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Machine learning-driven development of a brief suicide risk screening tool with network-derived mechanistic insights: a multicentre longitudinal study

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Abstract

Suicide is a major global public health challenge, claiming more than 720,000 lives annually. However, existing screening instruments suffer from excessive length and limited dimensional coverage. To address these needs, this study employed a combined cross-sectional and longitudinal design, using multicentre datasets to develop a suicide risk screening tool while simultaneously exploring the core mechanisms underlying suicide risk. From 2020 to 2024, 20,585 participants were included in the study for the preliminary development of the suicide screening tool and the exploration of its underlying mechanisms. Ten machine learning algorithms were compared to identify core items, and receiver operating characteristic curve (ROC), decision curve analysis (DCA), and structural equation modeling (SEM) were used to evaluate the predictive performance, and GLASSO network, Bayesian network and longitudinal network were used to explore potential mechanisms. To ensure the generalizability of the findings, data collected in 2025 from 9,658 participants across 11 institutions in five provinces were included for external validation of the screening tool and associated mechanisms. Elastic net regression was identified as the optimal algorithm, which selected eight core items for the construction of a brief suicide risk screening tool. Despite a 90.36% reduction in item count (75/83), the tool retained strong discriminative ability (AUC = 0.85). Depression emerged as a central predictor of suicide risk, while EPQN2 (“feeling miserable”) increased psychological vulnerability. Most suicide risk factors showed a worsening trend over the three-year follow-up period. External validation demonstrated favorable predictive performance (AUC = 0.88, 0.95). The tool is available at https://ykcnormgram.shinyapps.io/10282/.

Introduction

Suicide is among the most serious global public health challenges, claiming more than 720,000 lives annually and ranking as the third leading cause of death among individuals aged 15–29 years[1]. In China, this crisis is particularly pronounced among student populations, where the prevalence of suicide risk ranges from 15% to 19%[2,3]. Research on suicide risk assessment suggests that multiple psychological and social factors jointly determine individual vulnerability through complex interactive patterns[4,5]. Depression has consistently been identified as a major contributor to suicide risk[6], potentially increasing vulnerability by heightening sensitivity to psychological and somatic pain[7]. Personality traits represent another important factor influencing suicidal risk in adolescents[5], particularly neuroticism[8,9]. In addition, factors such as past experiences[10], life events[11,12], and social support[13] have varying degrees of influence on suicidal behavior.

Despite substantial evidence demonstrating significant associations between these factors and suicide risk, routine suicide screening continues to face considerable challenges in real-world practice[14,15]. Commonly used rapid suicide risk screening instruments still have notable limitations in terms of assessment scope, scale length, and the adequacy of psychometric validation. For example, the Columbia Suicide Severity Rating Scale, developed in 2011, provides a comprehensive assessment of

suicidal ideation and behavior with strong psychometric properties and has been widely adopted across clinical settings[16]. Its strengths include a detailed characterization of suicidal thoughts and behaviors, but it focuses primarily on current suicidal states while lacking systematic coverage of distal risk factors such as personality traits, early life experiences, and the social support systems mentioned above. The Ask Suicide-Screening Questions, developed in 2012, offer a brief 4-item instrument suitable for emergency department use with demonstrated sensitivity for detecting suicide risk[17]. While its brevity enables rapid screening, it omits critical domains, including depression severity, historical vulnerability factors, and protective elements, limiting its comprehensiveness for thorough risk assessment. Additionally, traditional suicide prediction studies based on regression analysis have faced notable limitations[18]. Even when interaction terms are included, such models often fail to capture the higher-order interaction patterns inherent in real-world psychological phenomena. This limitation hinders the exploration of the relative relationships among suicide-related factors, making it difficult to establish clear priorities for individualized suicide prevention and intervention.

In recent years, the emergence of novel analytical approaches has provided new possibilities for addressing the limitations of current suicide risk prediction methods[19,20]. Algorithms such as support vector machine (SVM)[21] and extreme gradient boosting (XGBoost)[22] have demonstrated promising performance in indirect suicide risk screening. By identifying key factors, machine learning methods offer a practical balance between comprehensiveness and efficiency, enabling further optimization of suicide screening and assessment tools. However, machine learning-based item reduction alone may remain a black box, offering limited insight into why selected items predict risk or which targets are most actionable for intervention. Network analysis provides a complementary perspective by facilitating the exploration of mechanisms underlying the relationships among psychological variables[23–25]. For example, previous studies have shown that depression is closely connected with suicide within network structures[26]. Integrating machine learning-derived item selection with network analysis can therefore support efficient screening and provide a clearer understanding of the structural pathways that may inform targeted prevention.

To better address the clinical needs of suicide risk screening, this study aimed to achieve two primary objectives using machine learning and network analysis: (1) to develop a suicide risk screening tool that achieves an optimal balance between comprehensiveness and efficiency and (2) to employ network analysis techniques to elucidate the interrelationships among suicide risk factors and identify complex interactions that traditional models fail to detect. Following the development of the suicide screening tool and the exploration of these interaction patterns, external validation was conducted across 11 institutions in five provinces in China to evaluate the generalizability of the findings in independent populations.

Methods

Study Design

To identify core items that can stably predict suicide risk and to explore the mechanisms through which suicide risk and its influencing factors operate both cross-sectionally and longitudinally, a combined cross-sectional and longitudinal design was applied. On the basis of multicentre datasets, we developed and validated a suicide risk screening tool and explored its underlying mechanisms. The data were collected over six years (2020–2025) and organized into two datasets. Dataset 1 was collected from February 2020 to June 2024 at a university in eastern China as part of the university's annual mental health survey, covering all enrolled students. On the basis of the study objectives, Dataset 1 was divided into a training cohort and a longitudinal cohort. The training cohort was used to develop and validate the suicide risk screening tool and to explore suicide-related mechanisms in cross-sectional analyses. The longitudinal cohort consisted of participants who completed follow-up assessments over three consecutive years and was used to investigate longitudinal trends in core suicide risk factors. Dataset 2 was collected in late 2025 and included participants from 11 institutions across five provinces to assess the applicability and generalizability of the suicide risk screening tool in external populations. The participant screening process and study procedure are presented in Fig. 1 and Supplementary Fig. S1. This study was approved by the Human Experimental Ethics Committee of Guangzhou Sport University (Approval No. 2024LCLL-93), the Medical Ethics Committee of Shaoxing No. 7 Hospital (Approval No. 2025-014-01), and the Ethics Committee of Jiangsu Vocational College of Medicine (Approval No. 2020002). The study was preregistered on the Open Science Framework (https://osf.io/y2xat/overview). All participants provided informed consent.

For Dataset 1, 20,585 students completed the survey. At each annual screening stage, participants were first required to complete the College Student Psychological Health Survey Questionnaire (CSPHSQ), which was used to evaluate distal multidimensional factors associated with suicide risk. Participants identified as having potential suicide risk were subsequently instructed to complete the Adolescent Suicidal Tendency Scale (ASTS), which directly assessed their current level of suicide risk. After data collection, quality control procedures were implemented. First, participants with invalid student IDs, abnormal response times (outside the 1st–99th percentile range), or abnormal ages (≤ 15 or ≥ 30 years) were excluded, resulting in 20,316 remaining participants. Subsequently, participants who demonstrated careless responses during the risk assessments or whose interval between two risk assessments was less than 180 days were excluded, yielding 18,752 participants. Finally, participants who had completed at least one valid direct suicide risk assessment were identified. A total of 4,568 participants were retained for the final analyses.

Cohorts were subsequently constructed according to the study objectives. For the cross-sectional analysis, we selected, for each participant, the record with the smallest time gap between the distal risk assessment and the corresponding direct suicide risk assessment to construct the training cohort (n = 4,568). Within this cohort, we compared ten machine learning algorithms to identify core CSPHSQ items and evaluated their structural and predictive performance using structural equation modeling (SEM), receiver operating characteristic curve (ROC) analysis, and decision curve analysis (DCA). After the core items were finalized, we applied GLASSO and Bayesian network analyses to examine associations among the core items and compared GLASSO network patterns between the high- and low-risk groups.

Furthermore, based on the training cohort, a high- and low-risk matched cohort was constructed using 1:1 matching. Participants with SuLevel > 0 were classified as high-risk, whereas the remaining participants were classified as low-risk. For the longitudinal analysis, we constructed a longitudinal cohort of participants who completed distal assessments for three consecutive years and a direct suicide risk assessment in the final year (n = 119). Longitudinal network models were used to investigate within- and between-person temporal dynamics and changes in the core items over time.

For Dataset 2, a total of 9,658 students completed the eight-item suicide risk screening tool developed in this study as well as the direct assessment of suicide risk level. On the basis of age, sex, and BMI, optimal matching was performed at a 1:1 ratio between participants who had exhibited suicide risk within the past 30 days and those without suicide risk, resulting in a matched sample of 394 participants included in the external validation dataset.

Measurement Instruments

During the tool development phase, the CSPHSQ was used to screen for potential suicide risk and to identify distal risk factors. The questionnaire consists of 83 items covering five dimensions: the GE (nonscale)[27], EPQN (Cronbach's α = 0.89)[28,29], ASLEC (α = 0.94)[30], SSRS (α = 0.80)[31,32], and BDI (α = 0.91)[33]. The Chinese version of the ASTS[34] was used as the primary instrument to measure the current SuLevel. The scale consists of 20 items (α = 0.86) assessing suicide risk. In the external validation phase, focusing on recent suicide risk allowed a more accurate evaluation of the clinical applicability and predictive performance of the developed screening tool. Therefore, this study adopted 30-day suicide risk as the dependent variable to assess suicide risk levels.

Selection of Core Items and Validation Strategy

On the basis of the training cohort, we compared ten machine learning models for predicting SuLevel and selected the optimal model for core item screening using an 8:2 split of the training and validation sets. The best-performing model was defined as the one that achieved the highest coefficient of determination (R^2). Guided by the output of this model and considering item stability, importance, and relevance, we finalized the core items to construct an efficient suicide risk screening tool, and the corresponding parameter settings are presented in Supplementary Table S2. For validation, we used SEM to test the structural relationships between the core items and SuLevel. The predictive performance of the model was evaluated under the elastic net regression with a parameter of α = 0.5[35]. ROC analysis was used to evaluate discrimination, and DCA was used to assess clinical utility. The confidence intervals for the AUC values were calculated using the DeLong method. The cutoff values, sensitivity, and specificity were determined on the basis of the Youden index. In the ROC and DCA analyses, SuLevel values ≥ 1 were coded as 1, whereas SuLevel values = 0 were coded as 0. External validation was conducted by splitting Dataset 2 into training and validation sets at an 8:2 ratio and reevaluating the selected core items using ROC analysis and DCA to examine generalizability. The ten models and their

corresponding R packages are listed in Supplementary Table S3. The scoring rules of the scale and the parameter settings are provided in Supplementary Table S4. The results are available online at https://ykcnormgram.shinyapps.io/10282.

Network Analysis

Network analysis provides an intuitive visualization of the relationships between nodes, facilitating research on suicide-related and closely associated topics[27,36,37]. GLASSO network analysis provides an intuitive visualization of the relationships between SuLevel and its influencing factors, enabling the identification of key pathways[38]. The Dice similarity coefficient was used to evaluate the consistency of GLASSO network structures between the primary validation phase and the external validation phase[39]. Bayesian network analysis further identified directional links between nodes, helping to identify factors with direct effects on SuLevel[40,41]. The hc algorithm was used to learn the Bayesian network structure, and arc weights were estimated using 50,000 bootstrap resamples. Samples with SuLevel = 0 were classified as low risk, while all remaining samples were classified as high risk, with each group comprising 50% of the total sample. Additionally, the high- and low-risk matched cohort (n = 3,714) was derived from the training cohort to compare network structures. The same GLASSO and Bayesian network procedures were replicated in the external validation training and validation sets to assess the robustness and generalizability of the identified influence mechanisms.

Dynamic Analysis of Core Items

Longitudinal network analysis can help identify how suicide risk factors in a given year influence those in the subsequent year. In this study, this technique was implemented using the graphical vector autoregression model to examine the temporal relationships among eight core items across longitudinal time points[42,43]. Furthermore, sequential paired comparisons were conducted to evaluate differences in the core items across three time points.

Statistical Methods

R (version 4.4.2) was used for data processing and analysis. Network stability was assessed using the CS coefficient, with a value ≥ 0.5 considered stable[44]. Informed by previous psychological network studies, the threshold for the GLASSO network in this study was set at 0.1[45]. Because longitudinal analyses tend to yield an excessive number of pathways, higher thresholds were applied to identify core pathways. Specifically, the thresholds were set to 0.15 for the temporal and contemporaneous networks and 0.4 for the between network. The significance level for pairwise comparisons was set at $p < 0.05$.

Results

Study Participant Characteristics

Data for Dataset 1 and Dataset 2 were collected in two phases. Dataset 1 was divided into a training cohort (further subdivided into high-risk and low-risk groups) and a longitudinal cohort. Dataset 2 was used to construct an external validation cohort. The training cohort consisted of 4,568 participants, with 30.0% male participants and a mean age of 19.6 years (SD = 1.1). The longitudinal cohort comprised 119 participants, with 32.8% male participants and a mean age of 20.3 years (SD = 1.2). The external validation cohort based on Dataset 2 consisted of 394 participants, with 29.8% male participants and a mean age of 15.6 years (SD = 2.4). Detailed information on the relevant variables and demographic characteristics of Dataset 1 is presented in Table 1, and the demographic characteristics of Dataset 2 are shown in Supplementary Table S5.

Table 1
Descriptive statistics for Dataset 1.

Characteristics	Cross-sectional design			Longitudinal design
	Training cohort	High-risk	Low-risk	Longitudinal cohort
Sample	4568	1857	1857	119
Age				
Mean (SD)	19.6 (1.1)	19.7 (1.3)	19.3 (0.9)	20.3 (1.2)
Median [Max, Min]	19.2 [16.3,29.4]	19.4 [16.6,29.4]	19.1 [16.3,26.8]	20.3 [17.5,24.6]
Gender				
Female	3196 (70.0%)	1273 (68.6%)	1279 (68.9%)	80 (67.2%)
Male	1372 (30.0%)	584 (31.4%)	578 (31.1%)	39 (32.8%)
Suicide level				
Mean (SD)	0.6 (0.8)	1.5 (0.7)	0 (0)	0.9 (0.8)
Median [Max, Min]	0 [0,4]	1 [1,4]	0 [0,0]	1 [0,3]
GE				
Mean (SD)	1.2 (2.1)	1.8 (2.6)	0.8 (1.6)	1.3 (2.0)
Median [Max, Min]	0 [0,15]	1 [0,15]	0 [0,11]	1 [0,15]
EPQN				
Mean (SD)	6.0 (3.9)	8.2 (3.4)	4.7 (3.6)	7.4 (3.4)
Median [Max, Min]	6 [0,12]	9 [0,12]	4 [0,12]	8 [0,12]
ASLEC				
Mean (SD)	24.5 (16.3)	31.4 (15.8)	21.2 (15.3)	29.4 (15.9)
Median [Max, Min]	22 [0,82]	32 [0,82]	18 [0,69]	28 [0,69]
SSRS				
Mean (SD)	16.5 (4.2)	14.9 (4.1)	17.6 (3.8)	15.6 (3.9)
Median [Max, Min]	17 [1,27]	15 [1,27]	18 [4,27]	16 [1,25]
BDI				
Mean (SD)	12.0 (9.4)	18.1 (8.8)	8.6 (7.6)	15.2 (8.2)
Median [Max, Min]	12 [0,59]	18 [0,59]	7 [0,44]	16 [0,44]

Core Item Selection Results

To develop an efficient suicide screening tool, machine learning algorithms were used to identify core items. We compared the predictive performance of ten machine learning algorithms for predicting SuLevel (suicide risk level), and the results showed that elastic net regression achieved the best performance (R^2 = 45.9%), as illustrated in Fig. 2a and Supplementary Table S3. This approach reduced the total number of items by 90.36%, resulting in the identification of eight core items: GE12 (GE, growth experience; history of mental disorders), GE14 (past suicidal ideation), EPQN2 (EPQN, neurotic personality traits; feeling miserable), ASLEC6 (ASLEC, adverse life events; school aversion), SSRS8 (SSRS, social support; help-seeking behavior), BDI2 (BDI, depressive symptoms; hopelessness), BDI7 (negative self-appraisal), and BDI9 (current suicidal thoughts). The detailed content and distribution of the items are presented in Supplementary Tables S2 and S6. To verify the representativeness of the selected items, comparative analyses using LASSO and GBM showed that both models included all core items identified by the elastic net model.

The Predictive Performance and Clinical Utility of the Core Items

To evaluate the predictive performance and clinical utility of the core items, analyses were conducted on the training cohort using SEM, ROC, and DCA. As shown in Fig. 2b, the SEM results demonstrated excellent model fit: CFI = 0.952, TLI = 0.93, SRMR = 0.032, and RMSEA = 0.059, all of which met the established criteria for SEM. The predictive performance of the model was evaluated using elastic net regression. Figure 2c shows that ROC analysis demonstrated good predictive performance in the training cohort, with an AUC of 0.85 (95% CI 0.84–0.86), accuracy of 78%, sensitivity of 80%, specificity of 77%, PPV of 78%, and NPV of 79%. As shown in Fig. 2d, DCA indicated that the model achieved higher net benefits than both the “full intervention” and “no intervention” strategies across threshold probabilities of 0–0.92.

To further assess whether the core items maintained robust predictive performance for suicide risk in an external population, the external validation cohort was used for evaluation and was divided into an external training set and an external validation set at a ratio of 8:2. The results of the external validation are shown in Fig. 2e and f. ROC analysis demonstrated good predictive performance, with AUCs of 0.88 (95% CI 0.85–0.92) in the external training set and 0.95 (95% CI 0.90–1.00) in the external validation set. The accuracy, sensitivity, specificity, PPV, and NPV were 87%, 96%, 78%, 82%, and 95%, respectively, in the external training set and 90%, 87%, 92%, 92%, and 88%, respectively, in the external validation set. DCA indicated that the model achieved greater net benefits than both the “full intervention” and “no intervention” strategies across threshold probabilities of 0–0.90 in the training set and 0–0.99 in the validation set.

Network Mechanism Analysis of the Core Items

Following the development and preliminary validation of the suicide risk screening tool, GLASSO and Bayesian network analyses were conducted on the training cohort to examine the strength of the

associations and potential causal relationships between SuLevel and the core items. GLASSO network analysis (Fig. 3a) revealed that depression-related items were central, with strength values of 0.55 (BDI2), 0.91 (BDI7), and 0.66 (BDI9); the path weights were 0.16 (BDI2–SuLevel), 0.13 (BDI7–SuLevel), and 0.30 (BDI9–SuLevel). The results of centrality indices derived from the GLASSO network analysis are shown in Supplementary Fig. S2. BDI7 and BDI9 also acted as key bridging nodes, with betweenness centrality values of 20 and 24, respectively. Social support was negatively associated with suicide risk level (SSRS8–SuLevel, weight = − 0.12), whereas personality traits were positively associated (EPQN2–SuLevel, weight = 0.10). The results of the Bayesian network analysis (Fig. 3b) were consistent with the results of the GLASSO model, indicating that the depression dimension remained central in the network. BDI2, BDI7, BDI9, and the growth experience item GE14 exhibited significant causal effects on suicide risk, with effect strengths of 1. Comparative analysis between the high- and low-risk groups revealed distinct connectivity patterns between ASLEC6 and EPQN2 with depression-related items. In the high-risk network (Fig. 3c), EPQN2 showed stronger links with depression items (EPQN2–BDI7, weight = 0.12; EPQN2–BDI9, weight = 0.14). In contrast, Fig. 3d shows that the low-risk network demonstrated significant associations between ASLEC6 and BDI7/BDI9, with path weights of 0.16 and 0.10, respectively.

To examine whether the identified mechanisms influencing suicide risk were generalizable to an external population, comparable networks were constructed in the external validation cohort, as shown in Supplementary Fig. S3. The structural consistency between the GLASSO networks was high (Dice coefficient = 0.81 and 0.73), indicating strong structural similarity and supporting the generalizability of the findings.

Dynamic Analysis of the Core Items

Based on the longitudinal cohort, we further employed longitudinal network analysis and sequential paired comparisons to examine temporal trends in the core items. For longitudinal network analysis, Fig. 4a shows that the temporal network indicated strong autoregressive effects for BDI2 and BDI9 (weights = 0.17 and 0.16) and a bidirectional causal link (cross-lagged effects = 0.17 and 0.19), suggesting a self-reinforcing depressive mechanism. As shown in Fig. 4b, the contemporaneous network revealed strong interitem correlations among depression variables (BDI2–BDI7, weight = 0.27; BDI2–BDI9, weight = 0.20; BDI7–BDI9, weight = 0.18). EPQN2 functioned as a cross-dimensional bridge, indirectly linking GE12 and SSRS8 to depression-related items. As shown in Fig. 4c, the between network indicated that EPQN2 functioned as a central bridging node, with GE12, ASLEC6, and SSRS8 exhibiting direct connections to it and forming indirect associations with depression-related items through this pathway. Individual differences were reflected primarily in patterns of depressive symptom expression. As shown in Fig. 4d, sequential paired comparisons indicated significant increases in the longitudinal stability of six core items over three years ($p < 0.05$), all except SSRS8 and BDI9, suggesting a cumulative increase in suicide risk.

Discussion

This study achieved two main objectives: developing an efficient screening tool and elucidating the fundamental network architecture underlying suicide risk. Our machine learning-driven approach achieved a 90.36% reduction in item count (from 83 to 8) while maintaining robust predictive performance (AUC = 0.85). To assess whether these findings generalize beyond the development sample, we conducted external validation across 11 institutions in five provinces nationwide to evaluate the tool's ability to predict acute suicide risk within 30 days in an independent dataset. The results confirmed the generalizability of the tool and its associated findings to other populations (AUC = 0.88 in the external training set; AUC = 0.95 in the external validation set). More importantly, our network analysis revealed critical mechanistic insights that enhance our understanding of how suicide risk emerges from complex interconnected systems rather than simple additive effects of isolated risk factors.

Our elastic net regression model is consistent with previous studies, demonstrating that machine learning can improve the predictive accuracy of suicide risk compared with traditional approaches[46,47]. In validations of other suicide risk screening tools, the AUC values for the C-SSRS, SAESRS, and their combination were 0.74, 0.79, and 0.80, respectively[48]. Compared with these tools, our instrument demonstrated an improvement in the AUC of 0.05–0.11 while requiring only 1–2 minutes to complete. In addition, our eight-item tool provides an assessment of distal risk factors for suicide. Compared with obtaining such information through structured diagnostic interviews such as the M.I.N.I[49]—which typically require 7–30 minutes or longer—our approach reduces administration time by more than 60%. This improvement in efficiency is particularly important, as time constraints remain a major barrier to implementing suicide screening in emergency and primary care settings[50].

Beyond methodological innovation, our network analyses revealed critical insights into the hierarchical structure and causal mechanisms underlying suicide risk. The network analysis demonstrated that depressive symptoms are not merely risk factors but also serve as central hubs that amplify and transmit risk signals from other domains. Depression-related items (BDI2, BDI7, and BDI9) occupied the most influential positions in the network, with BDI7 and BDI9 exhibiting the highest betweenness centrality (20 and 24, respectively). These findings are consistent with prior research demonstrating the association between depression and suicide and further provide empirical support for the notion that negative self-evaluation may constitute a continuum extending beyond these extreme thoughts and behaviors[6,51,52]. Furthermore, the directional relationships revealed by Bayesian network analysis provide crucial insights into the causal sequence underlying the development of suicide risk: past experiences may create enduring vulnerabilities through current psychological states, further emphasizing the importance of incorporating past behaviors into suicide prediction models[53].

Moreover, network differences between risk groups indicated that risk escalation reflected not only greater symptom intensity but also changes in connectivity. Compared with the low-risk group, the high-risk group exhibited more associative pathways between neuroticism and depressive symptoms, and school aversion was more strongly linked to hopelessness. These findings challenge the traditional

assumption of symptom independence, support the network perspective of symptoms, and highlight the importance of identifying key pathways of suicide risk across different contexts to inform targeted interventions[54,55]. In the dynamic analysis, the bidirectional “hopelessness–suicidal intent” loop provided new insights into the escalation of suicide risk. The bidirectional causal relationship between BDI2 (hopelessness) and BDI9 (suicidal intent), with cross-lagged effects of 0.17 and 0.19, suggests a self-reinforcing cycle in which decreased hope leads to increased suicidal intent, which further erodes hope. The BDI2–BDI9 loop supports models of rapid escalation in suicide risk, suggesting that hope-enhancing interventions may represent key therapeutic targets. Moreover, it helps explain why early intervention for suicide risk is critically important[56]. Additionally, the results of the between-network analysis revealed a previously underappreciated mechanism: neuroticism is not merely a risk factor but also a vulnerability amplifier that modulates the transmission of risk across psychological domains[5,8]. This finding suggests that the influence of personality traits should also be taken into account in suicide intervention efforts.

In summary, the clinical and public health implications of this study are as follows: (1) An efficient eight-item suicide risk screening tool was developed that achieved a 90.36% reduction in item count while maintaining strong predictive performance across multicentre datasets (AUC = 0.85 in the training cohort; AUC = 0.88 in the external training set; AUC = 0.95 in the external validation set). The tool can be completed in 1–2 minutes and integrates five distal risk factors, thereby addressing the limitations of traditional tools. (2) It enhances the understanding of suicide risk mechanisms: depressive symptoms play a central role in a self-reinforcing cycle, emphasizing the need for early intervention, while neuroticism amplifies vulnerability. (3) Comparisons between high- and low-risk groups support the view that symptoms are not independent entities. Targeted, multidimensional psychological intervention strategies should therefore be adopted. (4) An online version of the screening tool was developed that enables real-time calculation of suicide risk levels. In resource-limited settings, the tool can be deployed through an application to support routine suicide risk screening.

Despite its strengths, this study has several limitations. First, owing to the relatively low proportion of individuals reporting suicide risk within 30 days, only 394 of the 9,658 participants in Dataset 2 were included in the external validation cohort after data cleaning and matching. The limited sample size may lead to overfitting and constrain the generalizability of the conclusions. Second, the study relied on self-report questionnaires, which may be subject to recall bias, social desirability bias, and underreporting of risk behaviors. Third, although external validation was conducted in schools at different educational stages across multiple regions in China, participants from other cultural backgrounds were not included in the sample. In addition, the follow-up of high-risk individuals was limited primarily to the three-year period during which students were enrolled in school, which may limit the generalizability of the findings to other populations. Future research should incorporate more objective measurement approaches and more heterogeneous datasets to mitigate these biases and improve the robustness of the model.

Declarations

Ethics Statement

This study was approved by the Human Experimental Ethics Committee of Guangzhou Sport University (Approval No. 2024LCLL-93), the Medical Ethics Committee of Shaoxing No. 7 Hospital (Approval No. 2025-014-01), and the Ethics Committee of Jiangsu Vocational College of Medicine (Approval No. 2020002).

Competing Interests

The authors declare that they have no competing interests.

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Data Availability

The raw data supporting the conclusions of this article will be made available by the authors upon reasonable request, without undue reservation.

Code Availability

The code used in this study is available from the corresponding author upon reasonable request.

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Figures

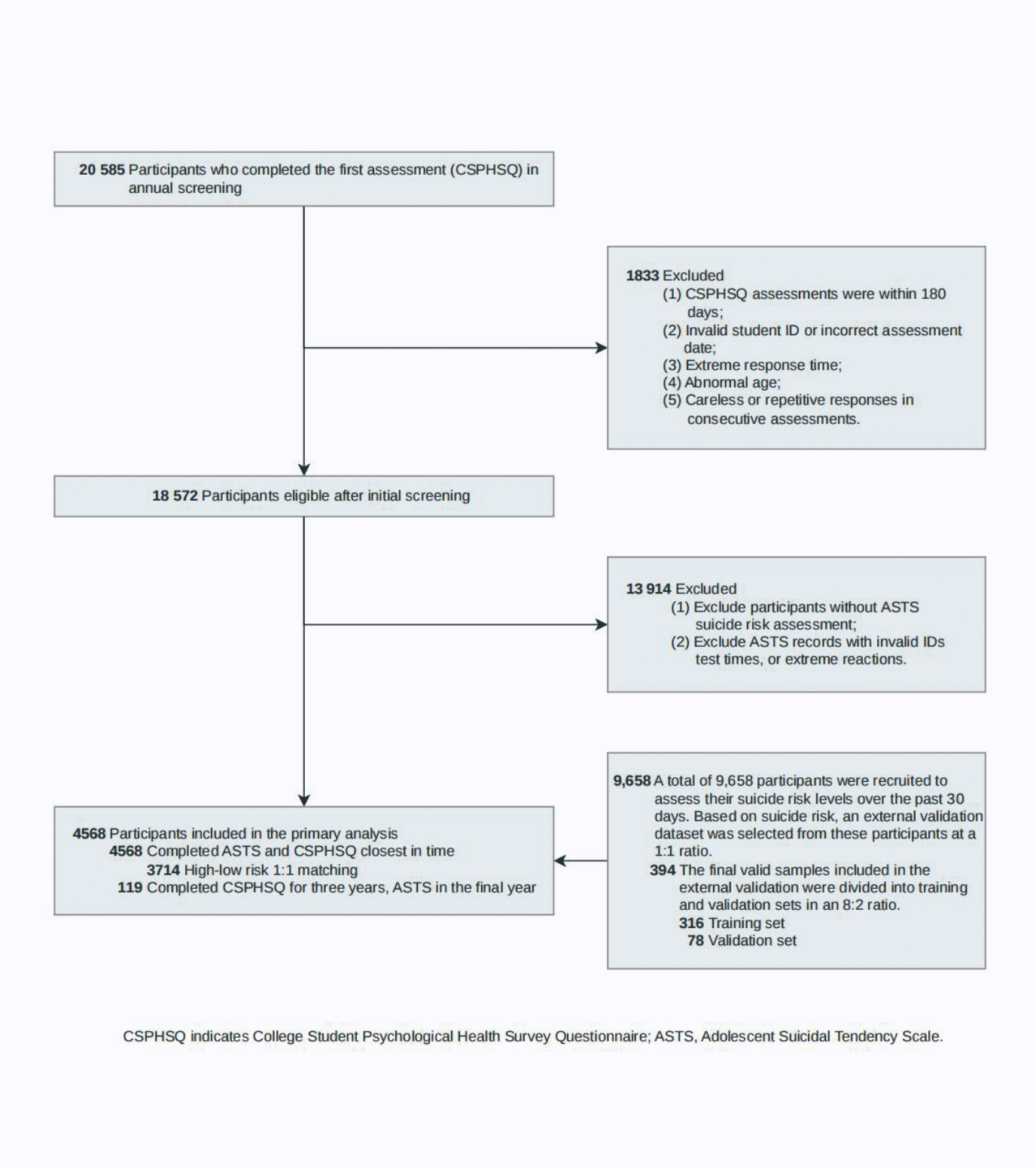


Figure 1

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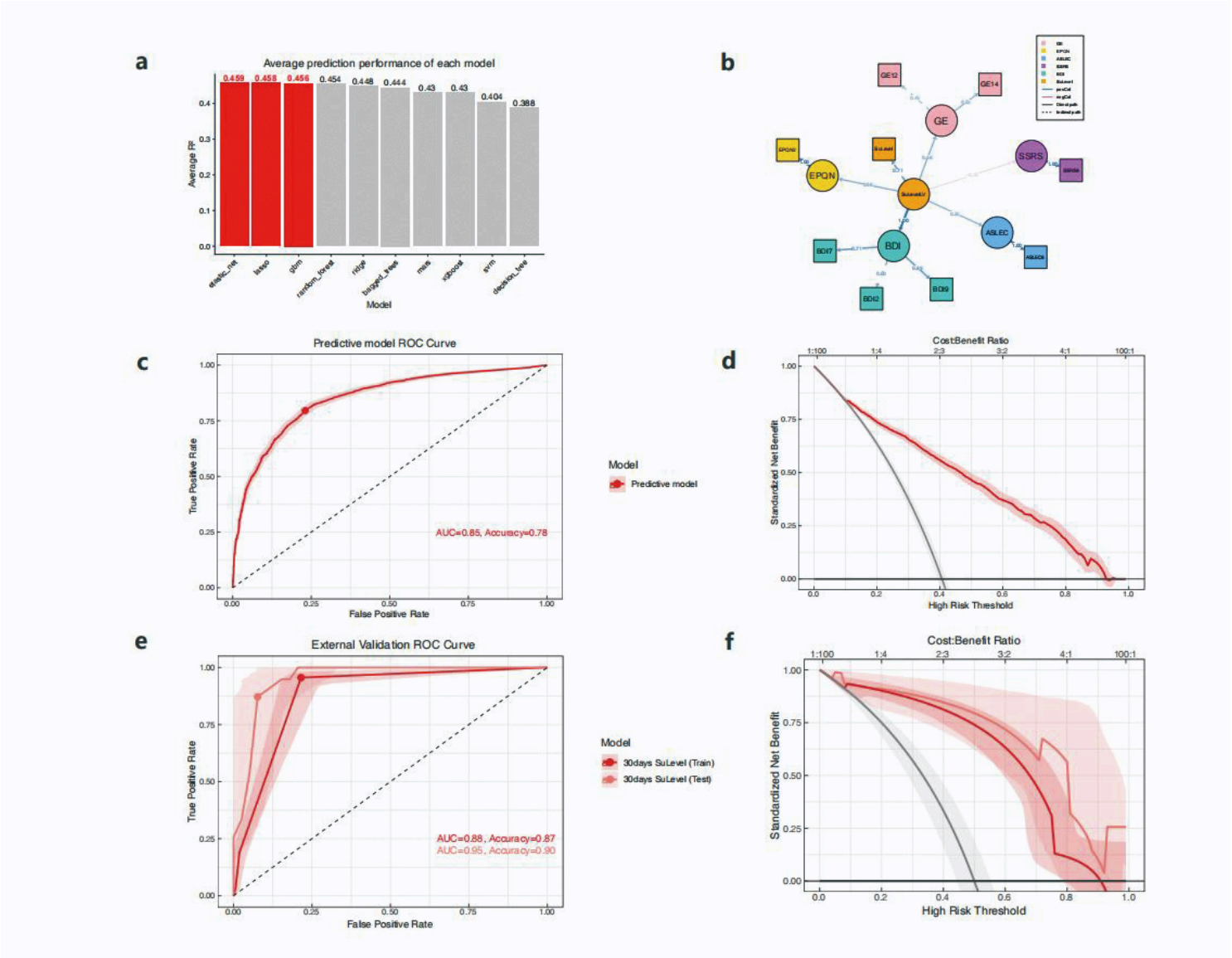


Figure 2

a). The Average prediction performance of each model. b). Core items SEM validation plot. c). Core items ROC Curve Validation Plot. d). Core items DCA Curve Validation Plot. e). Core items ROC Curve External Validation Plot. f). Core items DCA Curve External Validation Plot. In machine learning models, a higher average R^2 value indicates better performance. The nodes in the graph are the filtered core items, and circle nodes represent latent variables, and square nodes denote observed variables. The values in the diagram represent path coefficients or regression coefficients in the structural equation model. Solid lines indicate direct path, dashed lines reflect indirect path, blue lines denote positive relations, whereas red lines signal negative relations. The closer the AUC value is to 1, the better the model performance. In the DCA curve, a wider range where the model curve lies above the "None" and "All" strategies indicates better performance. GE, Growth Experience Subscale; GE12, mental illness; GE14, suicide history; EPQN, Eysenck Personality Questionnaire Neuroticism Subscale; EPQN2, unexplained misery; ASLEC, Adolescent Self-rating Life Events Checklist; ASLEC6, school aversion; SSRS, Social Support Rate; SSRS8,

help- seeking; BDI, Beck Depression Inventory; BDI2, hopelessness for the future; BDI7, self-contentment; BDI9, suicidal intents; SLV, The latent variable of suicide level; SuLevelLv, suicide level.

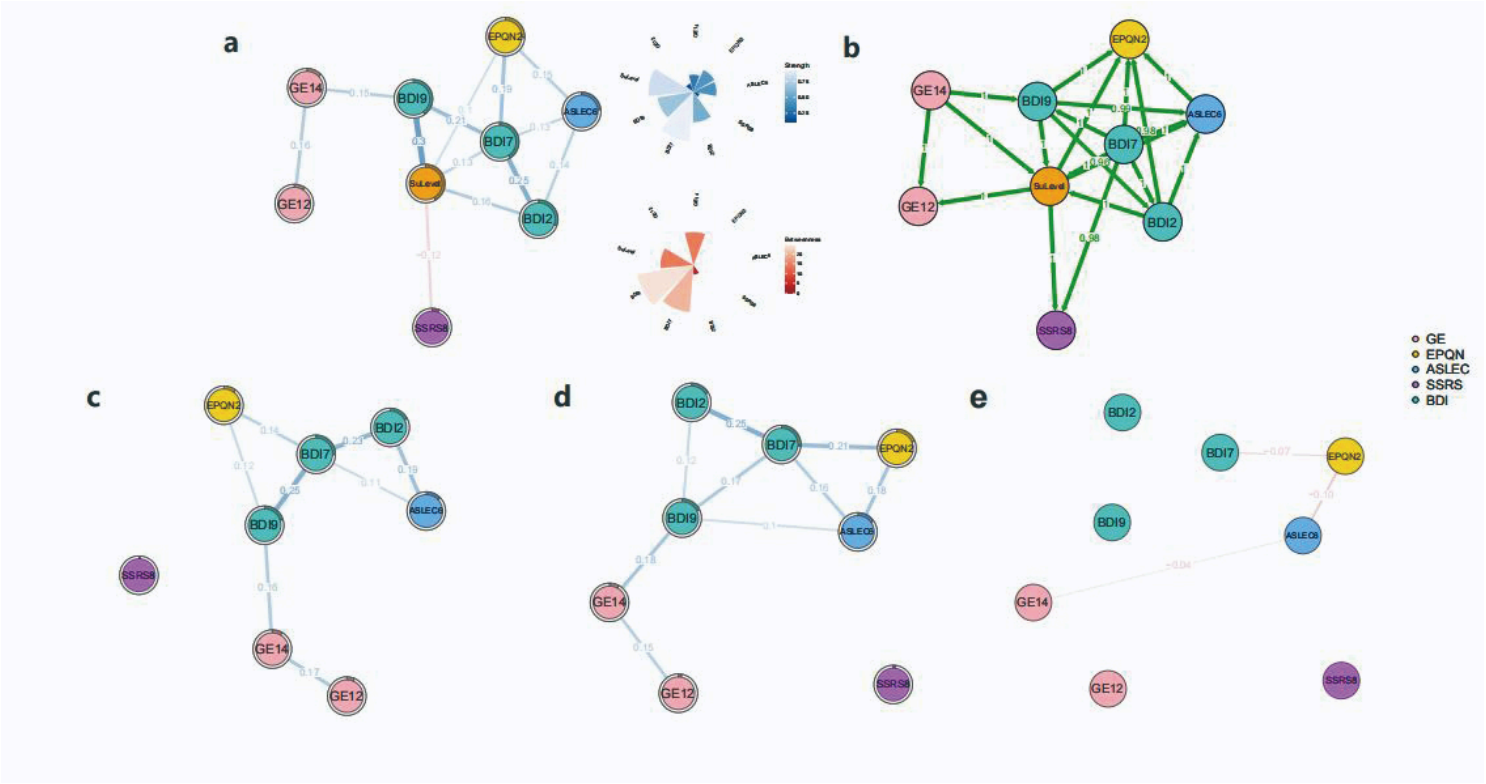


Figure 3

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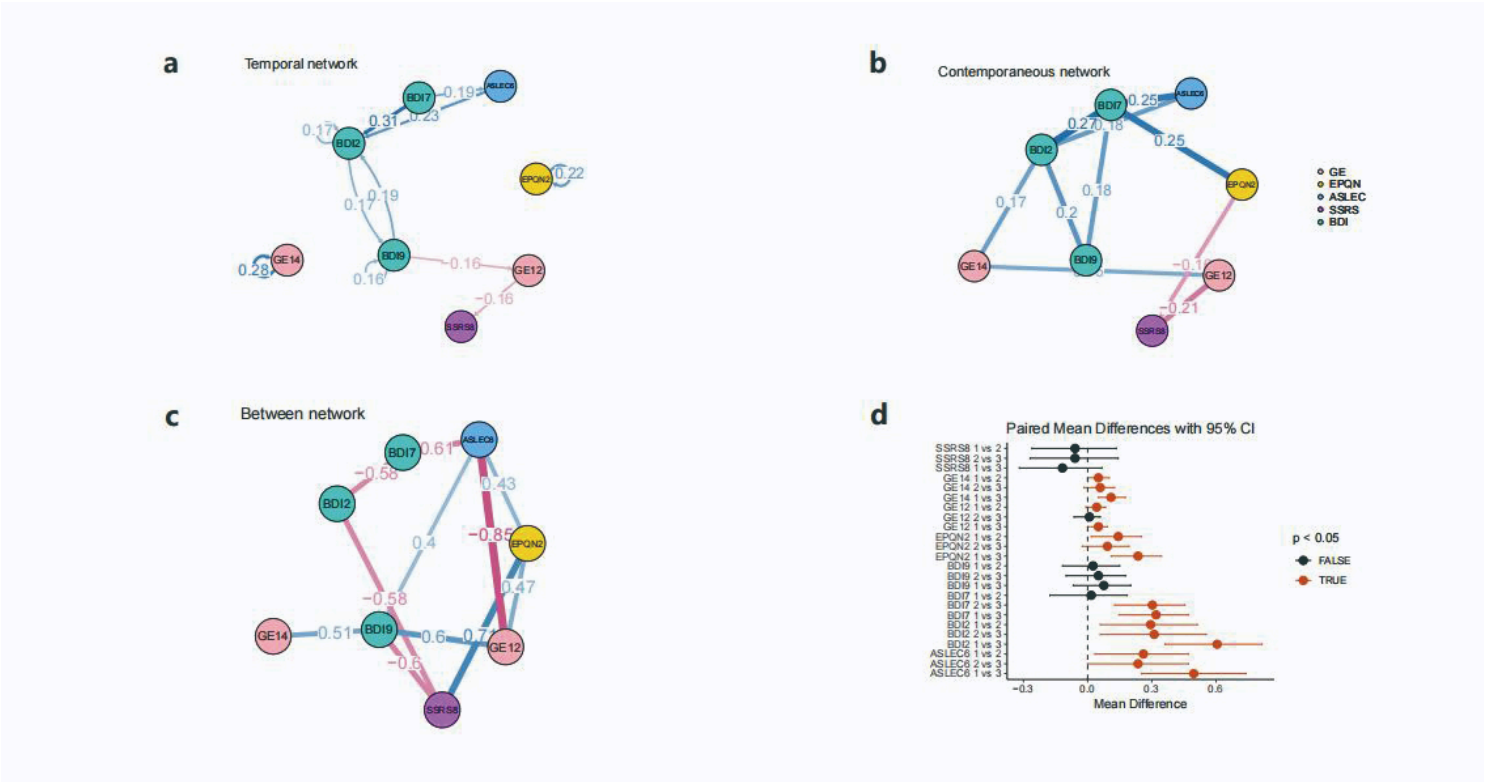


Figure 4

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