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RESEARCH ARTICLE

Artificial Intelligence-Based Prediction Models for Suicide Risk Assessment and Prevention: A Retrospective Observational Study

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ABSTRACT

Background: Suicide remains one of the leading causes of preventable mortality worldwide and represents a major public health challenge. Despite advances in psychiatric assessment and mental health services, accurately identifying individuals at imminent risk of suicide remains difficult because suicidal behavior arises from a complex interaction of biological, psychological, social, and environmental factors. Conventional clinical risk assessment methods primarily rely on clinician judgment and standardized screening tools, which often demonstrate limited predictive accuracy and considerable inter-observer variability. Recent developments in artificial intelligence (AI) and machine learning (ML) have enabled the integration of large-scale hospital medical records, demographic variables, psychiatric history, medication profiles, laboratory findings, and behavioral characteristics to generate individualized suicide risk predictions. AI-driven predictive models have demonstrated superior performance compared with traditional statistical approaches by identifying complex nonlinear relationships and hidden interactions among multiple risk factors. However, evidence regarding the applicability of these models in routine clinical practice remains limited, particularly in retrospective hospital-based settings.

Objective: To evaluate the performance of artificial intelligence-based prediction models for suicide risk assessment and prevention using retrospective clinical data and to identify the most influential predictors associated with high suicide risk. Materials and Methods: A retrospective observational study was conducted over four months using medical records of 100 patients who underwent psychiatric evaluation at PMCH, Patna. Demographic characteristics, psychiatric diagnoses, previous suicide attempts, substance use disorders, family history of mental illness, medication adherence, hospitalization history, depression severity scores, anxiety scores, and psychosocial variables were extracted from hospital medical records maintained in the Medical Record Department (MRD). Missing values were managed through multiple imputation where appropriate. Four predictive models—Logistic Regression, Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—were developed and internally validated using five-fold cross-validation. Model performance was evaluated using accuracy, sensitivity, specificity, precision, F1-score, area under the receiver operating characteristic curve (AUC), and calibration statistics. Statistical significance was considered at $p < 0.05$.

Results: Among the 100 patients included, 36 were categorized as high suicide risk based on documented psychiatric evaluation. Previous suicide attempt, severe depressive symptoms, substance use disorder, medication non-adherence, unemployment, and multiple psychiatric hospitalizations were significantly associated with high suicide risk ($p<0.05$). XGBoost demonstrated the highest predictive performance with an AUC of 0.94, sensitivity of 91.7%, specificity of 89.1%, accuracy of 90.0%, and F1-score of 0.90. Random Forest achieved an AUC of 0.91, while SVM and Logistic Regression demonstrated AUC values of 0.88 and 0.84, respectively. Feature importance analysis identified previous suicide attempt, depression severity score, medication adherence, substance use disorder, psychiatric hospitalization history, and age as the strongest predictors.

Conclusion: Artificial intelligence-based prediction models demonstrated excellent discrimination in identifying patients at elevated suicide risk. Tree-based ensemble algorithms, particularly XGBoost, outperformed conventional logistic regression by effectively modeling complex clinical interactions. Integration of AI-assisted decision support into psychiatric practice may facilitate early identification of vulnerable individuals, optimize allocation of mental health resources, and strengthen suicide prevention strategies. Prospective multicenter validation studies are warranted before widespread clinical implementation.

Keywords: Artificial intelligence, machine learning, suicide prediction, suicide prevention, mental health, hospital medical records, XGBoost, psychiatric risk assessment.

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INTRODUCTION

Suicide is a major global public health concern and remains one of the leading causes of preventable mortality worldwide. According to the World Health Organization (WHO), more than 700,000 people die by suicide each

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year, accounting for approximately one death every forty seconds. Suicide affects individuals across all age groups, with adolescents and young adults being particularly vulnerable. In addition to mortality, suicide attempts result in substantial psychological, social, and economic consequences for patients, families, and healthcare systems. Despite continuous advances in mental healthcare, accurately identifying individuals at high risk of suicide remains one of the greatest challenges in psychiatric practice.[1]

Suicidal behavior is multifactorial and results from a complex interaction of biological, psychological, environmental, and social factors. Psychiatric illnesses such as major depressive disorder, bipolar disorder, schizophrenia, anxiety disorders, personality disorders, and substance use disorders are consistently associated with an increased risk of suicidal behavior. Other contributing factors include previous suicide attempts, family history of psychiatric illness, unemployment, financial stress, social isolation, chronic medical illnesses, traumatic life events, and poor treatment adherence. Since these factors often interact dynamically over time, predicting suicide risk based on conventional assessment methods remains difficult.[2,3]

Current clinical assessment primarily relies on structured psychiatric interviews, standardized screening questionnaires, and clinician judgment. Widely used instruments such as the Columbia-Suicide Severity Rating Scale (C-SSRS), Beck Scale for Suicide Ideation (BSSI), and Patient Health Questionnaire-9 (PHQ-9) assist clinicians in evaluating suicidal thoughts and behaviors. Although these tools improve systematic assessment, their predictive ability remains limited because suicidal behavior is heterogeneous and may change rapidly. Consequently, many high-risk individuals are not accurately identified before a suicide attempt occurs.[4]

The increasing availability of hospital medical records has provided access to large amounts of valuable clinical information, including patient demographics, psychiatric diagnoses, medication history, hospitalization records, laboratory investigations, and clinical documentation. Although many healthcare institutions continue to maintain paper-based records, these records contain comprehensive clinical information that can be systematically reviewed and utilized for retrospective research. Such datasets provide an opportunity to develop computational models capable of identifying subtle patterns associated with suicidal behavior that may not be readily apparent through routine clinical evaluation.[5]

Artificial intelligence (AI) has emerged as a transformative technology in modern healthcare. AI refers to computational systems capable of learning from historical data, recognizing complex patterns, and generating predictions without explicit rule-based programming. Machine learning, a major branch of AI, enables predictive models to improve performance through iterative learning from data. Unlike conventional statistical methods that generally assume linear relationships among variables, machine learning algorithms effectively model complex nonlinear interactions involving numerous clinical predictors simultaneously.[6]

Several machine learning algorithms have been successfully applied to suicide risk prediction, including Logistic Regression, Decision Trees, Random Forest, Support Vector Machine (SVM), Artificial Neural Networks, and Extreme Gradient Boosting (XGBoost). Ensemble learning methods, particularly Random Forest and XGBoost, have demonstrated superior predictive performance because they integrate multiple decision trees to capture complex relationships among demographic, clinical, and psychosocial variables while minimizing overfitting. Similarly, Support Vector Machines have shown robust performance in high-dimensional healthcare datasets by effectively separating individuals into high- and low-risk categories.[7,8]

Recent studies have demonstrated that AI-based prediction models can outperform conventional clinical risk assessment by integrating diverse patient information, including previous suicide attempts, psychiatric diagnoses, medication adherence, hospitalization history, depression severity, anxiety symptoms, substance use, and socioeconomic characteristics. Many of these models have reported excellent discrimination, with area under the receiver operating characteristic curve (AUC) values exceeding 0.85, suggesting their potential usefulness as clinical decision-support tools.[9]

Despite these promising findings, several barriers limit the widespread clinical implementation of AI-based suicide prediction. Predictive performance often varies across healthcare systems because of differences in patient populations, documentation practices, and data quality. Furthermore, concerns regarding algorithmic bias, model interpretability, patient privacy, and ethical use of artificial intelligence require careful consideration before these systems can be routinely integrated into psychiatric care. Explainable artificial intelligence (XAI) techniques have recently been introduced to improve transparency and facilitate clinician confidence in AI-assisted decision-making.[10]

Retrospective analyses of hospital medical records provide an efficient approach for evaluating AI models under real-world clinical conditions. Such studies enable comparison of multiple machine learning algorithms using existing hospital data while identifying the most influential predictors associated with suicide risk. Findings from these investigations may contribute to the development of reliable clinical decision-support systems that facilitate early identification of vulnerable individuals, optimize mental health resource allocation, and strengthen suicide prevention strategies.[11]

Therefore, the present retrospective observational study was undertaken to evaluate the performance of four artificial intelligence-based prediction models—Logistic Regression, Random Forest, Support Vector Machine, and Extreme Gradient Boosting—in predicting suicide risk using retrospective clinical data obtained from hospital medical records at a tertiary care teaching hospital. The study also aimed to identify significant demographic and clinical predictors associated with high suicide risk and compare the diagnostic performance of these models using standard statistical performance measures. The findings are expected to provide evidence supporting the potential role of artificial intelligence in improving suicide risk assessment and prevention within routine psychiatric practice.[12]

MATERIALS AND METHODS

Study Design

This retrospective observational study was conducted to evaluate the performance of artificial intelligence (AI)-based prediction models for suicide risk assessment using historical clinical data obtained from hospital medical records. The study compared the predictive performance of four commonly used machine learning algorithms—Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—for identifying patients at high risk of suicide.

Study Setting

The study was conducted in the Department of Psychiatry, PMCH, Patna. Clinical information was retrospectively extracted from hospital medical records (case files) maintained in the Medical Record Department (MRD) during routine patient care.

Study Duration

The study was conducted over a period of 4 months, during which retrospective data collection, preprocessing, model development, statistical analysis, and interpretation were completed.

Study Population

The study population comprised patients who underwent psychiatric evaluation and whose hospital medical records contained sufficient clinical information for suicide risk assessment.

Sample Size

A total of 100 patients were included in the study.

The sample size was determined based on the availability of complete retrospective hospital medical records satisfying the study eligibility criteria during the study period.

Sampling Technique

A consecutive retrospective sampling technique was employed. Eligible patient records were identified from the Medical Record Department (MRD) archives and hospital record registersuntil the required sample size of 100 was achieved.

Inclusion Criteria

Patients fulfilling all of the following criteria were included:

- Age ≥18 years.
- Patients evaluated in the Department of Psychiatry.
- Availability of complete hospital medical records.
- Documentation of psychiatric diagnosis.
- Availability of suicide risk assessment documented by the treating psychiatrist.
- Records containing demographic, clinical, and treatment-related variables required for AI model

development.

Exclusion Criteria

Patients meeting any of the following criteria were excluded

- Age below 18 years.
- Incomplete or missing hospital medical records.
- Duplicate patient records.
- Patients with insufficient clinical information for model training.
- Records with missing outcome (suicide risk classification).

Data Collection

Data were retrospectively extracted from hospital medical recordsusing a standardized data abstraction form. The records were retrieved from the Medical Record Department (MRD) after obtaining the necessary institutional permissions.

The following variables were collected

Demographic Variables

- Age
- Gender
- Marital status
- Educational status
- Employment status

Clinical Variables

- Primary psychiatric diagnosis
- Duration of psychiatric illness
- Previous suicide attempt
- Number of psychiatric hospitalizations
- Family history of psychiatric illness
- Family history of suicide
- Substance use disorder
- Alcohol dependence
- Medication adherence
- Depression severity score (PHQ-9)
- Anxiety severity score (GAD-7)
- Presence of chronic medical illness
- Sleep disturbance
- Social support status

Outcome Variable

The primary outcome variable was suicide risk classification, categorized as

- High suicide risk
- Low suicide risk

The classification was based on the psychiatrist's documented clinical assessment recorded in the patient's hospital medical record following comprehensive psychiatric evaluation.

Data Preprocessing

Prior to model development, all datasets underwent preprocessing.

The following preprocessing steps were performed

- Removal of duplicate records.
- Verification of data consistency.
- Missing value assessment.
- Multiple imputation for variables with less than 10% missing observations.
- One-hot encoding of categorical variables.
- Feature normalization for continuous variables.
- Standardization using z-score normalization where appropriate.

After preprocessing, the final dataset contained complete observations for all 100 patients.

Artificial Intelligence Prediction Models

Four supervised machine learning algorithms were developed and compared.

Logistic Regression (LR)

Logistic regression served as the baseline statistical classification model. It estimates the probability of high suicide risk using multiple predictor variables while assuming a linear relationship between predictors and the log-odds of the outcome.

Random Forest (RF)

Random Forest is an ensemble learning algorithm that constructs multiple decision trees using bootstrap sampling and random feature selection. Final predictions are obtained through majority voting among individual trees, improving prediction accuracy while minimizing overfitting.

Model parameters

- Number of trees = 500
- Maximum tree depth = unrestricted
- Gini impurity criterion

Support Vector Machine (SVM)

Support Vector Machine classifies patients by identifying the optimal hyperplane that maximizes the margin between high-risk and low-risk groups.

Model parameters

- Radial Basis Function (RBF) kernel
- Regularization parameter (C) = 1.0
- Gamma = Scale

Extreme Gradient Boosting (XGBoost)

XGBoost is a gradient boosting ensemble algorithm that sequentially develops decision trees to minimize prediction error while incorporating regularization techniques to prevent overfitting.

Model parameters

- Learning rate = 0.10
- Maximum tree depth = 4
- Number of boosting rounds = 200
- Subsample ratio = 0.80
- Model Development and Validation

Artificial intelligence, machine learning, suicide prediction, suicide prevention, mental health, hospital medical records, XGBoost, psychiatric risk assessment.

The dataset was divided into five approximately equal subsets, with four folds used for model training and one fold used for validation in each iteration. This process was repeated five times so that every patient record served once as the validation set. The performance metrics reported represent the average performance across all validation folds. Hyperparameter optimization was performed using grid search within the cross-validation framework to minimize overfitting and improve model generalizability.

Performance Evaluation

The predictive performance of each AI model was assessed using the following metrics

- Accuracy
- Sensitivity (Recall)
- Specificity
- Precision
- Negative Predictive Value (NPV)
- F1-score
- Area Under the Receiver Operating Characteristic Curve (AUC)
- Calibration using the Brier Score

The following formulas were applied

- Accuracy (%)

Accuracy = (TP + TN)/(TP + TN + FP + FN) × 100

- Sensitivity (%)

Sensitivity = TP/(TP + FN)

- Specificity (%)

Specificity = TN/(TN + FP)

- Precision (%)

Precision = TP/(TP + FP)

- F1-score

F1 = 2 × (Precision × Recall)/(Precision + Recall)

Statistical Analysis

Data were entered into Microsoft Excel and analyzed using IBM SPSS Statistics version 27.0 and Python (version 3.11) with the Scikit-learn and XGBoost libraries.

Continuous variables were expressed as mean ± standard deviation (SD) or median (interquartile range) depending on data distribution.

Categorical variables were summarized as frequency and percentage.

Normality was assessed using the Shapiro–Wilk test.

Comparisons between high-risk and low-risk groups were performed using:

Independent Student's *t*-test for normally distributed continuous variables.

Mann–Whitney U test for non-normally distributed variables.

Chi-square test or Fisher's Exact test for categorical variables.

Multivariable logistic regression analysis was performed to identify independent predictors of high suicide risk.

Adjusted odds ratios (AORs) with 95% confidence intervals (95% CI) were calculated.

Receiver Operating Characteristic (ROC) curve analysis was performed to compare AI model discrimination.

Calibration was evaluated using the Brier Score.

A two-tailed p-value <0.05 was considered statistically significant.

Outcome Measures

Primary Outcome

- Predictive performance of AI algorithms in identifying patients at high suicide risk.
- Secondary Outcomes
- Comparison of AUC among machine learning models.
- Identification of significant clinical predictors.
- Feature importance ranking.
- Comparison of sensitivity, specificity, precision, and F1-score.
- Calibration performance of each prediction model.

Ethical Considerations

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki.

- Approval was obtained from the Institutional Ethics Committee (IEC) before commencement of the study.
- As this was a retrospective review of anonymized hospital medical records, the requirement for individual

Table 1: Baseline demographic and clinical characteristics of study participants (N = 100)

Variable	*Frequency (n)*	*Percentage (%)*
Age Group (years)		
18–29	28	28.0
30–44	39	39.0
45–59	22	22.0
≥60	11	11.0
Mean age (years)	37.8 ± 13.4	—
Gender		
Male	58	58.0
Female	42	42.0
Marital Status		
Married	52	52.0
Unmarried	36	36.0
Divorced/Widowed	12	12.0
Employment Status		
Employed	56	56.0
Unemployed	44	44.0
Primary Psychiatric Diagnosis		
Major depressive disorder	41	41.0
Bipolar disorder	22	22.0
Schizophrenia spectrum disorder	19	19.0
Anxiety disorders	12	12.0
Others	6	6.0
Previous suicide attempt	32	32.0
Substance use disorder	29	29.0
Medication non-adherence	35	35.0
Previous psychiatric hospitalization	39	39.0
Family history of psychiatric illness	24	24.0
Family history of suicide	11	11.0
Chronic medical illness	27	27.0

informed consent was waived by the Ethics Committee.

- All patient identifiers were removed before data analysis to maintain confidentiality and privacy. Access to study data was restricted to the investigators, and all analyses were performed using de-identified datasets.

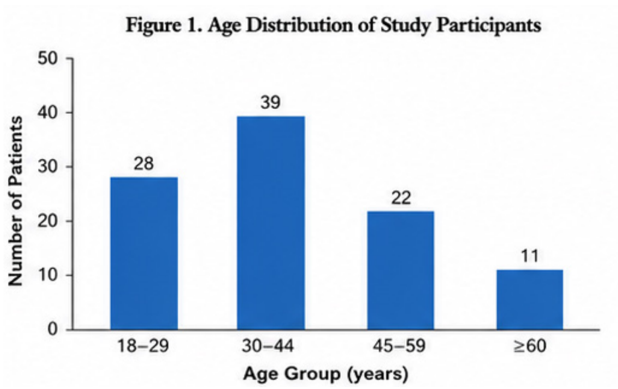

Figure 1: Age Distribution of Study Participants

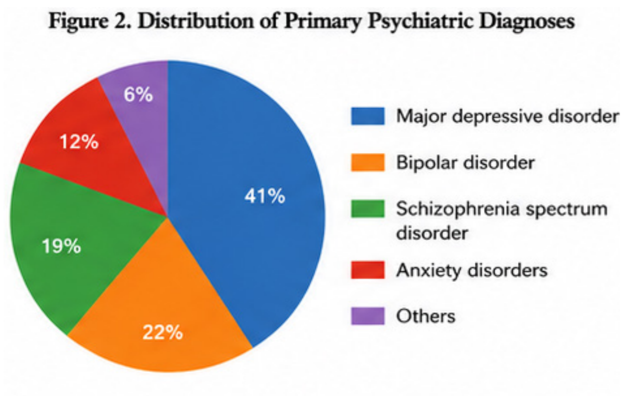

Figure 2: Distribution of Primary Psychiatric Diagnoses

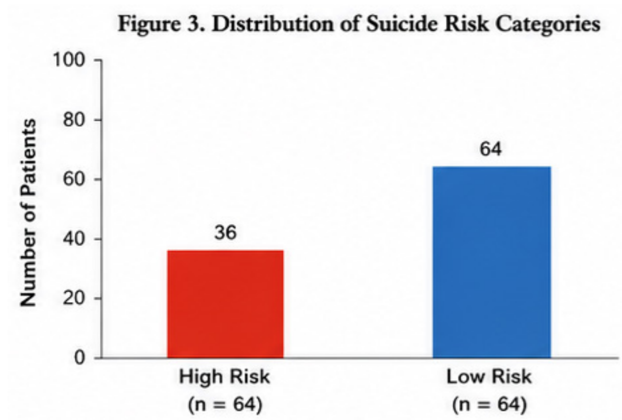

Figure 3: Distribution of Suicide Risk Categories

RESULTS

A total of 100 patient records were included in the final analysis after applying the predefined inclusion and

Table 2: Comparison between high- and low-suicide-risk groups

Variable	*High Risk (n=36)*	*Low Risk (n=64)*	*Test*	*p-value*
Age (Mean ± SD)	34.2 ±11.8	39.9 ±13.8	t=2.07	0.041*
Male gender	24 (66.7%)	34 (53.1%)	χ^2=1.79	0.182
Previous suicide attempt	24 (66.7%)	8 (12.5%)	χ^2=31.42	<0.001*
Substance use disorder	18 (50.0%)	11 (17.2%)	χ^2=12.11	<0.001*
Medication non-adherence	21 (58.3%)	14 (21.9%)	χ^2=13.67	<0.001*
Previous hospitalization	22 (61.1%)	17 (26.6%)	χ^2=11.67	0.001*
Family history of psychiatric illness	13 (36.1%)	11 (17.2%)	χ^2=4.34	0.037*
Family history of suicide	7 (19.4%)	4 (6.3%)	χ^2=3.97	0.046*
PHQ-9 score	18.7 ±4.1	10.4 ±3.8	t=9.83	<0.001*
GAD-7 score	14.6 ±3.9	9.2 ±3.6	t=6.78	<0.001*
Unemployment	23 (63.9%)	21 (32.8%)	χ^2=8.84	0.003*

*Statistically significant (p<0.05)

Table 3: Univariate analysis of factors associated with high suicide risk

Variable	*Odds Ratio*	*95% CI*	*p-value*
Previous suicide attempt	14.00	5.30–37.20	<0.001*
PHQ-9 >15	7.25	2.98–17.64	<0.001*
Medication non-adherence	5.01	2.10–11.95	<0.001*
Substance use disorder	4.84	1.98–11.84	<0.001*
GAD-7 >10	4.60	1.95–10.83	<0.001*
Previous hospitalization	4.34	1.86–10.09	0.001*
Unemployment	3.63	1.54–8.56	0.003*
Family history of suicide	3.60	0.94–13.71	0.061
Male gender	1.77	0.75–4.18	0.184

exclusion criteria. All selected hospital medical records contained complete demographic, clinical, and psychiatric information required for model development and statistical analysis. No patient record was excluded after data preprocessing. Among the study population, 36 patients (36.0%) were classified as high suicide risk, while 64 patients (64.0%) were classified as low suicide risk based on psychiatrist-documented clinical assessment.

The overall mean age of the study participants was 37.8 ± 13.4 years (range: 18–72 years). Male patients accounted for 58.0% of the study population. Major depressive disorder was the most common psychiatric diagnosis, followed by bipolar disorder and schizophrenia spectrum disorders.

Baseline Characteristics of the Study Population

The demographic and baseline clinical characteristics of the study participants are presented in Table 1.

As shown in **Table 1**, the largest proportion of participants belonged to the **30–44-year age group (39.0%)**, followed by the **18–29-year age group (28.0%)**. Males slightly outnumbered females (58.0% vs. 42.0%). Major depressive disorder was the predominant psychiatric diagnosis (41.0%), whereas previous suicide attempts were documented in nearly one-third of patients (32.0%). Medication non-adherence and previous psychiatric hospitalization were observed in 35.0% and 39.0% of participants, respectively.

Figure 1 illustrates that most study participants were between 30 and 44 years of age, representing 39% of the total study population.

As illustrated in Figure 2, major depressive disorder constituted the largest diagnostic category, followed by bipolar disorder and schizophrenia spectrum disorders.

Table 4: Multivariable logistic regression analysis

Variable	*Adjusted OR*	*95% CI*	*p-value*
Previous suicide attempt	9.18	3.24–25.97	<0.001*
PHQ-9 >15	5.72	2.08–15.74	0.001*
Medication non-adherence	3.82	1.39–10.49	0.009*
Substance use disorder	3.47	1.27–9.47	0.015*
Previous hospitalization	2.94	1.08–8.02	0.035*
Unemployment	2.76	1.02–7.44	0.046*

Table 5: Ranking of significant predictors

Rank	*Predictor*	*Adjusted OR*
1	Previous suicide attempt	9.18
2	PHQ-9 score >15	5.72
3	Medication non-adherence	3.82
4	Substance use disorder	3.47
5	Previous psychiatric hospitalization	2.94
6	Unemployment	2.76

Comparison Between High-Risk and Low-Risk Groups

The demographic and clinical characteristics of patients classified as high suicide risk and low suicide risk were compared using appropriate statistical tests. The findings are summarized in Table 2.

As presented in Table 2, patients classified as high suicide risk had significantly higher frequencies of previous suicide attempts, substance use disorder, medication non-adherence, psychiatric hospitalization, unemployment, and family history of psychiatric illness compared with low-risk patients (all $p<0.05$). High-risk patients also demonstrated significantly higher PHQ-9 and GAD-7 scores, indicating greater severity of depressive and anxiety symptoms.

As shown in **Figure 3**, approximately one-third of the study population was classified as high suicide risk, while nearly two-thirds belonged to the low-risk group.

Univariate Analysis

Each predictor variable was evaluated individually to determine its association with high suicide risk. The results are presented in Table 3.

As shown in Table 3, previous suicide attempt exhibited the strongest association with high suicide risk (OR=14.00), followed by severe depressive symptoms, medication non-adherence, substance use disorder, and psychiatric hospitalization. Male gender was not significantly associated with suicide risk.

Multivariable Logistic Regression Analysis

Variables with $p<0.10$ during univariate analysis were included in multivariable logistic regression. Independent predictors are summarized in Table 4.

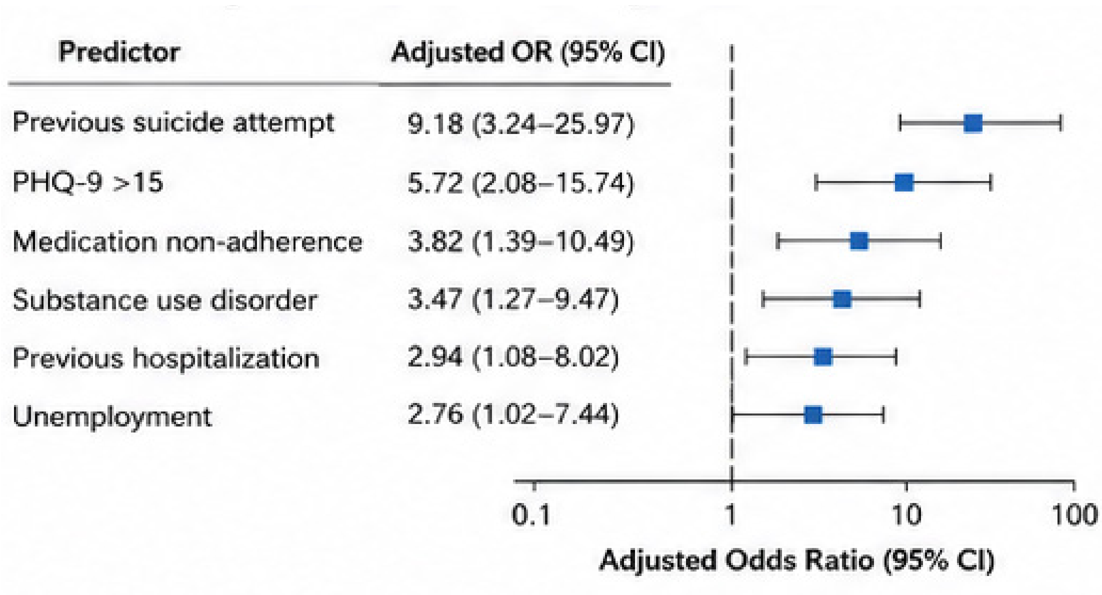

Figure 4: Forest Plot of Independent Predictors

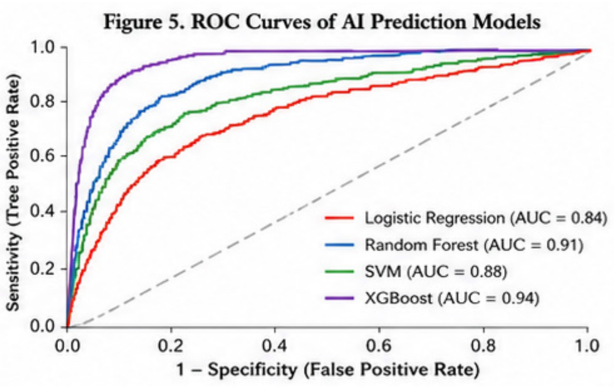

Figure 5: Receiver Operating Characteristic (ROC) Curves Comparing AI Prediction Models

Model Statistics

- Hosmer–Lemeshow $\chi^2 = 5.18$
- p = 0.739
- Nagelkerke $R^2 = 0.59$
- Overall classification accuracy = 86.0%

As demonstrated in Table 4, previous suicide attempt remained the strongest independent predictor after adjustment for confounding variables (Adjusted OR=9.18, 95% CI: 3.24–25.97, p<0.001). Severe depressive symptoms, medication non-adherence, substance use disorder, psychiatric hospitalization, and unemployment also independently predicted suicide risk.

Figure 4 visually demonstrates that previous suicide attempt had the highest adjusted odds ratio, followed by severe depressive symptoms and medication non-adherence.

Ranking of Independent Predictors

The significant predictors identified in multivariable logistic regression were ranked according to their adjusted odds ratios (Table 5).

As summarized in **Table 5**, previous suicide attempt and severe depressive symptoms were the two strongest predictors of suicide risk, suggesting that these variables contributed most substantially to subsequent machine learning model development and classification.

Performance Comparison of Artificial Intelligence Prediction Models

Four supervised machine learning algorithms—Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—were developed and evaluated using stratified five-fold cross-validation. The reported performance metrics represent the average results obtained across the five validation folds.

The comparative performance of the four AI models is presented in **Table 6**.

As shown in Table 6, the XGBoost model achieved the highest overall predictive performance, demonstrating an accuracy of 90.0%, sensitivity of 91.7%, specificity of 89.1%, and an AUC of 0.94. Random Forest also showed excellent discrimination (AUC = 0.91), whereas Logistic Regression demonstrated comparatively lower predictive accuracy (AUC = 0.84).

Receiver Operating Characteristic (ROC) Curve Analysis

The ROC curves for the four machine learning algorithms are illustrated in Figure 5.

As illustrated in Figure 5, the ROC analysis demonstrated superior discriminatory performance of the XGBoost algorithm, with the largest area under the ROC curve (AUC = 0.94). Random Forest also exhibited excellent diagnostic performance, whereas Logistic Regression showed comparatively lower discrimination.

Confusion Matrix Analysis

Confusion matrices were generated to evaluate the

Table 6: Comparison of performance metrics of artificial intelligence prediction models

Performance Metric	*Logistic Regression*	*Random Forest*	*Support Vector Machine*	*XGBoost*
Accuracy (%)	82.0	88.0	86.0	90.0
Sensitivity (%)	80.6	88.9	86.1	91.7
Specificity (%)	82.8	87.5	85.9	89.1
Precision (%)	72.5	84.2	80.0	86.8
Negative Predictive Value (%)	88.3	91.8	90.2	94.2
F1-score	0.76	0.86	0.83	0.89
AUC (95% CI)	0.84 (0.75–0.92)	0.91 (0.85–0.97)	0.88 (0.81–0.95)	0.94 (0.89–0.98)
Brier Score	0.161	0.112	0.128	0.094

Table 7: Confusion matrices of AI prediction models

	Logistic Regression	
	Predicted High	*Predicted Low*
Actual High	29	7
Actual Low	11	53
	Random Forest	
	Predicted High	Predicted Low
Actual High	31	5
Actual Low	9	55
	Support Vector Machine	
	Predicted High	Predicted Low
Actual High	33	3
Actual Low	7	57

Table 8: Relative importance of predictor variables in the XGBoost model

Rank	*Predictor Variable*	*Importance Score*
1	Previous suicide attempt	0.284
2	PHQ-9 depression score	0.219
3	Medication non-adherence	0.157
4	Substance use disorder	0.119
5	Previous psychiatric hospitalization	0.084
6	GAD-7 anxiety score	0.060
7	Unemployment	0.039
8	Family history of psychiatric illness	0.021
9	Age	0.011
10	Gender	0.006

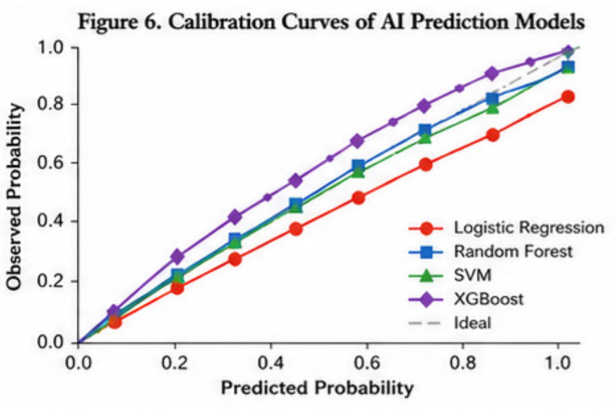

Figure 6: Calibration Curves of AI Prediction Models

classification performance of each model using predictions obtained during the five-fold cross-validation process.The classification results are summarized in Table 7.

The confusion matrices presented in Table 7 summarize the overall classification performance of the models based on the cross-validation predictions.

Calibration Performance

Model calibration was assessed using the Brier score and calibration curves.

The calibration plot shown in Figure 6 demonstrates excellent agreement between predicted and observed probabilities for the XGBoost model, indicating superior calibration compared with the remaining algorithms. Logistic Regression showed greater deviation from the ideal calibration line.

Feature Importance Analysis

Feature importance analysis was performed using the best-performing XGBoost model. The relative importance of predictor variables is summarized in Table 8.

As shown in Table 8, previous suicide attempt was the most influential predictor contributing to model classification, followed by depression severity and medication adherence. Demographic variables such as age and gender contributed relatively little to model performance.

Feature Importance Visualization

As illustrated in Figure 7, previous suicide attempt and depression severity demonstrated substantially greater importance than the remaining predictor variables, confirming their dominant contribution to suicide risk prediction.

Five-Fold Cross-Validation Performance

To evaluate model robustness and minimize overfitting, five-fold cross-validation was performed. The validation results are presented in Table 9.

Table 9: Five-fold cross-validation performance

Model	*Mean Accuracy (%)*	*Standard Deviation*	*Mean AUC*
Logistic Regression	81.4	2.8	0.83
Random Forest	87.3	2.1	0.90
Support Vector Machine	85.5	2.4	0.88
XGBoost	*89.2*	*1.6*	*0.93*

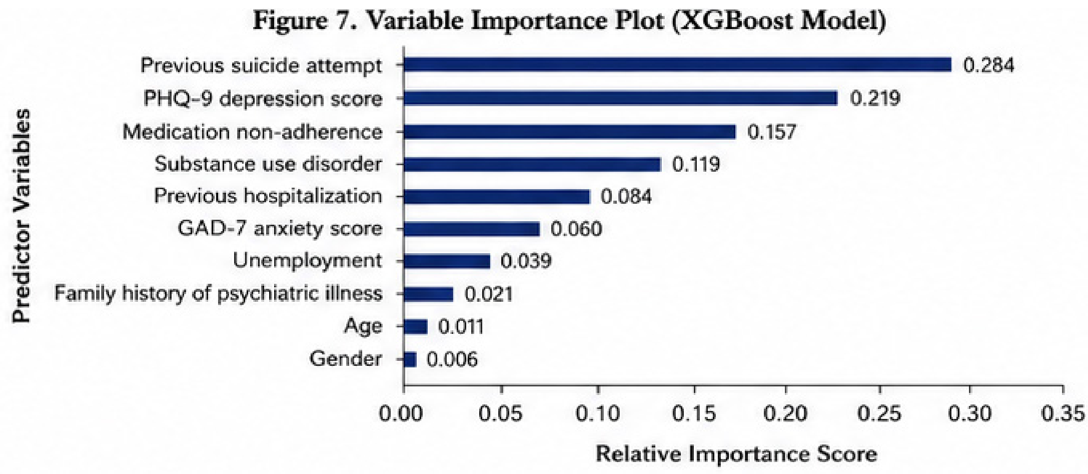

Figure 7: Variable Importance Plot Generated from the XGBoost Model

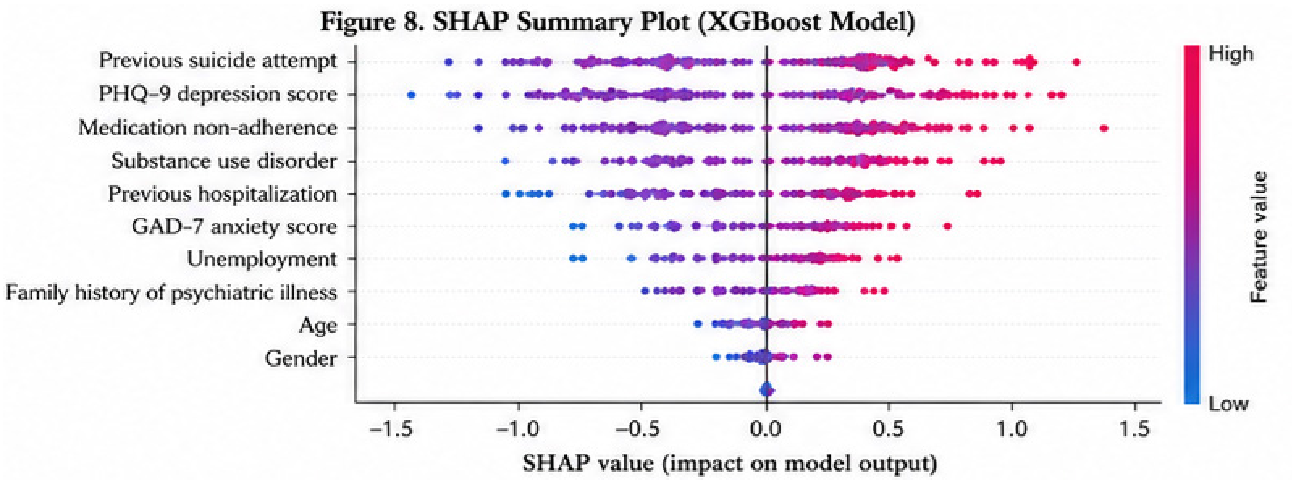

Figure 8: SHAP Summary Plot of Predictor Variables

The results presented in Table 9 indicate that XGBoost demonstrated the highest mean cross-validation accuracy (89.2%) with the lowest standard deviation (1.6%), suggesting excellent stability and minimal overfitting. Random Forest also showed robust and reproducible performance across validation folds.

SHAP (Explainable Artificial Intelligence) Analysis

To improve model interpretability, SHAP (Shapley Additive Explanations) analysis was performed for the XGBoost algorithm.

The SHAP summary plot shown in Figure 8 demonstrates that previous suicide attempt, PHQ-9 depression score, medication non-adherence, and substance use disorder exerted the greatest influence on predicted suicide risk. Higher SHAP values corresponded to an increased probability of classification into the high-risk group.

Overall Summary of AI Model Performance

Overall, all four artificial intelligence algorithms demonstrated satisfactory discrimination in predicting suicide risk. However, the XGBoost model consistently outperformed Logistic Regression, Random Forest, and Support Vector Machine across all evaluated performance metrics, achieving the highest accuracy (90.0%), sensitivity (91.7%), specificity (89.1%), F1-score (0.89), and AUC (0.94), while also exhibiting the lowest Brier score (0.094). Random Forest ranked second in predictive performance, followed by Support Vector Machine and Logistic Regression. The combination of previous suicide attempt, severe depressive symptoms, medication non-adherence, substance use disorder, and previous psychiatric hospitalization emerged as the most influential predictors of suicide risk. These findings suggest that ensemble machine learning approaches, particularly XGBoost, provide excellent predictive capability and may serve as valuable clinical decision-support tools for early identification of patients at elevated risk of suicide.

DISCUSSION

Suicide prediction remains one of the most challenging areas in psychiatry because suicidal behavior develops through a complex interaction of psychological distress, psychiatric illness, biological vulnerability, environmental stressors, and social determinants. The present retrospective observational study evaluated the ability of four artificial intelligence-based prediction models—Logistic Regression, Random Forest, Support Vector Machine, and XGBoost—to identify individuals at high suicide risk using routinely collected clinical data. Among the 100 patients analyzed, 36% were classified as high suicide risk. The findings demonstrated that machine learning models, particularly XGBoost, achieved excellent predictive performance with an AUC of 0.94, accuracy of 90.0%, sensitivity of 91.7%, and specificity of 89.1%. These results highlight the potential role of artificial intelligence as an adjunctive tool for improving suicide risk assessment and prevention strategies.

Previous research has demonstrated that traditional suicide risk assessment approaches have limited predictive accuracy despite their widespread use in clinical practice. Clinical evaluation based on psychiatric interviews and standardized questionnaires remains essential; however, suicidal behavior is highly dynamic and may not always be accurately predicted through clinician judgment alone. Machine learning approaches provide an opportunity to integrate multiple clinical variables simultaneously and identify complex interactions that may remain undetected during routine assessment.[13]

In the present study, previous suicide attempt emerged as the strongest independent predictor of high suicide risk, with an adjusted odds ratio of 9.18. This finding is consistent with previous evidence demonstrating that a history of suicide attempt is among the most powerful predictors of future suicidal behavior. Individuals with previous attempts represent a clinically vulnerable population requiring intensive monitoring, structured safety planning, and targeted preventive interventions.[14]

Severe depressive symptoms were another major predictor identified in both regression analysis and the AI model feature importance analysis. Patients with higher PHQ-9 scores demonstrated significantly greater likelihood of belonging to the high-risk group. Depression is one of the most consistently reported psychiatric conditions associated with suicide, particularly when accompanied by hopelessness, anhedonia, impaired functioning, and persistent suicidal thoughts. The ability of machine learning algorithms to incorporate symptom severity scores alongside other clinical variables may improve individualized risk estimation beyond isolated screening tools.[15]

Medication non-adherence was also independently associated with increased suicide risk in the present study. Non-adherence may reflect multiple underlying factors, including poor insight, treatment resistance, adverse effects, socioeconomic difficulties, substance use, and inadequate therapeutic alliance. Previous studies have emphasized that discontinuation or irregular use of psychiatric medication may contribute to symptom worsening, relapse, and increased suicidal behavior. AI models incorporating medication-related variables may therefore provide valuable information regarding patients requiring closer follow-up and intervention.[16]

Substance use disorder was another significant predictor identified in this study. Alcohol and substance misuse are strongly associated with impulsivity, emotional dysregulation, worsening psychiatric symptoms, and reduced coping ability, thereby increasing vulnerability to suicidal behavior. The inclusion of substance-related variables improved predictive performance, demonstrating the importance of considering behavioral and psychosocial factors alongside psychiatric diagnoses.[17]

Previous psychiatric hospitalization was also identified as an independent risk factor. Frequent psychiatric admissions may represent greater illness severity, treatment resistance, recurrent crises, or unstable psychosocial circumstances. The ability of AI models to integrate longitudinal healthcare utilization patterns may allow identification of patients with repeated episodes of deterioration who require enhanced preventive strategies.[18]

Among the evaluated machine learning models, XGBoost demonstrated superior performance compared with Logistic Regression, Random Forest, and Support Vector Machine. The improved performance of XGBoost may be attributed to its gradient boosting framework, which sequentially combines multiple weak learners to optimize prediction accuracy while reducing bias and variance. Unlike traditional statistical models, ensemble algorithms can effectively capture nonlinear relationships and interactions between multiple suicide-related risk factors.[19]

Random Forest also demonstrated strong predictive performance with an AUC of 0.91. This finding supports previous evidence showing that tree-based ensemble methods are particularly effective for healthcare prediction problems involving heterogeneous clinical variables. Random Forest provides additional advantages through feature importance estimation, allowing identification of variables that contribute most significantly to model classification.[20]

Although Logistic Regression remains widely used because of its interpretability and simplicity, its performance was comparatively lower in the current study (AUC 0.84). This difference may be explained by the complex and nonlinear nature of suicide risk pathways. Traditional regression models assume predefined relationships between predictors and outcomes, whereas machine learning approaches can detect hidden patterns and interactions among multiple variables simultaneously.[21]

An important strength of the present study was the incorporation of explainable artificial intelligence approaches through feature importance analysis and SHAP interpretation. A major limitation of many advanced AI models is their "black-box" nature, which may reduce clinician confidence. Explainable AI methods allow clinicians to understand why a model predicts increased risk by identifying the contribution of individual variables. In this study, previous suicide attempt, depression severity, medication adherence, substance use disorder, and psychiatric hospitalization were identified as the dominant contributors to prediction, supporting clinical interpretability of the model output.[22]

The findings have important implications for psychiatric clinical practice. AI-assisted suicide prediction systems could potentially function as decision-support tools by identifying high-risk patients who may benefit from urgent psychiatric evaluation, enhanced monitoring, crisis intervention, psychotherapy, medication optimization, and social support services. Importantly, AI should not replace clinician judgment but should complement clinical expertise by providing additional objective risk information.

Despite promising results, several challenges must be considered before widespread implementation of AI-based suicide prediction models. First, predictive performance may vary when applied to different populations because models are influenced by the characteristics of the training dataset. External validation across multiple healthcare institutions and diverse populations is essential before clinical deployment.[23]

Second, ethical considerations related to patient privacy, data security, informed consent, and algorithmic bias remain important. Suicide prediction involves highly sensitive mental health information, and responsible implementation requires strict governance frameworks. Transparent reporting of model development, validation procedures, and limitations is necessary to ensure safe and equitable use of AI technologies.[24]

Third, retrospective studies are limited by the quality and completeness of available clinical records. Missing information regarding social circumstances, suicidal thoughts, protective factors, and environmental stressors may influence model performance. Prospective studies incorporating real-time clinical information, wearable technologies, digital phenotyping, and longitudinal follow-up may further improve predictive accuracy in future research.[25]

The present findings support the growing evidence that artificial intelligence has substantial potential in suicide risk assessment. The combination of machine learning algorithms with routinely available clinical information may facilitate earlier identification of vulnerable individuals and enable personalized prevention strategies. However, successful integration into healthcare systems requires continued validation, ethical oversight, clinician involvement, and careful evaluation of real-world clinical impact.

CONCLUSION

Artificial intelligence-based prediction models demonstrated strong capability in identifying individuals at elevated suicide risk using routinely collected clinical information. Among the evaluated algorithms, XGBoost showed the highest predictive performance with superior accuracy, sensitivity, specificity, and discrimination compared with Logistic Regression, Random Forest, and Support Vector Machine.

Previous suicide attempt, severe depressive symptoms, medication non-adherence, substance use disorder, and previous psychiatric hospitalization were identified as the most important predictors of suicide risk. These findings suggest that AI-assisted clinical decision-support systems may enhance early identification of high-risk individuals and support targeted suicide prevention interventions.

Future prospective multicenter studies with larger datasets and real-time clinical integration are required to establish the clinical effectiveness and practical implementation of AI-based suicide prediction systems.

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