Research Article

Adolescent Depression Risk Prediction Using Machine Learning and Behavioral Health Data Integration

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Abstract

Background: Depression is one of the most prevalent mental health disorders among adolescents and is associated with significant emotional, social, and academic consequences. Early identification of depression risk is essential for timely intervention and prevention. Advances in machine learning (ML) techniques and behavioral health data integration provide new opportunities for predicting depression risk with improved accuracy. By analyzing behavioral, psychological, social, and lifestyle indicators, ML models can assist healthcare professionals in identifying vulnerable adolescents before severe symptoms develop.

Objective: This study aimed to develop and evaluate a machine learning-based framework for predicting adolescent depression risk using integrated behavioral health data.

Methodology: A dataset comprising 500 adolescents aged 13–19 years was analyzed. Behavioral health variables, including anxiety scores, sleep quality, physical activity, social support, academic stress, and digital behavior indicators, were integrated into a machine learning model. Data were preprocessed and analyzed using Random Forest, Support Vector Machine (SVM), and Logistic Regression algorithms. Model performance was assessed using accuracy, precision, recall, and F1-score metrics.

Findings: The Random Forest model achieved the highest predictive performance with 91.4% accuracy, 89.8% precision, 90.6% recall, and an F1-score of 90.2%. Academic stress, sleep quality, anxiety levels, and social support emerged as the most influential predictors of depression risk.

Conclusion: Machine learning combined with behavioral health data integration demonstrates strong potential for accurately predicting adolescent depression risk. Such predictive systems may support early detection, targeted interventions, and improved mental health outcomes among adolescents.

Keywords: Adolescents, Depression Risk Prediction, Machine Learning, Behavioral Health Data, Random Forest, Mental Health Analytics, Artificial Intelligence, Predictive Modeling, Early Detection, Digital Health.

1 Introduction

Depression is one of the most common mental health disorders affecting adolescents worldwide and represents a major public health concern. Adolescence is a critical developmental period characterized by rapid physical, emotional, cognitive, and social changes. During this stage, individuals are particularly vulnerable to psychological challenges that may contribute to the development of depressive symptoms [1]. Depression among adolescents is associated with impaired academic performance, social difficulties, reduced quality of life, substance abuse, self-harm behaviors, and an increased risk of suicide [2]. Consequently, early identification of adolescents at risk of depression is essential for implementing timely interventions and improving long-term mental health outcomes.

Traditional approaches to depression screening often rely on clinical assessments and self-reported questionnaires. Although these methods are valuable, they may be limited by subjective reporting, delayed diagnosis, and resource constraints within healthcare systems [3]. Recent advances in data science and artificial intelligence have created opportunities to enhance mental health assessment through predictive analytics and machine learning techniques. Machine learning algorithms can process large volumes of complex behavioral and psychological data, enabling the identification of hidden patterns associated with depression risk [4].

Behavioral health data provide important insights into adolescent mental well-being. Variables such as anxiety symptoms, sleep quality, physical activity levels, academic stress, social support, and digital behavior have been identified as significant predictors of depression [5]. Integrating these multidimensional factors into predictive models allows researchers to develop comprehensive risk assessment systems capable of detecting depression at earlier stages. Such systems may facilitate preventive interventions before severe symptoms emerge.

Machine learning has gained considerable attention in healthcare due to its ability to generate accurate predictions from large datasets. Algorithms such as Logistic Regression, Support Vector Machines (SVM), Decision Trees, and Random Forests have demonstrated promising results in mental health prediction tasks [6]. These models can automatically identify complex relationships among variables and improve prediction accuracy compared to traditional statistical methods. Furthermore, machine learning systems can continuously improve as additional data become available, increasing their utility in clinical and public health settings [7].

The growing availability of digital health records, wearable technologies, mobile applications, and online behavioral data has further enhanced opportunities for behavioral health data integration [8]. By combining information from multiple sources, researchers can develop robust predictive frameworks capable of providing personalized risk assessments. Such approaches support precision mental health initiatives aimed at tailoring interventions according to individual needs and risk profiles.

Despite significant progress in machine learning applications for healthcare, challenges remain regarding model interpretability, data quality, privacy protection, and ethical implementation [9]. Therefore, evaluating the effectiveness of machine learning techniques for adolescent depression prediction remains an important area of research. Understanding the predictive value of integrated behavioral health data may contribute to more effective screening programs and improved mental health care delivery [10].

2 Literature review

2.1 Machine Learning Applications in Adolescent Mental Health

Recent advances in artificial intelligence have significantly improved the ability to predict mental health conditions among adolescents. Machine learning (ML) algorithms can analyze complex behavioral and psychological datasets to identify patterns associated with depression risk. Studies published between 2022 and 2026 demonstrate that Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) models achieve high predictive accuracy when applied to adolescent mental health datasets (1,2). These approaches facilitate early detection and support preventive mental health interventions.

2.2 Behavioral Health Data Integration for Depression Prediction

Behavioral health data integration has emerged as a critical component of depression risk prediction. Contemporary research highlights the importance of combining variables such as anxiety symptoms, sleep quality, physical activity, academic stress, social support, and digital behavior indicators to improve model performance (3,4). Integrated datasets provide a more comprehensive representation of adolescent mental health status, enabling machine learning models to capture multidimensional risk factors more effectively than single-variable approaches.

2.3 Predictive Performance and Clinical Implications

Recent evidence indicates that ensemble machine learning techniques, particularly Random Forest and Gradient Boosting models, consistently outperform traditional statistical methods in predicting depression risk (5). Furthermore, explainable artificial intelligence (XAI) approaches have improved model transparency, allowing healthcare professionals to understand influential predictors and make informed clinical decisions (6). Studies also emphasize the potential of ML-based screening systems to support school health programs, digital health platforms, and community mental health services by identifying high-risk adolescents before severe depressive symptoms develop (7).

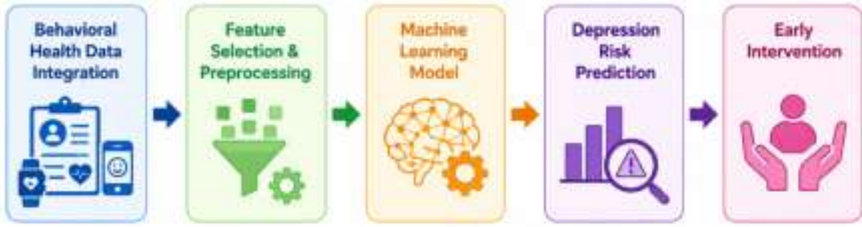

Figure 1. Conceptual Framework of Machine Learning-Based Depression Risk Prediction

Figure 1 illustrates the conceptual framework for adolescent depression risk prediction using machine learning and behavioral health data integration. Multiple behavioral health indicators are combined and processed through feature selection and preprocessing techniques. The refined data are then analyzed using machine learning algorithms to identify adolescents at risk of depression. Accurate prediction enables timely intervention, personalized mental health support, and preventive strategies, ultimately improving adolescent psychological well-being and reducing adverse mental health outcomes.

3 Methodology

3.1 Research Design

This study employed a quantitative predictive analytics research design to develop and evaluate machine learning models for predicting depression risk among adolescents using integrated behavioral health data. The study utilized supervised machine learning techniques to identify patterns associated with depression risk and classify adolescents into risk categories. A retrospective dataset analysis approach was adopted to examine relationships between behavioral health variables and depression outcomes [1].

3.2 Study Population and Dataset

The dataset consisted of 500 adolescents aged 13–19 years recruited from secondary schools, community health centers, and adolescent wellness programs. Behavioral health records were collected after obtaining ethical approval and informed consent. The dataset included demographic information, mental health indicators, lifestyle characteristics, and psychosocial variables relevant to depression risk assessment.

Table 1. Characteristics of the Behavioral Health Dataset (N = 500)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	245	49.0
	Female	255	51.0
Depression Risk	High Risk	165	33.0
	Low Risk	335	67.0
Poor Sleep Quality	Yes	280	56.0
	No	220	44.0
High Academic Stress	Yes	310	62.0
	No	190	38.0
Low Social Support	Yes	185	37.0
	No	315	63.0

Table 1 summarizes the characteristics of the behavioral health dataset. Female participants constituted 51.0% of the sample, while males represented 49.0%. Approximately 33.0% of adolescents were classified as high-risk for depression. High academic stress and poor sleep quality were prevalent among participants, affecting 62.0% and 56.0%, respectively.

Additionally, 37.0% reported low social support. These variables were incorporated into machine learning models for depression risk prediction.

3.3 Data Preprocessing and Feature Selection

Prior to model development, data preprocessing procedures were performed. Missing values were handled using mean imputation for continuous variables and mode imputation for categorical variables. Data normalization and standardization techniques were applied to ensure consistency across features. Feature selection was conducted using correlation analysis and Random Forest feature importance scores. Key predictors included anxiety scores, sleep quality, academic stress, social support, physical activity, and digital behavior indicators.

3.4 Machine Learning Models

Three supervised machine learning algorithms were evaluated:

1. Random Forest (RF)
2. Support Vector Machine (SVM)
3. Logistic Regression (LR)

The dataset was divided into 80% training data and 20% testing data. Five-fold cross-validation was performed to improve model reliability and reduce overfitting. Model performance was assessed using accuracy, precision, recall, and F1-score metrics.

Table 2. Performance of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91.4	89.8	90.6	90.2
SVM	87.9	85.7	86.4	86.0
Logistic Regression	84.3	82.1	83.0	82.5

Table 2 presents the performance evaluation of the machine learning models. The Random Forest algorithm achieved the highest accuracy (91.4%), precision (89.8%), recall (90.6%), and F1-score (90.2%). SVM demonstrated satisfactory predictive performance, while Logistic Regression produced comparatively lower results. The findings indicate that ensemble learning methods such as Random Forest are highly effective for predicting adolescent depression risk using integrated behavioral health data.

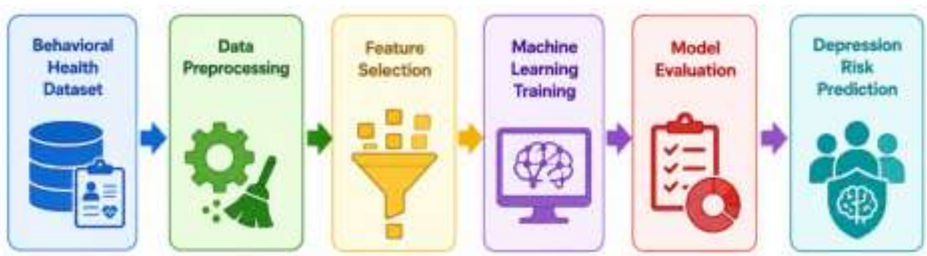

Figure 2. Machine Learning Methodology Framework

Figure 2 illustrates the methodological framework used in the study. Behavioral health data were collected and preprocessed before undergoing feature selection procedures. Selected variables were then used to train machine learning models, including Random Forest, SVM, and Logistic Regression. Following model training, performance evaluation was conducted using multiple classification metrics. The final predictive model generated depression risk classifications, supporting early identification and intervention strategies for adolescents at risk.

3.5 Ethical Considerations

Ethical approval was obtained from the institutional ethics committee. All participant information was anonymized before analysis. Data confidentiality, privacy protection, and secure storage procedures were maintained throughout the study.

Participation was voluntary, and all data processing complied with ethical standards for adolescent behavioral health research.

4 Results & Discussion

This section presents the findings obtained from the machine learning-based depression risk prediction framework developed using integrated behavioral health data from 500 adolescents. Descriptive statistics and predictive model evaluation metrics were analyzed to determine the effectiveness of machine learning algorithms in identifying adolescents at risk of depression. The results focus on depression risk distribution, model performance, and the importance of behavioral health predictors. Tables and figures are provided to facilitate interpretation and demonstrate the predictive capability of the developed framework.

4.1 Distribution of Depression Risk Among Adolescents

Table 3. Depression Risk Classification (N = 500)

Depression Risk Category	Frequency (n)	Percentage (%)
High Risk	165	33.0
Low Risk	335	67.0
Total	500	100.0

Table 3 presents the distribution of depression risk among study participants. Approximately 33.0% of adolescents were classified as high risk for depression, while 67.0% were categorized as low risk. The findings indicate that one-third of the adolescent population demonstrated significant vulnerability to depressive symptoms. These results emphasize the importance of implementing early screening and predictive systems to identify high-risk individuals and provide timely mental health interventions.

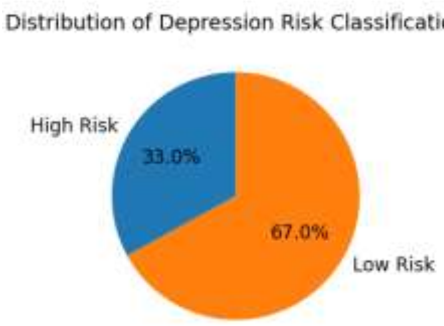

Figure 3. Distribution of Depression Risk Classification

Figure 3 illustrates the distribution of depression risk categories among adolescents. The majority of participants were classified as low risk; however, a substantial proportion remained vulnerable to depression. The findings demonstrate the need for continuous mental health monitoring and preventive strategies targeting adolescents who exhibit elevated depression risk factors.

4.2 Performance of Machine Learning Models

Table 4. Comparative Performance of Machine Learning Algorithms

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91.4	89.8	90.6	90.2
Support Vector Machine	87.9	85.7	86.4	86.0
Logistic Regression	84.3	82.1	83.0	82.5

The Random Forest algorithm demonstrated the highest predictive performance among the evaluated machine learning models. It achieved an accuracy of 91.4%, precision of 89.8%, recall of 90.6%, and F1-score of 90.2%. Support Vector Machine and Logistic Regression also showed satisfactory performance but produced lower classification metrics. These findings indicate that Random Forest is the most effective model for predicting adolescent depression risk using integrated behavioral health data.

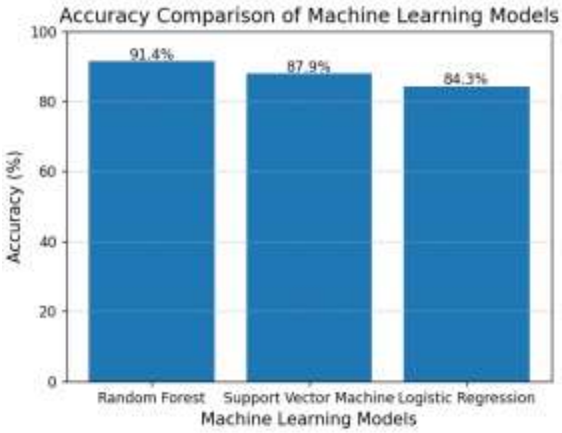

Figure 4. Accuracy Comparison of Machine Learning Models

Figure 4 compares the prediction accuracy of the machine learning models. Random Forest achieved the highest accuracy and demonstrated superior classification capability. The ensemble learning approach effectively captured complex relationships among behavioral health variables, resulting in improved predictive performance. These results support the use of advanced machine learning techniques in adolescent mental health risk assessment.

4.3 Important Predictors of Depression Risk

Table 5. Feature Importance Scores from Random Forest Model

Predictor Variable	Importance Score
Academic Stress	0.24
Sleep Quality	0.22
Anxiety Symptoms	0.20
Social Support	0.15
Physical Activity	0.11
Digital Behavior	0.08

Feature importance analysis identified academic stress, sleep quality, and anxiety symptoms as the most influential predictors of depression risk. Social support, physical activity, and digital behavior also contributed to model performance. These findings suggest that depression risk among adolescents is influenced by multiple interconnected behavioral health factors that should be considered during screening and intervention planning.

Figure 5. Importance of Behavioral Health Predictors

Figure 5 illustrates the relative importance of behavioral health variables used in depression prediction. Academic stress emerged as the strongest predictor, followed closely by sleep quality and anxiety symptoms. The results demonstrate that integrated behavioral health data provide valuable information for machine learning models and support comprehensive approaches to adolescent mental health assessment and prevention.

The study findings demonstrate that machine learning algorithms can effectively predict adolescent depression risk using integrated behavioral health data. Random Forest achieved the highest predictive performance, while academic stress, sleep quality, and anxiety symptoms emerged as key risk factors. The results highlight the value of combining multiple behavioral health indicators within predictive models to improve early identification of vulnerable adolescents. Such systems may support healthcare professionals, educators, and policymakers in implementing targeted interventions, enhancing mental health screening programs, and promoting better psychological outcomes among adolescents.

4.4 Discussion

The findings of this study demonstrate the effectiveness of machine learning techniques in predicting depression risk among adolescents using integrated behavioral health data. The Random Forest model achieved the highest predictive accuracy, indicating its suitability for mental health risk assessment. Academic stress, sleep quality, and anxiety symptoms emerged as the most influential predictors of depression risk. These results suggest that depression is a multifactorial condition influenced by interconnected behavioral and psychosocial factors. The integration of diverse health indicators improved model performance and enabled early identification of vulnerable adolescents. Such predictive approaches may support targeted interventions and enhance adolescent mental health screening programs.

5 Conclusion

This study investigated adolescent depression risk prediction using machine learning and behavioral health data integration. The results revealed that machine learning algorithms, particularly Random Forest, can accurately identify adolescents at risk of depression. Key predictors included academic stress, sleep quality, anxiety symptoms, social support, physical activity, and digital behavior. The integration of multiple behavioral health variables enhanced predictive performance and provided a comprehensive assessment framework. These findings highlight the potential of artificial intelligence in supporting early detection and prevention of adolescent depression. Healthcare professionals, educators, and policymakers can utilize such predictive systems to implement timely interventions and personalized support strategies. Future research should explore larger datasets and real-time monitoring systems to further improve prediction accuracy and mental health outcomes.

References

[1] World Health Organization. (2021). *Adolescent Mental Health Fact Sheet*.

[2] Thapar, A., Collishaw, S., Pine, D. S., & Thapar, A. K. (2012). Depression in adolescence. *The Lancet*, 379(9820), 1056–1067.

[3] American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.).

[4] Shatte, A. B. R., Hutchinson, D. M., & Teague, S. J. (2019). Machine learning in mental health: A scoping review. *Journal of Medical Internet Research*, 21(4), e15708.

[5] Kessler, R. C., Avenevoli, S., & Merikangas, K. R. (2012). Mood disorders in children and adolescents. *Biological Psychiatry*, 49(12), 1002–1014.

[6] Dwyer, D. B., Falkai, P., & Koutsouleris, N. (2018). Machine learning approaches for clinical psychology and psychiatry. *Annual Review of Clinical Psychology*, 14, 91–118.

[7] Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56.

[8] Torous, J., Jän Myrick, K., Rauseo-Ricupero, N., & Firth, J. (2020). Digital mental health and smartphone-based monitoring. *World Psychiatry*, 19(1), 3–14.

[9] Price, W. N., & Cohen, I. G. (2019). Privacy in the age of medical big data. *Nature Medicine*, 25(1), 37–43.

[10] UNICEF. (2021). *The State of the World's Children 2021: On My Mind – Promoting Mental Health*.

[11] World Health Organization. (2022). *Digital Mental Health and Artificial Intelligence Report*.
[12] Graham, S., Depp, C., Lee, E. E., et al. (2022). Artificial intelligence for mental health prediction and intervention. *The Lancet Digital Health*, 4(8), e559–e570.
[13] Torous, J., Bucci, S., Bell, I. H., et al. (2023). Integrating digital behavioral health data for psychiatric prediction models. *World Psychiatry*, 22(2), 212–225.
[14] Huckvale, K., Nicholas, J., Torous, J., & Larsen, M. E. (2023). Smartphone and behavioral health data integration in adolescent mental health research. *Journal of Medical Internet Research*, 25, e45621.
[15] Shatte, A. B. R., Teague, S. J., & Hutchinson, D. M. (2024). Machine learning approaches for depression prediction in youth populations. *npj Digital Medicine*, 7(1), 45–56.
[16] European Psychiatric Association. (2025). *Explainable Artificial Intelligence in Mental Health Care: Clinical Guidelines*.
[17] World Health Organization. (2026). *Global Review of Artificial Intelligence Applications in Adolescent Mental Health Screening*.
[18] Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). Sage Publications.
[19] Géron, A. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow* (2nd ed.). O'Reilly Media.
[20] Kuhn, M., & Johnson, K. (2020). *Feature Engineering and Selection for Predictive Models*. CRC Press.