*Original article*

# Procedure for Identifying Negative Emotional States in Military Personnel

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**Abstract**:

***Objective:*** The development of a paradigm for enhancing the emotional state of service members and a method for identifying their negative states as a result of psychological stresses is of the utmost importance in the context of today's pressing issues. To that end, the purpose of this study is to develop and subjectively test the effectiveness of a procedure for identifying negative emotional states in service members (cadets from Kazakhstan's military institutes). ***Materials and methods:*** A two-stage procedure is proposed to identify a risk group for negative emotional states. The methodology for identifying negative emotional states is divided into two stages: screening and deep. ***Results and discussion:*** It will be discussed how the algorithm performed when tested on a sample of cadets from two military universities in Kazakhstan. According to the results, nearly all the people in the sample studied (approximately 95%) exhibited relatively positive indicators of psychological health, including low levels of depression, aggression, and anxiety. Negative emotional states were present in 5% of the service members. Additional ongoing dynamic assessment and monitoring of the risk group is required. ***Conclusion:*** The obtained results provide sufficient evidence to discuss how the proposed algorithm could be used. The research has practical value because it can be used to implement the applied method at training ranges in the contemporary military era.

**Keywords:** anxiety; depression; military personnel; negative emotions.

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## Introduction:

Recent sociopolitical events, both globally and in Kazakhstan, necessitate a greater focus on the psychological well-being of soldiers, cadets, and officers. Military psychologists are asked to study the personalities of soldiers and military teams to improve combat readiness and military discipline, as well as to do preventive work to stop bad social and psychological things from happening among military personnel.[1] When a person joins the military, they go through a series of tests to screen for mental disorders such as suicidal ideation, depression, and other conditions. Despite this, the problem of extra-uniform relationships, incidents of violence, instances of bullying, and suicides within the Armed Forces continue to be a pressing issue.[2]

Because of this, it is important to make algorithms that recognise negative emotional states in service members, especially anxiety, depression, and anger. Such an algorithm saves a lot of time and people when it comes to identifying negative emotions. It also makes it possible to start psychocorrective

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and psychotherapeutic measures early, and for a command to make decisions based on scientific evidence to boost morale and prevent emotional disorders in service members.

There is great attention to the ability to distinguish emotions in various fields of psychology. Thus, Qader et al.,[3] determine that the treatment tactics for patients with postcovid mental disorders should be based on protocols of cognitive behavioral therapy of hypochondriacal and generalized anxiety disorder, in combination with antidepressants and non-benzodiazepine tranquilizers. This approach ensures the stabile and positive results of therapeutic measures, confirmed by our research.[3]

In a study of nursing students' perception of caring behavior, Karaman argues that students' high attitude to care leads to positive progress in their professional life and allows them to become qualified medical professionals.[4] In their research on the definition of depression, anxiety and stress, Rom et al.,[5] claim that there is an urgent need to solve the problem of mental health and provide structured support to the individuals that need it. At the same time, the scientific works by Yusoff[6] show that there is a disorder associated with a negative affect – neuroticism. This affect is considered predisposing to mental disorders; therefore, it is crucial to control and monitor the psychoemotional state of a person.

It is important to note that Koliadenko et al.,[7] insist that a trauma from the past actually exists in cognitive memory. Moreover, the trauma can even be fixed in the center of self-consciousness and personal identity. In this regard, the psycho-emotional state requires monitoring. Weiss et al.,[8] conducted a research on the formation of the connection between negative affect, violation of emotion regulation and inducements to risky behavior among veterans of the armed forces undergoing inpatient treatment. The scientist emphasizes the potential usefulness of treatment aimed at violation of emotion regulation to reduce risky behavior among veterans of the armed forces.[8]

Theoretically, this concept may be defined in a variety of ways; however, it is universally acknowledged as essential to the study of social cognition.[9,10]

The following studies were particularly interesting within this experimental research trend: recognition of human emotions based on physiological signals;[11,12] definition of the emotions, and the further application of the experimental results in software development.[13]

The most significant and intriguing studies conducted in the past five years focused on the following topics: categories and dimensions of emotions in facial affective communication: a comprehensive approach;[14] nomological network of understanding the human emotional state and knowledge about emotions: the results of two new outcome-based tests;[15] dynamic determination of expressive facial features,[16] perceptual systematisation of facial gestures,[17] the GERT methodological development for measuring the level of awareness of how emotions are expressed.[18]

More in-depth studies of emotion recognition have recently been published that examine how this process relates to other mental processes as well as speech and thought functions.[19-22] The researches of this field also note that in context of natural language processing (NLP), emotion recognition in the conversation process is a popular and new research direction since it is possible to extract opinions from a wide range of publicly available conversation data on YouTube, Facebook, Reddit, Twitter and other websites. Thus, Faizul and Abu[23] note that social networks are a communication platforms, the use and influence of which has experienced exponential growth in recent years, democratizing the communication process. Social networks also provide an opportunity to inform about risks/crises with excellent access to the public, large distribution and its enormous speed. Informing about risks and crisis situations is valuable for improving preparedness and response, as they help to increase the level of citizens' awareness and their ability to take appropriate sustainable measures.[23]

Therefore, emotion recognition has many potential applications, for example, as a tool for psychological analysis in the field of healthcare, for example, to understand students' frustration in education, and etc. Taking emotion recognition in a behavioural direction is a fascinating new direction to explore. Its proponents examine this procedure by looking at how people's body language conveys their feelings.[24-29] This direction shows work on both recognising emotions based on postures and gestures and figuring out a person's mood based on how they change over time, even with the help of electronic-automatic devices.

The most effective clinical and preventative strategies in use today are based on lists of risk factors with prognostic time frames that can range from five to twenty years. Nonetheless, the concept of a warning sign for military suicide assumes an imminent or short-term risk in the next few days or weeks. Content on social media can warn about suicidal thoughts and other things that could be dangerous. For instance, states in the US with higher suicide rates also have a higher rate of tweets about military suicide.[30] Thus, the changes in negative emotions in military personnel and vulnerability theory offer a practical framework for recognising and conceptualising "warning signs" of suicide, which act as markers of temporarily increased suicide risk, but almost no empirical support.[31]

In the last 20 years, researchers have also talked about how the accuracy of recognising emotions may depend not only on a person's stable traits but also on their changing, situation-based traits, especially their current emotional state.[32]

## Literature Overview

Mimic scholars think that emotion recognition is more objective when it is done automatically.[33-41] These authors usually identify numerous methods that can automatically recognize emotions by a person's facial expression.

The expression of feelings through one's face serves a number of important adaptive purposes in social contexts. Because of the immediate nature with which facial expressions can convey biologically significant information, such as the presence of a predator or the availability of food, they have provided an evolutionary advantage.[42] Thus, the work by Minaee et al.,[42] analyzing photographs of happy, angry and neutral faces in the paradigm of visual search, revealed the value of recognizing emotional facial expressions of other people. Participants' responses to the existence of various expressions were reflected in the pictures that were displayed in a row. The results showed that detecting a face with angry emotions among a group of people with distracted neutral emotions takes less time than detecting a neutral face among a group of angry faces. Additionally, the studies by Rued et al.,[43] demonstrated that the RT for identifying a neutral person in a group of people with neutral emotions was lower than for identifying them in an emotionally charged group. These results show that detecting emotional facial expressions is more efficient than detecting neutral facial expressions.

The fundamental building block of ED systems is emotion models, which specify how feelings are visualised. For models to work, it is essential to differentiate between emotional states.[44] It is necessary to first define an emotion model to be used before engaging in any ED-related activity. The ED field is also used in programmes that look for emotions in suicide notes, capture emotions in multimedia tags, detect abusive sentences in conversations, and so on. However, while there is a large body of knowledge on emotion detection in voice/speech, images, and other multimodal methods, there is a scarcity of textual research. Texts, unlike multimodal methods, may not depict specific emotional features.[44] In addition, the difficulty of defining emotions in short texts, the use of emoticons, grammatical errors and the constant appearance of new words can be serious obstacles. Perikos and Hatzilygeroudis[45] in order to automatically detect emotions in texts used a set of classifiers. This set included an instrument with the keyword approach, and two ML statistical methods: maximum student entropy and NB. To collect information, the researchers used sets of data on emotional texts and an International Study of the Emotions Antecedents and Reactions (ISEAR). Stanford Parser was used to conduct an analysis at the level of sentences. After the removal of stop words and lemmatization, the functions were presented using Bag-of-Words (BOW). After that, the information was transferred to the classifier set, which determined whether a sentence contained an emotion and, if so, what kind of emotion it was. Their results demonstrate that a group of classifiers outperformed situations in which a single classifier was used.[46]

Individuals in the digital age tend to express their emotions, and thoughts, and disclose their daily lives through various social media platforms such as Facebook, Twitter and Instagram.[47] This expression can take the form of images, videos, and, most notably, text. Because these social media platforms are so popular and reach so many people, there is a lot of user data that can be used to study things like how people feel in different groups.[48] Textual data, as the most common form of communication, possesses a number of characteristics that make it the best choice for human emotion data analysis.[49] However, Li et al.,[50] state that the use of artificial intelligence in emotions is the future research area in sentiment analysis, with the goal of using machine learning techniques and algorithms to detect emotions. Consistent efforts in the field of artificial intelligence of emotions will inevitably lead to advancements in large-scale public opinion analysis, market research, and disease diagnosis.

## Problem Statement

The selected research materials and methods can be used to confirm the research hypothesis in the form of methods for the screening and in-depth stages of the procedure for identifying negative emotional states in military personnel. Military psychologists can use them to find out who is in the risk group because they can tell how much anger, anxiety, depression, and happiness a person has.

The purpose of the study was to develop and evaluate a method for identifying negative emotional states in military personnel (cadets at military institutes). The following were the objectives:

1. Develop an algorithm for identifying negative emotional states in military personnel, consisting of a screening and deep stage
2. Test the effectiveness of the algorithm for identifying negative emotional states.

## Methods and Materials:

### *Sample*

In August and September 2022, the procedure for recognising negative emotional states was tested at the Sagadat Nurmagambetov Military Institute of Kazakh Ground Forces (AVOKU) and the Military Engineering Institute of Radio Electronics and Communications (VIIREiS) of the Ministry of Defence of the Republic of Kazakhstan. Full-time cadets in their first through fourth years who completed all four questionnaires were eligible for inclusion in the screening stage group.

The first screening stage included 360 cadets in total. These consisted of 159 VIIREiS cadets and 201 AVOKU cadets.

The distribution by training course was as follows: first year 144 (40.0%), second year 62 (15.2%), third year 92 (25.6%), and fourth year 62 (10.4%) of the total sample. Cadets had an average age of 18.6 years. The Russian-speaking sample included 72 people, while the Kazakh-speaking sample included 288 people.

The acceptable sampling error did not exceed p = 4.83 based on the total number of service members studying at these universities. As such, the sample used could be thought of as representative enough for the claimed purposes.

## Research Design

The procedure for identifying negative emotional states is divided into two stages: screening (SS) and deep (DS).

The screening survey is an express diagnosis of military personnel's psycho-emotional state. It involves the whole class and a preliminary selection of cadets based on whether they are in a high-risk group for negative emotional states. This stage concludes with the identification of a "potential risk group" that will be studied by a psychologist in the subsequent stage. The subjects were split into two groups at this point: group A was the "subjects without risk of negative emotional states" and group B was the "subjects with the potential risk of negative emotional states" (group B). It should be noted that the presence of elevated values in at least one technique was the criterion for inclusion in group B.

For the screening stage, four methodologies that had been tested in earlier stages of the project using Cronbach's alpha version were selected as follows:

1. The PHQ-9 depression scale (Patient Health Questionnaire-9).[24,28] The Cronbach's alpha score for the Russian-language version is 0.703; whereas the score for the Kazakh-speaking version is 0.767.
2. The GAD-7 (Generalised Anxiety Disorder - 7) anxiety scale.[51] The Cronbach's alpha score for the Russian-speaking version is 0.830, whereas the score for the Kazakh-speaking version is 0.836.
3. Buss-Perry aggression level scale.[52] The Cronbach's alpha score for the Russian-speaking version is 0.805; whereas the score for the Kazakh-speaking version is 0.842. The technique reveals a general index of aggression, the level of physical aggression, anger and hostility.
4. Subjective well-being scale.[52,53] The Cronbach's alpha index for the Russian-speaking version is 0.703, whereas the score for the Kazakh-speaking version is 0.815.

The screening stage lasted only 5-10 minutes (for the whole group). Each participant had to provide their own answers on paper for the test. Only service members who scored in the "potential risk group" using at least one of the screening stage techniques are chosen for the second, deep stage of the algorithm for recognising negative emotional states. These were the service members who had at least one of the following A-D indicators:

A. Moderate, medium or high levels of anxiety (GAD-7 Anxiety Scale);
B. Mild, moderate, major depression (PHQ-9 Depression Scale);
C. Overall aggression rate exceeding the average normative level of aggression for males (according to the authors of the Russian-language version of the Buss-Perry Aggression Level Scale;
D. Low level of subjective well-being (Subjective well-being scale)

The deep stage consists of one-on-one work with each cadet, which calls for advanced psychological expertise. Non-standardised techniques are used here, including a semi-structured interview, observation of behaviour during the interview, and Sobchik’s Drawn Apperception Test (DAT) projective technique.[54-56] The maximum time allowed for this stage to be completed by a single service member is 15 minutes. The semi-structured interview included 10-12 questions about a service member’s psycho-emotional and somatic state. The observation scheme entailed evaluating the verbal and non-verbal components of behaviour during the interview, as well as the DAT performance. The DAT was an outline of story pictures, and the examinee was required to create a short story based on the information provided. The data from the DAT were analysed using a modified method proposed in this article.

The semi-structured interview questions focus on the week before the study and ask about the person’s physical and mental health.

### *Data Analysis*

The following qualitative-quantitative criteria were used: Smirnov-Kolmogorov normality test, frequency analysis, calculation of mean values, Mann-Whitney U-test and Kruskal-Wallis H-test, multiple regression analysis, content analysis (DAT, semi-structured interview).

### *Research Limitations*

The small sample size is a limitation. Larger samples, while sufficient to detect meaningful results, are required to investigate more nuanced temporal patterns. For instance, there can be a big difference between first-year and fourth-year students in the patterns of change linked to depressive states. Similar distinctions between gender groups may exist in temporal trajectories. To ascertain whether other pertinent factors and variables have an impact on the observed change processes, large samples are required.

## Ethical Clearance:

All the people who took part in the experiment agreed to the use of their personal information and were given information about how the research would be done. The research stages were discussed and approved by the ethics committees at both of the universities that were involved in the study.

## Results:

When the data were checked to see if the distribution was normal, it was discovered that it wasn’t normal for the entire sample, allowing non-parametric statistical methods to be used.

Group A included 273 cadets (35.5% first-year, 13.6% second-year, 29.7% third-year, and 21.2% fourth-year students), while Group B included 87 cadets (54.4% first-year, 28.7% second-year, 12.6% third-year, and 4.6% fourth-year students), with scores calculated using four different methods.

Figure 1 displays the percentage-based numerical breakdown of groups A and B.

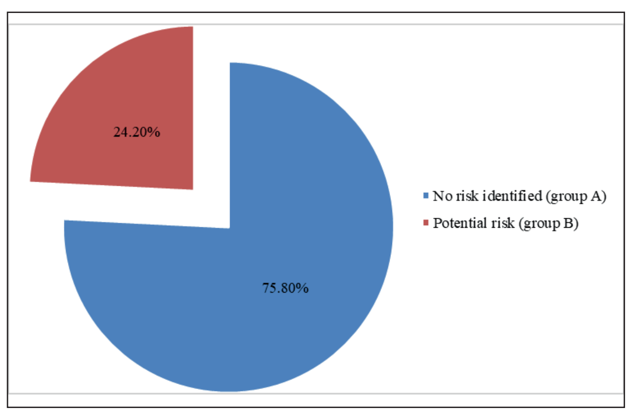


**Figure 1.** Percentage ratio of groups A and B at the end of SS

As a result, nearly one in every four cadets was placed in a high-risk group.

The average values for all methods are shown in Table 1.

**Table 1.** Indicators of SS questionnaires

| Scales | Group A | | Group B | | Mann-Whitney U-test | Significance |
|---|---|---|---|---|---|---|
| | M | M | M | m | | |
| Anxiety | 0.73 | 1.17 | 3.8 | 3.85 | 5184.5 | > 0.001 |
| Depression | 0.27 | 0.72 | 2.58 | 3.22 | 5935 | > 0.001 |
| Average score_walls | 1.78 | 1.33 | 3.71 | 1.87 | 4706 | > 0.001 |
| Average score_stress | 9.07 | 3.01 | 11.80 | 3.29 | 6458 | > 0.001 |
| Average score_psycho-emotional_symptom | 6.43 | 3.35 | 11.02 | 4.50 | 4940.5 | > 0.001 |
| Average score_mood | 3.02 | 1.82 | 4.52 | 2.25 | 5834 | > 0.001 |
| Average score_environmental | 5.21 | 2.69 | 6.67 | 3.29 | 8024 | > 0.001 |
| Average score_health | 3.05 | 1.84 | 4.75 | 2.63 | 5980 | > 0.001 |
| Average score_specific_activities | 6.93 | 3.16 | 9.43 | 4.06 | 7338 | > 0.001 |
| Aggressiveness | 41.86 | 10.94 | 67.19 | 20.49 | 3138.5 | > 0.001 |
| Physical_aggression | 16.77 | 6.91 | 31.48 | 15.84 | 4324 | > 0.001 |
| Anger | 13.30 | 3.70 | 17.09 | 5.05 | 6417 | > 0.001 |
| Hostility | 11.78 | 4.26 | 18.62 | 7.35 | 4992 | > 0.001 |

First, it is important to remember that participants in groups A and B exhibit significant differences at very high levels of statistical significance for all indicators To put it another way, the criteria this research used to divide the groups were successful in doing so and can be a differentiating basis for SS.

However, neither group A nor group B exhibit sharp critical values, indicating that the sample as a whole contains people who exhibit high levels of anxiety, depression, aggression, and subjective well-being.

The subjects' results are shifted to the region of low values in group A, where no risk was found. There is very little anxiety and depression, service members are very satisfied with their lives, and there is no inner tension. Aggressiveness indicators are also low and fall below the average normative aggression values (according to data obtained by the authors of the Russian version of the Buss-Perry questionnaire).

Group B, which is referred to as the "potential risk group" in this study, also has fairly good indicators on all methods; more specifically, they are within the range of the norm for that particular technique. However, within this norm, this group experiences slightly more anxiety, depression, and a decrease in subjective well-being than group A does.

For the indicator of depression, statistically significant differences (according to the Kruskal-Wallis H-criterion) were discovered between the subjects of the group in terms of the year of study when comparing the scales of negative emotional states (see Table 2).

**Table 2.** Results of the PHQ9 method in group B

| Scale | First-year cadets | | Second-year cadets | | Third-year cadets | | Fourth-year cadets | |
|---|---|---|---|---|---|---|---|---|
| | M | m | M | m | M | m | M | m |
| Depression | 4.89* | 3.9 | 1.8* | 1.2 | 4.0* | 2.3 | 4.25* | 1.5 |

Note* - Differences are significant at the p=0.03 level

Thus, first-year cadets had the highest rates of depression, reaching the level of mild depression, and second-year cadets had the lowest rates. There was an increase in the number of cadets who suffer from depression during their third and fourth years.

At the deep stage, an individual examination using non-standard techniques was made available to the participants in the "potential risk group." As previously stated, this is a semi-structured interview, with scheme-based observation and the DAT technique (Sobchik). Given the need for expert knowledge in this area, the work is carried out by a licenced psychologist. In addition, when the psychologist has reached the deep stage of recognising negative emotional states, he or she directly evaluates and records unique form aspects of the service member’s behaviour such as:

- Appearance (e.g. unkempt clothing, no haircut)
- Posture, facial expressions,
- General neurodynamics,
- Features of speech,
- Predominant current emotions,
- Personality traits,
- Presenting yourself and making contact with the psychologist.

Two psychologists analysed 87 service members in the deep stage of the procedure and identified 18 individuals (20.6%) from group B as high-risk for negative emotional states. This group will be referred to as “group C” from now on. In 69 people, the likelihood of experiencing negative emotions was not confirmed. Consequently, some participants dropped out again. Group C accounts for 5% of all service members in comparison to the original sample size (see Figure 2).

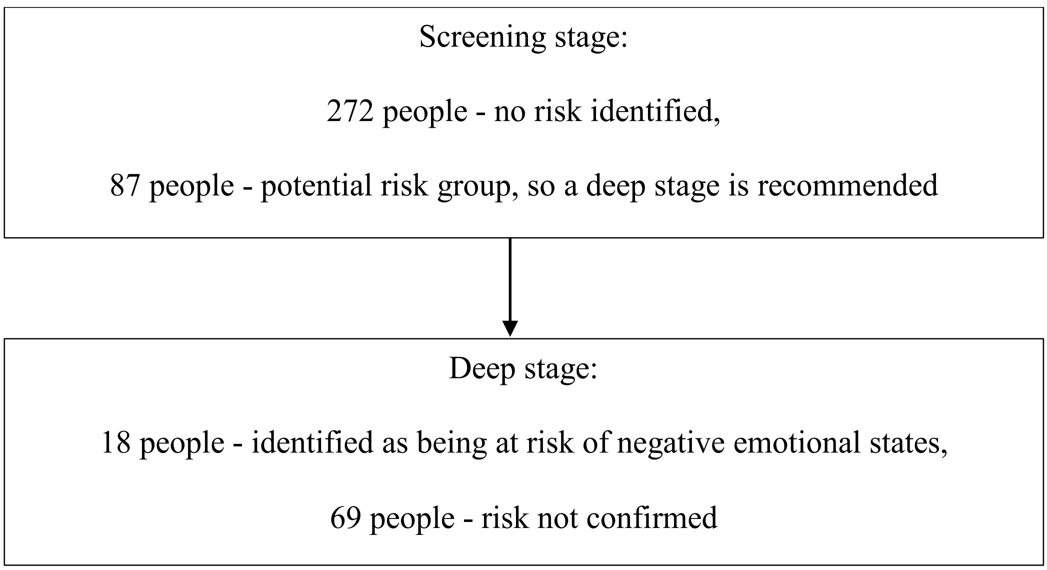


**Figure 2.** Quantitative data on SS and SD subjects

Consider some of the most significant results of the high-risk group (group C) based on non-standard procedures.

Thus, based on observational data, group C cadets exhibited signs of behaviour like excessive relaxation or, on the contrary, the tension more frequently than other cadets during the study. They exhibited greater instances of depression, melancholy, slight motor restlessness, coldness, and detachment. More often than not, fine motor skills were a reflection of a restless, fidgety inner state.

Data from semi-structured interviews revealed that service members in group C took a little longer on average to build trust, but they were also more likely to tend toward giving brief responses (such as “yes-no”), to avoid talking about themselves, and to react negatively.

Compared to other service members in the at-risk group, the subjects had feelings of loneliness, fear, anguish, anxiety, depression, irritation, asthenic experiences, and fatigue 35% more often.

A multiple regression analysis was done to study the details of the relationship between depression and emotional states. This made it possible to figure out how strongly emotional states contributed to the development of depression in service people in the norm group and the risk group. Indeed, depression is widely recognised as a major contributor to the development of suicide risk, greatly amplifying it.[31]

Multiple regression analysis was used to compare the results for the identified risk group (18 individuals) and the remaining sample (342 people). Each group received a unique regression equation.

The resulting equation accounts for 45% of the variance; the D criterion (Durbin-Watson) value of 1.941 indicates that there are no autocorrelations in the sequence of emotional state predicates in the service members under study; the regression coefficient is F=25.993 and p=0.0001.

Regression Equation for the Non-Risk Group:

Depression= -2.134 (Constant) + 0.344 Anxiety + 0.150 Average score_psycho-emotional symptom + 0.229 Average score_health + 0.169 Average score_specific_activity - 0.019 Physical_aggression + 0.057 Anger + 0.082 Hostility + 0.091 Average score_stress -0.062 Average score

The resulting equation accounts for 99% of the variance; the D criterion (Durbin-Watson) value of 1.315 indicates that there are no autocorrelations in the sequence of emotional state predicates observed in the service members under study; the regression coefficient is F=90.901 and p=0.000.

The Equation in the Risk Group:

Depression = -4.736 (Constant) + 0.896 Average score_psycho-emotional_symptom + 1.738 Average score_ mood + 0.713 Average score_environment + 0.996 Average score_health - 0.355 Physical_ aggression + 0.264 Anger + 0.121 Hostility -0.393 Average score

The data indicate the need for preventative measures to prevent the onset of depressive states, particularly among first- and fourth-year students (here, depression scores are closest to the norm, with a score of 5 representing "mild depression").

## Discussion:

Implemented complex meta-analysis of 11 studies agrees with the overall trends found in the systematic review.[1] According to this meta-analysis, only about 29% of military personnel who were diagnosed with mental problems used mental health care in the past year. The results of this article are also in line with a review of 32 studies that found that an average of 43.7% of people with depression use mental health services.

The correlation between physical and mental state was confirmed in the studies of Zainulabid.[57] The results showed that patients with hepatitis C, but with higher rates of mental stability, were more likely to have a better quality of life compared to those who were less mentally stable.[57] Moreover, the research by Alan and Kurt[58] revealed the correlation between the level of anxiety and patients' perceptions of pain. Therefore, further study of this issue in different samples will contribute to the reduction of patients' anxiety.[58]

Griffith[59] emphasizes that modern military forces face a complex and intimidating web of stress factors. The researcher also notes that small structural shifts can help the military cope with those factors. The obtained results also substantiate the need to monitor the psychological state of military personnel during deployment in order to prevent negative consequences for mental health and ensure the successful performance of military units.[59] Agius[60] claimes that during the conscription period the prevalence of symptoms associated with depression and anxiety increased, followed by social phobias. Nevertheless, the levels of mental exhaustion and sleep disorders somewhat decreased.[60]

Highly valuable research has been conducted by Nakkas et al.,[61] The scientists indicate that the recruits recommended for promotion showed a more favorable stress profile and fewer psychological disorders during basic training; they also approved more effective and more prosocial survival strategies. These emotion-cognition peculiarities not only contribute to resilience, but are also consistent with leadership research, pointing to the importance of emotional stability and prosocial behavior for successful leaders.[61]

Notably, some of the studies in this review showed that less than 25% of people with depression used mental health services, while others said that about 75% of people with depression did so. Between studies, there are big differences in how many people said they used mental health services. This could be a methodological error caused by important differences in the tools used to measure and define results for military personnel.

Structured diagnostic interviews in military settings are often used as a benchmark for evaluating the validity of new assessment tools, as they are effective for assessing severe depression.[62] Structured diagnostic tests are usually carried out by qualified specialists. Consequently, the tests have a low classification error, despite the fact that they may not always be exactly consistent with the diagnoses of mental health specialists. In other words, the majority of military personnel diagnosed with depression was more likely to be genuinely optimistic and undoubtedly needed psychiatric help. In addition, screening tools were usually used separately, which is the least obvious way to apply them and always leads to false positive results.[2] For example, a patient's health questionnaire consisting of nine items (PHQ-9) is characterized by a sensitivity range from 28 to 95%, and a specificity range from 61 to 98% for different groups of observed patients. Consequently, the results of at least 20% of people who were classified as depressed on the PHQ-9 scale, will be false positive. Therefore, they will not need the same level of psychiatric care compared to those who really meet the criteria for major depression. These false positive results may lead to a reassessment of gaps in the treatment of major depression if they are included in the denominator.[63]

## Conclusions:

The analysis supports the hypothesis that methods of the screening and deep stage of the procedure for identifying negative emotional states in service members can be used by military psychologists as a tool for identifying a risk group. These methods allow for the disclosure of the degree of aggression, anxiety, depression, and subjective well-being. The suggested method combines qualitative and quantitative techniques to evaluate the psychoemotional state of service members, allowing one to first pinpoint, then hone in on, and then broaden, information about the psychological state of service members and their inner world. On the other hand, there are a few changes that need to be made to the proposed procedure in order to simplify the working process and assist future users in learning even more about the relevant population of interest.

The study revealed that approximately 95% of the service members in our sample had low levels of depression, aggression, and anxiety as well as relatively favourable indicators of psychological well-being. 5% of service members were at risk for negative emotional states. Additional dynamic assessment and monitoring are required for the risk group. Preventing the onset of depressive states, one of the predictors and risk factors of suicidal behaviour, is possible. To that end, special consideration should be given to various indicators of subjective emotional well-being and a decrease in physical aggression and anger in the risk group.

When working with military cadets, a more differentiated, course-specific approach is required in general. In the future, researchers might also develop a short course for military psychologists to teach them how to use the algorithm to recognise negative emotional states.

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**Data availability.** Data will be available on request.

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