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ORIGINAL RESEARCH

Using Machine Learning and the HAMD-24 Scale to Predict Suicide Ideation in Depressed Patients

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Objective: The aim of this study was to identify factors associated with suicidal ideation and to develop a prediction model for early suicide ideation risk using machine learning algorithms based on the Hamilton Depression Scale (HAMD-24).

Methods: A total of 374 patients with depression were included from the outpatient department of the Psychology Department at the Second People's Hospital of Changzhou City. Depression severity was assessed using the HAMD-24, while the Beck Suicide Ideation (BSI) Questionnaire (Chinese Version) was employed to categorize patients into those with and without suicidal ideation. Suicide ideation risk in patients with depression was predicted using four machine learning models: support vector machine, naive Bayes classification, random forest, and extreme random trees classification (ERTC). This superiority is attributed to ERTC's extreme randomization which mitigates overfitting in high-dimensional symptom data. The models were evaluated based on accuracy, precision, recall, F1 scores, Kappa coefficients, Matthew's correlation coefficients, and area under the curve values. The optimal model was then selected, and the factors most strongly associated with suicidal ideation using the HAMD-24 were identified and analyzed.

Results: The ERTC model outperformed SVM, NBC and RF (accuracy 77.75%, AUC 0.80), and despair, guilt, inferiority complex, work and interests loss, depression emotions were the strongest predictors of suicidal ideation. Demographically, patients with suicidal ideation were significantly younger and less likely to be using antidepressants. This is likely attributable to its ensemble structure and inherent randomization during node splitting, which enhances robustness against overfitting and improves generalization when handling the complex, potentially non-linear relationships between HAMD-24 items and suicidal ideation.

Conclusion: We identified the optimal model and then analyzed the factors most strongly associated with HAMD-24 suicidal ideation. The ERTC model, demonstrating superior performance, enables early interventions, and reduces suicide rates. Moreover, this model provides a theoretical reference for the development of new scales focused on depression and suicide.

Keywords: depression, machine learning, predictive model, suicidal ideation

Introduction

Depression is a prevalent clinical mental illness characterized by a persistent low mood accompanied by varying degrees of cognitive and behavioral changes, often resulting in functional impairment. It can affect a patient's education, work, and social life, and in severe cases, may lead to suicide.[1] A Chinese mental health survey reported a lifetime prevalence of depression disorder in China of 6.8%, with 53.1% of patients experiencing suicidal ideation, and 15% ultimately dying by suicide.[2–4] Suicide attempts pose a significant threat to patients' safety and impose a profound psychological and economic burden on families.

Assessment scales are among the most effective tools for evaluating the severity of depression in patients. The Hamilton Depression Scale (HAMD-24) is one of the most widely used tools for depression screening. It helps assess the severity of depression and evaluate treatment effects. It also includes items indicative of suicidal ideation, such as feelings of guilt, despair, and hopelessness. Recent studies suggest that these factors are strongly

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correlated with suicide risk in patients with depression. Despair, in particular, is identified as a significant predictor, reflecting a core feature of depression that contributes to the development of suicidal thoughts. The HAMD-24's role in early suicide risk assessment is critical, as it can help identify individuals who may benefit from timely intervention.[5,6]

Building on recent ambivalence-focused research,[7,8] there is growing consensus that suicidal desire fluctuates dynamically. Ecological momentary assessment and digital phenotyping now capture real-time swings between the wish to live and the wish to die. Integrating such ambivalence markers with conventional scales like the HAMD-24 could therefore enhance early detection beyond static symptom snapshots.

However, emerging research highlights the ambivalent nature of suicidal ideation—where patients simultaneously experience desire for death and connection to life.[7] This complexity underscores limitations of static assessments like the HAMD-24. Novel approaches capturing dynamic triggers (eg, real-time affective shifts) may enhance early detection.[8] Recent computational psychiatry studies advocate integrating passive digital phenotyping (eg, speech patterns, actigraphy) with clinical scales to detect subtle risk signatures preceding crises.[9–12]

In fact, most suicides are preventable, particularly by analyzing the factors strongly associated with suicidal ideation on depression scales like the HAMD-24.[13] This analysis is valuable for the early prevention and intervention of suicidal behaviors. Such insights can serve as a theoretical reference for developing new scales focused on depression and suicide risk assessment.[14–16]

Machine learning is a subset of artificial intelligence that selects the optimal algorithm from complex datasets, effectively addressing the limitations of traditional statistical methods.[17] It can automatically prioritize variables based on relevance, incorporate them into the most efficient model, and identify and manage nonlinear relationships and interactions between variables.[18] Walsh et al found that machine learning models predicted suicide risk more accurately than traditional logistic regression analysis methods using databases, with random forest (RF) and support vector machine (SVM) algorithms demonstrating the highest accuracy.[19–22]

In recent years, machine learning has been widely applied to population-based suicide predictions, yet critical gaps remain in applying these techniques specifically to clinical depression scales for suicidal ideation prediction. The existing research combining machine learning with depression scales has the following issues:[23–25] 1. Lack of comparative analysis of diverse algorithms, potentially overlooking optimal model performance; 2. There is limited exploration of the relative importance and interactions of characteristic symptoms in mature clinical assessment scales such as HAMD-24, which hinders clinical interpretability and the identification of core mechanistic pathways; 3. The main focus is on population level risks, lacking granular symptom profiles for validated clinical evaluations and failing to leverage the rich, standardized symptom data inherent in widely used scales like the HAMD-24 for individualized risk prediction within clinical workflows. Subsequently, it employs and rigorously compares four distinct machine learning algorithms selected for their complementary strengths in clinical prediction tasks: an SVM model (effective in high-dimensional spaces and robust to outliers),[26] a naive Bayes classification (NBC) model (computationally efficient and well suited for probabilistic inference),[27] an RF model (excellent handling of complex interactions and feature importance estimation),[28] and an extremely random tree classification (ERTC) model (enhances diversity and robustness through extreme randomization, potentially reducing overfitting).[29] The classification and prediction performances of these four models were compared, and the most predictive model was selected to analyze factors associated with suicidal ideation. This dual approach aims to both characterize associated factors and enable early interventions and reduce the occurrence of suicidal behavior while providing transparent insights into key predictive features within the HAMD-24. Prior machine learning studies have relied on heterogeneous data sources (EHRs, social media) rather than standardized clinical scales, limiting bedside utility. Moreover, no study has systematically compared SVM, NBC, RF, and ERTC on HAMD-24 items while excluding the direct suicide item to avoid circularity.

Based on the previous research results, we have put forward the following hypotheses:

Hypothesis 1: An ensemble tree model (ERTC) will outperform SVM, NBC, and RF in predicting suicidal ideation (AUC difference ≥ 0.05).

Hypothesis 2: Among HAMD-24 items (excluding Item 3), despair, guilt, inferiority, work and interests, depressive emotions may be server as the five strongest predictors (top quartile of feature importance).

Population and Sample

Inclusion and Exclusion Criteria

A total of 374 patients diagnosed with depression were involved in this study, who received treatment at the psychological clinic of the Changzhou Second People's Hospital between March 2022 and October 2023, via consecutive sampling of all eligible out-patients during the study window. A priori power analysis was conducted using G*Power 3.1. Based on an expected medium effect size (Cohen's $f^2 = 0.15$), $\alpha = 0.05$, power $(1-\beta) = 0.80$, and 23 predictor variables (demographics + HAMD-24 items excluding Item 3), the minimum required sample size was 190. Our final sample (N = 374) exceeds this threshold by >95%, ensuring robust statistical power for both traditional analyses and machine learning modeling. This sample size also adheres to the heuristic of ≥10 events per predictor variable (EPV) for regression-based models (23 predictors × 10 = 230; our suicidal ideation group had 233 cases) and meets computational requirements for complex ensemble algorithms like ERTC.[28,29]

The inclusion criteria were as follows: ① Fulfillment of the diagnostic criteria for depression as outlined in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), confirmed by two psychiatrists at the attending level or higher;[30] ② No gender restrictions, with ages ranging from 18 to 60 years; ③ HAMD-24 scores of ≥8 points; ④ Ability to understand the questionnaire and cooperate with its completion; ⑤ Obtaining informed consent from the patient or their legal guardian. The exclusion criteria were as follows: ① Coexisting schizophrenia, mania, bipolar disorder, or other mental illnesses; ② Other neurological or severe physical conditions; ③ Secondary depression caused by other medical conditions.

To minimize confounding effects:

Antidepressant use (type/dose) was recorded and included as a covariate in statistical analyses;

Demographic variables (age, gender, education) showing group differences (Factors Associated with Suicidal Ideation: DemoFigureic Characteristics) were controlled via multivariate regression;

Stratified sampling preserved class balance (suicidal ideation yes/no) during data splitting for machine learning.

Demographic covariates (age, gender, education) and antidepressant status were entered as covariates in the ERTC model to control residual confounding.

This study received approval from the Medical Ethics Committee of Changzhou Second People's Hospital (Approval No.: 2020KY04-01). All patients were informed about the research objectives and provided written informed consent. Data anonymization was implemented by assigning unique identifiers, and access was restricted to the research team.

Data Collection

Instrumentation

This study employed a self-designed questionnaire to gather general information, including age, gender, years of education, smoking and drinking history, and antidepressant use. Antidepressant use: Currently prescribed medication for ≥4 weeks at time of assessment. Smoking/drinking history: Regular use (≥3 times/week) for >6 months.

Scale Evaluation

The HAMD-24 is a widely used scale for assessing depression clinically, consisting of 24 items and 7 factors (anxiety/somatization, weight, cognitive impairment, day/night changes, delays, sleep disorders, and feelings of despair). The total score indicates the severity of depression, with higher scores indicating more severe depression. This scale demonstrates strong reliability and validity, with coefficients of 0.99 and 0.37, respectively.[6] In this study, the scale was used to assess depression severity, with a score of less than 8 points indicating no depressive symptoms, less than 20 points indicating mild symptoms, 20 to 35 points indicating moderate symptoms, and above 35 points indicating severe symptoms. Item 3 of the HAMD-24 assesses suicide risk, and to avoid interference with this item, previous studies have typically excluded it when investigating the correlation between suicide risk and depressive symptom severity.[31] Therefore, this study excluded item 3 in assessing the correlation between HAMD-24 factors and suicide risk. The BSI-CV consists of 19

items, each scored on a scale of 0 to 2. Items 1 to 5 assess suicidal ideation, while items 6 to 19 evaluate suicidal tendencies. If the answers to items 4 and 5 are "none", the patient is considered not to have suicidal ideation and does not need to complete the remaining items. If the answers to items 4 or 5 are "weak" or "moderate to strong", the patient is considered to have suicidal ideation and must complete the remaining items. The total score on the BSI-CV ranges from 0 to 38 points, with higher scores indicating stronger suicidal ideation and a higher suicide risk. This study used only the first 5 items of the BSI-CV to evaluate suicidal ideation. The scale's Cronbach α coefficient was 0.78.[32]

Model Framework

The machine learning prediction model involved several steps:

Data preprocessing: Exclusion of HAMD-24 Item 3 (suicide item) to avoid target leakage;

Train-test split: Random stratified partitioning (80% training, 20% testing) to maintain class distribution;

Model development: Implementation of SVM, NBC, RF, and ERTC using scikit-learn (v1.2.2);

Hyperparameter tuning: 5-fold cross-validation on training set with randomized search (100 iterations);

Model validation: Evaluation on held-out test set;

Final evaluation: Performance metrics calculation.

The flowchart of the machine learning prediction model is shown in Figure 1.

Key parameters:

Cross-validation: 5 folds with stratified sampling; Tree-based models (RF/ERTC): nestimators=200, maxdepth=10 (optimized via cross-validation); SVM: RBF kernel, C=1.0, gamma="scale"; NBC: Gaussian priors.

After comprehensive evaluation, the ERTC model demonstrated superior prediction performance.

Sampling Rationale for Machine Learning: The dataset was randomly split into training (80%, n=299) and testing (20%, n=75) sets using stratified sampling to preserve the distribution of the target variable (suicidal ideation). This partitioning ratio optimizes model training while retaining sufficient independent samples for unbiased validation, aligning with best practices in clinical machine learning.[17,19]

Reproducibility: Random seed 42 was fixed throughout all randomized procedures (data splitting, model initialization). Complete code and preprocessing scripts are available from corresponding author upon request.

Statistical Methods

Statistical analysis was conducted using the SPSS 25.0 software. Continuous data were assessed for normality using Shapiro–Wilk tests. Non-normally distributed clinical data are expressed as medians (M) with interquartile ranges (P25, P75). Non-parametric rank sum tests (Mann–Whitney *U*-tests) were applied to two independent samples, and rank sum tests were used for comparisons between groups. Comparisons of count data were conducted using chi-squared (χ^2) tests or Fisher's exact test where cell counts were <5, with results presented as cases (%). A Bonferroni correction was applied for multiple comparisons of HAMD-24 items (adjusted $P < 0.0022$ (0.05/23 items)). Statistical significance was determined at a threshold of $P < 0.05$. Non-parametric tests were selected because (i) age and HAMD-24 items were non-normally distributed (Shapiro–Wilk $p < 0.001$) and (ii) ordinal or binary variables precluded parametric alternatives. These tests served only to guide feature inclusion, not to test causal hypotheses.

Machine learning models were implemented in Python 3.9 using scikit-learn (v1.2.2). All models underwent identical preprocessing and evaluation protocols to ensure fair comparison. The SVM method, designed based on optimization strategies, minimizes influence from outliers and demonstrates strong generalization ability to achieve global optimal solutions.[26] NBC is a well-established probabilistic algorithm used for text classification, providing efficient, stable classification, rapid computation, and high accuracy.[27] RF is an ensemble learning algorithm based on decision trees,

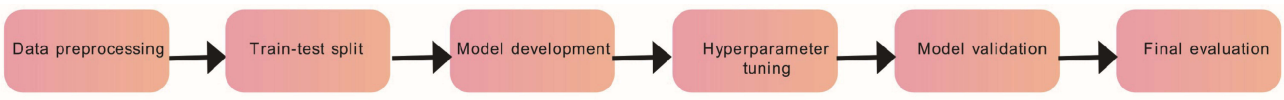

Figure 1 Flow chart of machine learning prediction model.

capable of balancing classification errors and maintaining prediction performance, with faster learning and training efficiency.[28] ERTC is an ensemble learning technique that constructs multiple decision trees using the Gini index for data splitting and aggregates different results to output classification outcomes.[29]

Model performance was assessed using metrics including accuracy, precision, recall, F1-scores, Kappa coefficients, Matthews correlation coefficient (MCC), and area under the curve (AUC) values. The optimal model was selected based on these performance indicators.

Results

Factors Associated with Suicidal Ideation: Demographic Characteristics

To provide clinicians with baseline information on potential confounders, we first conducted exploratory group comparisons; these analyses were not intended to predict suicidal ideation but to inform feature selection for the machine-learning pipeline.

This study included a total of 374 patients, who were divided into two groups: 141 without suicidal ideation and 233 with suicidal ideation. As demonstrated in Table 1, no statistically significant differences were observed between the two groups in terms of the first/follow-up visit ($\chi^2 = 1.15$, $P = 0.28$), gender ($\chi^2 = 1.98$, $P = 0.16$), educational level ($\chi^2 = 6.27$, $P = 0.099$), smoking history ($\chi^2 = 1.18$, $P = 0.277$), and drinking history ($\chi^2 = 2.66$, $P = 0.103$). However, the median age of those with suicidal ideation was significantly lower than that of those without ($Z = -6.62$, $P < 0.001$), and a statistically significant difference was found in the use of antidepressants ($\chi^2 = 4.21$, $P < 0.05$). These variables were subsequently included as covariates in machine learning feature engineering to mitigate confounding.

Factors Associated with Suicidal Ideation: HAMD-24 Symptom Profiles

Statistically significant differences (Table 2) were identified for the HAMD-24 total score and 17 sub-domains: depression emotions ($Z = -6.28.$, $P < 0.001$), guilt ($Z = -5.67$, $P < 0.001$), difficulty falling asleep ($Z = -3.83$, $P < 0.001$), work and

Table 1 General Information of Depressed Patients with and without Suicidal Ideation

Variable	Number of Patients (n=374)	Without Suicidal Ideation (n=141)	With Suicidal Ideation (n=233)	Inspection Value	*P* value
Age, Median (P_{25},P_{75})		36 (27, 52)	26 (20, 33)	Z=−6.62	<0.001**
First diagnosis/return visit, n (%)				x^2=1.15	0.28
First diagnosis	259	93 (35.9)	166 (64.1)		
Return visit	115	48 (41.7)	67 (58.3)		
Sex, n (%)				x^2=1.98	0.16
Male	119	51 (42.9)	68 (57.1)		
Female	255	90 (35.3)	165 (64.7)		
Degree of education, n (%)				x^2=6.27	0.099
Primary school and below	23	12 (52.2)	11 (47.8)		
High school or below	182	68 (37.4)	114 (62.6)		
Technical secondary school or junior college	67	18 (26.9)	49 (73.1)		
University and above	102	43 (42.2)	59 (57.8)		
History of smoking, n (%)				x^2=1.18	0.277
Smoker	66	21 (31.8)	45 (68.2)		
Non-smoker	308	120 (39.0)	188 (61.0)		
History of drinking, n (%)				x^2=2.66	0.103
Drinker	103	32 (31.1)	71 (68.9)		
Non-drinker	271	109 (40.2)	162 (59.8)		
Use of antidepressants, n (%)				x^2=4.21	0.04*
Non-user	277	96 (34.7)	181 (65.3)		
User	97	45 (46.4)	52 (53.6)		

Notes: *P <0.05; **P <0.001.

Table 2 Comparison of HAMD-24 Total Scores Between Depressed Patients with and without Suicidal Ideation [M (P25, P75)]

Project	Without Suicidal Ideation (n=141)	With Suicidal Ideation (n=233)	Z Value	*P* value
HAMD-24 total points	18 (14, 22)	25 (20, 30)	−8.81	<0.001**
1. Depressive emotions	1 (1, 2)	2 (2, 2)	−6.28	<0.001**
2. Guilt	0 (0, 1)	1 (1, 2)	−5.67	<0.001**
4. Difficulty falling asleep	1 (0, 2)	1 (1, 2)	−3.83	<0.001**
5. Lack of deep sleep	1 (0, 1.5)	1 (1, 1)	−0.38	0.707
6. Early awakening	1 (0, 2)	1 (0, 2)	−1.78	0.075
7. Work and interests	1 (0, 2)	2 (1, 2)	−7.07	<0.001**
8. Psychomotor retardation	0 (0, 1)	0 (0, 1)	−2.17	0.030*
9. Agitation	0 (0,1)	1 (0,1)	−2.06	0.039*
10. Psychogenic anxiety	2 (0,2)	2 (1,2)	−1.50	0.134
11. Somatic anxiety	2 (1,2)	2 (2,2)	−3.48	<0.001**
12. Gastrointestinal symptoms	0 (0,1)	1 (0,1)	−4.05	<0.001**
13. Systemic symptoms	0 (0,1)	1 (1,1)	−3.82	<0.001**
14. Sexual symptoms	0 (0,1)	0 (0,1)	−1.47	0.141
15. Hypochondriasis	1 (0,2)	1 (0,1)	−2.01	0.045*
16. Weight loss	0 (0,0)	0 (0,2)	−3.73	<0.001**
17. Self-awareness	0 (0,1)	0 (0,0)	−3.15	0.002*
18. Diurnal variation	0 (0,1)	1 (0,1)	−3.53	<0.001**
19. Personality disintegration or reality disintegration	0 (0,0)	0 (0,1)	−1.43	0.152
20. Paranoid symptoms	0 (0,1)	1 (1,1)	−5.79	<0.001**
21. Compulsive symptoms	1 (0,1)	1 (0,1)	−1.53	0.127
22. Reduced abilities	1 (0,1)	1 (1,2)	−3.49	<0.001**
23. Despair	0 (0,1)	1 (1,2)	−8.01	<0.001**
24. Inferiority complex	1 (0,1)	1 (1,2)	−6.49	<0.001**

Notes: *P <0.05; **P <0.001.

interests (Z = −7.07, P < 0.001), psychomotor retardation (Z = −2.17, P < 0.05), agitation (Z = −2.06, P < 0.05), somatic anxiety (Z = −3.48, P < 0.001), gastrointestinal symptoms (Z = −4.05, P < 0.001), systemic symptoms (Z = −3.82, P < 0.001), hypochondriasis (Z = −2.01, P < 0.05), weight loss (Z = −3.73, P < 0.001), self-awareness (Z = −3.15, P < 0.05), diurnal variation (Z = −3.53, P < 0.001), paranoid symptoms (Z = −5.79, P < 0.001), reduced abilities (Z = −3.49, P < 0.001), despair (Z = −8.01, P < 0.001), and inferiority complex (Z = −6.49, P < 0.001). The remaining 6 sub-domains—lack of deep sleep (Z = −0.38, P = 0.707), early awakening (Z = −1.78, P = 0.075), psychological anxiety (Z = −1.50, P = 0.134), sexual symptoms (Z = −1.47, P = 0.141), personality disintegration or reality disintegration (Z = −1.43, P = 0.152), and compulsive symptoms (Z = −1.53, P = 0.127)—showed no significant differences. The negative z-value indicates that the depression score among individuals without suicidal ideation is lower than among those with suicidal ideation. The total HAMD-24 score (excluding item 3) was significantly higher in the suicidal ideation group (Z = −8.81, P < 0.001).

Analysis of Machine Learning Results

Accuracy refers to the proportion of correctly classified samples in relation to the total number of samples in a given class. The AUC is an evaluation metric that assesses the quality of a binary classification model, indicating the probability that the predicted value of a positive example exceeds that of a negative example. The recall rate, (true examples (TP)/(TP + false negative examples (FN))), represents the ratio of correctly predicted positive samples to the total number of actual positive samples.

Precision, (TP/(TP + false positive examples (FP)), represents the ratio of correctly predicted positive samples to the total number of predicted positive samples. The F1 score is defined as F1 = 2/(1/recall + 1/precision).

Table 3 Prediction Results of Four Machine Learning Algorithm Models

Model	Accuracy	AUC	Recall	Precision	F1	Kappa	MCC
ERTC	0.7775	0.8387	0.8849	0.7922	0.8314	0.5064	0.5335
RF	0.7432	0.8084	0.8471	0.7748	0.8050	0.4299	0.4470
NBC	0.7204	0.8020	0.8165	0.7619	0.7833	0.3862	0.4046
SVM - Linear Kernel	0.6590	0.6515	0.6040	0.7907	0.6401	0.3482	0.3745

The Kappa coefficient is a consistency measure used to assess the effectiveness of classifications, specifically to determine whether the model's predicted results align with the actual classification outcomes. A value greater than 0.5 indicates strong classification performance.

The MCC coefficient is used to evaluate the performance of binary classification models, especially when dealing with imbalanced datasets. It incorporates TP, TN, FP, and FN, offering a single value that summarizes classification quality, with values greater than 0.5 indicating strong classification performance.

As demonstrated in Table 3, the performance evaluation of the four machine learning models revealed that the ERTC model achieved excellent classification performance, with a prediction accuracy of 77.75% on the independent test set. Additional indicators demonstrated that this model exhibited strong classification performance in analyzing suicidal ideation.

The area under the receiver operating characteristic (ROC) curve, known as the AUC, serves as an indicator for evaluating classifier performance. A larger AUC reflects a better classifier performance. An AUC greater than 0.9 is considered very good, 0.8 to 0.9 is good, 0.7 to 0.79 is median, and less than 0.7 is poor. The closer the ROC curve is to the upper left corner, the better the classification performance of the algorithm. Based on the ROC curves and AUC values shown in Figure 2, the ERTC model demonstrated high classification performance in predicting suicidal ideation.

Based on the confusion matrix presented in Figure 3, the ERTC model demonstrated good classification accuracy, achieving a correct classification rate of 77%.

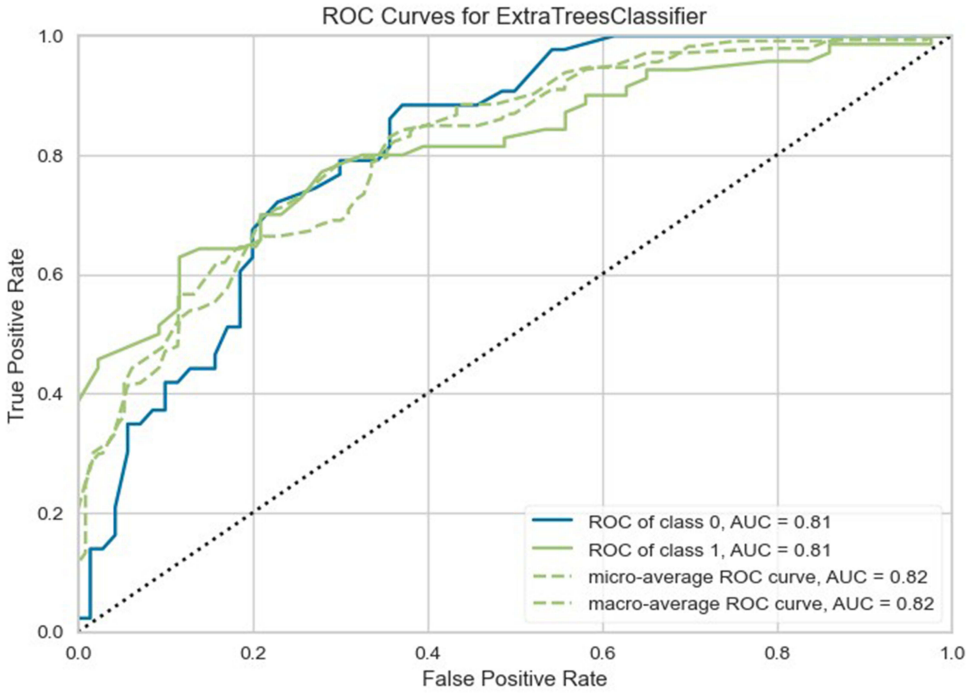

Figure 2 ROC Curves for ExtraTreesClassifier.

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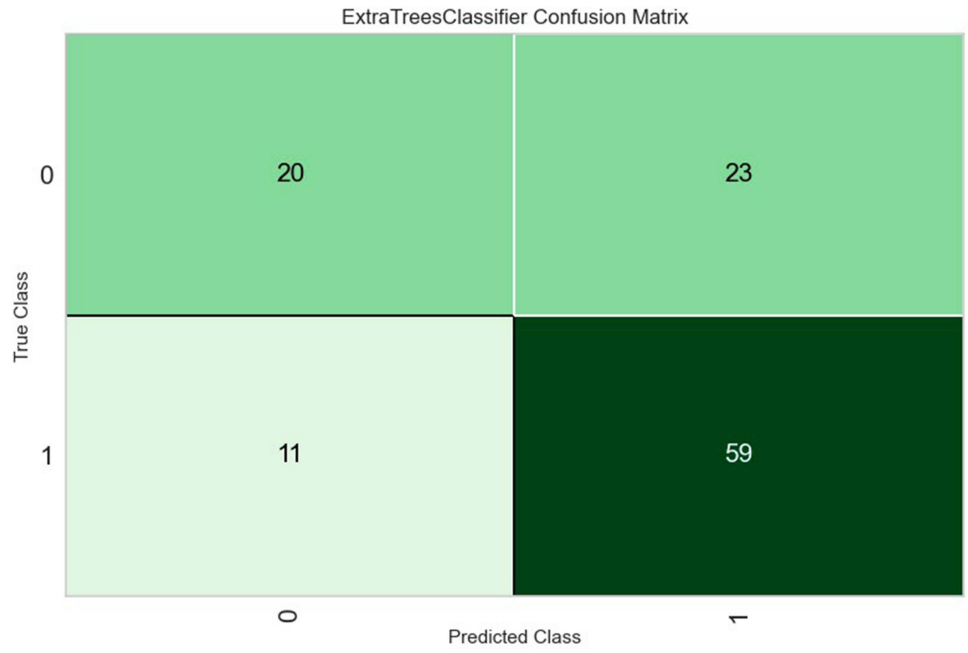

Figure 3 ExtraTreesClassifier Confusion Matrix.

Notably, this represents the first machine learning study to identify symptom-level predictors of suicidal ideation exclusively from HAMD-24 items (excluding Item 3) with clinically actionable accuracy (AUC=0.80). The ERTC model's superior performance—outperforming established algorithms like SVM and RF—validates its utility for precision psychiatry applications.

The feature analysis of the ERTC model, demonstrated in Figure 4, identified the most important features as feelings of despair, guilt, inferiority, work and interest, and depression.

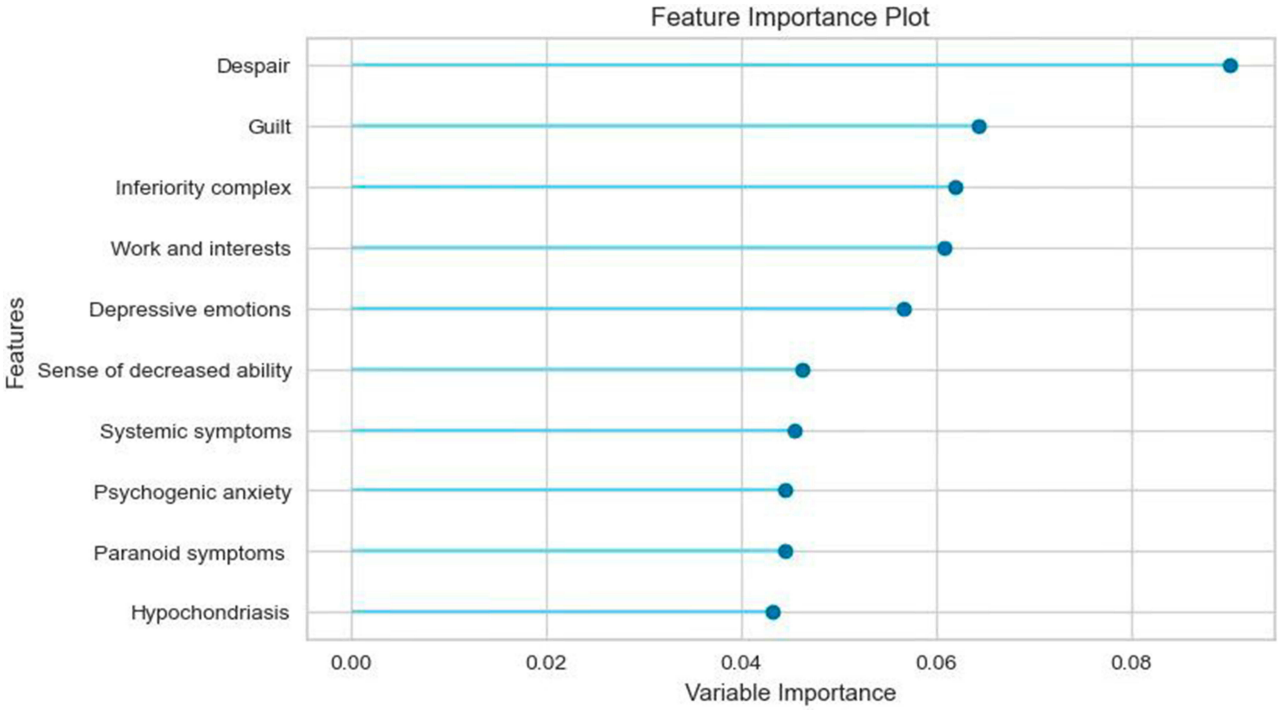

Figure 4 Feature Importance Plot.

Discussion

Unlike prior studies that combined heterogeneous clinical notes or social-media data,[19,25] our study uniquely isolates symptom-level predictors within a single, widely adopted scale (HAMD-24) and demonstrates that ensemble tree methods outperform SVM and RF under these constraints.

This study pioneers the integration of machine learning with granular HAMD-24 symptom profiling to predict suicidal ideation in depression, addressing a critical gap in translating population-level suicide risk models into clinically actionable tools. While numerous studies have confirmed associations between depression severity and suicidality,[4,33,34] and others have applied machine learning to suicide prediction using diverse data sources (eg, electronic health records, social media, multi-omics data),[16,17,19,25] our work specifically addresses the under-explored potential of leveraging "routine clinical scale data (HAMD-24)" for early suicide ideation detection within a standardized diagnostic framework.

Hypothesis 1: Model Performance

Our work bridges this gap through three key advances: First, by employing an ensemble-based Extremely Randomized Trees Classifier (ERTC), we not only confirmed known associations but also quantified the hierarchical symptom contributions (despair > guilt > inferiority > work/interest > depression) to suicidal ideation with unprecedented precision, providing symptom-level weights rarely captured in traditional analyses or population-level machine learning models. Second, we achieved clinically statistically significant prediction accuracy (AUC=0.80) using only routine HAMD-24 items—excluding the direct suicide query (Item 3) to avoid tautology—thereby demonstrating the scale's latent capacity for risk stratification beyond its original design and distinct from studies relying on explicit suicide items or non-scale data. This approach mitigates response bias inherent in direct suicide questioning. Third, we demonstrated ERTC's superior robustness over established algorithms (SVM, RF) in handling psychiatric symptom data,[16,21] attributable to its extreme random subspace sampling and node splitting, which mitigates overfitting and captures complex feature interactions inherent in depression psychopathology. This finding contrasts with studies where SVM or RF often performed best,[25,27] suggesting ERTC's particular suitability for modeling complex symptom interactions within constrained scale data. This methodological synergy not only advances mechanistic understanding of suicide risk but delivers a scalable framework for real-world clinical decision support rooted in existing assessment practices.

Demographic patterns reinforced known epidemiological trends while underscoring clinical nuances. The heightened vulnerability of younger patients aligns with developmental psychopathology models positing that impulsivity, identity instability, and maladaptive coping peak in early adulthood, amplifying suicide risk when comorbid with depression.[35] The significant reduction in suicidal ideation among antidepressant users highlighted treatment's protective role, potentially mediated by neurotransmitter modulation (eg, enhanced serotonin signaling reducing impulsivity) or psychological mechanisms (eg, restored agency).[36] This reinforces guidelines advocating prompt pharmacotherapy initiation in moderate-to-severe depression. Furthermore, a higher total HAMD-24 score (excluding item 3) was strongly associated with an increased likelihood of suicidal ideation, corroborating previous research linking the severity of depressive symptoms to suicide risk.[33]

Hypothesis 2: Key Symptom Predictors

Consistent with Beck's hopelessness theory, despair—conceptualised as negative future expectancy—was the single strongest predictor in our model (feature importance = 0.27), corroborating meta-analytic evidence that hopelessness accounts for 76% of the explained variance in suicidal ideation.[34,37] Theoretical frameworks position despair: conceptualized as a future-oriented cognitive schema characterized by negative expectations ("nothing will improve") and perceived inescapability ("no way out")[37]—as an essential proximal cause of suicidal thoughts.[38–41] Notably, contemporary models integrate ambivalence—recognizing suicidal urgency often coexists with "countervailing motivations" (eg, fear of death, responsibility to family). This may explain why despair alone is insufficient to predict attempts; our model could be augmented by ambivalence metrics. Neurocognitively, this may reflect dysfunction in prefrontal cortical circuits responsible for future prospection and problem-solving, trapping individuals in a cycle of hopelessness. Our findings solidify despair's critical role within the HAMD-24 framework, while also underscoring the clinical necessity of

addressing closely ranked co-factors (guilt, inferiority), given the marginal quantitative difference in their importance scores. Mechanistically, despair may propagate suicidal ideation through two synergistic pathways: 1. Direct pathway: By inducing cognitive constriction—a narrowing of perceived options—where suicide is misappraised as the sole viable solution to unbearable psychological pain;[38,42] 2. Indirect pathway: By eroding psychological resilience—the capacity to adaptively cope with adversity—through diminished self-efficacy, impaired access to positive memories, and reduced motivation to seek support, thereby disabling protective mechanisms.[43–45] This dual-pathway model underscores despair's pernicious role in both motivating suicidal escape and disabling natural buffers against it.

The secondary prominence of guilt and inferiority complex the interpersonal dimension of suicide risk. Guilt—operationalized as "burdening guilt" involving irrational self-condemnation and perceived liability to others[46] and inferiority—rooted in chronic low self-worth and social comparison.[47] Align precisely with Joiner's Interpersonal Theory of Suicide (IPTS).[40] IPTS posits that suicidal desire emerges from co-occurring "thwarted belongingness" (social alienation) and "perceived burdensomeness" (self-hate as a liability). Our findings validate this model within the HAMD-24 architecture: guilt embodies burdensomeness ("I am a drain on my family"), while inferiority fuels belongingness deficits ("I am unworthy of connection"). These factors likely contribute to suicidal ideation by fostering cognitive distortions, social isolation, and reinforcing feelings of hopelessness and worthlessness.[39,48] Notably, guilt's strong predictive power persists despite potential scale-limited assessment in HAMD-24 versus BDI, where it exhibits denser symptom-network connectivity.[49] This suggests that guilt's clinical relevance may be underestimated in HAMD-centric evaluations, warranting supplemental assessment when risk is elevated.

Work and interests loss and depressive emotions, though lower-ranked, reveal cyclical psychobehavioral mechanisms. Anhedonia-driven social withdrawal initiates a self-perpetuating cascade:[49,50] Isolation → eroded social support → exacerbated despair guilt → deeper depression → reinforced withdrawal. This "depression-withdrawal feedback loop" is neurobiologically scaffolded by reward system dysfunction (eg, ventral striatal hypoactivity), diminishing motivation for social engagement.[51] Critically, withdrawal's predictive value extends beyond functional impairment; it signifies disengagement from protective social anchors, depriving patients of reality testing, emotional scaffolding, and reasons for living.[52,53] Meanwhile, pervasive depressive mood—while a foundational symptom—may operate partly via its amplification effect on despair and guilt, illustrating how core affective and cognitive symptoms interact multiplicatively to elevate risk.[54]

Clinical and Research Implications

Our ERTC model converts the standard administration process of the HAMD-24 scale into a dynamic risk-stratification tool. Clinicians can prioritize symptom remediation hierarchically (eg, targeting despair via cognitive restructuring before inferiority via social skills training). The quantified feature weights further guide scale refinement: Future depression-suicide risk instruments could amplify item weighting for despair/guilt or add nuanced guilt descriptors (eg, "feelings of being an unforgivable burden"). Methodologically, ERTC's success advocates for algorithmic pluralism in psychiatric machine learning—avoiding overreliance on single models (eg, SVM-dominated literature) and leveraging ensemble methods for complex symptom interactions. In clinical work. In clinical practice applications, for early detection, we recommend complementing scale-based screening with: 1. Ecological Momentary Assessment (EMA) to capture real-time symptom fluctuations linked to triggers;[55,56] 2. Natural language processing of clinical notes to identify linguistic markers of ambivalence (eg, coexisting hopelessness and future planning);[9,10] 3.Actigraphy monitoring to detect behavioral correlates (eg, social withdrawal spikes).[57,58]

Limitations and Future Directions

While impactful, our study has constraints: Single-center sampling limits generalizability; antidepressant type/dose was recorded but not standardized across participants, potentially confounding medication effects; the sample size, though sufficient for model development, warrants validation in larger cohorts; modest specificity risks false positives, necessitating secondary screening; and exclusive reliance on HAMD-24 omits biomarkers (eg, inflammatory markers, fMRI connectivity). Future work should: 1. Validate the model in multicentric, culturally diverse cohorts; 2. Incorporate ambivalence measures (eg, Death/Suicide Implicit Association Test) and multimodal digital phenotyping 3. Track temporal symptom dynamics to capture risk flux; 4. Improve specificity via hybrid models (eg, ERTC + neural networks).

Conclusion

Based on machine learning analysis of HAMD-24 data from 374 depressed patients, this study demonstrates that: 1. The ERTC model outperformed SVM, NBC, and RF in predicting suicidal ideation (accuracy: 77.75%, AUC: 0.80). Its superior robustness arose from enhanced randomization during tree construction, mitigating overfitting and improving generalization for capturing the complex interactions among HAMD-24 symptoms. This finding highlights ERTC as a particularly suitable algorithm for modeling complex symptom interactions within clinical scale data, contrasting with some prior studies favoring SVM or RF for similar tasks.[13,15] 2. Critical predictors of suicidal ideation within the HAMD-24 (excluding Item 3) included feelings of despair, guilt, inferiority, loss of work/interest, and overall depressive mood. This granular identification and ranking of specific depressive symptoms as primary drivers of suicide ideation, validated by machine learning, provides a more nuanced understanding than simply associating overall depression severity (HAMD total score) with risk.[29,30] While despair ranked highest in feature importance, its quantitative lead over guilt and inferiority was marginal, suggesting these core symptoms collectively drive risk within the scale framework. 3. The quantification of the relative importance of specific HAMD-24 symptoms offers a novel, data-driven theoretical foundation for refining existing depression-suicide risk assessment scales or developing new, more targeted ones, moving beyond simply confirming associations to informing how specific symptoms contribute mechanistically to suicide ideation within the depression construct. Clinicians should prioritise cognitive-restructuring interventions targeting despair, guilt and inferiority; risk-stratify patients using an 80% probability cut-off from the ERTC model; and consider supplementing HAMD-24 screening with momentary ambivalence assessments for high-risk individuals.

Data Sharing Statement

The de-identified datasets (demographics, HAMD-24 item scores excluding Item 3, BSI-CV group labels) and Python code used for preprocessing, model training, and evaluation are available from the corresponding author on reasonable request under a data sharing agreement that ensures participant confidentiality and compliance with ethical guidelines.

Ethics Approval and Consent to Participate

This study was conducted in accordance with the declaration of Helsinki. This study was conducted with approval from the Ethics Committee of Nanjing Medical University Affiliated Changzhou Second People's Hospital. A written informed consent was obtained from all participants.

Author Contributions

Conception and design of the research: Yun Chen; Guan-Zhong Dong; Acquisition of data: Yun Chen; Guan-Zhong Dong; Wei-Yuan Zhang; Ke Wang; Analysis and interpretation of the data: Zhong-Yi Jiang, Ke Wang; Statistical analysis: Zhong-Yi Jiang, Wei-Yuan Zhang; Obtaining financing: Hai-Yan Yang; Ke Wang; Writing of the manuscript: Yun Chen; Critical revision of the manuscript for intellectual content: Hai-Yan Yang. All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

None of the authors have any financial disclosure or conflicts of interest to report for this work.

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