

# Artificial Intelligence as a Tool to Prevent Autoaggressive Destructive Behavior Among Children and Adolescents: a Brief Overview

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Received: 2024-11-08.

Accepted: 2024-12-12.



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J Clin Med Kaz 2024; 21(6): 24–29

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## Abstract

Suicides and suicidal behaviors are complex disorders with diverse symptoms, often lacking clear etiology, especially in spontaneous or childhood cases. This complicates timely diagnosis, therapy, and treatment. As a result, research into markers for depression and suicidal behavior continues. The use of artificial intelligence represents a significant advancement in suicide prevention, offering new tools for early detection and intervention to improve outcomes for at-risk individuals. According to the World Health Organization (WHO), 726,000 people commit suicide, not counting the much larger number of people who attempt suicide each year. Suicides occur throughout life, but in 2021 they became one of the leading causes of death among 15-29 year-olds worldwide. This problem is also relevant in Kazakhstan, and this article is the first to reflect an interdisciplinary approach to suicide prevention among minors using AI methods in application to scientific data obtained in the study of respondents with suicidal behavior. Suicide is a significant public health issue with profound societal impacts. Its effects extend beyond the loss of life, leading to emotional suffering for families and loved ones, and economic losses from reduced productivity and increased healthcare costs. For each suicide, there are over 30 attempted suicides, compounding the social and economic burden. The repercussions affect countless individuals, both directly and indirectly, leaving long-lasting emotional and financial strain. Additionally, the economic impact includes treatment costs for psychosomatic and mental disorders in those left behind, highlighting the extensive and multifaceted consequences of suicidal behavior.

**Keywords:** suicide prevention, risk factors, age-related ontogenesis, children and adolescents, young people, artificial intelligence, machine learning, neural networks.

## Introduction

The problem of the autodestructive behavior of minors is one of the main medical and socio-psychological problems of modern science, since destructions are most clearly manifested precisely in adolescence – one of the most difficult periods in the development of each person. A destructive behavior model can develop as a result of the action of many factors – a genetic predisposition (with a burdened heredity with mental diseases with a debut

in age-related crises of ontogenetic development); increased susceptibility of characterological reactions to external psychogenic factors with transformation into pathoharacterological reactions and development (reactions of protest, emancipation, hypercompensation, opposition, grouping, imitation, hobby-reactions, reactions caused by the formation of sexual desire – masturbation, petting, etc.).

In the last decade, self-harm without suicidal intentions has become widespread – this is also one

of the forms of destruction characteristic of adolescence. For a growing child's body, when every year of life is associated with the need to meet new requirements of society, the need to adapt to new constantly changing requirements of the surrounding reality, due to small life experience, this is a rather serious problem – a teenager cannot always use the protective mechanisms of the psyche, build a psychological strategy. The experience of family education will play an important role in overcoming emerging conflicts. One of the most dangerous in adolescence is primarily destructive intrapersonal behavior, manifested by self-destruction (suicide), self-harm (risky behavior), self-modification (body modifications, tattoos, piercings, excessive use of alcohol and drugs, involvement in destructive games). With the growing number of suicides in adolescence, there is an urgent need for a systematic approach to both early diagnosis and timely psychological and psychotherapeutic correction of these adolescent perturbations and timely initiation of psychopharmacotherapy in the presence of mental disorders, as well as the search for new methods of identifying the risk group using new technologies, for example, artificial intelligence.

**The purpose of this article** is to study research papers in order to find possible solutions for the early detection of suicidal ideation among children and adolescents, youth using artificial intelligence (AI) technologies, which describe the prediction of possible suicidal attempts at an early stage and can serve as one of the tools to prevent suicide attempts.

## Materials and Methods

To find relevant scientific papers, we conducted a search on popular scientific platforms (Science Direct, Research Gate) for the following keywords: suicide prevention, artificial intelligence, machine learning, neural networks, children, adolescents, youth. During the search, 367 articles were found, 10 of which met the search criteria and were analyzed and compared.

Many researchers use artificial intelligence to predict suicide attempts as accurately as possible. For this reason, from 2018 to 2024, many studies were conducted around the world using machine learning and neural networks to predict the risk of suicide. Accordingly, we have established selection criteria – a deep search for scientific sources in the period 2018-2024 devoted to the use of AI to predict suicide risks among young people.

## Problem

The situation with the early identification of a risk group among minors with autodestructive behavior is complicated by the presence of age-related ontogenesis of understanding death and crisis periods of development, which have their own difference in almost every year of a child's or teenager's life. Thanatopsychological education has studied the formation of the concept of death in children according to age, where the family factor plays the most important role, religion, education, cognitive and intellectual functions, somatic and mental health status have also been noted [2-4]. The age from 12 to 15 years and older deserves special attention in the context of studying this problem.

At this age, there is a transition from childhood to the so-called "growing up", and against the background of increasing social influences and the presentation of new "adult" requirements to the child, respectively, the child experiences a number of events such as the loss of "ideal parents", the loss of naive ways of knowing the world around him, which can violate

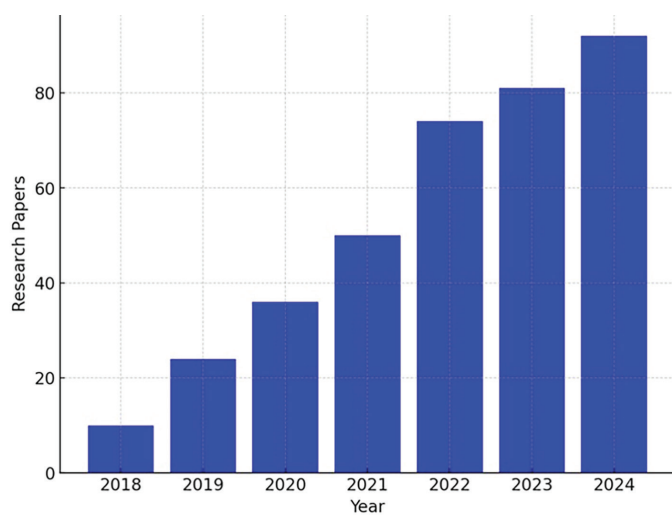
child-parent attachment. Also in this age period (and this is an active prepubertal), children experience such an ontogenetically phenomenon of personality formation as the so-called "social death" (a term in adolescent psychology) – it is at this age that children feel lonely, experience isolation from a group of peers, a feeling of loneliness is formed, the level of anxiety increases, which can lead to the so-called "normal teenage mourning" (a term of adolescent psychology). And another important point is that all of the above is one end of the so-called "scissors", at the other end of which the phenomenon of "personal myth" peculiar to this age is optimism, vivacity of reactions, the child's faith in his uniqueness, immortality, the belief that other people are mortal, but this will not affect the child himself, which, as it increases the external adverse factors are gradually weakening. And it is precisely such contradictions – between the seemingly optimistic features of adolescence and its losses – that create a special attraction to the topic of death, the need to understand it, and at the same time an increased fear caused by these experiences. It can be said that suicidality in adolescence is associated with a poor understanding of death and suicidal ideas for a child or teenager are a tool of avoidance and death is seen as a way out of a situation of deprivation (if the child is experiencing distress).

Also we should not forget that behind the facade of psychological ontogenetic "growing up" there is the main ontogenetic period of reproductive system formation (average age from 12-16 years), when the activity of sex hormones (estradiol, testosterone, progesterone) leads to thickening of bones, increasing their density – children and adolescents feel that the body has become "dense", "heavy", feel the heaviness of the body, a kind of adolescent "clumsiness". Physiological emotional instability, irritability, and the manifestation of active forms of characterological reactions caused by the activity of sex hormones form undesirable behavior of adolescents, familiar to everyone as the difficult "puberty" [5]. All this complicates the early diagnosis of suicidal ideation among minors and the use of AI methods can serve the purpose of early identification of a risk group for suicide. The above is only part of the changes in the psyche of children and adolescents who, throughout their lives, before moving into the so-called "adult state", experience a number of age-related crises.

## Results and discussions

In recent decades, AI has been widely used by many experts from various fields of human activity. This is due to its effectiveness in finding various patterns and its ability to predict results based on available data. Machine learning (ML) is a branch of AI that is designed to allow computers to learn from data and improve their performance when performing a specific task without explicitly programming for that task [6]. Neural networks (NW) are another approach to function approximation, inspired by how the human brain works [7]. These methods are designed to predict possible suicide attempts, mainly based on data collected by experts in the field of child mental health. However, there are cases when researchers use NLP (natural language processing) and NW to analyze text data obtained from the Internet.

The number of studies conducted in this direction increases over time. This can be seen in Figure 1, which shows the distribution of the found articles by year from ScienceDirect. According to him, the number of research papers has increased from 10 in 2018 to more than 90 in 2024. This shows that interest in using AI to combat suicide is growing.



**Figure 1** – Annual distribution of research papers found using the ScienceDirect platform

Many studies have reviewed various approaches to suicide prevention using AI. Similar work [8] was carried out by Alban Lejeune et al., where the authors compared studies published between 2014 and 2020 aimed at predicting suicide risks. The authors concluded that AI performance was good, although it varied depending on different algorithms and application settings. The studies reviewed in this paper show that various machine learning algorithms, including ridge regression, classification trees, and random forests, provide promising predictive capabilities for determining suicide risk in adolescents and young adults, reaching AUC values from 0.8 to 0.9.

In another work by Rebecca A. Bernert et al. [9] considers AI and ML in predicting suicidal behavior. The results demonstrated a high level of accuracy (over 90%) and strong predictive efficacy (AUC) in the studies. The authors conclude that AI and ML applications may be crucial for early detection of suicide risk, with important methodological and statistical caveats.

In the work of Lin et al. [10], the authors collected data on psychiatric hospital patients diagnosed with suicide in the National Database of Health Insurance Research. Machine learning methods were used to develop models for predicting the risk of future multiple suicide attempts. The authors' experimental results showed that Adaboost+DT is best suited for predicting the behavior of multiple suicide attempts among psychiatric patients.

The authors Kharrat et al. [11] developed gender-sensitive machine learning models to predict suicide risk using data from the Integrated Monitoring System for Chronic Diseases of Patients from Québec, which included more than 20,000 cases of suicide from 2002 to 2019. The study demonstrated the potential of explicable AI in improving suicide prevention efforts, while emphasizing the need for caution in interpreting predictive associations.

An observational study conducted by the authors Servi et al. [12] was aimed at identifying early predictors of suicidal risk among 237 inpatient patients with suicidal behavior and thoughts in the emergency department of child and adolescent psychiatry at the Meyer Children's Hospital in Florence (Italy). The researchers collected epidemiological and psychopathological data and stratified patients into two groups: "patients with suicidal will" and "patients with suicidal motivation", finding that factors such as age under 12, diagnosis of destructive disorders, previous

suicide attempts and intoxication are statistically correlated with increased risk.

Artificial intelligence analysis confirmed these risk factors with 86.7% accuracy, which highlights the potential of AI to help doctors assess suicidal risk, while recognizing the limitations of the study due to its retrospective design.

The study by authors Su et al. [13] was aimed at developing machine learning models for predicting suicidal behavior in children and adolescents using longitudinal clinical records from the Connecticut Children's Medical Center. The authors analyzed data from 41721 patients aged 10 to 18 years from October 2011 to September 2016. The obtained models achieved areas under the curve (AUC) in the range from 0.81 to 0.86, accurately identifying 53-62% of subjects with positive suicidal status with 90% specificity, thereby demonstrating that regularly collected electronic medical records can be effectively used to predict suicide risk in the pediatric population.

A study by Tan et al. [14] examines the effectiveness of explicable artificial intelligence (EAI) in predicting suicide risk based on medical tabular data, solving the problem of limited datasets in health-related machine learning applications through data augmentation. The researchers used Shapley Additive explanations (SHAP) along with traditional correlation analysis to rank the importance of traits, identifying key factors such as anger problems, depression, and social isolation as significant predictors of suicide risk, while it was found that people with high incomes, respected professions, and higher education have lower the risk.

The study done by the authors Walsh et al. [15] was aimed at improving the prediction of suicide risk among adolescents by using machine learning algorithms applied to regularly collected clinical data from a synthetic Vanderbilt derivative, including 974 adolescents with nonfatal suicide attempts and various control groups. The results show that machine learning approaches using longitudinal clinical data can improve screening of nonfatal suicide risk in adolescents by providing a scalable solution that bypasses the limitations of traditional face-to-face screening methods.

Navarro et al. [16] used data from the Québec Longitudinal Study of Child Development to assess the predictive power of early life factors for suicide attempts in adolescents and young adults from the general population, tracking participants from birth to 20 years of age. Using random forest classification algorithms, the researchers evaluated 150 variables in various areas of early life, revealing moderate prediction efficiency with areas under the curve of 0.72 for women and 0.62 for men, as well as low sensitivity, but good specificity and negative predictive values.

The study by Nobles et al. [17] solves an important problem of suicide prevention among young people by focusing on the development of a predictive model using text messages from people with a history of suicidal thoughts and behavior. The researchers used a promising study design, reconstructing the chronology of recent suicidal behavior through retrospective clinical interviews, to analyze whether text messages can effectively predict periods of suicidality, including suicidal thoughts and nonfatal suicide attempts, as opposed to simple depressive episodes.

Another study done by Bhandarkar et al. [18] was the development of an artificial intelligence model for natural language processing trained on patient portal messages to predict 30-day suicide-related events (SRE).

The aim of the study by Xu et al. [19] was to improve suicide detection in online counseling systems by developing

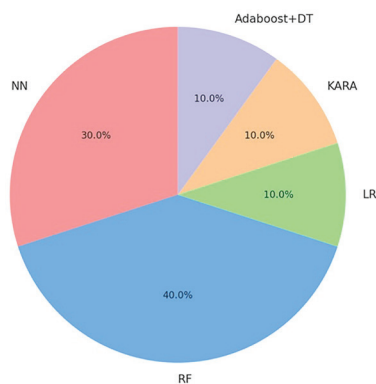
a risk assessment model based on knowledge in a subject area called KARA, using a substantial dataset of conversations in Cantonese between help seekers and counselors. The data set included 5,682 conversations, of which 682 disclosed suicide

intentions, and a suicide knowledge graph was built to embed relevant domain knowledge into a deep learning model. The results of the review are presented in Table 1.

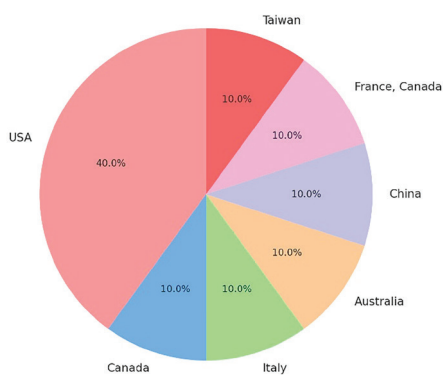
**Table 1** Review of selected articles

Author	Year	Country (Countries)	Size and type of training data	The best algorithm/model	Peak performance (with metric)
Lin et al. [10]	2022	Taiwan	523 (tabular)	Adaboost+DT	0.971 (accuracy)
Kharrat et al. [11]	2018	Canada	9440 (tabular)	RF	0.87 (AUC)
Servi et al. [12]	2023	Italy	237 (tabular)	NN	0.89 (accuracy)
Su et al. [13]	2020	USA	641708 (tabular)	LR	0.80 > (AUC)
Tan et al. [14]	2024	Australia	1000 (tabular)	RF	0.97 (AUC)
Walsh et al. [15]	2018	USA	2247 (tabular)	RF	0.83 (AUC)
Navarro et al. [16]	2021	France, Canada	1623 (tabular)	RF	0.72 (AUC)
Nobles et al. [17]	2018	USA	136347 (text)	NN (DNN)	0.75 (F1)
Bhandarkar et al. [18]	2023	USA	840 (text)	NN	0.710 (AUC-ROC)
Xu et al. [19]	2021	China	5682 (text)	KARA	0.815 (AUC-ROC)

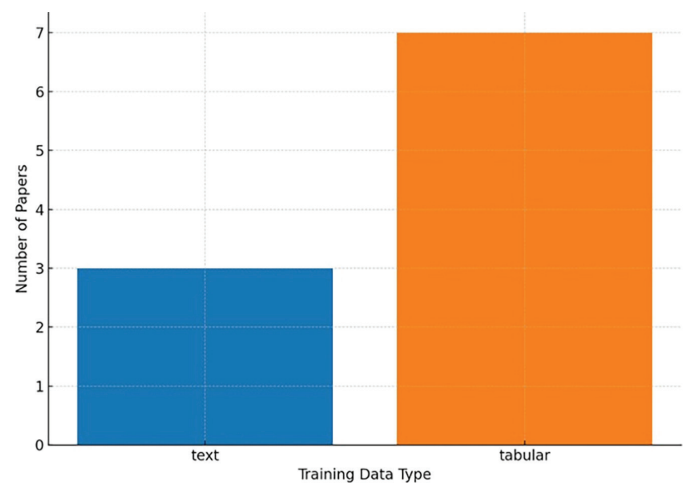
The models developed by the authors show peak performance results starting from 70%. For convenience, some comparisons are displayed in the form of diagrams (Figure 2 – Figure 4).



**Figure 2** – Distribution of the most efficient algorithms/models



**Figure 3** – Distribution by country



**Figure 4** – Distribution by type of training data

Figure 2 illustrates the distribution of the most effective models according to the articles considered. NN and RF (Random Forest) models turned out to be the most popular algorithms used in the articles (30% and 40%, respectively).

Researchers from Taiwan [10] have shown that the combined model (Adaboost + Decision Trees) returns the highest accuracy of peak performance: 0.971. On the contrary, RF models often showed good results with AUC values of 0.97 [14] and 0.87 [11]. This indicates that RF and ensemble methods are well suited for such a forecasting task.

The geographical distribution shown in Figure 3 showed that the majority of the selected articles were written by researchers from the USA – 40% [13, 15, 17, 18]. Other countries have the same percentage distribution – 10% [10, 11, 12, 14, 16, 19].

Table 1 and Figure 4 show the different sizes and types of training data. This shows that most researchers used the tabular type [10-16]. Textual information is used less frequently [17-

19], but one study by Nobles et al. [17] effectively applied it with NN. The preference for tabular data may be due to their structured nature, which leads to easier processing and analysis [11].

The training data varies significantly in size, ranging from small datasets such as the 237 data used by Servi et al. [12], up to much larger ones, such as 641,708 samples in the study by Su et al. [13]. This range shows that models can be adapted to handle different scales of data.

## Conclusion

The results we have obtained show that research on the use of AI models to predict and prevent suicide rates among young people is growing.

We concluded that the reviewed research articles show good effectiveness (more than 0.70%) in predicting suicide attempts.

Overall, although it is difficult to single out a universally superior model due to the variety of data and contexts, RF and NN seem to be the most reliable choices among the various datasets. In the future, the authors of the article plan to use various AI methods to predict possible suicide cases using both text and tabular data.

It is relevant to early identify possible clinical and psychological markers of deviant behavior using text materials of suicides (suicide notes, correspondence, messages about an impending act of attempt on life, etc.), which can be the basis for the development of an information system using machine learning methods and models to predict suicidal tendencies in children in order to increase the effectiveness of early identification and prevention of suicidal actions in educational and medical practices.

Further research and development of AI suggests the creation and adaptation of specific algorithms focused on the

analysis of biopsychosocial risk factors combining knowledge of medicine, age, crisis psychology, pedagogy, sociology and information technology, which will contribute to the development of a comprehensive view of the problem and will allow more accurately predicting the likelihood of suicidal intentions.

**Author Contributions:** Conceptualization K.S.; methodology K.S. and M.Zh.; formal analysis M.Zh.; investigation K.S. and M.Zh.; resources M.Zh. and G.K.; data curation M.Zh.; writing – original draft preparation K.S. and M.Zh.; writing – review and editing K.S., M.Zh., G.K. and V.S.; visualization M.Zh.; supervision K.S.; project administration K.S.; funding acquisition K.S. All authors have read and agreed to the published version of the manuscript.

**Disclosures:** There is no conflict of interest for all authors.

**Acknowledgements:** None.

**Funding:** This study was supported by grants from the Ministry of Education and Science of the Republic of Kazakhstan Grant Funding 2024–2026 (Funder Project Reference: AP23490290 "Development of a comprehensive system for the prevention of autodestructive and destructive behavior among the children's population of the Republic of Kazakhstan"). K.S. is a principal investigator of the projects.

**Ethical Considerations:** This study received approval from the Al-Farabi Kazakh National university's Ethics Committee on 11/20/2023, Protocol No. IRB-A705 dated 11/20/2023 (IRB00010790 al-Farabi Kazakh National University IRB№1). All study participants were informed about the study aims, methods, and potential risks and benefits.

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