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Research paper

Prevalence of depressive symptoms and associated factors during the COVID-19 pandemic: A national-based study

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ABSTRACT

Background: Previous studies have reported that the prevalence of depression and depressive symptoms was significantly higher than that before the COVID-19 pandemic. This study aimed to explore the prevalence of depressive symptoms and evaluate the importance of influencing factors through Back Propagation Neural Network (BPNN).
Methods: Data were sourced from the psychology and behavior investigation of Chinese residents (PBICR). A total of 21,916 individuals in China were included in the current study. Multiple logistic regression was applied to preliminarily identify potential risk factors for depressive symptoms. BPNN was used to explore the order of contributing factors of depressive symptoms.
Results: The prevalence of depressive symptoms among the general population during the COVID-19 pandemic was 57.57 %. The top five important variables were determined based on the BPNN rank of importance: subjective sleep quality (100.00 %), loneliness (77.30 %), subjective well-being (67.90 %), stress (65.00 %), problematic internet use (51.20 %).
Conclusions: The prevalence of depressive symptoms in the general population was high during the COVID-19 pandemic. The BPNN model established has significant preventive and clinical meaning to identify depressive symptoms lay theoretical foundation for individualized and targeted psychological intervention in the future.

1. Introduction

Coronavirus disease 2019 (COVID-19), which initially originated in Wuhan, China, in December 2019, has become a global public health emergency, posing a serious and constant threat to both physical and mental health among segments of the general public (Ornell et al., 2020). In particular, China has maintained a dynamic zero-tolerance quarantine policy to ensure maximum public safety since the beginning of the COVID-19 pandemic. Based on the current characteristics of the novel coronavirus and China's national conditions, the Chinese government issued a series of new policies on prevention and control efforts in December 2022 in response to the COVID-19 pandemic. Therefore, it is critical to understand the mental health conditions of the general public in the context of unique prevention and control policies in China.

1.1. Depression and depressive symptoms

Depression, as a common mental health disorder, has become a major public health problem worldwide, severely affecting human physical and mental health conditions (Malhi and Mann, 2018; Zou et al., 2020). According to reliable statistics, depression has become a major contributor to the global burden of disease and the second major contributor in China (GBD 2017 Disease and Injury Incidence and Prevalence Collaborators, 2018). It has been demonstrated that the prevalence of depression and depressive symptoms among outpatients in developing countries is higher than that in developed countries (J. Wang et al., 2017). Thus, the prevalence of depression and depressive

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symptoms in China, the world's largest developing country, requires particular attention. A recent meta-analysis has shown that the major adverse health outcomes in China during the pandemic were stress (prevalence rate: 48.1 %), depression (prevalence rate: 26.9 %) and anxiety (prevalence rate: 21.8 %) (Bareeqa et al., 2021). Depressive symptoms, as a subclinical form of depression, are not diagnosed according to the international diagnostic criteria of depression; however, their impact on the population cannot be ignored (Cuijpers and Smit, 2008). A longitudinal study in China suggested a pre-pandemic prevalence of depressive symptoms of 21.6 % and a post-pandemic prevalence of 26.3 % (Li et al., 2021). With the volatile progress of the epidemic, normalized prevention and control has become an inevitable trend in China. Hence, it is essential to understand the prevalence and influencing factors of depression and depressive symptoms in the context of the COVID-19 pandemic.

1.2. Influencing factors for depression and depressive symptoms

Depression, a major threat to human health, is characterized by sustained long-term sadness, loss of interest and decreased energy in daily activities. Due to the potential increased social burden and health care expenditure associated with depression and depressive symptoms, their incidence, influencing factors, assessment tools, and possible interventions have attracted the attention of many scholars. The key to dealing with depression is to identify the risk factors that may cause or exacerbate depression or depressive symptoms, and formulate personalized and adapted psychological intervention programs (Fan et al., 2021; Smith, 2014). Multifactor disease models can be performed to account for the progression of depressive symptoms and to identify associated biological, psychological and social risk factors (Blazer and Hybels, 2005). Numerous studies have demonstrated that the occurrence and development of depression and depressive symptoms are significantly correlated with socioeconomic demographic variables, including age, gender, ethnicity, residency, education level, monthly income and status of living alone (Liu et al., 2022; Lu et al., 2021; Mao et al., 2019; Salk et al., 2017). Variables related to the social environment, such as social status, neighborhood and negative life events, are significantly associated with depression (Gao et al., 2023; Richardson et al., 2015; Vidal and Latkin, 2020; Z. Wang et al., 2020). Previous studies have proven that stress and loneliness are risk factors for depressive symptoms, while self-efficacy, social support and subjective well-being are protective factors (Cattelino et al., 2021; Lee et al., 2021; Nakamura et al., 2022; Suh et al., 2021). Problematic internet use and poor subjective sleep quality may contribute to the development of depressive symptoms (Gecaite-Stonciene et al., 2021; Kojima et al., 2021; Thiagarajah et al., 2022).

1.3. Back Propagation Neural Network

Most previous studies on risk factors for depression or depressive symptoms have focused on specific populations and evaluated the role of these risk factors individually. This study incorporated multi-dimensional variables, including sociodemographic variables, social environment, subjective indicators, individual behavior, and COVID-19-related variables, to establish a comprehensive multi-angle prediction model. On the one hand, psychological change is a process in which various factors interact and regulate each other, and traditional models based on linear operations cannot clearly explain its internal relationships and functions. On the other hand, some variables are not all linear, independent, normally distributed and homogeneous due to realistic factors. Misuse of some statistical methods may lead to deviations between the results and the actual situation, which then brings limitations in generalization and application. Artificial Neural Network (ANN) is an information processing system simulating the ability of a biological neural network of the human brain, such as learning and generalization, to establish a mathematical or computational model. The Back Propagation Neural Network (BPNN), the most widely used and relatively mature method of ANN, is a backpropagation feedforward network with good prediction ability, fast operation speed and good stability. BPNN builds accurate prediction models through machine self-learning and training and has accurate classification ability and multi-dimensional function mapping ability. According to previous studies, BPNN has a better prediction function than multiple logistic regression models in complex model fitting and distribution approximation (Kulkarni et al., 2021; Schmidhuber, 2015). BPNNs have been widely used in the fields of clinical medicine, computer science, engineering and so on (Ning et al., 2021; Shao et al., 2021; Zheng, 2021). However, very few examples of the application of BPNN are available in previous research in the field of mental health (Fan et al., 2021; J. Lv et al., 2022). Therefore, it is of great significance to establish a prediction model based on BPNN to improve the prediction accuracy and propose targeted prevention strategies for depression and depressive symptoms.

1.4. The current study

The current study aimed to: (a) investigate the mental health status of the general public in the context of the epidemic, identify the influencing factors of depressive symptoms, and propose targeted interventions; (b) establish a prediction model of depressive symptoms based on BP neural network models, screen the high-risk groups of depressive symptoms and provide identification and prediction tools for early intervention. Normalized prevention and control will certainly become a long-term policy context in China, so it is crucial for the general public to explore the risk factors for depression and depressive symptoms.

2. Methods

2.1. Study population and sample

The data used in this study were sourced from the psychology and behavior investigation of Chinese residents (PBICR) (Wang et al., 2022). This large-scale cross-sectional survey was conducted in 23 provinces, 5 autonomous regions, and 4 municipalities in mainland China from 20 June 2022 to 31 August 2022. A multi-stage national probability sampling procedure was performed that comprised two stages: (a) probability sampling and equal probability sampling (stratified sampling) at the provincial, municipal, district and county levels, townships/towns/sub-districts and communities/villages levels; (b) non-equal probability sampling (quota sampling) at community/village to individual level. A pre-tested structured questionnaire was used to collect information through a face-to-face interview with each participant. If the face-to-face investigation could not be realized, the investigator would carry out the online video investigation and distributed electronic questionnaires directly to the participant.

Individuals were retained if he or she (a) was older than 12 years; (b) was permanent resident of China (annual departure time $\leq$ 1 month); (c) had nationality of the People's Republic of China; (d) provided an informed consent form to voluntarily participate in the study; (e) completed the questionnaire on their own or with the help of an investigator; and (f) was able to understand the meaning of each item in the questionnaire. Individuals with any of the following criteria were excluded: (a) were confused, mentally abnormal or had cognitive impairment; (b) were participating in other similar studies; and (c) were unwilling to participate in this study. Finally, a total of 21,916 individuals (response rate = 71.8 %; eligibility rate = 96.8 %) were included as the final sample for analysis.

2.2. Measures

2.2.1. Dependent variable

The depressive symptoms of participants were evaluated by the 9-

item Patient Health Questionnaire (PHQ-9), containing nine questions based on the Diagnostic and Statistical Manual (DSM) diagnostic criteria for depression (e.g., "Little interest or pleasure in doing things?") (Kroenke et al., 2001). The PHQ-9 has been proven to be a psychometrically valid and reliable measure of depression in a variety of populations and is widely used for assessing depressive symptoms in clinical practice (Kroenke et al., 2001; Moriarty et al., 2015). The Chinese version of the PHQ-9 has been validated to have good reliability and validity in the general population in China (Wang et al., 2014). Each of the items was rated on a 4-point Likert-type scale ranging from 0 (not at all) to 3 (nearly every day). The possible total score ranges from 0 to 27, with higher scores indicating higher levels of depressive symptoms. A total score <5 signified the absence of depressive symptoms, while a score of 5 or more was set to indicate any degree of depressive symptoms (Kroenke et al., 2001). Cronbach's alpha of the PHQ-9 was 0.921 for the entire scale in the current study.

2.2.2. Independent variable

2.2.2.1. Sociodemographic variables. The sociodemographic variables included age, gender (men vs. women), ethnicity (Han vs. non-Han), residency (urban vs. rural), educational level (illiterate/semi-literate, primary school students, middle school students, college students, graduate/doctoral students), monthly income [≤1000/1001-3000/3001-5000/>5000 China Yuan (CNY)] living alone (yes vs. no) and negative life events (yes vs. no).

2.2.2.2. Social environment. Social environment was assessed through social status, neighborhood, and negative life events. Social status was assessed with the question, "How do you feel about your family's place in society?" Response options ranged from 1 (the lowest) to 7 (the highest). Neighborhood was measured by asking the participants about the relationship between their family and their neighbors, with the same response options as social status. Negative life events were divided into yes (e.g., seriously injured or seriously ill, difficulty in purchasing materials, theft or property damage, family financial difficulties) and no.

2.2.2.3. Subjective indicators. Subjective indicators contained stress, self-efficacy, social support, loneliness, and subjective well-being. The Perceived Stress Scale-4 items (PSS-4), adapted from the 14-item PSS, was used to evaluate the perceived psychological stress of participants (Cohen et al., 1983). The shortened version of the New General Self-efficacy Scale (NGSES) is a validated and self-administered instrument designed to assess the self-efficacy of participants (Chen et al., 2001; Feng and Chen, 2012). The shortened version Multidimensional Scale of Perceived Social Support (MSPSS) was applied to investigate self-perceived social support from three sources: family, friends and significant others (Zimet et al., 1990). Loneliness was measured using the Three-Item Loneliness Scale (T-ILS), which contained three items and a simplified set of response categories (Hughes et al., 2004). Subjective well-being was evaluated by the 5-item World Health Organization Well-Being Index (WHO-5), which was derived from the WHO-10(Bech et al., 1996). The above scales have been proven to have satisfactory reliability and validity in Chinese populations (Chiu and Tsang, 2004; Leung et al., 2010; Lin et al., 2013; Liu et al., 2020; G. Lv et al., 2022; Y. Wang et al., 2017). Cronbach's alpha of the PSS-4, the NGSES, the MSPSS, the T-ILS and the WHO-5 were 0.668, 0.925, 0.888, 0.862 and 0.933, respectively.

2.2.2.4. Individual behavior. Problematic internet use of participants was assessed by the Problematic Internet Use Questionnaire-Short Form-6 (PIUQ-SF6), which was extracted from the original 18-item version (Demetrovics et al., 2016; Demetrovics et al., 2008). The PIUQ-SF6 consists of three dimensions (obsessions, neglect and control), and each dimension contains two items. Each item was scored on a 5-point Likert scale from 1 (never) to 5 (always/almost always) with a total score ranging from 6 to 30. Higher scores on the PIUQ-SF-6 indicated more severe the participants' problems with internet use. The Brief Version of the Pittsburgh Sleep Quality Index (B-PSQI), extracted from the PSQI, was used to measure the subjective sleep quality of the participants during the last month (Buysse et al., 1989; Sancho-Domingo et al., 2021). Six questions were asked in the B-PSQI, which yielded five scored items (bedtime and rise time are used to calculate sleep efficiency). The global B-PSQI score ranged from 0 to 15, with higher scores indicating poorer sleep quality. The reliability and construct validity of the PIUQ-SF6 and B-PSQI have been tested in previous studies (Balci et al., 2018; Sancho-Domingo et al., 2021). Cronbach's alpha of the PIUQ-SF-6 and B-PSQI were 0.932 and 0.686, respectively.

2.2.2.5. COVID-19 related variables. Home quarantine situation was measured by using the question "Are you currently under home quarantine?" (yes vs. no). The lockdown situation was determined by asking the question "Is your city under lockdown?" (yes vs. no). The community closure situation lays its foundation on the response of the participants for "Is your community being closed down?" (yes vs. no). Influence on daily life was assessed by one broad question: "To what extent do you think COVID-19 has affected your normal life?" Participants were rated on a scale of 0 to 100 in which higher scores indicate greater impact of the pandemic.

2.3. Back Propagation Neural Networks

BPNN, proposed by Rumelhart and Mccelland in 1986, is a multi-layer feedforward neural network trained according to the error back propagation algorithm (Rumelhart et al., 1986). Artificial Neural Network (ANN) is a large-scale parallelism nonlinear dynamic system, and BPNN is one of the most widely used and relatively mature methods (Tang et al., 2013). The typical structure of BPNN generally consists of three layers: the input, hidden, and output layers. Its algorithm flow is composed of two processes of forward propagation of information and backward propagation of error. The input signal enters the feedforward neural network from the input layer through the hidden layer to the output layer, from which the output value can be obtained. If the output value does not match the expected value, the error is back propagated from the output layer to the input layer, after which the forward propagation adjusts the weights of the neurons and starts working again. Fig. 1 presents the basic structure of a typical three-layer BPNN.

The current study utilized the BPNN Multi-Layer Perceptron (MLP), and all continuous variables in the model were standardized. Significant variables from multiple logistic regression analysis were identified as the input signals in the BPNN model. The input layer neuron, which generally refers to the dependent variable, was depressive symptoms (binary variable) in this study. Adding the number of hidden layers can reduce error but increase complexity and even decrease accuracy in modeling. Furthermore, there is currently no recognized algorithm to define the optimal number of hidden layers or the number of neurons in advance. Therefore, we adopted a typical three-layer BPNN with one input layer, one hidden layer, and one output layer. The number of neurons in the hidden layer was automatically calculated by the BPNN model. Tan-sigmoid and SoftMax activation functions were applied in the hidden layer and output layer, respectively. Approximately 70 % of the samples were selected as the training set for the self-learning training of the neural network model, and about 30 % of the samples were selected as the test set to validate the accuracy of the model and the prediction accuracy of the established model. The major variables that influence the dependent variables were ranked in decreasing order of importance.

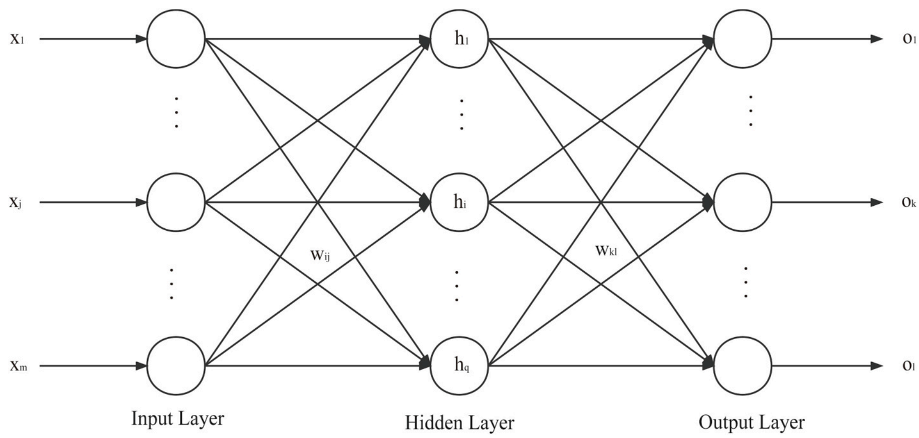

Fig. 1. The basic structure image of a typical three-layer BPNN.

2.4. Statistical analysis

SPSS version 25.0 software was used for statistical analysis. Descriptive statistics were expressed as mean ± standard deviation (SD) for quantitative variables and frequency (percentage) for categorical variables. Student's *t*-test and the chi-square test were performed to determine the association between the independent variables and depressive symptoms. Multiple logistic regression analysis was conducted to identify potential risk factors for depressive symptoms. The BPNN model was developed to explore the order of contributing factors of depressive symptoms. Effect estimates, including odds ratios (ORs) and their corresponding 95 % confidence intervals (CIs), were used to assess the strength of the independent variables and depressive symptoms. The area under the curve (AUC) of receiver operating characteristic (ROC) was used to evaluate the performance of the BPNN model. A p value (two-sided) < 0.05 was considered to be statistically significant.

3. Results

3.1. The characteristics of the participants

The description of the participants is provided in Table 1. In total, 21,916 participants (50.00 % men) were included in this cross-sectional study, with an average age of 39.43 ± 18.85 years (mean ± SD). The majority of the participants were Han descent (91.12 %), lived in urban areas (69.30 %) and did not live alone (85.67 %). Monthly income was classified into less than or equal to 1000 CNY, between 1001 and 3000 CNY, between 3001 and 5000 CNY, and >5000 CNY, with proportions of 6.27 %, 26.71 %, 30.37 % and 36.65 %, respectively. A total of 40.81 % of participants received college education, 39.84 % received middle school education, 10.19 % received primary education, 5.38 % were illiterate or semi-literate and 3.39 % received graduate or doctoral education. A total of 58.20 % of the participants reported that they had experienced one or more negative life events in the past year. Most of the participants were not under home quarantine (96.22 %), lockdown (94.32 %) or community closure (95.75 %).

3.2. Prevalence of different levels of depressive symptoms

The comparison of participants with depressive symptoms to those without is presented in Table 1. Among 21,916 participants, 12,618 were considered to have depressive symptoms (prevalence: 57.57 %). The univariable analysis revealed that participants with depressive symptoms were younger than those without ($p < 0.001$). Depressive symptoms were more common in women, urban residents, and solitary individuals (all $p < 0.001$). Participants who experienced negative life events, home quarantine, lockdown and community closure were more likely to develop depressive symptoms (all $p < 0.001$). Participants with depressive symptoms had significantly lower social status and poorer neighborhood relationships than those without (all $p < 0.001$). High levels of stress, loneliness and low levels of self-efficacy, social support and subjective well-being were significantly correlated with the occurrence of depressive symptoms (all $p < 0.001$). Participants with depressive symptoms reported higher levels of COVID-19 impact on their daily lives than normal people ($p < 0.001$).

3.3. Results of multiple logistic regression

Table 2 shows the results of the multiple logistic regression analysis. Variables identified as significant factors in the univariate analysis were included in multiple logistic regression analysis. The higher the age, the higher the risk of depressive symptoms (OR = 1.003, 95 % CI: 1.000–1.005, $p = 0.017$). Men reported a significantly lower risk of depressive symptoms than women (OR = 0.893, 95 % CI: 0.832–0.958, $p = 0.002$). Participants who lived in urban areas had a 1.143 times higher risk for depressive symptoms than those living in rural areas (OR = 1.143, 95 % CI: 1.053–1.241, $p = 0.001$). Desirable neighborhood may be a protective factor for depressive symptoms (OR = 0.966, 95 % CI: 0.936–0.996, $p = 0.027$). Higher levels of stress and loneliness may contribute to the occurrence of depressive symptoms (OR = 1.125, 95 % CI: 1.110–1.140, $p < 0.001$; OR = 1.911, 95 % CI: 1.857–1.966, $p < 0.001$). Self-efficacy, social support and subjective well-being appeared to produce a protective effect against depressive symptoms (OR = 0.967, 95 % CI: 0.947–0.988, $p < 0.002$; OR = 0.961, 95 % CI: 0.947–0.974, $p < 0.001$; OR = 0.933, 95 % CI: 0.926–0.940, $p < 0.001$). Problematic internet use and poor subjective sleep quality may serve as potential risk factors for depressive symptoms (OR = 1.099, 95 % CI: 1.090–1.108, $p < 0.001$; OR = 1.150, 95 % CI: 1.135–1.166, $p < 0.001$).

3.4. Results of BPNN

Table 3 lists the importance ranking of all the included factors in the BPNN model. For the number of neurons included in each layer of the BPNN, the input layer involved 13 neurons, the hidden layer involved 5 neurons and the output layer involved 1 neuron. The importance of the included influencing factors associated with depressive symptoms ranged from high to low: subjective sleep quality (100.00 %), loneliness (77.30 %), subjective well-being (67.90 %), stress (65.00 %), problematic internet use (51.20 %), self-efficacy (25.00 %), neighborhood (24.30 %), social support (22.90 %), age (17.20 %), monthly income (10.50 %), residency (6.70 %), negative life event (5.50 %) and gender (5.40 %). Table 4 demonstrates the performance of the BPNN in predicting depressive symptoms. 15,057 cases (69.8 %) and 6501 cases (30.2 %) were included in the training set and test set, respectively. The

Table 1
Demographic characteristics of the study participants.

Characteristics	Total (n = 21,916)	Participants with depressive symptoms (n = 12,618)	Participants without depressive symptoms (n = 9298)	p value
Sociodemographic variables				
Age (years)	39.43 (18.85)	38.26 (18.69)	41.02 (18.95)	<0.001
Gender				<0.001
Men	10,958 (50.00)	6138 (48.64)	4520 (51.84)	
Women	10,958 (50.00)	6438 (51.36)	4478 (48.16)	
Ethnic				
Han	19,970 (91.12)	11,504 (91.17)	8466 (91.05)	0.759
Non-Han	1946 (8.88)	1114 (8.29)	832 (8.95)	
Residency				<0.001
Urban	15,188 (69.30)	8622 (68.33)	6566 (70.62)	
Rural	6728 (30.70)	3996 (31.67)	2732 (29.38)	
Education level				<0.001
Illiterate/semi-literate	1178 (5.38)	654 (5.18)	524 (5.64)	
Primary school	2234 (10.19)	1153 (9.14)	1081 (11.63)	
Middle school	8731 (39.84)	4828 (38.26)	3903 (41.98)	
College	8943 (40.81)	5489 (43.50)	3454 (37.15)	
Graduate/doctoral	830 (3.79)	494 (3.91)	336 (3.61)	
Monthly income (CNY)				< 0.001
≤1000	1375 (6.27)	902 (7.15)	473 (5.08)	
1001–3000	5854 (26.71)	3316 (26.28)	2538 (27.30)	
3001–5000	6655 (30.37)	3674 (29.12)	2981 (32.06)	
>5000	8032 (36.65)	4726 (37.45)	3306 (35.56)	
Living alone				<0.001
Yes	3141 (14.33)	2029 (16.08)	1112 (11.96)	
No	18,775 (85.67)	10,589 (83.92)	8186 (88.04)	
Social environment				
Social status	4.39 (1.30)	4.23 (1.31)	4.51 (1.27)	<0.001
Neighborhood	5.76 (1.25)	5.61 (1.32)	5.97 (1.13)	<0.001
Negative life events				<0.001
Yes	9160 (41.80)	6513 (51.62)	2647 (28.47)	
No	12,756 (58.20)	6105 (48.38)	6651 (71.53)	
Subjective indicators				
Stress	6.08 (3.07)	6.68 (2.85)	5.26 (3.17)	<0.001
Self-efficacy	7.79 (2.42)	7.26 (2.27)	8.50 (2.44)	<0.001
Social support	12.03 (3.78)	11.11 (3.53)	13.28 (3.75)	<0.001
Loneliness	4.56 (1.62)	5.29 (1.57)	3.57 (1.05)	<0.001
Subjective well-being	14.37 (5.97)	12.57 (5.38)	16.80 (5.87)	<0.001

Table 1 (*continued*)

Characteristics	Total (n = 21,916)	Participants with depressive symptoms (n = 12,618)	Participants without depressive symptoms (n = 9298)	p value
Individual behavior				
Problematic internet use	11.72 (5.50)	13.47 (5.63)	9.33 (4.28)	<0.001
Subjective sleep quality	4.37 (2.95)	5.14 (3.03)	3.34 (2.50)	<0.001
COVID-19 related variables				
Home quarantine				<0.001
Yes	828 (3.78)	543 (4.30)	285 (3.07)	
No	21,088 (96.22)	12,075 (95.70)	9013 (96.93)	
Lockdown				<0.001
Yes	1245 (5.68)	792 (6.28)	453 (4.87)	
No	20,671 (94.32)	11,826 (93.72)	8845 (95.13)	
Community closure				<0.001
Yes	932 (4.25)	603 (4.78)	329 (3.54)	
No	20,984 (95.75)	12,015 (95.22)	8969 (96.46)	
Influence on daily life	60.48 (26.76)	61.11 (26.24)	59.64 (27.43)	<0.001

Note: CNY = China Yuan.

accuracy of the BPNN model constructed during training and testing was 83.92 % and 84.65 %, respectively. The AUC of the ROC of the BPNN model was 0.854 (Fig. 2).

4. Discussion

Based on national cross-sectional data of all age groups, this study examined the prevalence of depressive symptoms and explored potential risk factors in the general population in the context of the pandemic. The results revealed that subjective sleep quality, loneliness, subjective well-being, stress and problematic internet use were stronger contributors to depressive symptoms than other factors. The findings provided a certain theoretical basis for their identification, prevention and treatment for depression and depressive symptoms.

4.1. The prevalence of depressive symptoms

Our results suggested that the prevalence of depressive symptoms was 57.57 % in the general population during the COVID-19 pandemic. Many domestic and foreign epidemiological studies have reported different prevalence of depression and depressive symptoms during the COVID-19 pandemic. A global-based cross-sectional study showed that 58.6 % of participants exhibited depression during the pandemic, which is similar to our results (Shah et al., 2021). The prevalence of depression among Chinese adolescents was 43.7 % during COVID-19 pandemic (Zhou et al., 2020). A national study in Italy showed that 32.4 % of participants had high or extremely high levels of depression (Mazza et al., 2020). Variations in the prevalence of depressive symptoms can be explained by differences in population composition in the various studies, assessment tools and selected cut-off points. The PHQ-9 has been demonstrated to be a reliable and valid measure to screen depression, and it has been widely applied in studies related to the COVID-19 pandemic (Costantini et al., 2021; Levis et al., 2019). Thus, the prevalence of depressive symptoms measured by the PHQ-9

Table 2
Multivariable logistic regression analysis of depressive symptoms.

Characteristics	Standard B	OR	95 % CI	p
Sociodemographic variables				
Age (years)	0.002	1.003	1.000–1.005	0.017
Gender				
Women	Ref.	1.000		
Men	−0.113	0.893	0.832–0.958	0.002
Residency				
Rural	Ref.	1.000		
Urban	0.134	1.143	1.053–1.241	0.001
Education level				
Graduate/doctoral	Ref.	1.000		
College students	0.058	1.059	0.874–1.284	0.557
Middle school	0.001	1.001	0.824–1.216	0.993
Primary school	−0.094	0.910	0.730–1.135	0.404
Illiterate/semi-literate	−0.127	0.881	0.685–1.132	0.320
Monthly income (CNY)				
>5000	Ref.	1.000		
3001–5000	−0.123	0.884	0.810–0.965	0.006
1001–3000	−0.134	0.875	0.794–0.963	0.006
≤1000	−0.029	0.971	0.823–1.147	0.732
Living alone				
Yes	Ref.	1.000		
No	0.051	1.052	0.946–1.169	0.348
Social environment				
Social status	0.013	1.013	0.983–1.043	0.396
Neighborhood	−0.035	0.966	0.936–0.996	0.027
Negative life events				
Yes	Ref.	1.000		
No	−0.271	0.762	0.707–0.822	<0.001
Subjective indicators				
Stress	0.118	1.125	1.110–1.140	<0.001
Self-efficacy	−0.033	0.967	0.947–0.988	0.002
Social support	−0.040	0.961	0.947–0.974	<0.001
Loneliness	0.648	1.911	1.857–1.966	<0.001
Subjective well-being	−0.069	0.933	0.926–0.940	<0.001
Individual behavior				
Problematic internet use	0.094	1.099	1.090–1.108	<0.001
Subjective sleep quality	0.140	1.150	1.135–1.166	<0.001
COVID-19 related variables				
Home quarantine				
Yes	Ref.	1.000		
No	−0.120	0.887	0.675–1.164	0.386
Lockdown				
Yes	Ref.	1.000		
No	0.126	1.134	0.875–1.471	0.341
Gated community				
Yes	Ref.	1.000		
No	−0.057	0.945	0.680–1.312	0.734
Influence on daily life	0.001	1.001	0.999–1.002	0.460

Note: CNY = China Yuan; OR = odds ratio; CI = confidence intervals.

remained reliable in this study.

4.2. Sleep quality as an indicator for depressive symptoms

The BPNN was able to simulate the complex processes of psychological changes and discover the importance of each influencing factor of depressive symptoms. Hence, the results of BPNN were more in accordance with the actual circumstances than those of the traditional logistic regression model. According to the results of the BPNN, sleep quality was the most significant factor influencing depressive symptoms during the pandemic, which is similar to previous results (J. Lv et al., 2022; Baglioni et al., 2011; Paunio et al., 2015). The decline in sleep quality may weaken the emotional-regulation ability of individuals, leading to decreased positive experience and increased negative emotional experience, such as depression and anxiety (Mauss et al., 2013; Watling et al., 2017). A meta-analysis of randomised controlled trials suggested that improvements in sleep quality exerted dose-dependent improvements in mental health (Scott et al., 2021). The results revealed that participants with poor sleep quality have a higher risk for depressive symptoms.

Table 3
The rank of importance of factors influencing depressive symptoms in BP neural network.

Rank	Characteristics	Importance	Normalized importance
1	Subjective sleep quality	0.209	100.00 %
2	Loneliness	0.161	77.30 %
3	Subjective well-being	0.142	67.90 %
4	Stress	0.136	65.00 %
5	Problematic internet use	0.107	51.20 %
6	Self-efficacy	0.052	25.00 %
7	Neighborhood	0.051	24.30 %
8	Social support	0.048	22.90 %
9	Age	0.036	17.20 %
10	Monthly income	0.022	10.50 %
11	Residency	0.014	6.70 %
12	Negative life event	0.012	5.50 %
13	Gender	0.011	5.40 %

Table 4
Prediction effect evaluation of BP neural network.

Group	Detection	Prediction		
		Depressive symptoms		Accuracy rate
		No	Yes	
Training set	No	4471	2018	68.90 %
	Yes	1378	7190	83.92 %
	Total accuracy rate	38.85 %	61.25 %	77.45 %
Test set	No	1887	843	69.12 %
	Yes	579	3192	84.65 %
	Total accuracy rate	37.93 %	62.07 %	78.13 %

4.3. Loneliness as an indicator for depressive symptoms

In addition, our results demonstrated that loneliness was the second most important influencing contributor of depressive symptoms. Loneliness is a negative emotional experience that occurs due to the gap between the actual and desired social interaction of an individual (Scott et al., 2021). Lonely people tend to have negative evaluations and biased social cognition, and they tend to have low feelings of belonging and low beliefs about social interactions, contributing to the development of depression (Lee et al., 2021). Therefore, we speculated that loneliness played a crucial role in the occurrence of depressive symptoms.

4.4. Subjective well-being as an indicator for depressive symptoms

Consistent with previous findings, the current study confirmed that subjective well-being was a strong predictor of depressive symptoms (Carandang et al., 2019; Lee, 2022; Nordbakke and Schwanen, 2014). Subjective well-being refers to the overall evaluation of one's quality of life and emotional feelings, which is closely related to individual physical and mental health (Diener et al., 2016). Individuals reporting higher levels of subjective well-being tend to have better physical conditions, better interpersonal relationships, higher economic levels and job satisfaction, and are less likely to be affected by depression or depressive symptoms (Winefield et al., 2012). To some extent, subjective well-being can promote positive emotions and decrease negative emotions, thus reducing or alleviating the occurrence of depressive symptoms (Fan et al., 2021). In summary, we believe that subjective well-being can be used as a protective factor against depressive symptoms.

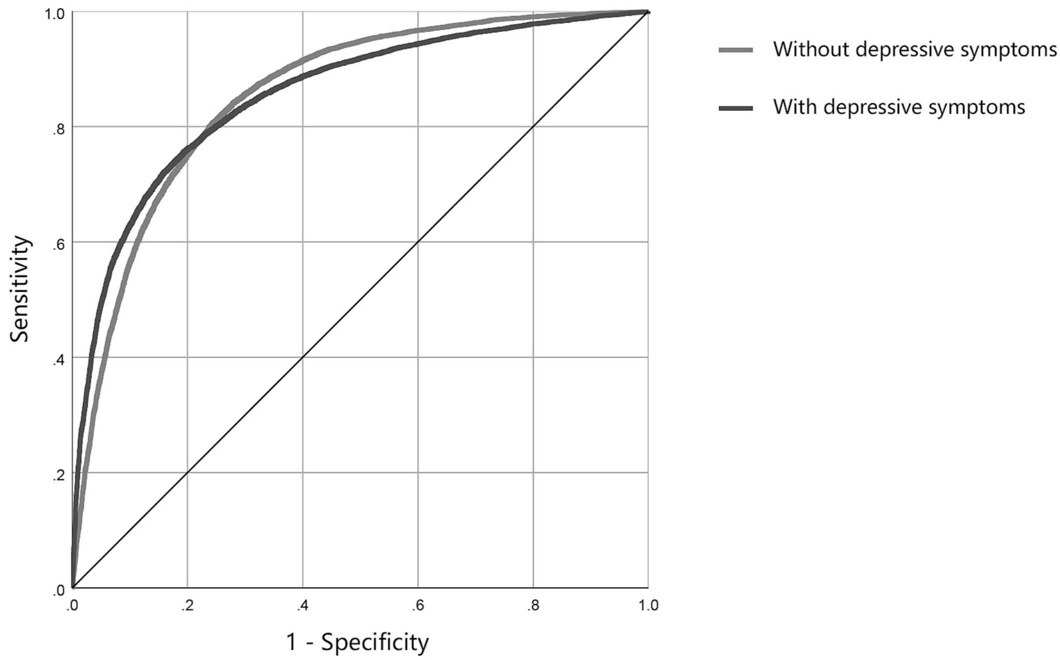

Fig. 2. ROC curve of the total sample for the BPNN model.

4.5. Stress as an indicator for depressive symptoms

The current findings suggest that stress is one of the significant factors influencing depressive symptoms, which is consistent with previous studies (Frieri et al., 2015; Huang et al., 2022). A mediating analysis showed that stressful life events not only directly predicted depressive symptoms but also mediated this relationship through different coping styles (Evans et al., 2015). Stressful life events might negatively affect the activation of reward circuits by inhibiting dopamine activity, thus predicting the occurrence of depressive symptoms (Burani et al., 2021). Recent studies have elucidated the neural (autonomic nervous system) and endocrine mechanisms (hypothalamic-pituitary-adrenal axis) that link stress to depressive symptoms (Lucas-Thompson et al., 2018; Wang et al., 2019). As a result, stress emerged as an important predictor of depressive symptoms according to previous and current findings.

4.6. Problematic Internet use as an indicator for depressive symptoms

In addition, the results showed a strong association between problematic Internet use and depressive symptoms, which is consistent with previous research (Ramón-Arbués et al., 2020). Internet use is harmless in general and may even help people relieve stress, but in the context of the COVID-19 pandemic, people's overuse of the internet may lead to addiction and eventually mental health disorders (Ramón-Arbués et al., 2020). A study during the COVID-19 pandemic suggested that problematic Internet use significantly predicted depressive symptoms, and this relationship was partially mediated by impulsivity (Gecaite-Stonciene et al., 2021). Therefore, we concluded that participants with problematic Internet use were at higher risk for depressive symptoms.

4.7. Other contributors for depressive symptoms

In addition, self-efficacy, neighborhood, social support, age, education level, residency, negative life events, and gender were also found to be influencing factors for depressive symptoms. Notably, the COVID-19-related variables included in the current study have no effect on depressive symptoms in the multivariate analysis. Prospective studies at home and abroad suggested no significant changes in the level of depression and depressive symptoms before and after the COVID-19 pandemic, which supported our findings (van der Velden et al., 2021; C. Wang et al., 2020). However, the emergence of the new Omicron strain of COVID-19 not merely triggered a new global outbreak, but also caused a range of mental health disorders that were different from those identified in the early stages of the pandemic (Araf et al., 2022). Therefore, the impact of the pandemic on the mental health of the general public requires additional exploration.

4.8. Strengths and limitations

This study employed a large sample size that included nationwide sampling of the study participants, indicating that our results are representative and reliable of the general population. In addition, multidimensional factors were included in this study, making the results more comprehensive and conclusive. However, several limitations of the current study should be mentioned. First, the cross-sectional design limited the capacity to infer causal relationships. Future longitudinal studies are strongly warranted to validate causal associations. Second, the PHQ-9 was applied to screen for depressive symptoms rather than to diagnose depression. The use of clinical criteria for depression could be considered a classification for future research. Third, self-reported scales may introduce information bias and human error, and objective measures are desirable for subsequent studies.

5. Conclusions

This study fully took into account the daily life of the general public during the COVID-19 pandemic, combined with typical epidemic prevention and control policies in China, to develop a targeted mental health prediction model. According to the BPNN, the main factors affecting the prevalence of depressive symptoms during the pandemic period were: subjective sleep quality, loneliness, subjective well-being, stress and problematic Internet use. By constructing a BPNN model for predicting depressive symptoms and selecting potential risk factors, it may assist in identifying high-risk groups at an early stage and provide a basis for later individualized and targeted psychological intervention.

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CRediT authorship contribution statement

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Conflict of interest

The authors declare that there are no conflicts of interest in relation to the subject of this study.

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