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Construction of a troublemaking risk assessment tool for patients with severe mental disorders in community of China

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Objective Construction a troublemaking risk assessment tool to predict the risk of troublemaking for patients with severe mental disorders in the community of China.
Methods 28,000 cases registered in the Jiangsu Provincial Severe Mental Disorder Management System from January 2017 to December 2019 were collected. The risk factors of troublemaking among patients with severe mental disorders in the community were analyzed through Logistic regression analysis, then the troublemaking risk assessment tool was established and verified.
Results The incidence of troublemaking among patients with severe mental disorders in the community was 7.15%. The results of multivariate logistic regression analysis showed that males, ≤ 44 years old, duration of disease ≤ 14 years, high school education and below, unemployed, subsistence allowances, schizophrenia, major symptoms > 1, psychiatric visits ≥ 1 time per year, unwilling to participate in community management and community rehabilitation activities, and delayed diagnosis < 2 months were risk factors for troublemaking. The above factors were incorporated into the nomogram model, and the area under the ROC curve of the nomogram model was 0.688 (95%CI: 0.563–0.726). The calibration curve proved that the probability predicted by the model was in good agreement with the actual probability.
Conclusion The established troublemaking risk assessment tool for patients with severe mental disorders in the community based on Logistic regression analysis had good predictive performance, which could be applied to assess the probability of troublemaking among patients with severe mental disorders in the community.

Keywords Prediction model, Troublemaking, Severe mental disorder, Community, China

Under the influence of psychiatric symptoms such as command hallucinations and delusions, individuals with mental disorders are prone to disruptive behaviors, including harming others, damaging property, arson, and suicide. This is particularly true for patients with severe mental disorders, such as schizophrenia, intellectual disability with comorbid psychiatric disorders, bipolar disorder, schizoaffective disorder, paranoid psychosis, and epilepsy-related mental disorders, which can severely disturb public order and social stability[1,2]. In China, there are approximately 16 million individuals with severe mental disorders, with about 10% of them exhibiting disruptive behaviors[3]. By the end of 2018, the registered number of patients with severe mental disorders was 5,994,054, with a detection rate of 4.3% (5,994,054/1,379,837,956)[4]. Clearly, the number of diagnosed and managed severe mental disorder patients is significantly lower than the likely true number, posing an unpredictable risk of violent incidents to society. Recent studies on violent incidents involving patients with severe mental disorders in China reveal significant regional differences in the incidence rates, such as 3.9% in Shenzhen[5], 11.93% in Shaoxing[6], and 24.9% in Chengdu[7]. According to the authors' previous research, the local incidence rate of violent incidents is 7.18%[16]. These variations may be due to differences in sample selection and community registration management policies across studies.

Patients with severe mental disorders, due to the instability of their condition and poor emotional and behavioral control, more frequently engage in suicidal behaviour or major criminal activities such as harming others or damaging property. Their violent behaviors are often characterized by concealment, severity, and recurrence, leading to substantial losses. These actions not only pose a serious threat to public safety but also place a heavy psychological and financial burden on their caregivers[8]. A recent domestic meta-analysis found

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that factors such as unemployment, inconsistent medication adherence, male gender, low education level, schizophrenia, being unmarried, and family history are risk factors for high-risk behaviors in patients with severe mental disorders[9]. International studies have also identified gender and age of onset as related to the risk of violence[10].

In many Western countries, structured assessment tools such as the Violence Risk Screening (V-RISK-1)[11]; Brøset Violence Checklist (BVC)[12]; Psychopathy Checklist-Revised (PCL-R)[13]; Historical, Clinical, Risk Management-20 (HCR-20)[14]; and Level of Service Inventory-Revised (LSI-R)[15], are widely used for violence risk assessment in forensic and general psychiatric settings. Although these tools are commonly used in clinical practice, their purposes, benefits, limitations, and abilities to predict future violence vary.

We found that machine learning methods for predicting violent risk behaviors in patients with schizophrenia are considered to have good accuracy and stability. In a systematic review of machine learning systems for risk assessment in schizophrenia patients[16], it was observed that most models predicting violent risk used patients' socio-demographic and clinical characteristics. Some studies found that factors such as age[16–18], gender, and educational attainment[19,20] are helpful in predicting violence risk. However, other studies reported that these demographic factors do not significantly correlate with the occurrence of violent behavior[21].

Other research has linked the accumulation and types of stressors in patients' histories[22], different psychiatric prescriptions[23,24], and scores from various tools such as the Brief Psychiatric Rating Scale (BPRS)[19], the Positive and Negative Syndrome Scale (PANSS)[19], the Insight and Treatment Attitudes Questionnaire (ITAQ)[19], the Family APGAR[19], the Social Support Rating Scale (SSRS)[19], the Family Burden Scale of Disease (FBS)[19], and the Social Disability Screening Schedule (SDSS)[20] as factors associated with violence risk. Additionally, some studies have incorporated neurological imaging data[19,21], biochemical markers[25,26], and fMRI or COMT gene data[27] to predict violence risk.

Moreover, several studies reported a positive correlation between the daily olanzapine equivalent dosage during previous hospitalizations and violence risk in schizophrenia patients[28]. Emergency factors such as a history of compulsory psychiatric treatment or separation from primary caregivers during childhood or adolescence were also found to be associated with violence risk[29]. The reliability of models in current research is typically expressed through the AUROC and Accuracy values, representing the reliability and validity of predictive models. The range of AUROC values reported in most studies is between 0.56 and 0.95, while Accuracy values range from 0.54 to 0.91, indicating considerable variability in model performance[15].

Currently, domestic research is also limited to violence risk assessment in patients with schizophrenia. For example, Jiang Yizhou et al.[30] used logistic regression analysis to create risk prediction models for violent behavior among community-dwelling schizophrenia patients of different genders. The study found that different risk factors should be considered to prevent violence risk in male and female community-dwelling schizophrenia patients, with strong predictive ability (AUC Male = 0.779; AUC Female = 0.822). Another study[31], also using the same method, developed a comprehensive risk prediction model for violent behavior in community-dwelling schizophrenia patients. The AUC for the modeling cohort was 0.78 (CI: 0.74–0.81), which provides a certain reference value. Both studies were focused on schizophrenia patients. Another study[32] targeted hospitalized schizophrenia patients and constructed a predictive model for impulsive behavior risk using the same method. The AUC was 0.769, but the sensitivity was relatively low at 0.59. Additionally, some domestically developed models for assessing the risk of mental illness showed predictive validity mostly ranging from poor to moderate levels[33].

Although many violence risk assessment tools abroad can be used to help predict the risk of violence, their applicability to the economic and cultural context of China remains a topic for discussion. Currently, reports on the prediction of violent behavior in community-dwelling individuals with severe mental disorders in China are still relatively scarce. Some studies have preliminarily developed a risk assessment tool for violent behavior in this population[34]. This research ultimately formulated a Severe Mental Disorders Violence Risk Assessment Scale, consisting of five dimensions and 19 items, with good reliability and validity. In addition to basic information, the scale also includes family information, economic status, disease type, history of violent behavior, and treatment status, providing a foundation for our research. However, we must also acknowledge that certain biological factors influencing violent behavior in psychiatric patients, such as genetic factors, remain difficult to measure. Nonetheless, our research findings indicate that environmental factors and patients' socio-demographic characteristics provide a certain degree of predictability for violent incidents.

Although monitoring, assessing, predicting, preventing, and controlling violent behaviors in patients with severe mental disorders has become an important part of mental health services[35], few studies focus on the risk factors for disruptive behaviors, such as diagnostic and treatment information, social support, and symptoms[36,37]. This study aims to develop a risk assessment tool for disruptive behaviors among patients with severe mental disorders based on the cultural context. This tool is intended to provide community workers with an effective means of early identification of the risk of disruptive behaviors in patients with severe mental disorders in Chinese communities.

Materials and methods
Objects
A total of 28 000 patients with severe mental disorders (schizophrenia, mental retardation with mental disorders, bipolar disorder, schizoaffective disorder, Paranoid psychosis, mental disorder caused by epilepsy)[38] registered in the Jiangsu Provincial Severe Mental Disorder Management System from January 2017 to December 2019 were selected as the research objects. Inclusion criteria: (1) ≥ 14 years old; (2) Have a clear diagnosis of mental illness and a reporting unit. Patients with missing basic information and those who moved out of the management system were excluded.

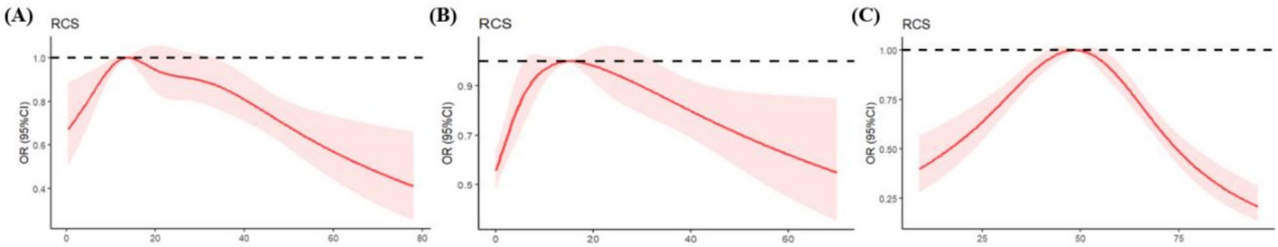

Fig. 1. RCS analysis of course of disease (A), duration of medication (B) and age (C).

Variable	Assignment
Troublemaking	0 = no, 1 = yes
Age	0 = 45–59, 1 = ≤ 44, 2 = ≥ 60
Gender	0 = female, 1 = male
Educational level	0 = college and above, 1 = high school and below
Occupation	0 = on duty of retired, 1 = unemployed
Basic living allowances	0 = no, 1 = yes
Schizophrenia	0 = no, 1 = yes
Disease duration (years)	0 = 15–27, 1 = ≤ 14, 2 = ≥ 28
Medication duration (years)	0 = 6–18, 1 = ≤ 6, 2 = ≥ 19
No of previous major symptoms	0 = 0–1, 1 = > 1
No. of psychiatric visits/year	0 = 0, 1 = ≥ 1
Agree to community management	0 = yes, 1 = no
Disability certificate	0 = no, 1 = yes
Participate in community rehabilitation activities	0 = yes, 1 = no
Delayed time (months)	0 = > 12,1 = < 2, 2 = 2–12

Table 1. Variable assignment for multivariate logistic regression analysis.

The basic information, diagnosis and treatment information, social support and accident information of the research subjects were collected. Basic information included gender, age, education level, occupation, marital status, and economic status, etc.; medical information includd diagnosis and classification, course of disease, and duration of medication; social support included subsistence allowances, disability certificates, and participation community management of basic public health projects, community rehabilitation services, etc.; troublemaking behaviors were confirmed by the Municipal Public Security Bureau. Poverty is defined as a household per capita monthly income lower than twice the minimum subsistence income standard in Wuxi.

Construction of the nomogram model

Variables with $P < 0.05$ in the univariate analysis were included in the multivariate Logistic regression analysis. For continuous variables (age, course of disease, duration of medication, and delayed months), we used restricted cube plots to explore their association with accidents. It was found that the first three exhibited a nonlinear relationship (Fig. 1). Since delayed months appeared to be linear, we recoded the variables, and age, medication, disease duration and delayed months were all reclassified according to their respective P33 and P67. The codes of the variables were shown in Table 1. The risk factors obtained from the Logistic regression analysis were subjected to construct a nomogram of the incidence of troublemaking among patients with severe mental disorders in the community. In the model, β represents the regression coefficients of each risk factor in the logistic regression analysis. The constant term α is the natural logarithm of the ratio between the incidence rate of violent behavior and the non-incidence rate during the study period, calculated using the formula: α=ln[P/(l—P)]. The logistic function for predicting violent behavior among patients with severe mental disorders in the community is expressed as $\mathrm{logit}(P)\alpha\beta\beta_1\times_1\beta_2\times_2\beta_3\times_3\ldots\ldots\beta_n X_n$ where X_n represents the nth risk factor, and β_n represents the regression coefficient for the nth risk factor. Based on the scores assigned to each risk factor, the score range is calculated. The probability of violent behavior is then computed using the formula $P = e^{\mathrm{logit}(P)}/(1 + e^{\mathrm{logit}(P)})$, and a corresponding table is created that maps the score to the predicted risk probability.

Statistical analysis

The measurement data were expressed by x ± s, and the t test was used for comparison between two groups; the enumeration data were expressed by rate or composition ratio, and the χ2 test was used for comparison between groups. Multivariate logistic regression was used to analyze the influencing factors of troublemaking. R 4.30 software was used to draw restricted cube plots, nomograms, calibration curves, ROC curves, and related data analysis. The test level α=0.05. We validated the model using data from 2,680 newly identified severe mental illness patients from 2022 to 2023. The reliability and effectiveness of the model were assessed through the area under the ROC curve (AUC) and its 95% confidence interval, accuracy, sensitivity, and specificity.3 Results.

Univariate analysis of troublemaking among patients

Excluding 47 cases of severe incomplete information and data duplication, a total of 27 953 people were included in this study, including 13 188 males (47.18%) and 14 765 females (52.82%), aged (51.0 ± 15.7) years old, and disease duration (22.85 ± 14.58) years, and the duration of medication was (14.97 ± 13.42) years. The average troublemaking rate of patients with severe mental disorders in the community was 7.15% (1998/27 953). There were significant differences between gender, age, education level, occupation, marital status, economic status, subsistence allowances, diagnosis classification, duration of disease (years), duration of medication (years), whether to participate in community management, disability certificate, the number of major mental symptoms, the number of psychiatric visits per year, and whether to participate in community rehabilitation activities ($P < 0.05$), see Table 2.

Multivariate logistic regression analysis of troublemaking among patients

Statistically significant variables and delayed time (month) in the univariate analysis results were included in the multivariate logistic regression analysis model. After screened by the stepwise method, the three variables of medication duration, economy, and marriage were excluded. The results showed that, male, ≥ 60 years old, disease duration ≤ 14 years, high school education and below, unemployed, subsistence allowances, schizophrenia, major symptoms > 1, psychiatric visits ≥ 1 time/year, unwilling to participate in community management and community rehabilitation activities, and delayed diagnosis < 2 months were risk factors for troublemaking, and the differences were statistically significant ($P < 0.05$). See Table 3.

Construction and performance of nomogram prediction model

On the basis of Logistic regression analysis, age, gender, course of disease, education level, occupation, subsistence allowances, diagnostic classification, duration of medication, number of previous main symptoms, number of psychiatric visits per year, whether to participate in community management, whether to have disability certificate, whether to participate in community rehabilitation services were included in the nomogram analysis. The value of each of variable was given a score on the point scale axis. A total score could be easily calculated by adding each single score and, by projecting the total score to the lower total point scale, we were able to estimate the probability of the risk of accidents and disasters. See Fig. 2. Then, the ROC curve was applied to evaluate the discriminative ability of the nomogram model. The area under the ROC curve of the nomogram model was 0.688 (95% CI: 0.563 ~ 0.726), and the predictive performance was at a medium to high level (Fig. 3A). The calibration curve of the nomogram showed that the troublemaking probability predicted by the nomogram was in good agreement with the actual probability (Fig. 3B).

Establishment of the troublemaking risk assessment tool

Transform according to the regression coefficient β of each factor in the model, so as to assign scores to each risk factor, gender (male = 64 points, female = 0 points), age (≤ 44 = 27 points, 45–59 = 50 points, > 60 = 0 points), duration of disease (≤ 14 years = 25 points, 15–27 years = 5, ≥ 28 years = 0 points), education level (high school and below = 56 points, college and above = 0 points), occupation status (on duty or retired = 0 points, unemployed = 43 points), subsistence allowances (yes = 44 points, no = 0 points), diagnostic classification (schizophrenia = 24 points, non-schizophrenia = 0 points), number of main symptoms (0–1 = 0 points, > 1 = 100 points), the number of psychiatric visits per year (0 = 0 points, ≥ 1 = 99 points), community management services (participation = 0 points, non-participation = 73 points), disability certificate (no = 0 points, yes = 12 points), delayed diagnosis (< 2 months = 0 points, 2–12 months = 20 points, > 12 months = 33 points), community rehabilitation activities (participation = 0 points, not participating = 83 points). See Table 4. The correspondence table between assessment score and risk prediction probability was shown in Table 5.

Model validation

The results showed that the area under the ROC curve (AUC) was 0.708 (95% CI: 0.583–0.749), with an accuracy of 79.43%, sensitivity of 76.74%, and specificity of 83.57%. The constructed model demonstrated good reliability and effectiveness in predicting violence risk.

Discussion

Troublemaking behaviors of patients with severe mental disorders are often destructive and sudden[39], seriously threatening public safety. However, neither psychiatry, mental hygiene, nor sociology can make accurate predictions and interventions alone. The prediction and intervention of troublemaking behaviors of patients with severe mental disorders is not a problem that can be solved by a single discipline, but requires the joint participation of multiple disciplines[40,41]. Therefore, it is urgent to construct a troublemaking risk prediction model suitable for patients with severe mental disorders in the community, so as to provide risk assessment tool for community workers to solve the difficulties in risk assessment.

Currently, structured assessment tools are commonly used for violence risk assessment in forensic and inpatient psychiatric patients[42,43]. Although these tools are widely utilized in clinical practice, their purposes, benefits, limitations, and abilities to predict future violence vary. Applying these scales to the routine follow-up management of community-dwelling patients with severe mental illnesses is less appropriate. Furthermore, these Western-developed scales yield different results across racial and ethnic groups. For example, certain items on the HCR-20 scale are interpreted differently by different populations, leading to significant variation in scores[42].

Factors	No. of non-troublemaking (%)	No. of troublemaking (%)	*P*
Gender			< 0.001
Male	12,000(46.2)	1188(59.5)	
Female	13,955 (53.8)	810 (40.5)	
Age			< 0.001
≤44	8921 (34.4)	696 (34.8)	
45–59	8154 (31.4)	762 (38.1)	
≥60	8880 (34.2)	540 (27.0)	
Education level			0.006
High school and below	24,056 (92.7)	1885 (94.3)	
College and above	1899(7.3)	113(5.7)	
Occupation			< 0.001
Unemployed	8163(31.5)	850(42.5)	
On duty or retired	17,792 (68.5)	1148 (57.5)	
Marital status			< 0.001
Unmarried	8496 (32.7)	734 (36.7)	
Married	14,430 (55.6)	978 (48.9)	
Widowed	990 (3.8)	64 (3.2)	
Divorce	1706 (6.6)	209 (10.5)	
Unknown	333 (1.3)	13 (0.7)	
Poverty			< 0.001
Yes	6150(23.7)	636(31.8)	
No	19,805 (76.3)	1362 (68.2)	
Basic living allowances			< 0.001
Yes	4355 (16.8)	501 (25.1)	
No	21,600(83.2)	1497(74.9)	
Schizophrenia			< 0.001
No	12,035(46.4)	691(34.6)	
Yes	13,920 (53.6)	1307 (65.4)	
Disease duration (years)			0.005
≤14	8544 (32.9)	667 (33.4)	
15–27	8779 (33.8)	732 (36.6)	
≥28	8632 (33.3)	599 (30.0)	
Medication duration (years)			< 0.001
≤6	9000 (34.7)	557 (27.9)	
6–18	8017 (30.9)	717 (35.9)	
≥19	8938 (34.4)	724 (36.2)	
Agree to community management			< 0.001
Yes	23,816 (91.8)	1768 (88.5)	
No	2139(8.2)	230(11.5)	
Disability certificate			< 0.001
No	14,354(55.3)	997(49.9)	
Yes	11,601 (44.7)	1001 (50.1)	
No. of previous major symptoms			< 0.001
≤ 1	2342 (9.0)	435 (21.8)	
> 1	23,613(91.0)	1563(78.2)	
No. of psychiatric visits/year			< 0.001
≥ 1	13,258 (51.1)	1426 (71.4)	
0	12,697(48.9)	572(28.6)	
Delayed time (months)			0.112
<2	8660 (33.4)	621 (31.1)	
2–12	8381 (32.3)	669 (33.5)	
>12	8914 (34.3)	708 (35.4)	
Participate in community rehabilitation activities			< 0.001
No	24,871(95.8)	1945(98.3)	
Yes	1084 (4.2)	53 (1.7)	

Table 2. Univariate analysis of troublemaking among patients.

Coefficients	Estimate	SE	OR(95%CI)	Z	*P*
intercept	-2.296	0.159		-14.402	< 0.001
Age ≤ 44	-0.172	0.060	0.842(0.751 ~ 0.944)	-2.876	0.004
Age ≥ 60	-0.381	0.060	0.683(0.604 ~ 0.772)	-6.091	< 0.001
Male	-0.491	0.049	0.612(0.556 ~ 0.673)	-10.122	< 0.001
Disease duration ≤ 14 years	0.151	0.059	1.163(1.036 ~ 1.306)	2.083	0.037
Disease duration ≥ 28 years	-0.038	0.062	0.963(0.853 ~ 1.088)	-1.027	0.305
High school and below	0.430	0.104	1.204(1.038 ~ 1.356)	4.059	< 0.001
Unemployed	0.329	0.050	1.389(1.261 ~ 1.531)	-6.750	< 0.001
Have basic living allowances	0.334	0.058	1.397(1.246 ~ 1.563)	5.750	< 0.001
Schizophrenia	0.187	0.054	1.206(1.084 ~ 1.342)	3.363	< 0.001
No. of previous major symptoms > 1	0.764	0.061	1.654(1.348 ~ 1.953)	12.587	< 0.001
No. of psychiatric visits/year ≥ 1	0.755	0.057	2.127(1.905 ~ 2.378)	13.321	< 0.001
Agree to community management	0.577	0.113	1.781(1.437 ~ 2.236)	5.101	< 0.001
Have disability certificate	0.090	0.050	1.094(0.992 ~ 1.207)	1.767	0.077
Participate in community rehabilitation activities	0.632	0.093	1.880(1.563 ~ 2.248)	6.856	< 0.001
Delayed diagnosis < 2 months	-0.250	0.059	0.779(0.697 ~ 0.870)	-4.216	< 0.001
Delayed diagnosis 2–12 months	-0.097	0.061	0.907(0.804 ~ 1.022)	-1.596	0.111

Table 3. Multivariate logistic regression analysis of factors related to troublemaking.

In some cultures, verbal conflicts may be seen as a normal form of emotional expression, while in others, they may be perceived as indicators of violent tendencies. Such cultural differences may not be adequately accounted for, resulting in biased assessment outcomes. Additionally, these single scales are relatively limited, as they fail to include biological indicators. Research using machine learning methods to predict violent behaviors in schizophrenia patients has incorporated factors such as neurobiology and genomics[27,44,45], representing further exploration in violence risk prediction. However, the factors influencing violence risk in psychiatric patients are multifaceted, varying according to different societal models and economic influences. The expression of symptoms, including violent behaviors, differs across countries due to variations in mental health services, social assistance policies, and the level of community acceptance and understanding, which also influence policy changes[46].

Domestic scholars are working to develop prediction models tailored to local conditions. In addition, the large number of community-dwelling patients with severe mental disorders in China, combined with relatively scarce community mental health resources[47], highlights the need for practical tools that are simple and easy to use. Incorporating imaging and biological factors is not only financially prohibitive but also poses challenges in terms of time, labor, and patient cooperation. Currently, most risk prediction efforts focus on schizophrenia patients at high risk of violence, which does not apply to the six categories of mental illnesses covered under the National Basic Public Health Service Standards. The goal is to develop a predictive model for severe mental disorders suitable for community management and services. Clearly, existing domestic models are not fully applicable to community settings. Our research focuses on demographic and social environment factors, diagnostic and treatment information, social support, and symptom data[48]. These data are either pre-existing in patient records or can be obtained through simple surveys. Community mental health workers can access this information during their routine work for risk assessment, making the approach relatively feasible.

This study found that the average incidence of troublemaking among patients with severe mental disorders in Wuxi from 2017 to 2019 was 7.15%. In this study, males were more likely to troublemaking than women, which was consistent with the results of Wan et al.[49] and Miao et al.[50]. The reason was that men tend to bear more financial burdens of the family, which lead to the relapse of mental illnesses. In terms of age, compared with the 45–60 age group, patients with severe mental disorders ≤ 45 years old were more likely to troublemaking, which was consistent with the results of Jiang et al.[7]. Young and middle-aged people are more energetic and energetic, and they bear greater pressure in society and family. However, young and middle-aged people are also an important age group for the first onset of severe mental disorders, such as schizophrenia, which easily to be ignored, leading to the delayed diagnosis and troublemaking.

Compared with non-schizophrenic patients, schizophrenic patients were more likely to troublemaking, which was proved by Song et al.[51]. Patients with schizophrenia often have aggressive behaviors due to symptoms such as delusions of persecution and command auditory hallucinations, which lead more prone to impulsive injury and destructive behavior. In terms of occupation, unemployed patients were more likely to troublemaking[52], because the persistence of mental symptoms leads to loss of social function, unemployment and loss of economic resources. We also found that patients with more main symptoms in the past and more visits to psychiatrists each year were also risk factors for troublemaking. In terms of social support, patients who did not participate in community management and community rehabilitation activities were more likely to troublemaking. Patients who participate in community management and community rehabilitation activities could receive social attention, including regular follow-up visits by psychiatrists, care from neighborhood or neighborhood committees, and planned rehabilitation activities by mental rehabilitation therapists, which can

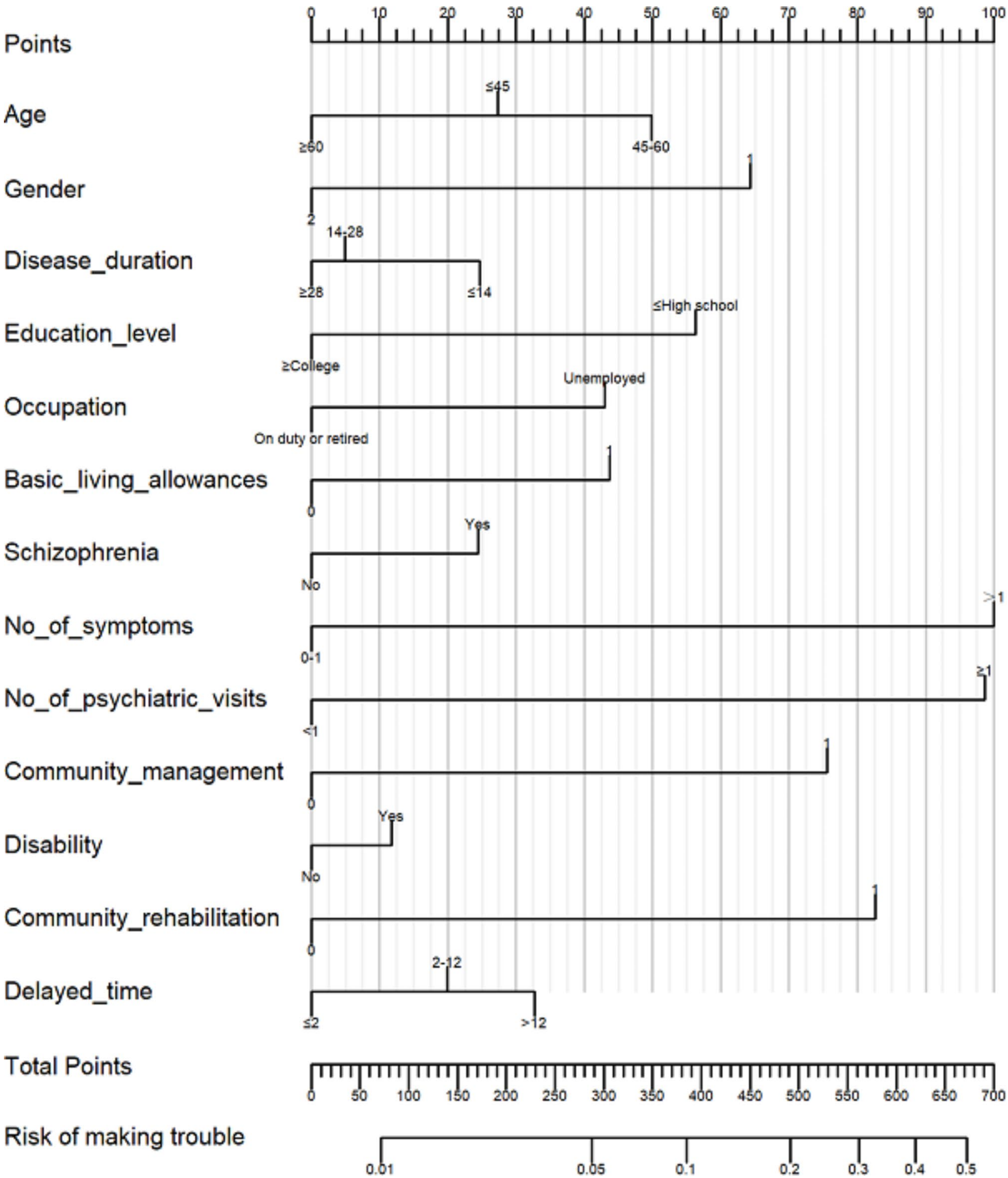

Fig. 2. A nomograph for predicting the risk of troublemaking among patients with severe mental disorders in the community.

promote the recovery of patients, improve the living ability[53], reduce the stigma[54], and reduce the burden on families. These patients receive free management services in the national basic public health service, which could effectively reduce the occurrence of troublemaking[55]. A meta-analysis of the effect of community comprehensive management interventions for patients with severe mental disorders also proved that community comprehensive management interventions can reduce the occurrence of troublemaking[56].

Patients with mental disability certificates were more likely to be at risk of troublemaking, since these patients have more serious illnesses, cognitive dysfunction, lack self-awareness and unable to take medication

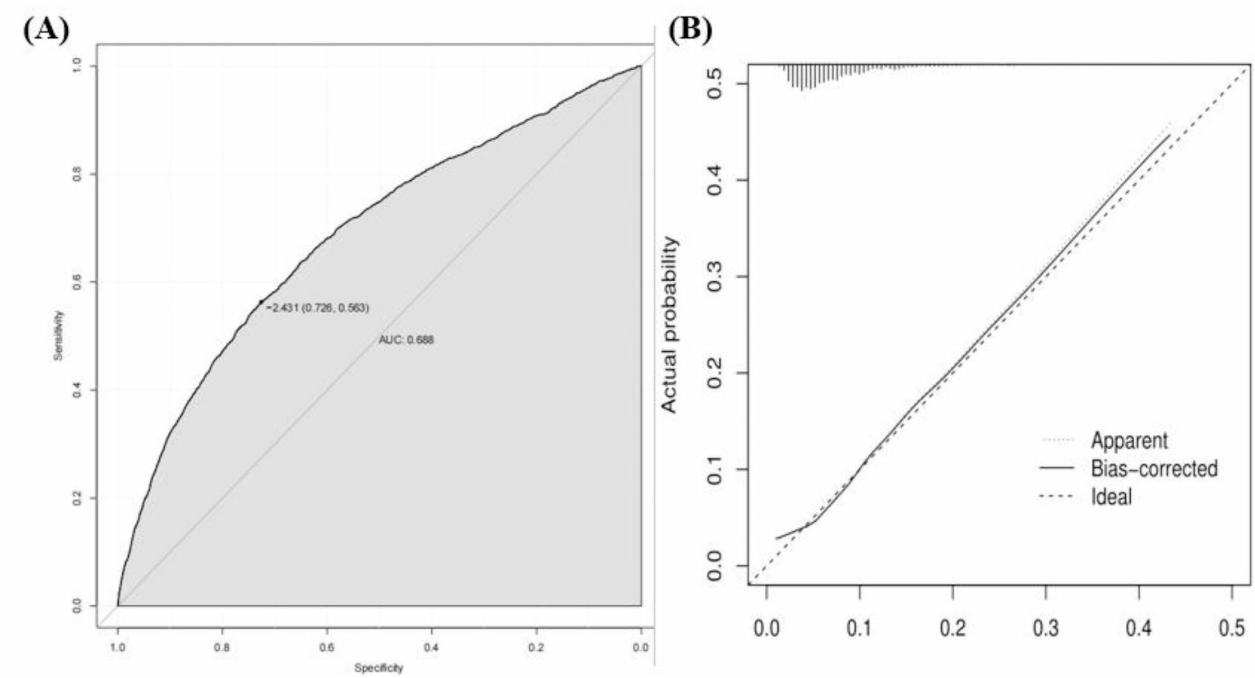

Fig. 3. Verification of the nomogram prediction model, (A) ROC curve, (B) calibration curve.

regularly (which could reduce the risk of violence)[57]. Patients with subsistence allowances were also high-risk groups of troublemaking, since they have financial difficulties, un-guaranteed family life, and unregular treatment[58]. Compared with patients with higher education, patients with high school education and below were more likely to cause accidents, because of their early onset, decline in learning ability, impairment of social work and adaptability, and more severe disease severity. Studies[59,60] also found that the rate of troublemaking decreased with the increase of education level. Shorter course of disease and delayed diagnosis were risk factors for troublemaking, which have been confirmed that patients with severe mental disorders who have just been discovered and treated for a short period of time are more likely to be involved in troublemaking because of the lack of awareness of mental illness[61].

This study also has certain deficiencies. First, the incidence of troublemaking varies greatly in different regions. Additionally, due to factors such as stigmatization, the prevalence of severe mental disorders is significantly underestimated, which also affects the reported incidence of violent behavior. Therefore, the ability of our model to predict troublemaking risks requires more research in different regions to verify its authenticity and stability. Secondly, although more than 10 influencing factors were included in our study, the grouping of each factor is still not clear or detailed. Whether the risk of troublemaking caused by different diseases can be analyzed together requires further analysis. At the same time, more attention could be paid to other risk factors not included in this study, such as the content of clinical treatment, the type and amount of medication, drug side effects, family stress events, etc.

In conclusion, a large-sample Logistic regression analysis was applied to screen out influential factors with evaluation value against troublemaking to build a risk prediction model. The evaluation content was practical and the model was stable. The area under the ROC curve of the model was 0.688(95%CI:0.563 ~ 0.726). In order to facilitate the implementation of classified management services for the prevention and treatment of mental illness in the community and the implementation of risk assessment interventions for clinical medical workers, a nomogram model of the risk of troublemaking was established, and assigned the risk factors according to the regression coefficient β of each factor in the Logistic regression model, and a score and risk prediction probability correspondence table was provided to help community workers to carry out early risk assessment, so as to implement classified intervention measures and prevent troublemaking among patients with severe mental disorders in the community.

Risk factor	Categories	Points
Gender		
	Female	0
	Male	64
Age		
	≤ 44	27
	45–59	50
	> 60	0
Disease duration		
	≤ 14	25
	15–27	5
	≥ 28	0
Education level		
	College and above	0
	High school and below	56
Occupation		
	On duty of retired	0
	Unemployed	43
Basic living allowances		
	No	0
	Yes	44
Schizophrenia		
	No	0
	Yes	24
No. of previous major symptoms		
	0–1	0
	> 1	100
No. of psychiatric visits/year		
	0	0
	≥ 1	99
Agree to community management		
	Yes	0
	No	76
Disability certificate		
	No	0
	Yes	12
Delayed time (months)		
	< 2	0
	2–12	20
	> 12	33
Participate in community rehabilitation activities		
	Yes	0
	No	83

Table 4. The assigned scores of each risk factor.

Point total	Estimate of risk
72	0.01
287	0.05
385	0.10
491	0.20
562	0.30
620	0.40
673	0.50

Table 5. Correspondence between score and risk prediction probability.

Data availability

The dataset generated during and analyzed during the current study are available from the corresponding author on reasonable request.

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Author contributions
Shiming Li and Qitao Yin conceived the study; Shiming Li, Queping Yang, Yingying Ji collected the data; Jieyun Yin and Shiming Li performed the data analysis; Shiming Li and Haohao Zhu wrote the manuscript and edited the manuscript. All authors reviewed the manuscript.

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Declarations

Ethics approval and consent to participate
This study was approved by the Ethics Committee of Wuxi Mental Health Centre. The informed consent have been waived by the Ethics Committee of Wuxi Mental Health Center. All methods were performed in accordance with relevant guidelines and regulations.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Additional information
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