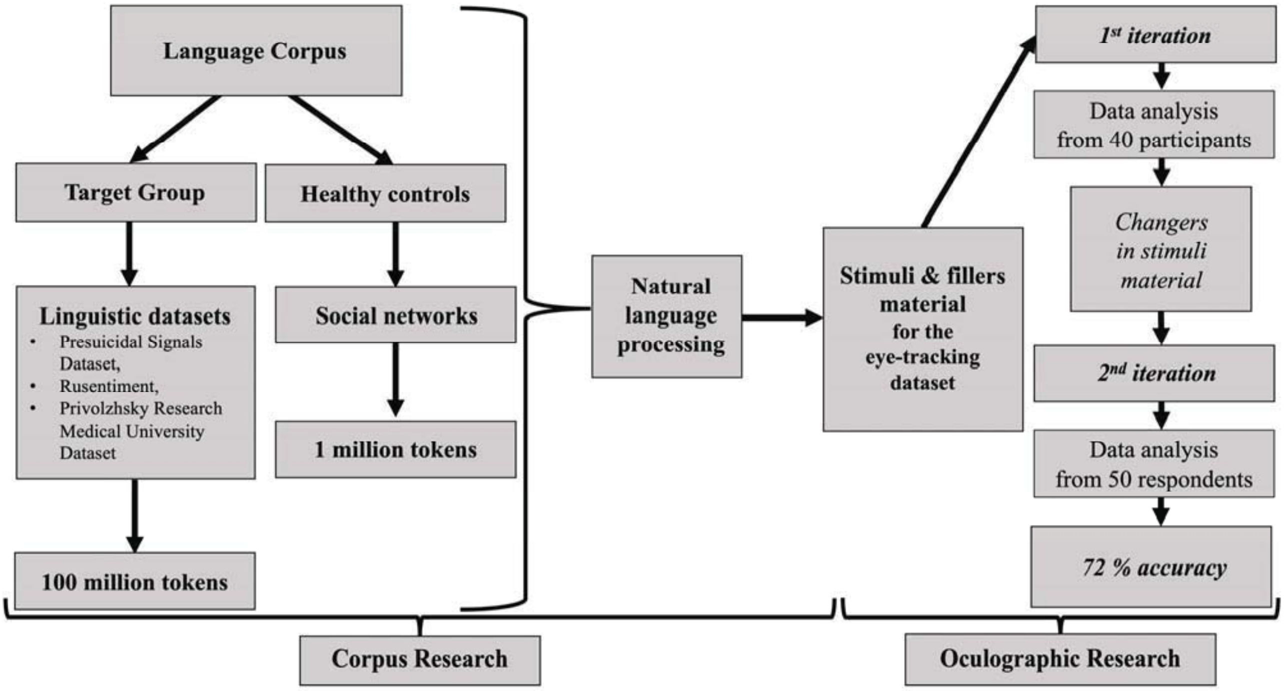

Figure 1. The study design and procedure demonstrating the application of language corpus and eye-tracking technology to target the autoaggression assessment in young people

To visualize the differences in gaze delay time between the control and target groups as a percentage excess during the first iteration, we used the following formula:

$$\text{Percentage excess} = \frac{\text{ATTG - ATCG}}{\text{ATCG}} \times 100\%$$

Note: ATTG - average time in target group;
ATCG - average time in control group

We used interpretive and statistical approaches to analyze the results. Statistical analysis starred from determining the gaze delay data from control and target groups followed a non-normal distribution. Subsequently, the Mann-Whitney U test ($p \leq 0.05$) was applied to evaluate statistical significance for each stimulus element. To address multiple comparisons, the Benjamini-Hochberg (FDR) corrections were employed (p (FDR) $\leq$ 0.05). The obtained statistical data were interpreted by the research team. This approach allowed us to determine which stimulus material was most relevant for analyzing written speech perception.

RESULTS

The results from the eye trackers were data matrices containing information about gaze delay on elements of the stimulus material and the avoidance of those elements. To interpret the data, we developed vocabularies with the weights of each element of the diagnostic material. For this purpose, the experimental material was placed in the oculograph to test the system. The materials included verbal stimuli, visual stimuli, and multimodal texts. The target group – the group with autoaggression – showed a longer gaze delay (Table 1).

Visual stimuli included pseudo-self-portraits and images of characters from computer games and anime. The statistical analysis of visual components showed that the gaze delay time for each stimulus was significantly higher in the target group. For example, the average gaze delay on the pseudo-self-portrait in the target group was 26% longer than in the control group (6.47 sec vs. 4.77 sec; p = 0.001, p (FDR) = 0.003), and the delay for anime character images was 36% longer (Image 1: 3.16 sec vs. 2.01 sec, p = 0.002, p (FDR) = 0.004; Image 2: 1.68 sec vs. 1.07 sec, p = 0.005, p (FDR) = 0.008).

The analysis of respondents' reactions to verbal stimuli showed that the average gaze delay for self-identification vocabulary, I-group pronouns, and words with figurative meanings in the target group exceeded the average gaze delay of the control group for all instances (Table 2). The percentage deviation for I-group pronouns in the target group surpassed that of the control group by 12.5 to 24.6% (for example, *in my / в моей* p-value = 0.015, p (FDR) = 0.03). Words and expressions presented in the semantic field of death, such as *to get rid of the shackles of this world / избавиться от оков этого мира* with a mean gaze delay of 1.66 sec in the target group versus 1.42 sec in the control group (p-value = 0.025, p (FDR) = 0.05), and *thoughts about death / мысли о смерти* with 1.08 sec versus 0.92 sec (p-value = 0.03, p (FDR) = 0.05), also demonstrated longer attention time in the target group. The stimuli *suicide / суицид* showed a gaze delay of 0.63 sec in the control group compared to 0.71 sec in the target group (p-value = 0.05, p (FDR) = 0.05), and *death / смерть* had a delay of 0.44 sec in the control group versus 0.19 sec in the target group, resulting in negative percentage deviations (-11.9% and -129%, respectively; p-value = 0.001, p (FDR) = 0.01). This demonstrates that individuals in the target group distinctly tended to avoid directly naming death and suicide. Some elements exhibit insignificant differences in gaze delay between the control and target groups: the word *deliverance / избавление* attracted the attention of the control group more than that of the target group (1.26 sec vs. 1.18 sec; p-value = 0.32, p (FDR) = 0.36).

Thus, some stimuli elements were excluded from the materials, and a relevance scale was created for the remaining elements. The weights for the stimulus vocabulary were distributed from one to three, where three points signifies a high weighting; these elements provided the greatest information gain for classifying the respondent as belonging to the target group when the gaze was fixed on them for an extended period. For example, such a weight is assigned to lexemes and their combinations related to eating disorders and tactile contact. A score of two points represents a medium degree of information gain, attributed to lexemes such as *fatigue / усталость*, *life / жизнь*, and *beauty / красота*. A score of one point indicates a low degree, assigned to such terms like *child / ребенок* and *teenager / подросток*. A zero score is given to neutral elements, which would be perceived equally by both the target and control groups; this constitutes the filler material (Table 3).

Table 1. The ratio of gaze delay-related multimodal elements to total element count in oculographic examination of verbal, visual, and vultimodal stimuli (Target Group vs. Healthy Controls)

Stimulus type	Ratio		
• Emoji	3/4		
• Posts imitating people with autoaggressive behavior on social media	*"Relationships"* 14/18	*"Death"* 8/8	*"Diseases"* 7/7
• Images of computer game characters chosen due to their connection with certain fandoms recognizable in the self-harm community	1/1		
• Images of anime characters chosen due to their connection with certain fandoms recognizable in the self-harm community	1/1		
• Isolated verbal stimuli statistically relevant to the discourse of people with autoaggressive behavior	*"Relationships"* 7/10	*"Death"* 6/14	*"Diseases"* 1/5

Table 2. The ratio of gaze delay-related verbal elements to total element count in oculographic examination (Target Group vs. Healthy Controls)

Stimulus type	Ratio		
• Self-identification vocabulary	11/11		
• I-group pronouns	6/6		
• Words describing the semes of certain semantics	*"Relationships"* *12/12*	*"Death"* *5/6*	*"Diseases"* *10/11*
• Lexemes expressing a negative emotional state	22/25		
• Vocabulary with a positive connotation	11/12		
• Words with a figurative meaning	14/14		

Table 3. The relevance scale based on designation of stimuli and fillers elements with information weight degree: a scoring example

Word Rus / Eng	Gaze delay time	Stimulus / Filler	Average gaze delay time	Designation rule	Comparison sign	Weight scoring
• Я /*'I'*	0.06	filler	1.48	*If the gaze delay time for a particular element is longer than the average gaze delay, then the element is assigned a score*	–	0
• понимаю / *'understand'*	3.52	*stimulus*			>	2
• это / *'this'*	2.45	*stimulus*			>	2
• состояние / *'state'*	3.07	*stimulus*			>	2
• мне /*'Me'*	0.92	filler			–	0
• тоже / *'also'*	0.89	filler			–	0
• не нравятся / *'don't like'*	2.42	*stimulus*			>	3
• люди / *'people'*	0.03	filler			–	0

Some elements were assigned a negative score ranging from -3 to -1, indicating the degree of the target group's tendency to deliberately avoid certain stimuli, where -3 represents a high degree of avoidance, -2 indicates an average degree, and -1 signifies a low degree. For example, individuals prone to autoaggression tend to avoid the word *death / смерть* - the direct naming of what they are concerned about. This lexeme would receive a weight of -3. All visual stimuli have been assessed using the same scoring system (Table 3).

Final Stimulus Material Testing

The design of the experiment was as follows: participants perceive a series of stimuli (verbal and visual) displayed on the computer screen; eye-tracking technology collected information about the gaze delay on each particular object. To validate the effectiveness of the automatic algorithm, the obtained data were analyzed independently by an expert group (including psychiatrists and psycholinguists) as well as automatically by the computer algorithm. The automatic algorithm is based on a mathematical model that incurporates the weight characteristics of each element and determines whether a person falls into the risk zone for autoaggression or not.

In the second analytical stream, we found that among the 50 participants (27 females, 23 males; average age = 19.9), the automatic classifier provided the correct answer in 36 cases (25 females, 11 males). Of the 14 cases where an error was detected, three situations were considered borderline by both the psychiatric experts and the automatic classifier. Therefore, the automatic classifier yielded the correct result in 72% of cases, while in another 6%, the result was incorrect, but close to the expert conclusion. In 22% of cases, the automatic classifier was in error, resulting in either a false positive (16%) or a false negative (6%) decision.

DISCUSSION

The study presented a novel approach to identify autoaggressive tendencies among young people through a combination of psycholinguistic analysis and eye-tracking technology, which, being separate from each other, previously demonstrated promising evidence to disentangle suicidal attempters and cases of non-suicidal depression among young and older populations (Barsznica et al. 2021, Cramer et al. 2019, Carvalho et al. 2015, Ferrari et al. 2016, Li et al. 2023, Niveau et al. 2019, Xu et al. 2023, Zhu et al. 2024). Our intermediate data analysis based on the experimental small-sized population reveals that individuals exhibiting these tendencies display distinct gaze patterns when confronted with verbal, visual, and multimodal stimuli. This suggests a complex interplay between cognitive (suicidal thoughts) and emotional (depression) processes, highlighting the potential for gaze patterns related to linguistic stimuli to serve as diagnostic markers of invisible autoaggression and related non-verbalized risks of suicides.

The methodology employed is particularly noteworthy, as far as analyzing over 100 million tokens from various datasets, the study identified linguistic markers associated with autoaggression. The use of Python libraries for automated text processing allowed for a robust statistical analysis, revealing that self-referential pronouns and metaphorical expressions related to death elicited prolonged gaze durations in the target group vs. normal controls. The prolonged gaze durations on self-referential pronouns and metaphorical expressions related to death indicate an internal (hidden) struggle (suicidal ideation, suicidal intentions) that may be a characteristic of individuals at risk for autoaggression. Increased use of the first-person pronouns has been found in people with depression speaking different languages, in the context of suicidality risks or history of suicidal attempts, highlighting the self-focusing language style, self-preoccupation state, and self-identity issues of disintegration between the individual's ongoing life or presence and intention to die or disappearance (Eichstaedt et al. 2018, Mowery et al. 2017, Smirnova et al. 2018, Smith et al. 2017). Sticking the gaze on the "I/Me" pattern, or a fixation on self-/autoaggression, is also consistent with data on young people being disconnected in communication despite active use of social media and during pandemic lockdown, losing a sense of direction in life or experiencing a sense of purposelessness because of high standards of destructive perfectionism and lack of emotional face-to-face relationships during the industrial era with AI-driven values rejecting the need for personality (i.e., human values related to social emotions - feelings, - and emotional intelligence) and the need for affect (vs. need for cognition) avoidance as a strong predictor of suicides (Abrutyn et al. 2019, Banerjee et al. 2021, Cramer et al. 2019, Fountoulakis et al. 2022a,b, Kholmogorova et al. 2019, 2022, Kholmogorova & Garanyan 2004, Kar & Singh 2023, Mueller et al. 2021, Niveau et al. 2019, Syunyakov et al. 2022, Tsatsulin & Kholmogorova 2024, Turner 2015, Vrublevska et al. 2021). Our present finding of longer gaze time spent on metaphorical statements rather than direct references to the language expression using the word "death" follows upon our earlier findings on the increased use of figurative language (e.g., metaphors, comparisons, phraseologisms) in mild depression, whereby the risk of suicide may be higher than in severe depression patients with diminished motor activities and capacity to complete actions (i.e., suicidal acts) (Smirnova et al. 2018). Metaphorical language (e.g., "to get rid of the shackles of this world") also switches from and hides the direct message (i.e., "death", intention to die) which is related to fear, and, moreover, it reminds recent research findings on suicidal attempters rather focusing their gaze on some sort of negative (e.g., disgust, fear) and neutral emotions, compared to another negative (e.g., anger, sadness) or positive emotions stimuli (Barsznica et al. 2021). This finding also may reflect an internalized stigma or fear associated with suicide-related sociocultural concepts, including the orthodox religion-related notion on the sin of suicide, and basic unconscious fear of death associated with the decline of the self-preservation instinct in people with autoaggressive tendencies (Frankel 2001, Giegling et al. 2018, Kernberg 2009, Kirsch et al. 2022, Pöldinger 1989). Clinicians would note that those people who have already decided to commit suicide compared to those who just think about death or hesitate to act usually do not discover their planning or do not directly verbalize their plans for suicide. Based on our findings, we might speculate that figurative language is a stronger predictor of suicidal risk than direct complaints. The behavioral patterns mentioned above underscore the importance of understanding the current psychological landscape of at-risk youth, as it may reflect deeper emotional conflicts and cognitive dissonance in people experiencing autoaggressive tendencies. This also highlights the need for developing sensitive diagnostic tools that can navigate these evident complexities.

Our CL-algorithm created for automated analysis-based diagnostics of autoaggressive tendencies among young people (using objective markers, i.e., the gaze delay time patterns in a psycholinguistic context) demonstrated a commendable accuracy of 72%, indicating its potential utility in clinical settings. However, the study also acknowledges the limitations inherent in the classification process, particularly the occurrence of false positive and negative indications. This calls for further refinement of the algorithm and additional validation through larger sample sizes and diverse populations.

CONCLUSIONS

To sum up, the study demonstrates the feasibility of using a multimodal approach to detect autoaggressive tendencies in young people. The integration of psycholinguistic methods and eye-tracking technology offers a promising avenue for enhancing suicide prevention strategies. The findings advocate for the implementation of these diagnostic tools in clinical practice, emphasizing the need for timely intervention in vulnerable populations of young people. Future research should focus on refining the diagnostic algorithm, expanding the dataset to include a broader demographic, and exploring the underlying psychological mechanisms that drive the observed gaze delay behaviors. By advancing our understanding of the autoaggression phenomenon and its indicators, we can equip mental health professionals with a linguistic corpus of autoaggression (i.e., increased suicidality risk) and a CL-driven screening tool based on the eye-tracking of the dataset of visual linguistic stimuli, to address the pressing issue of youth suicidality more effectively.

Limitations

The main limitation of the study is the oculography technology itself, which uses a standard laptop camera. This technology was validated using a hardware oculography (registration accuracy: 0.5–1 deg; sampling rate: 60 Hz (150 Hz in GP3 HD model); 5- or 9-point calibration; head movement freedom area during calibration: horizontal – at least 25 cm; vertical – at least 11 cm; forward/backward – at least 15 cm; dimensions: 320 x 45 x 40 mm), showing its reliability under certain limitations. Thus, a non-hardware oculograph is not able to accurately capture the fixation of the gaze on a verbal element of two or fewer symbols. The overall share of element recognition by a non-hardware oculograph is always lower than by hardware: 68% versus 100%. It is precisely the inaccuracies in defining objects that mainly lead to the distortion of data in the analytical block of the automatic algorithm for detecting the presence/absence of tendencies towards autoaggression. Current data analysis is based on a small sample size and represents preliminary findings. A larger sample population is needed to increase the reliability of the results, based on the study design that combines language corpus selection and eye-tracking algorithms. Moreover, recent sociocultural changes, as well as psychosocial pathmorphosis of depression (e.g., alexithymia, difficulties in verbalizing emotions and feelings, excessive anxiety, prevalence of somatic over mental health-related complaints) should be taken into account to design the study protocol generating language corpus and stimuli dataset (Krasnov et al. 2023, Tsatsulin & Kholmogorova 2024). Changes in language of young people due to the excessive presence of technologies in daily life, and the increased use of social networks /media also contribute to this line of research discovering the language patterns / markers of depression, suicidality, autoaggression, and variety of affective states and symptoms (Abrutyn et al. 2019, Kar & Singh 2023, Kholmogorova et al. 2019, 2022, Kholmogorova & Garanyan 2004, Niveau et al. 2019, Mueller et al. 2021, Turner 2015).

Team of professionals

Current research represents intermediate results of collaboration project performed the multidisciplinary team of professionals, i.e.:

- **Linguistic group** (Center for Language and Brain & Laboratory of Theory and Practice of Decision-Making Support Systems, HSE University),
- **Clinical psychiatry group** (Institute of Mental Health, University "Reaviz" & Department of Psychiatry, Privolzhsky Research Medical University),
- **Technical group** (Department of Digital Data Processing Technologies, MIREA – Russian Technological University).

Acknowledgements:

Authors express their sincere gratitude to Adjunct Professor Paul Cumming, School of Psychology and Counselling, Queensland University of Technology, Brisbane, Australia, for language review and critical reading of the manuscript.

Funding: The part of the research was prepared within the framework of the Academic Fund Program at HSE University (grant №25-00-027 "True or False? Determining the Reliability/Unreliability of Information from a Multimodal Text").

Conflict of interest: None to declare.

Contribution of individual authors:

Study design: Anna Khomenko, Marina Svyatogor, Lala Kasimova.

Literature review: Anna Khomenko, Kseniya Bikbaeva, Elena Sloeva, Daria Smirnova.

Data collection: Evgeniy Sychugov, Anastasiya Komratova, Polina Domozhirova, Alina Aisina.

Comprehesive data analysis (including intermediate statistical analysis): Anna Khomenko, Marina Svyatogor, Lala Kasimova, Elena Sloeva, Daria Smirnova, Danil Trofimov.

Clinical interpretation of linguistic data: Anna Khomenko, Lala Kasimova, Daria Smirnova.

Manuscript writing: Anna Khomenko, Daria Smirnova.

First Authorship: Anna Khomenko.

Senior authorship: Daria Smirnova.

All authors approved the final manuscript.

References

1. *Abrutyn, S., Mueller, A. S., & Osborne, M. (2019). Rekeying Cultural Scripts for Youth Suicide: How Social Networks Facilitate Suicide Diffusion and Suicide Clusters Following Exposure to Suicide. Society and Mental Health, 10(2), 112-135. https://doi.org/10.1177/2156869319834063*
2. *Banerjee, D., Kosagisharaf, J. R., & Sathyanarayana Rao, T. S. (2021). 'The dual pandemic' of suicide and COVID-19: A biopsychosocial narrative of risks and prevention. Psychiatry research, 295, 113577. https://doi.org/10.1016/j.psychres.2020.113577*
3. *Barra, S., Fittipaldi, D., Retz-Junginger, P., Merscher, J., Turner, D., & Retz, W. (2025). Borderline personality disorder and antisocial traits in justice-involved males: Associations with aggression, violent crime, and adverse childhood experiences. Psychiatry research, 348, 116427. https://doi.org/10.1016/j.psychres.2025.116427*
4. *Barsznica, Y., Noiret, N., Lambert, B., Monnin, J., De Pinho, C., Hickel, J., Masse, C., Richard-Devantoy, S., Morgny, C., Bennabi, D., Haffen, E., Laurent, E., Vandel, P., & Chopard, G. (2021). Saccadic Eye Movements in Elderly Depressed Patients With Suicidal Behaviors: An Exploratory Eye-Tracking Study. Frontiers in psychology, 12, 712347. https://doi.org/10.3389/fpsyg.2021.712347*
5. *Baydili, İ., Tasci, B., & Tasci, G. (2025). Deep Learning-Based Detection of Depression and Suicidal Tendencies in Social Media Data with Feature Selection. Behavioral sciences (Basel, Switzerland), 15(3), 352. https://doi.org/10.3390/bs15030352*
6. *Bellman, V., & Namdev, V. (2022). Suicidality Among Men in Russia: A Review of Recent Epidemiological Data. Cureus, 14(3), e22990. https://doi.org/10.7759/cureus.22990*
7. *Carvalho, N., Laurent, E., Noiret, N., Chopard, G., Haffen, E., Bennabi, D., & Vandel, P. (2015). Eye Movement in Unipolar and Bipolar Depression: A Systematic Review of the Literature. Frontiers in psychology, 6, 1809. https://doi.org/10.3389/fpsyg.2015.01809*
8. *Cooper, R., Sahasrabudhe, R., Choi, K. W., Kelleher, I., & Jalbrzikowski, M. (2025). Using Electronic Health Records to Identify Medical Presentation for Self-harm as a Predictor of Psychotic or Bipolar Disorders: A Systems-level Alternative to the Clinical High-risk Approach. Schizophrenia bulletin, sbaf098. https://doi.org/10.1093/schbul/sbaf098*
9. *Coulthard, M. (2004). Author identification, idiolect, and linguistic uniqueness. Applied Linguistics, 24(4): 431–447. doi:10.1093/applin/25.4.431*
10. *Cramer, R. J., Rasmussen, S., Webber, W. B., Sime, V. L., Haile, C., McFadden, C., & McManus, M. C. (2019). Preferences in Information Processing and suicide: Results from a young adult health survey in the United Kingdom. The International journal of social psychiatry, 65(1), 46–55. https://doi.org/10.1177/0020764018815206*
11. *Eichstaedt, J. C., Smith, R. J., Merchant, R. M., Ungar, L. H., Crutchley, P., Preoţiuc-Pietro, D., Asch, D. A., & Schwartz, H. A. (2018). Facebook language predicts depression in medical records. Proceedings of the National Academy of Sciences of the United States of America, 115(44), 11203–11208. https://doi.org/10.1073/pnas.1802331115*
12. *Ferrari, G. R., Möbius, M., van Opdorp, A., Becker, E. S., & Rinck, M. (2016). Can't Look Away: An Eye-Tracking Based Attentional Disengagement Training for Depression. Cognitive therapy and research, 40(5), 672–686. https://doi.org/10.1007/s10608-016-9766-0*
13. *Fountoulakis, K. N., Karakatsoulis, G., Abraham, S., Adorjan, K., Ahmed, H. U., Alarcón, R. D., Arai, K., Auwal, S. S., Berk, M., Bjedov, S., Bobes, J., Bobes-Bascaran, T., Bourgin-Duchesnay, J., Bredicean, C. A., Bukelskis, L., Burkadze, A., Abud, I. I. C., Castilla-Puentes, R., Cetkovich, M., Colon-Rivera, H., … Smirnova, D. (2022). Results of the COVID-19 mental health international for the general population (COMET-G) study. European Neuropsychopharmacology: the Journal of the European College of Neuropsychopharmacology, 54, 21–40. https://doi.org/10.1016/j.euroneuro.2021.10.004*
14. *Fountoulakis, K. N., Karakatsoulis, G. N., Abraham, S., Adorjan, K., Ahmed, H. U., Alarcón, R. D., Arai, K., Auwal, S. S., Berk, M., Bjedov, S., Bobes, J., Bobes-Bascaran, T., Bourgin-Duchesnay, J., Bredicean, C. A., Bukelskis, L., Burkadze, A., Abud, I. I. C., Castilla-Puentes, R., Cetkovich, M., Colon-Rivera, H., … Smirnova, D. (2022). The effect of different degrees of lockdown and self-identified gender on*

anxiety, depression and suicidality during the COVID-19 pandemic: Data from the international COMET-G study. Psychiatry research, 315, 114702. https://doi.org/10.1016/j.psychres.2022.114702

15. *Frankel, J. (2001). A witness breaks his silence: the meaning of a therapist's response to an adolescent's self-destruction. American journal of psychoanalysis, 61(1), 85–99. https://doi.org/10.1023/a:1002709526548*
16. *Giegling, I., Olgiati, P., Hartmann, A. M., Calati, R., Möller, H. J., Rujescu, D., & Serretti, A. (2009). Personality and attempted suicide. Analysis of anger, aggression and impulsivity. Journal of psychiatric research, 43(16), 1262–1271. https://doi.org/10.1016/j.jpsychires.2009.04.013*
17. *Grant, J. E., & Collins, M. (2024). Non-suicidal self-injury in trichotillomania and skin picking disorder. CNS spectrums, 29(4), 268–272. https://doi.org/10.1017/S1092852924000294*
18. *Hames, J. L., Rogers, M. L., Silva, C., Ribeiro, J. D., Teale, N. E., & Joiner, T. E. (2018). A Social Exclusion Manipulation Interacts with Acquired Capability for Suicide to Predict Self-Aggressive Behaviors. Archives of suicide research : official journal of the International Academy for Suicide Research, 22(1), 32–45. https://doi.org/10.1080/13811118.2017.1304309*
19. *Heesen, K., Mérelle, S., van den Brand, I., van Bergen, D., Baden, D., Slotema, K., Gilissen, R., & van Veen, S. (2024). The forever decision: a qualitative study among survivors of a suicide attempt. EClinicalMedicine, 69, 102449. https://doi.org/10.1016/j.eclinm.2024.102449*
20. *Jenssen, H., Jakobsen, S. G., Larsen, C. P., & Christiansen, E. (2025). Differences Between Adolescents with Self-Harm Ideation and a History of Self-Harm. A Cross-Sectional Study Among Adolescents in Denmark. Archives of suicide research : official journal of the International Academy for Suicide Research, 1–13. https://doi.org/10.1080/13811118.2025.2490153*
21. *Kar, S. K., & Singh, S. (2023). Anomic suicides on rise during recently emerging crises: revisiting Durkheim's model. CNS spectrums, 28(6), 655–656. https://doi.org/10.1017/S1092852923002341*
22. *Kernberg, O. (2009). The concept of the death drive: a clinical perspective. The International journal of psycho-analysis, 90(5), 1009–1023. https://doi.org/10.1111/j.1745-8315.2009.00187.x*
23. *Kholmogorova, A.B., & Garanyan, N.G. (2004). Narcissism, perfectionism, and depression. Moscow Journal of Psychotherapy,(1): 18–35.*
24. *Kholmogorova, A.B., Garanyan, N.G., & Tsatsulin, T.O. (2019) Dynamics of perfectionism indicators and symptoms of emotional distress in the Russian student population over the past ten years: A cohort study. Cultural-Historical Psychology, 15(3):41-50. doi: 10.17759/chp.2019150305*
25. *Kholmogorova, A.B., Kazarinova, E.Y., & Rakhmanina, A.A. (2022) Students' positions in educational activities and their preferred content on the Internet as factors of problematic use of the World Wide Web. Psychological Science and Education, 27(3):104-116. doi: 10.17759/pse.2022270308*
26. *Kim, D., Jung, W., Nam, S., Jeon, H., Baek, J., & Zhu, Y. (2022). Understanding information behavior of South Korean Twitter users who express suicidality on Twitter. Digital health, 8, 20552076221086339. https://doi.org/10.1177/20552076221086339*
27. *Kirsch, M., Dimitrijevic, A., & Buchholz, M. B. (2022). "Death drive" scientifically reconsidered: Not a drive but a collection of trauma-induced auto-addictive diseases. Frontiers in psychology, 13, 941328. https://doi.org/10.3389/fpsyg.2022.941328*
28. *Kli, M. (2018). Eros and Thanatos: A Nondualistic Interpretation: The Dynamic of Drives in Personal and Civilizational Development From Freud to Marcuse. Psychoanalytic review, 105(1), 67–89. https://doi.org/10.1521/prev.2018.105.1.67*
29. *Krasnov, V. N., Kryukov, V. V., & Trushchelev, S. A. (2023). Psikhosotsial'nyi patomorfoz depressii [Psychosocial pathomorphosis of depressions]. Zhurnal nevrologii i psikhiatrii imeni S.S. Korsakova, 123(11-2) 30–37. https://doi.org/10.17116/jnevro202312311230*
30. *Krylova, E. S., Kuleshov, A. A., & Kaleda, V. G. (2023). Psikhopatologicheskie korrelyaty depressii s nesuitsidal'nymi samopovrezhdeniyami pri nepsikhoticheskikh psikhicheskikh zabolevaniyakh yunosheskogo vozrasta [Psychopathological correlates of depression with non-suicidal self-harm in non-psychotic mental illnesses of adolescence]. Zhurnal nevrologii i psikhiatrii imeni S.S. Korsakova, 123(11. Vyp. 2), 74–78. https://doi.org/10.17116/jnevro202312311274*
31. *Le, G. H., Wong, S., Au, H., Badulescu, S., Gill, H., Vasudeva, S., Teopiz, K. M., Rhee, T. G., Ho, R., Kwan, A. T. H., Mansur, R. B., Rosenblat, J. D., & McIntyre, R. S. (2025). Association between rumination, suicidal ideation and suicide attempts in persons with depressive and other mood disorders and healthy controls: A systematic review and meta-analysis. Journal of affective disorders, 368, 513–527. https://doi.org/10.1016/j.jad.2024.09.118*
32. *Litvinova, T.A. (2019) Idiolekt kak ob"ekt korpusnoj idiolektologii: k stanovleniyu novogo lingvisticheskogo napravleniya [Idiolect as an object of corpus and idiolectology: toward the formation of a new linguistic trend]. Uchenye zapiski Novgorodskogo gosudarstvennogo universiteta, 7(25):1-5. (In Rus).*
33. *Litvinova, T.A., & Litvinova, O.A. (2017) Yazykovyye osobennosti russkoyazychnykh tekstov lits, sovershivshikh suitsid, i lits s vysokim riskom autoagressivnogo povedeniya [Linguistic parameters of russian texts by suicides and persons with a high risk of self-destructive behaviour]. Studia Humanitatis, 4: 18. (In Rus) (https://cyberleninka.ru/article/n/yazykovye-osobennosti-russkoyazychnyh-tekstov-lits-sovershivshih-suitsid-i-lits-s-vysokim-riskom-autoagressivnogo-povedeniya (assessed on 13.07.2025)*
34. *Litvinova, T.A., Seredin, P.V., Litvinova, O.A., & Zagorovskaya O.V. (2017) Identification of Suicidal Tendencies of Individuals Based on the Quantitative Analysis of Their Internet Texts. Computación y Sistemas, 21(2): 243-252.*
35. *Malinina, E. V., Zabozlaeva, I. V., & Mityushkin, A. E. (2023). Povedencheskie fenomeny depressii v podrostkovom vozraste [Behavioral phenomena of depression in adolescence]. Zhurnal nevrologii i psikhiatrii imeni S.S. Korsakova, 123(11. Vyp. 2), 9–13. https://doi.org/10.17116/jnevro20231231129*
36. *Martin, S., Del Monte, J., & Howard, R. (2025). The relationship between emotional impulsivity (Urgency), aggression, and symptom dimensions in patients with borderline personality disorder. Borderline personality disorder and emotion dysregulation, 12(1), 19. https://doi.org/10.1186/s40479-025-00292-5*
37. *McCloskey, M. S., Look, A. E., Chen, E. Y., Pajoumand, G., & Berman, M. E. (2012). Nonsuicidal self-injury: relationship to behavioral and self-rating measures of impulsivity and self-aggression. Suicide & life-threatening behavior, 42(2), 197–209. https://doi.org/10.1111/j.1943-278X.2012.00082.x*
38. *McMenami, G.R. (2002) Forensic Linguistics: Advances in Forensic Stylistics (1st ed.). CRC Press:360 p. doi:10.1201/9781420041170*
39. *Mowery, D., Smith, H., Cheney, T., Stoddard, G., Coppersmith, G., Bryan, C., & Conway, M. (2017). Understanding Depressive Symptoms and Psychosocial Stressors on Twitter: A*

Corpus-Based Study. Journal of medical Internet research, 19(2), e48. https://doi.org/10.2196/jmir.6895

40. Mueller, A. S., Abrutyn, S., Pescosolido, B., & Diefendorf, S. (2021). The Social Roots of Suicide: Theorizing How the External Social World Matters to Suicide and Suicide Prevention. Frontiers in psychology, 12, 621569. https://doi.org/10.3389/fpsyg.2021.621569

41. Niveau, G., Frioud, E., Aguiar, D., Ruch, P., Auckenthaler, O., Baudraz, J., & Fracasso, T. (2019). Suicide Notes: Their Utility in Understanding the Motivations Behind Suicide and Preventing Future Ones. Archives of suicide research: official journal of the International Academy for Suicide Research, 23(4), 576–589. https://doi.org/10.1080/13811118.2018.1480985

42. Onat, M., Nas Ünver, A. B., Şenses Dinç, G., Çöp, E., & Pekcanlar Akay, A. (2025). Comparisons between obsessive-compulsive disorder and trichotillomania in terms of autistic traits and repetitive behaviors in adolescents. Nordic journal of psychiatry, 79(1), 34–41. https://doi.org/10.1080/08039488.2024.2431116

43. Otte, S., Streb, J., Rasche, K., Franke, I., Segmiller, F., Nigel, S., Vasic, N., & Dudeck, M. (2019). Self-aggression, reactive aggression, and spontaneous aggression: Mediating effects of self-esteem and psychopathology. Aggressive behavior, 45(4), 408–416. https://doi.org/10.1002/ab.21825

44. Pöldinger W. J. (1989). The psychopathology and psychodynamics of self-destruction. Crisis, 10(2), 113–122.

45. Rubtsova, I.I., Ermolaeva, E.I., Bezrukova, A.I. (2007). Kompleksnaya metodika proizvod-stva avtorovedcheskikh ekspertiz: Metodicheskiye rekomendatsii [Comprehensive methodology for producing authorship examinations: Methodological recommendations]. Moscow: Forensic Science Center of the Ministry of Internal Affairs of Russia:192 p. (In Rus)

46. Smirnova, D., Cumming, P., Sloeva, E., Kuvshinova, N., Romanov, D., & Nosachev, G. (2018). Language Patterns Discriminate Mild Depression From Normal Sadness and Euthymic State. Frontiers in Psychiatry, 9, 105. https://doi.org/10.3389/fpsyt.2018.00105

47. Smith, R. J., Crutchley, P., Schwartz, H. A., Ungar, L., Shofer, F., Padrez, K. A., & Merchant, R. M. (2017). Variations in Facebook Posting Patterns Across Validated Patient Health Conditions: A Prospective Cohort Study. Journal of medical Internet research, 19(1), e7. https://doi.org/10.2196/jmir.6486

48. Sharma, V., Marshall, D., Fortune, S., Prescott, A. E., Boggiss, A., Macleod, E., Mitchell, C., Clarke, A., Robinson, J., Witt, K. G., Hawton, K., & Hetrick, S. E. (2024). Prevention of self-harm and suicide in young people up to the age of 25 in education settings. The Cochrane database of systematic reviews, 12(12), CD013844. https://doi.org/10.1002/14651858.CD013844.pub2

49. Syunyakov, T., Pavlichenko, A., Morozov, P., Fedotov, I., Filatova, V., Gayduk, A., Ignatenko, Y., Spikina, A., Yashikhina, A., Patsali, M., Fountoulakis, K., & Smirnova, D. (2022). Modeling Suicidality Risks and Understanding the Phenomenon of Suicidality Under the Loupe of Pandemic Context: National Findings of the COMET-G Study in the Russian Population. Consortium psychiatricum, 3(2), 15–36. https://doi.org/10.17816/CP167

50. Syunyakov T, Ashurov Z, Magzumova S, Astafeva D, Vlasov A, Pavlichenko A, Vrublevska J, Gonda X, Tavormina G, Thibaut F, Cumming P, De Sousa A, Fountoulakis KN & Smirnova D: Risk Assessment Suicidality Scale (RASS)-Based On-Line Calculator Targeting Early Prevention of Suicides in General Population: from COMET-G Study Results Towards Integration of the Screening Tool into Routine Clinical Practice. Psychiatr Danub 2024;.36(Suppl 2):225–231

51. Tsatsulin, T.O., & Kholmogorova, A.B. (2024) Destructive perfectionism and protective factors of emotional well-being among university students. Cultural-Historical Psychology, 20(2): 50-59. doi: 10.17759/chp.2024200206

52. Turner, A. (2015) Generation Z: Technology and Social Interest. The Journal of Individual Psychology, 71(2):103-113. Project MUSE, doi:10.1353/jip.2015.0021

53. Vrublevska, J., Sibalova, A., Aleskere, I., Rezgale, B., Smirnova, D., Fountoulakis, K. N., & Rancans, E. (2021). Factors related to depression, distress, and self-reported changes in anxiety, depression, and suicidal thoughts during the COVID-19 state of emergency in Latvia. Nordic journal of psychiatry, 75(8), 614–623. https://doi.org/10.1080/08039488.2021.1919200

54. World Health Organization (WHO) (2024). Suicide. 18 September 2024, Assessed on 14th July 2025; https://www.who.int/news-room/questions-and-answers/item/suicide

55. Xu, Y., Zheng, P., Feng, W., Chen, L., Sun, S., Liu, J., Tang, W., Bao, C., Xu, L., Xu, D., & Zhao, K. (2023). Patterns of attentional bias in antenatal depression: an eye-tracking study. Frontiers in behavioral neuroscience, 17, 1288616. https://doi.org/10.3389/fnbeh.2023.1288616

56. Zhu, D., Wang, Y., Wang, H., Li, Z., Li, X., Chen, X., Su, B., & Wang, Z. (2024). Assessment of eye tracking and facial expression as a model for depression identification: A preliminary study. General hospital psychiatry, 87, 144–145. https://doi.org/10.1016/j.genhosppsych.2023.09.004

Correspondence:
Anna Khomenko, MD
Center for Language and Brain & Laboratory of Theory and Practice of Decision-Making Support Systems, HSE University
25/12 Bolshaya Pechyorskaya, 603155 Nizhny Novgorod, Russia
E-mail: akhomenko@hse.ru