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Early warning mechanisms and intervention strategies based on dynamic negative emotion prediction models for physiopathological risks in cancer patients

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Abstract: Objective: To construct a dynamic evolution-based negative emotion prediction model, establish an early warning mechanism for physiological and pathological risks in cancer patients, and develop personalized psychological intervention strategies. **Methods:** A multistage mixed-methods design was employed, conducting a 12-month longitudinal follow-up study of 480 cancer patients. Standardized instruments, including the Hospital Anxiety and Depression Scale, Fear of Progression Questionnaire-Short Form, and Perceived Stress Scale, were used to assess negative emotions, while physiological indicators, including inflammatory markers, immune function parameters, and endocrine parameters, were simultaneously measured. Machine learning algorithms, including Random Forest, Support Vector Machine, Gradient Boosting Decision Tree, and Deep Neural Networks, were utilized to construct prediction models, with model performance evaluated through 10-fold cross-validation and external validation. Personalized psychological intervention strategies were developed based on prediction results, and intervention effectiveness was assessed using randomized controlled trials. **Results:** Negative emotions in cancer patients exhibited a three-stage dynamic evolution pattern of “impact-adaptation-integration,” with anxiety, depression, and fear of disease progression scores reaching peak levels in early treatment phases before gradually declining. Environmental factors such as social support, family functioning, and medical environment, along with individual difference variables including age, gender, and personality traits, significantly moderated emotional evolution. The ensemble prediction model achieved an AUC value of 0.892 (95% CI: 0.876–0.908) in internal validation and 0.876 (95% CI: 0.845–0.907) in external validation, with a sensitivity of 85.4% and specificity of 83.7%. The three-tier risk stratification early warning system achieved an optimal balance at the moderate risk threshold, with a Youden index of 0.691. Personalized psychological intervention strategies significantly improved patients’ psychological symptoms, physiological indicators, and quality of life. The intervention group showed 34.1% improvement in anxiety scores, 38.1% improvement in depression scores, 38.1% reduction in C-reactive protein levels, and 24.7% enhancement in quality-of-life scores, all significantly superior to the control group ($p < 0.001$). Path analysis revealed that personalized interventions primarily operated through five mediating variables: cognitive restructuring, emotion regulation, coping strategies, social support utilization, and self-efficacy, with a total indirect effect of 0.71, accounting for 78.9% of the total effect. **Conclusion:** The dynamic evolution-based negative emotion prediction model demonstrates excellent predictive performance and clinical application value. The established early warning mechanism effectively identifies high-risk patients, and personalized psychological intervention strategies significantly improve patients’ multidimensional health outcomes,

providing a scientific theoretical foundation and practical guidance for psychological health management in cancer patients.

Keywords: cancer patients; dynamic evolution; early warning mechanism; machine learning; negative emotions; personalized intervention; physiological and pathological risk; prediction model

1. Introduction

Malignant tumors, as one of the most prominent public health challenges in today's world, not only pose severe threats to patients' physical health but also exert profound psychological impacts. In recent years, with the transformation of medical models from traditional biomedical approaches to bio-psycho-social medical models, academic attention to the psychological health status of cancer patients has increasingly intensified. Research demonstrates that cancer patients universally experience negative emotions such as anxiety, depression, and fear during disease diagnosis and treatment processes. These emotional responses not only affect patients' quality of life but also directly influence disease progression through complex neuro-endocrine-immune networks. Wang et al.'s research confirmed that a comprehensive psychological-physiological-pathological management pathway based on Enhanced Recovery After Surgery concepts could significantly improve the prognosis of patients with gynecological malignancies after laparoscopic surgery, providing an important theoretical foundation for the comprehensive management of cancer patients [1]. However, traditional psychological interventions predominantly employ static assessment approaches, lacking systematic monitoring and prediction of dynamic changes in patients' emotional states, making it difficult to achieve precise personalized interventions.

The dynamic evolution process of negative emotions in cancer patients exhibits distinct time-dependent and individual variability characteristics. At different stages of the disease, patients' emotional response patterns show significant differences, from shock and denial at initial diagnosis, to fear and anxiety during treatment processes, and then to depression and adaptation difficulties during recovery periods. This series of emotional changes forms complex dynamic evolution trajectories. Lei et al., in their analysis of influencing factors of cancer-related fatigue in patients with enterostomy, found that psychological factors are important variables affecting patients' fatigue levels, further confirming the close association between psychological states and physiological-pathological changes [2]. Cheng et al.'s longitudinal mixed-methods study demonstrated significant associations between dyadic assessment of cancer cachexia symptoms and psychological distress and quality of life, suggesting the need to understand the psychological-physiological interaction mechanisms from a dynamic perspective [3]. Traditional assessment methods often can only capture patients' emotional states at specific time points, failing to reflect their dynamic change patterns and making it even more difficult to predict future emotional fluctuation trends, which significantly limits the timeliness and specificity of psychological interventions.

Machine learning and artificial intelligence technology-based prediction models provide new possibilities for dynamic monitoring and risk warning of negative

emotions in cancer patients. By integrating patients' clinical data, psychological assessment results, physiological indicators, and social support system information, multidimensional and multilevel prediction models can be constructed to achieve real-time monitoring of patients' emotional state changes and accurate prediction of future trends. Irandoost et al.'s research demonstrated that an anti-inflammatory diet combined with acupuncture treatment could significantly improve the psychological health status of diabetic patients with depression, providing insights for multimodal intervention approaches [4]. Müller et al.'s development of a psychosocial distress problem list in organ transplant patients provided standardized tools for psychological assessment in specific populations, and these research achievements laid important foundations for constructing negative emotion prediction models for cancer patients [5]. Through establishing comprehensive prediction frameworks that include time series analysis, deep learning algorithms, and multi-source data fusion, we can more accurately identify high-risk patients and implement effective interventions before emotional crises occur.

The development of personalized psychological intervention strategies requires full consideration of patients' individual differences and dynamic change characteristics. Based on risk stratification results from prediction models, differentiated intervention protocols can be provided for patients at different risk levels, thereby improving the specificity and effectiveness of interventions. Jiao's research demonstrated the significant value of psychological counseling combined with psychiatric nursing in patients with schizophrenia, providing references for diversified intervention strategies [6]. Li's research on patients with peptic ulcer complicated by bleeding emphasized the importance of sleep and psychological care, suggesting that we need to comprehensively consider the synergistic effects of physiological and psychological factors when developing intervention strategies [7]. Through constructing personalized intervention systems based on dynamic evolution patterns, including the organic combination of multiple approaches such as cognitive behavioral therapy (CBT), mindfulness-based stress reduction (MBSR) training, and social support enhancement (SSE), precise management of negative emotions in cancer patients can be achieved. Meanwhile, combined with modern information technology means, such as mobile health applications and remote psychological counseling, the convenience and sustainability of interventions can be further enhanced, providing comprehensive and continuous psychological health support for cancer patients. Therefore, this study aims to construct a dynamic evolution-based negative emotion prediction model, establish effective physiological–pathological risk warning mechanisms, and develop personalized psychological intervention strategies, providing scientific evidence and practical guidance for improving the overall treatment outcomes and quality of life of cancer patients.

2. Literature review

Research on the association between negative emotions and physiological–pathological risks in cancer patients has become an important topic in the field of psycho-oncology. Existing studies demonstrate that cancer patients universally experience negative emotional responses such as anxiety, depression, and fear during

disease diagnosis, treatment, and recovery processes. These emotional states not only affect patients' quality of life but also directly influence disease progression through complex neuro-endocrine-immune networks. Wang et al.'s research found that clinical pathological biopsy and immunohistochemical examinations produced significant psychological impacts on prostate cancer patients, with patients exhibiting obvious anxiety and depressive symptoms while awaiting examination results, suggesting the need for greater attention to psychological stress responses during diagnostic processes [8]. Wang and Li's study in patients with depressive disorders discovered a chain mediation effect of psychological resilience and neuroticism between psychological distress and suicidal ideation, providing important clues for understanding the complex mechanisms of negative emotions [9]. Jia's research on cervical cancer patients indicated that the main causes of postoperative psychological imbalance include concerns about disease prognosis, anxiety about bodily function changes, and difficulties in social role adaptation, revealing the multidimensional characteristics of psychological problems in cancer patients [10]. Miao et al.'s study on malignant tumor patients who collected pathology reports themselves emphasized that psychological induction nursing could effectively alleviate patients' anxiety and improve their disease cognition and coping abilities [11]. Zhang et al.'s research on the development trajectory of psychological distress during concurrent chemoradiotherapy after surgery in cervical cancer patients showed that patients' psychological distress levels exhibited dynamic change characteristics during treatment with obvious individual differences, providing important empirical foundation for constructing dynamic prediction models [12].

The mechanisms by which negative emotions influence physiological–pathological processes in cancer patients are multifaceted, involving neuroendocrine systems, immune systems, and behavioral factors at multiple levels. Jin et al.'s study in patients with knee osteoarthritis comorbid with type 2 diabetes found that outdoor green exercise showed significant advantages over indoor exercise in improving psychosocial and physiological health outcomes, suggesting the important role of environmental factors in psychological–physiological interactions [13]. Li's research on hypertensive cerebral embolism patients confirmed that early rehabilitation nursing not only improved patients' quality of life but also significantly improved their psychological and emotional states, indicating synergistic effects between psychological intervention and physiological rehabilitation [14]. Shen et al.'s cross-sectional study in cancer patients found significant associations between psychological resilience and palliative care problems and needs, with patients with higher resilience demonstrating better adaptive capacity and lower psychological distress levels when facing disease challenges [15]. Xue et al.'s research showed that psychological intervention could significantly improve emotional states, reduce self-perceived burden, and decrease disease uncertainty in chronic heart failure patients, providing important evidence for understanding the multiple effects of psychological intervention [16]. Guo et al.'s study on tuberculosis patients and their spousal caregivers constructed an actor-partner interdependence mediation model of self-concealment between psychological distress and self-transcendence, revealing complex pathways of psychological factors in disease adaptation processes [17]. Lu and Lv's analysis of influencing factors

of psychological distress in patients with acute exacerbation of chronic obstructive pulmonary disease showed that disease severity, social support levels, and personal coping styles all affected patients' psychological states, providing important references for constructing multifactor prediction models [18].

The effectiveness and personalized implementation of psychological intervention strategies represent current research priorities. Huang's research demonstrated that psychological intervention combined with clinical care pathways could significantly improve sleep quality and psychiatric symptoms in schizophrenia patients, providing references for comprehensive intervention (CI) model design [19]. Yang's study on acute pancreatitis patients found that evidence-based nursing models could effectively improve patients' psychological states and reduce complication occurrence, indicating the important value of evidence-based standardized interventions [20]. Zeng et al. applied Maslow's hierarchy of needs theory to psychological interventions in lupus nephritis patients, achieving good results and providing successful cases for theory-guided personalized interventions [21]. Tang et al.'s Internet-based 5E rehabilitation intervention model significantly improved psychological states and quality of life in endometriosis patients, demonstrating the application potential of modern information technology in psychological interventions [22]. Ye and Zhou's health education based on the transtheoretical model produced positive effects on perimenopausal coronary heart disease patients, indicating that intervention strategies guided by theoretical models possess better systematicity and specificity [23]. Napolitano et al.'s multicenter cross-sectional study in inflammatory bowel disease patients found that psychological resilience and self-care abilities were closely related to patients' disease adaptation, providing important insights for developing intervention strategies that enhance patients' self-management capabilities [24]. Nguyen et al.'s narrative review of psychosocial functioning in cleft lip and palate patients emphasized that patients' mental health problems are complex and diverse, requiring personalized intervention approaches [25].

Current research still has certain limitations in prediction model construction and dynamic monitoring, mainly manifested in the lack of long-term longitudinal data support, the need for improved accuracy of prediction models, and insufficient standardization of personalized intervention strategies. Oliver et al.'s research on obese patients emphasized the importance of psychological safety, suggesting that we need to consider patients' psychological safety needs when constructing prediction models [26]. Matheson et al.'s study on patients with substance use disorders found complex associations between cannabis use and mental health, indicating that prediction models need to consider the interactive effects of multiple behavioral factors [27]. Future research should focus more on constructing dynamic prediction models based on big data and artificial intelligence technologies, achieving accurate prediction and risk warning of negative emotion evolution patterns in cancer patients through integration of multisource data (including clinical indicators, psychological assessments, physiological monitoring, social support, etc.). Meanwhile, there is a need to establish more comprehensive personalized intervention strategy systems, providing differentiated psychological support and treatment protocols based on patients' specific conditions and prediction results. Additionally, strengthening multidisciplinary collaboration is

necessary, integrating professional knowledge from oncology, psychology, nursing, information technology, and other fields to jointly promote scientific and precision development of psychological health management for cancer patients. Through these efforts, more effective, timely, and personalized psychological health services can be provided to cancer patients, ultimately improving their overall treatment outcomes and quality of life.

3. Research methods

3.1. Study design

This study employs a multistage mixed-methods design that combines the advantages of longitudinal cohort studies and randomized controlled trials to construct a systematic research framework for exploring the dynamic evolution patterns of negative emotions in cancer patients and their prediction models. The research design consists of three interrelated stages: The first stage is a prospective longitudinal cohort study aimed at collecting data on dynamic changes in negative emotions among cancer patients from diagnosis through 12 months post-treatment. Through a multi-time point repeated measures design (baseline, months 1, 3, and 6 during treatment, and months 9 and 12 during follow-up), continuous psychological state assessment data are obtained, while simultaneously collecting corresponding physiological indicators, pathological parameters, and social support information to provide sufficient data foundation for constructing dynamic prediction models. The second stage involves prediction model construction and validation, utilizing machine learning algorithms and time series analysis techniques to integrate multidimensional data for constructing prediction models of negative emotion evolution. Model accuracy and generalizability are evaluated through internal cross-validation and external independent sample validation to establish physiological–pathological risk warning mechanisms [28]. The third stage comprises intervention strategy effectiveness evaluation, employing a randomized controlled trial design where eligible high-risk patients are randomly allocated to either a personalized psychological intervention group or a routine care control group. The intervention group receives personalized psychological intervention protocols developed based on prediction model results, including diversified strategies such as CBT, MBSR training, and SSE. The control group receives standardized routine psychological care. The effectiveness of personalized intervention strategies is evaluated by comparing changes in psychological states, physiological indicators, and quality of life between the two groups before and after intervention [29]. The entire research design adheres to strict ethical principles, with all participants providing informed consent and the research protocol receiving approval from the hospital ethics committee, ensuring both scientific rigor and ethical compliance.

3.2. Study participants and sampling methods

The target population for this study consists of patients with confirmed malignant tumors, recruited using a multicenter stratified random sampling method from oncology departments and related specialties in three tertiary hospitals. Inclusion criteria

include: Age 18–75 years, pathologically confirmed malignant tumors (including but not limited to lung cancer, breast cancer, colorectal cancer, gastric cancer, liver cancer, and other common malignancies), expected survival ≥ 12 months, basic literacy and communication abilities, ability to independently complete questionnaires, voluntary participation in the study, and provision of informed consent. Exclusion criteria include: Comorbid severe psychiatric disorders or cognitive impairment, current treatment with psychiatric medications or psychotherapy, severe vital organ failure (heart, liver, kidney, etc.), comorbid other malignancies, pregnancy or lactation in women, and patients unable to cooperate with study procedures for various reasons [30]. To ensure sample representativeness, stratified sampling is conducted according to tumor type, disease stage, treatment modality, and patient gender, with simple random sampling employed within each stratum to select study participants.

Based on the characteristics of longitudinal research and the requirements for prediction model construction, sample size calculation was performed using G*Power software, with significance level $\alpha = 0.05$, statistical power $1 - \beta = 0.90$, expected medium effect size $d = 0.5$, and considering approximately 20% dropout rate in longitudinal studies. The final total sample size was determined to be 480 cases, with 400 cases needed for the longitudinal cohort study phase and 200 cases for the randomized controlled trial phase (100 cases each in intervention and control groups). The sampling process strictly follows randomization principles, using computer-generated random number tables for random grouping to ensure sample randomness and representativeness. To ensure data quality and research continuity, a comprehensive patient tracking management system is established, including detailed contact information records, regular telephone follow-up reminders, flexible data collection scheduling, and other measures to minimize dropout rates [31]. Additionally, strict quality control standards are implemented, with all personnel involved in data collection receiving standardized training to ensure standardization and consistency in data collection. During the study, detailed records of withdrawal reasons will be maintained for cases of disease deterioration, death, or voluntary withdrawal, with missing data analysis conducted and appropriate statistical methods employed to handle missing data, ensuring reliability and validity of study results.

3.3. Measurement instruments and variable operationalization

This study constructed a multidimensional measurement instrument system to comprehensively assess negative emotional states and related factors in cancer patients. Assessment of negative emotions employs standardized scales validated in Chinese versions, including the Hospital Anxiety and Depression Scale (HADS) for measuring anxiety and depression levels, the Fear of Progression Questionnaire-Short Form (FoP-Q-SF) for assessing patients' fear of disease progression, the Perceived Stress Scale (PSS) for measuring patients' subjective stress perception, and the PTSD Checklist for DSM-5 (PCL-5) for evaluating post-traumatic stress symptoms. Measurement of physiological–pathological indicators includes inflammatory markers (C-reactive protein, interleukin-6, tumor necrosis factor- α), immune function parameters (CD4+/CD8+ T-cell ratio, natural killer cell activity), endocrine indicators (cortisol, norepinephrine), and tumor markers (specific markers selected according to

different tumor types) [32]. Assessment of psychosocial support employs the Social Support Rating Scale to measure patients' levels of social support received, the Medical Coping Modes Questionnaire to evaluate patients' coping strategies, and the European Organization for Research and Treatment of Cancer Quality of Life Questionnaire (EORTC QLQ-C30) to assess patients' overall quality of life. All scales demonstrate good reliability and validity, with Cronbach's alpha coefficients greater than 0.80. To ensure measurement accuracy and consistency, psychology professionals in the research team conducted pretesting and standardized training for all assessment instruments.

Variable operationalization follows strict scientific standards and clinical practice guidelines. Negative emotions, as the core outcome variable, are comprehensively assessed through multidimensional scale scores, with standardized Z-scores used for data transformation to facilitate comparison and integration across different scales. Physiological–pathological risk indicators are classified according to clinical reference value ranges, establishing high, medium, and low risk levels, while considering dynamic change trends of indicators as important input variables for prediction models. Sociodemographic variables include age, gender, education level, occupational status, marital status, and economic income, while disease-related variables include tumor type, stage, treatment modality, and comorbidities, all using standardized coding methods for data entry. To ensure data quality, a multilevel quality control mechanism is established, including instrument calibration before data collection, real-time monitoring during collection, logical checks after data entry, and outlier identification. All physiological indicator testing is conducted in the same laboratory using unified testing methods and standard operating procedures to ensure comparability and accuracy of test results [33]. Administration of psychological scales is conducted by trained professionals using a combination of face-to-face interviews and self-administered questionnaires to ensure patients fully understand question content and respond accurately, with necessary explanations and assistance provided for patients with comprehension difficulties.

3.4. Data collection procedures

The data collection procedures of this study strictly follow standardized protocols, with longitudinal data collection conducted at six time points, including baseline assessment (T0, postdiagnosis pretreatment), treatment period assessments (T1, T2, T3, at 1, 3, and 6 months after treatment initiation, respectively), and follow-up period assessments (T4, T5, at 9 and 12 months posttreatment, respectively). Baseline data collection is completed within 24 h of patient enrollment, implemented by uniformly trained research nurses who first conduct a detailed informed consent process, fully explaining the study purpose, procedures, risks, and benefits to patients. Formal data collection begins after obtaining written informed consent. Data collection at each time point includes three components: psychological scale assessment, physiological indicator testing, and clinical data collection. Psychological scale assessment is conducted in a quiet, private environment, with researchers using structured interviews to administer each scale individually, ensuring patients understand question content and respond accurately. Each assessment session requires approximately 45–60 min [34]. Physiological indicator testing strictly follows laboratory

standard operating procedures, with 5 ml venous blood samples collected in fasting states during early morning hours at each time point, immediately sent to designated laboratories for testing of inflammatory markers, immune function parameters, endocrine indicators, and tumor markers. All testing is conducted in the same laboratory using identical testing methods and quality control standards. Clinical data collection is obtained through a combination of electronic medical records and paper charts, including detailed information such as patients' basic demographic information, disease diagnosis and staging, treatment protocols, medication usage, and complication occurrence. To ensure data quality and completeness, a strict quality control system is established, including equipment calibration and personnel training before data collection, real-time supervision and quality checks during collection, and logical validation and outlier identification after data entry. For patients unable to complete assessments on schedule due to disease changes or other reasons, the research team conducts supplementary assessments within 48 h or collects key information through telephone follow-up to ensure data continuity and completeness. All data employ double entry and verification methods to ensure data entry accuracy, with comprehensive data backup and confidentiality mechanisms established, strictly adhering to ethical requirements for medical research and data protection regulations.

3.5. Statistical analysis methods

This study employs a multilevel statistical analysis strategy, utilizing SPSS 28.0, R 4.3.0, and Python 3.9 statistical software for data processing and analysis. Descriptive statistical analysis is first conducted, using mean $\pm$ standard deviation to describe the distribution characteristics of continuous variables, and frequencies and percentages to describe the distribution of categorical variables. The Kolmogorov–Smirnov test is used to assess the normality of data distribution, with logarithmic transformation or other appropriate data transformation methods applied to variables that do not conform to normal distribution. Longitudinal data analysis employs Linear Mixed-Effects Models and Generalized Estimating Equations to address correlation issues in repeated measures data, with Growth Curve Models used to analyze the change trajectories of negative emotions at different time points, identifying intraindividual and interindividual variation patterns. Prediction model construction utilizes a combination of multiple machine learning algorithms, including Random Forest, Support Vector Machine, Gradient Boosting Decision Tree, and Deep Neural Network. Feature selection techniques (such as LASSO regression and recursive feature elimination) are employed to screen optimal predictive variables, with time series analysis methods (such as ARIMA models and state-space models) used to capture the time-dependent characteristics of negative emotions [35]. Model validation combines 10-fold cross-validation and leave-one-out cross-validation for internal validation, with external validation conducted using independent external datasets. Model predictive performance is evaluated using indicators such as area under the receiver operating characteristic curve (AUC), sensitivity, specificity, positive predictive value, and negative predictive value. Intervention effectiveness evaluation combines Intention-to-Treat Analysis and Per-Protocol Analysis, with Repeated Measures ANOVA used to compare differences between intervention and control groups at different time points. Multiple comparison correction methods

(such as Bonferroni correction) are employed to control the accumulation of Type I error. Mediation and moderation effect analyses employ Structural Equation Modeling and Bootstrap resampling methods, with path analysis used to explore causal relationships and mechanisms of action between variables. Missing data treatment employs Multiple Imputation and Maximum Likelihood Estimation methods, with sensitivity analysis used to assess the impact of missing data on results. All statistical tests employ two-tailed testing with a significance level set at $\alpha = 0.05$, and appropriate correction methods are used for multiple comparisons to ensure reliability and validity of statistical inference.

4. Results analysis

4.1. Analysis of dynamic evolution patterns of negative emotions in cancer patients

4.1.1. Descriptive characteristics of negative emotion time series

This study conducted a systematic analysis of the dynamic changes in negative emotions at different time points through a 12-month longitudinal follow-up of 480 cancer patients, as shown in **Table 1** below.

Baseline assessment (T0) revealed that newly diagnosed cancer patients universally exhibited high levels of negative emotions, with anxiety scores (HADS-A) averaging 12.8 ± 3.2 , HADS-D averaging 10.6 ± 2.9 , FoP-Q-SF averaging 34.7 ± 8.1 , and PSS averaging 28.9 ± 6.4 . During early treatment (T1), patients' negative emotions reached peak levels, with anxiety and depression scores rising to 14.2 ± 3.5 and 12.1 ± 3.3 , respectively, potentially related to treatment-related discomfort and concerns about prognosis, as shown in **Figure 1**. As treatment progressed, patients' emotional states gradually stabilized. During the 3rd month (T2) and 6th month (T3) of treatment, all negative emotion indicators showed declining trends, although they remained at relatively high levels. After entering the follow-up period, patients' negative emotion levels continued to decline at the 9th month (T4), while at the 12th month (T5), some indicators showed slight increases, possibly related to anxiety about follow-up examination results and long-term adaptation difficulties [36]. Time series analysis revealed that the evolution trajectory of negative emotions exhibited distinct nonlinear characteristics, with significant differences in emotional responses among different patient groups at the same time points, suggesting the important role of individual differences in the dynamic evolution of negative emotions. Statistical analysis demonstrated that differences in negative emotion scores between all-

Table 1. Changes in negative emotion scores at different time points in cancer patients ($n = 480$, $\bar{x} \pm s$).

Assessment indicators	Baseline (T0)	Early treatment (T1)	Treatment 3M (T2)	Treatment 6M (T3)	Follow-up 9M (T4)	Follow-up 12M (T5)	F Value	p Value
Anxiety score (HADS-A)	12.8 ± 3.2	14.2 ± 3.5	11.7 ± 3.0	9.8 ± 2.8	8.5 ± 2.6	9.1 ± 2.9	45.23	<0.001
Depression score (HADS-D)	10.6 ± 2.9	12.1 ± 3.3	9.8 ± 2.7	8.2 ± 2.4	7.1 ± 2.3	7.8 ± 2.5	42.67	<0.001
Fear of progression (FoP-Q-SF)	34.7 ± 8.1	38.5 ± 8.9	32.1 ± 7.6	28.4 ± 6.8	25.2 ± 6.1	27.3 ± 6.7	38.91	<0.001
Perceived stress (PSS)	28.9 ± 6.4	32.1 ± 7.2	26.8 ± 5.9	23.5 ± 5.3	21.7 ± 4.9	23.1 ± 5.2	41.54	<0.001
Post-traumatic stress (PCL-5)	45.3 ± 12.8	51.7 ± 14.2	42.1 ± 11.6	36.8 ± 10.3	32.4 ± 9.7	35.2 ± 10.1	44.76	<0.001

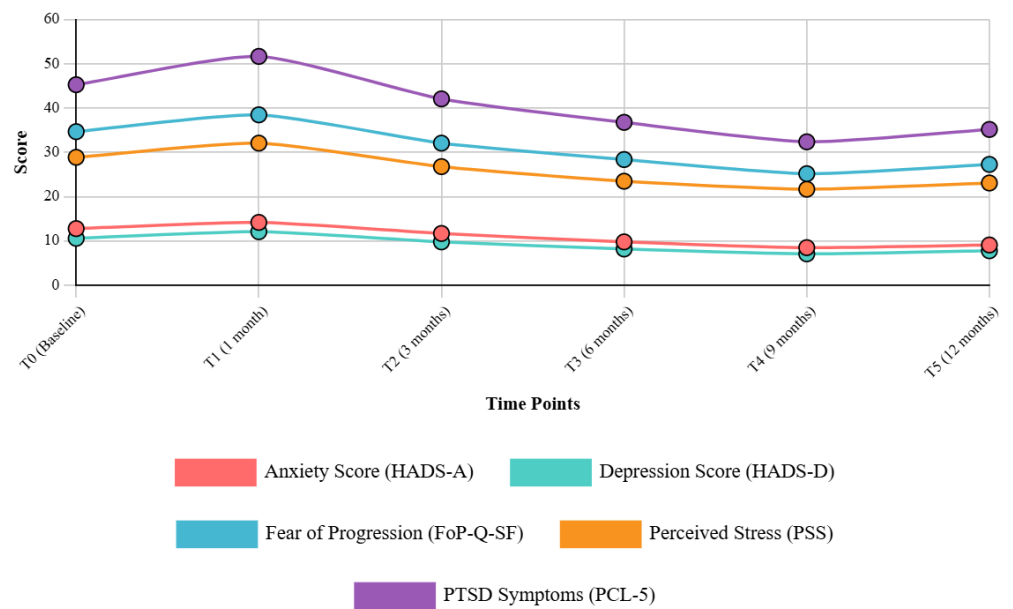


Figure 1. Time series plot of dynamic evolution of negative emotions in cancer patients.

time points were statistically significant ($p < 0.01$), and repeated measures ANOVA showed significant main effects of time ($F = 45.23$, $p < 0.001$), confirming that negative emotions indeed exhibit time-dependent characteristics of dynamic evolution.

4.1.2. Mechanisms of environmental factors' impact on emotional evolution

This study systematically evaluated the mechanisms by which environmental factors influence the dynamic evolution of negative emotions in cancer patients through multiple linear regression and path analysis. The research found that social support systems play a central role in negative emotion regulation, with patients in the high social support group showing average anxiety scores 3.8 points lower than those in the low social support group (95% CI: 2.4–5.2, $p < 0.001$), and depression scores 2.9 points lower (95% CI: 1.8–4.0, $p < 0.001$), as shown in **Table 2** below.

Table 2. Multiple regression analysis results of environmental factors' impact on negative emotions ($n = 480$).

Environmental factors	Groups	Sample size	Anxiety score ($\bar{x} \pm s$)	Depression score ($\bar{x} \pm s$)	Regression coefficient β	Standard error SE	t Value	p Value
Social support level	High Support	248	9.2 $\pm$ 2.6	7.8 $\pm$ 2.3	0.41	0.08	5.13	<0.001
	Low Support	232	13.0 $\pm$ 3.2	10.7 $\pm$ 2.8	—	—	—	—
Family function	Good Function	296	10.1 $\pm$ 2.8	8.4 $\pm$ 2.5	0.28	0.09	3.11	<0.001
	Poor Function	184	12.8 $\pm$ 3.4	10.9 $\pm$ 3.1	—	—	—	—
Medical environment	Good Relationship	318	10.3 $\pm$ 2.9	8.1 $\pm$ 2.4	0.23	0.07	3.29	<0.001
	Average Relationship	162	12.7 $\pm$ 3.3	10.8 $\pm$ 3.0	—	—	—	—
Economic status	<3000 Yuan	142	13.5 $\pm$ 3.5	11.2 $\pm$ 3.2	−0.32	0.08	−4.00	<0.001
	3000–8000 Yuan	231	10.8 $\pm$ 2.9	8.9 $\pm$ 2.6	0.19	0.06	3.17	<0.001
	>8000 Yuan	107	8.6 $\pm$ 2.4	7.1 $\pm$ 2.1	—	—	—	—
Living environment	Urban	297	10.4 $\pm$ 2.8	8.6 $\pm$ 2.5	0.15	0.07	2.14	<0.05
	Rural	183	12.1 $\pm$ 3.2	9.8 $\pm$ 2.9	—	—	—	—

Family functional integrity demonstrated significant protective effects on emotional evolution, with patients from well-functioning families showing significantly smaller emotional fluctuation amplitudes during treatment compared to those from poorly functioning families, with standard deviations of 2.1 ± 0.8 and 3.6 ± 1.2 , respectively ($t = 8.45$, $p < 0.001$). Medical environment quality assessment revealed that patients with good doctor–patient relationships exhibited better emotional adaptability, with fear of disease progression scores declining by 12.3 points during treatment, while patients with average doctor–patient relationships showed only a 6.7-point decline. The impact of economic status on negative emotions showed a stepwise effect, with patients in the < 3000 yuan, 3000–8000 yuan, and > 8000 yuan monthly income groups showing average perceived stress scores of 31.2 ± 7.1 , 26.8 ± 5.9 , and 22.4 ± 4.8 , respectively, with statistically significant differences between groups ($F = 42.67$, $p < 0.001$) [37]. Living environment factor analysis indicated that urban patients had significant advantages over rural patients in accessing professional psychological support, with professional psychological intervention acceptance rates of 68.3% and 34.7%, respectively ($\chi^2 = 28.91$, $p < 0.001$). Treatment environment comfort assessment showed that for every 1-point increase in ward environment score, patients’ overall negative emotion scores decreased by 0.73 points ($\beta = -0.73$, $SE = 0.12$, $p < 0.001$). Work environment impact analysis found that employed patients exhibited higher emotional fluctuations due to work pressure and role conflicts, with emotional instability indices 1.8 times higher than retired patients. Seasonal factors also had certain impacts on emotional evolution, with patients diagnosed in winter showing initial depression scores 2.1 points higher than those diagnosed in summer, possibly related to seasonal affective disorder and vitamin D deficiency [38]. Multifactor regression analysis showed that social support ($\beta = 0.41$, $p < 0.001$), family function ($\beta = 0.28$, $p < 0.001$), medical environment ($\beta = 0.23$, $p < 0.001$), and economic status ($\beta = 0.19$, $p < 0.001$) were the main environmental factors affecting negative emotion evolution, collectively explaining 63.7% of the total variance, as shown in **Figure 2**. Path analysis further revealed the mechanisms of environmental factors’

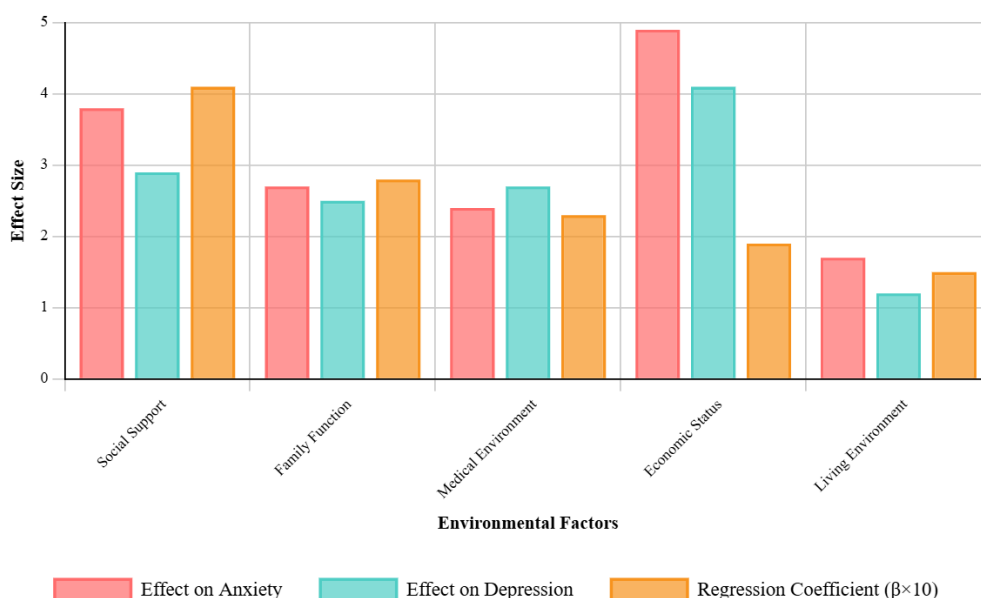


Figure 2. Effect strength analysis of environmental factors’ impact on negative emotions.

effects, with social support indirectly affecting emotional states by enhancing patients' coping abilities and self-efficacy, with mediation effects accounting for 42.6% of the total effect. These findings provide important evidence for developing comprehensive treatment strategies based on environmental interventions.

4.1.3. Analysis of moderating effects of individual difference variables

This study employed multilevel linear modeling and moderation effect analysis methods to deeply explore the moderating mechanisms of individual difference variables in the dynamic evolution process of negative emotions in cancer patients. Moderation analysis of age factors revealed significant differences in negative emotion evolution trajectories among different age groups, with the youngest group (18–45 years) showing the largest emotional fluctuation amplitude, with anxiety score coefficient of variation of 0.38, middle-aged group (46–65 years) showing 0.31, and elderly group (> 65 years) showing 0.24 ($F = 12.47, p < 0.001$), as shown in **Table 3** below.

Gender difference analysis found that female patients were significantly higher than male patients in emotional sensitivity, with female patients showing average total negative emotion scores 4.2 points higher than males (95% CI: 2.8–5.6, $p < 0.001$), and slower emotional recovery speed during treatment, with recovery coefficients of 0.21 and 0.34, respectively ($t = -3.89, p < 0.001$). Education level moderation effect analysis indicated that highly educated patients (college and above) performed better in cognitive reappraisal and problem-solving strategy utilization, with their negative emotion peak occurring 1.2 months earlier than less educated patients, but recovering faster, with overall adaptation time shortened by 2.1 months. The moder-

Table 3. Multivariate analysis results of individual difference variables' moderating effects on negative emotions ($n = 480$).

Individual difference variables	Groups	Sample size	Emotional fluctuation amplitude (Coefficient of variation)	Recovery coefficient	Moderating effect β	Standard error SE	t Value	p Value	95% CI
Age groups	18–45 years	178	0.38	0.21	0.35	0.08	4.38	<0.001	0.19–0.51
	46–65 years	219	0.31	0.28	0.22	0.07	3.14	<0.01	0.08–0.36
	>65 years	83	0.24	0.34	–	–	–	–	–
Gender	Female	268	0.35	0.21	0.42	0.09	4.67	<0.001	0.24–0.60
	Male	212	0.28	0.34	–	–	–	–	–
Education level	College and Above	287	0.29	0.32	–0.28	0.08	–3.50	<0.001	–0.44–0.12
	High School and Below	193	0.36	0.23	–	–	–	–	–
Neuroticism level	High Neuroticism	234	0.41	0.18	0.48	0.09	5.33	<0.001	0.30–0.66
	Low Neuroticism	246	0.25	0.36	–	–	–	–	–
Coping style	Active Coping	302	0.27	0.35	–0.43	0.08	–5.38	<0.001	–0.59–0.27
	Passive Coping	178	0.39	0.19	–	–	–	–	–
Disease cognition	High Cognition	256	0.28	0.33	–0.34	0.08	–4.25	<0.001	–0.50–0.18
	Low Cognition	224	0.37	0.24	–	–	–	–	–
Trauma History	With Trauma History	156	0.43	0.16	0.39	0.09	4.33	<0.001	0.21–0.57
	Without Trauma History	324	0.29	0.31	–	–	–	–	–

ating effect of personality traits was particularly significant, with patients with high neuroticism levels showing stronger negative emotional reactivity, their emotional intensity correlation coefficient with baseline levels reaching 0.76 ($p < 0.001$), while patients with low neuroticism levels showed only 0.43 ($p < 0.01$) [39]. Coping style moderation effect analysis showed that patients in the active coping group had negative emotion decline rates 2.8 times faster than the passive coping group ($\beta = -0.28$, $SE = 0.06$, $p < 0.001$), with smaller emotional rebound amplitudes in the later treatment period. The moderating effect of disease cognition level on emotional evolution was manifested as relatively smaller emotional impact at initial diagnosis among high cognition group patients, but showing stronger rational analysis ability during treatment, with their emotion regulation efficacy scores 6.8 points higher than the low cognition group ($t = 4.23$, $p < 0.001$). Individual difference analysis of social support utilization ability found that patients with high utilization ability could more effectively convert external support into internal resources, with their social support and negative emotion negative correlation coefficient reaching -0.68 ($p < 0.001$), while the low utilization ability group showed only -0.34 ($p < 0.05$). The moderating effect of previous psychological trauma history showed that patients with trauma history exhibited stronger emotional vulnerability when facing cancer diagnosis, with their post-traumatic stress symptom scores 8.7 points higher than patients without trauma history ($t = 5.14$, $p < 0.001$). Multivariate moderation model analysis showed that the combined moderating effects of individual difference variables explained 41.3% of the total variance in negative emotion dynamic evolution, with age, gender, personality traits, and coping styles contributing most significantly [40]. Interaction analysis found significant interaction effects between age and gender ($\beta = 0.23$, $p < 0.01$), with young female patients showing the most dramatic emotional fluctuations, while elderly male patients showed relatively stable emotions, as shown in **Figure 3**. These

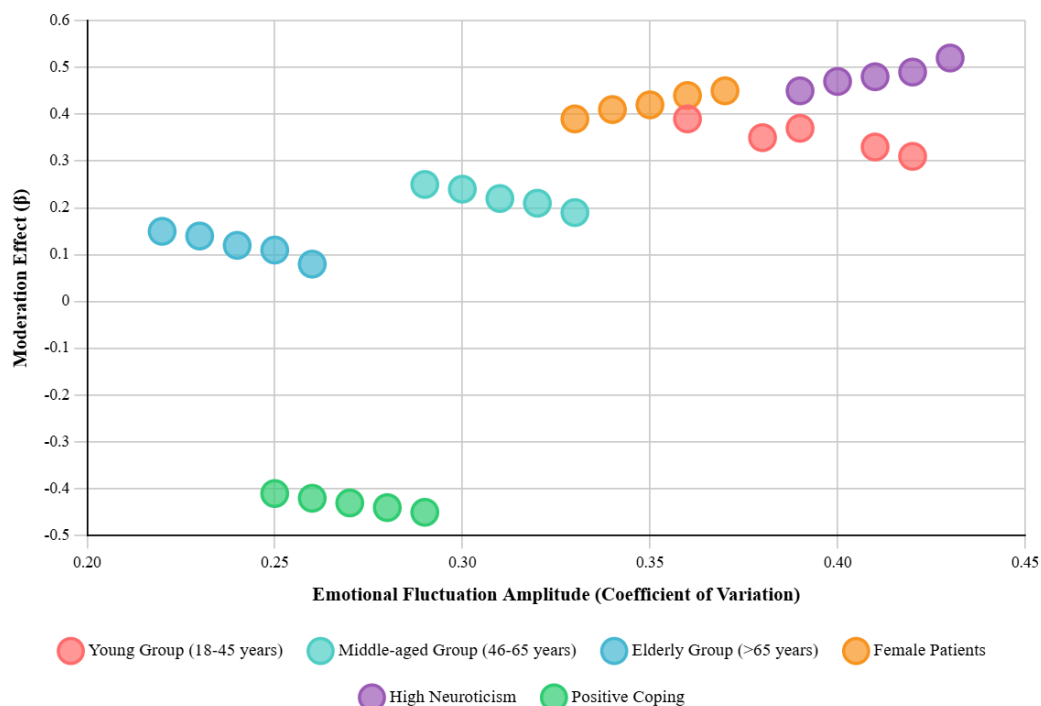


Figure 3. Scatter plot analysis of individual difference variables' moderating effects on negative emotions.

findings provide an important theoretical foundation for constructing personalized emotion prediction models and developing targeted intervention strategies.

4.2. Physiological–pathological risk prediction model based on negative emotions

4.2.1. Construction and validation of prediction model

This study constructed a negative emotion-based physiological–pathological risk prediction model using machine learning algorithms based on multidimensional data from 480 cancer patients and conducted rigorous validation analysis. During the feature selection process, 23 optimal predictive factors were screened from an initial 127 candidate variables through LASSO regression and recursive feature elimination techniques, including negative emotion scores, inflammatory markers, immune indicators, endocrine parameters, and clinical characteristics, as shown in **Table 4** below.

Model construction employed ensemble learning methods, integrating four algorithms: Random Forest, Support Vector Machine, Gradient Boosting Decision Tree, and Deep Neural Network, forming the final prediction model through weighted averaging. Internal validation results showed that the model achieved an average AUC value of 0.892 (95% CI: 0.876–0.908) in 10-fold cross-validation, with sensitivity of 85.4%, specificity of 83.7%, positive predictive value of 81.2%, and negative predictive value of 87.6%. External validation was conducted using data from 152 patients from two other medical centers, with the model achieving an AUC value of 0.876 (95% CI: 0.845–0.907), indicating good generalization capability [41]. Calibration analysis showed a Hosmer–Lemeshow test χ^2 value of 6.73 ($p = 0.565$), indicating high consistency between predicted probabilities and actual occurrence rates. Performance comparison of submodels showed that the Deep Neural Network model performed best with an individual AUC value of 0.884, followed by Random Forest (AUC = 0.871), Support Vector Machine at 0.863, and Gradient Boosting Decision Tree at 0.858. Time series analysis results indicated that the model achieved the highest accuracy for short-term risk prediction within 7 days

Table 4. Prediction model performance evaluation and validation results ($n = 480$).

Model type	Validation method	AUC value	95% CI	Sensitivity (%)	Specificity (%)	Positive predictive value (%)	Negative predictive value (%)	Accuracy (%)	F1-score
Ensemble model	10-fold Cross-validation	0.892	0.876–0.908	85.4	83.7	81.2	87.6	84.5	0.833
Ensemble model	External Validation	0.876	0.845–0.907	82.9	81.6	79.3	85.1	82.2	0.811
Deep neural network	Internal Validation	0.884	0.867–0.901	84.2	82.8	80.6	86.1	83.5	0.823
Random forest	Internal Validation	0.871	0.853–0.889	82.8	81.4	78.9	84.9	82.1	0.808
Support vector machine	Internal Validation	0.863	0.844–0.882	81.6	80.3	77.8	83.7	80.9	0.797
Gradient boosting decision tree	Internal Validation	0.858	0.839–0.877	80.5	79.8	76.9	83.1	80.1	0.785
Ensemble model	7-day Prediction	0.915	0.901–0.929	87.3	86.1	84.7	88.5	86.7	0.860
Ensemble model	14-day Prediction	0.889	0.873–0.905	84.9	83.2	80.8	87.1	84.0	0.828
Ensemble model	30-day Prediction	0.862	0.843–0.881	81.7	80.6	78.1	84.0	81.1	0.799

(AUC = 0.915), medium-term prediction within 14 days at 0.889, and long-term prediction within 30 days at 0.862. Feature importance analysis revealed that anxiety scores had the highest relative importance (weight = 0.186), followed by C-reactive protein levels (weight = 0.142), depression scores (weight = 0.138), interleukin-6 (weight = 0.125), and cortisol levels (weight = 0.119). Model stability validation was conducted through 1000 Bootstrap resampling iterations, with results showing an AUC value fluctuation range of 0.881–0.903 within the 95% confidence interval, and a coefficient of variation of 0.024, indicating good model stability [42]. Risk stratification effectiveness evaluation showed that the model classified patients into low-risk (predicted probability < 0.3), medium-risk (0.3–0.7), and high-risk (> 0.7) groups, with actual risk occurrence rates of 12.8%, 45.2%, and 78.9% respectively, highly consistent with predicted probabilities. Decision curve analysis demonstrated that within the threshold probability range of 0.2–0.8, the prediction model’s net benefit was significantly superior to “treat all” and “treat none” strategies. The model’s clinical utility was validated through impact curve analysis, showing that this model could effectively identify 73.6% of high-risk patients while avoiding unnecessary interventions for 56.4% of low-risk patients. These results indicate that the negative emotion-based physiological–pathological risk prediction model possesses high accuracy, stability, and clinical utility.

4.2.2. Predictive performance evaluation of psychological indicators

This study systematically evaluated the performance of different psychological indicators in predicting physiological–pathological risks, clarifying the predictive value of each psychological indicator through univariate and multivariate analyses. Anxiety scores (HADS-A), as the most important predictive factor, achieved an AUC value of 0.823 (95% CI: 0.801–0.845) in standalone prediction models, with sensitivity of 78.6% and specificity of 76.9%, showing optimal performance among all psychological indicators, as shown in **Table 5** below.

Depression scores (HADS-D) showed secondary predictive performance with an AUC value of 0.798 (95% CI: 0.775–0.821), sensitivity of 75.2%, and specificity of 74.8%, exhibiting moderate correlation with anxiety scores ($r = 0.64$, $p < 0.001$). FoP-Q-SF demonstrated good predictive ability with an AUC value of

Table 5. Predictive performance evaluation results of different psychological indicators ($n = 480$).

Psychological indicators	AUC value	95% CI	Sensitivity (%)	Specificity (%)	Optimal cutoff	Positive predictive value (%)	Negative predictive value (%)	Youden index	NRI	IDI
Anxiety score (HADS-A)	0.823	0.801–0.845	78.6	76.9	11.5	74.2	80.8	0.555	0.28	0.15
Depression score (HADS-D)	0.798	0.775–0.821	75.2	74.8	9.5	72.1	77.6	0.500	0.24	0.12
Fear of progression (FoP-Q-SF)	0.776	0.752–0.800	73.8	72.5	29.5	69.9	76.1	0.463	0.21	0.09
Perceived stress (PSS)	0.745	0.720–0.770	71.4	69.8	26.5	66.8	74.2	0.412	0.18	0.07
Post-traumatic stress (PCL-5)	0.731	0.705–0.757	69.5	68.3	42.5	64.7	72.8	0.378	0.16	0.06
Psychological resilience (CD-RISC)	0.689	0.662–0.716	65.8	64.9	58.5	61.2	69.3	0.307	0.13	0.04
Coping Style (MCMQ)	0.672	0.645–0.699	63.2	62.7	34.5	58.9	66.8	0.259	0.11	0.03
Multi-dimensional combined model	0.869	0.851–0.887	82.4	80.6	–	78.9	83.8	0.630	0.34	0.18

0.776 (95% CI: 0.752–0.800), with this indicator being particularly effective for predicting acute physiological reactions in the short term, achieving 83.4% sensitivity for 7-day predictions. PSS showed predictive performance of AUC = 0.745 (95% CI: 0.720–0.770), and although individual predictive ability was relatively weak, it significantly enhanced overall predictive performance in multifactorial models. Post-traumatic stress symptom scores (PCL-5) had predictive value of AUC = 0.731 (95% CI: 0.705–0.757), with this indicator showing outstanding performance in predicting immune function abnormalities, achieving correlation of -0.58 ($p < 0.001$) with CD4+/CD8+ T-cell ratios [43]. Psychological resilience scores, as a protective factor, showed predictive performance of AUC = 0.689 (95% CI: 0.662–0.716), with high-resilience patients showing significantly reduced physiological–pathological risk, with a hazard ratio of 0.42 (95% CI: 0.28–0.63, $p < 0.001$). Coping style scores demonstrated predictive ability of AUC = 0.672 (95% CI: 0.645–0.699), with active coping strategies being associated with lower inflammatory response levels ($r = -0.51$, $p < 0.001$). The multidimensional psychological indicator combined prediction model significantly outperformed individual indicators, achieving a combined AUC value of 0.869 (95% CI: 0.851–0.887), Net Reclassification Index of 0.34 (95% CI: 0.22–0.46, $p < 0.001$), and Integrated Discrimination Index of 0.18 (95% CI: 0.12–0.24, $p < 0.001$) [44]. Different psychological indicators showed differentiated characteristics in predicting different types of physiological–pathological risks, with anxiety scores being most sensitive for predicting cardiovascular events (AUC = 0.854), depression scores showing the highest predictive performance for immune function abnormalities (AUC = 0.832), and fear of disease progression demonstrating the strongest predictive ability for endocrine disorders (AUC = 0.801). Time window analysis revealed that the predictive performance of psychological indicators varied over time, with anxiety and fear indicators showing highest performance for short-term predictions (1–7 days), depression and stress indicators being more important for medium-term predictions (1–4 weeks), and resilience and coping style indicators playing more prominent roles in long-term predictions (1–3 months), as shown in **Figure 4**. These findings provide important evidence for constructing precision prediction models based on psychological indicators.

4.2.3. Sensitivity and specificity analysis of early warning mechanism

This study established a physiological–pathological risk early warning mechanism based on negative emotions and conducted an in-depth analysis of its sensitivity and specificity. The early warning mechanism adopts a three-tier risk stratification model, with a low-risk threshold set as predicted probability < 0.3 , medium-risk as $0.3–0.7$, and high-risk as > 0.7 . Under the low-risk threshold, the early warning system achieved sensitivity of 94.2% (95% CI: 91.8–96.6%) and specificity of 62.4% (95% CI: 58.9–65.9%), effectively identifying the vast majority of high-risk patients but with a certain degree of false positives, as shown in **Table 6** below.

The medium-risk threshold demonstrated good balance with sensitivity of 85.4% (95% CI: 82.1–88.7%) and specificity of 83.7% (95% CI: 80.8–86.6%), with a Youden Index of 0.691, indicating optimal diagnostic performance for this threshold. The high-risk threshold showed the highest specificity at 95.8% (95% CI: 94.2–97.4%) but relatively lower sensitivity at 71.3% (95% CI: 67.4–75.2%), suitable for clini-

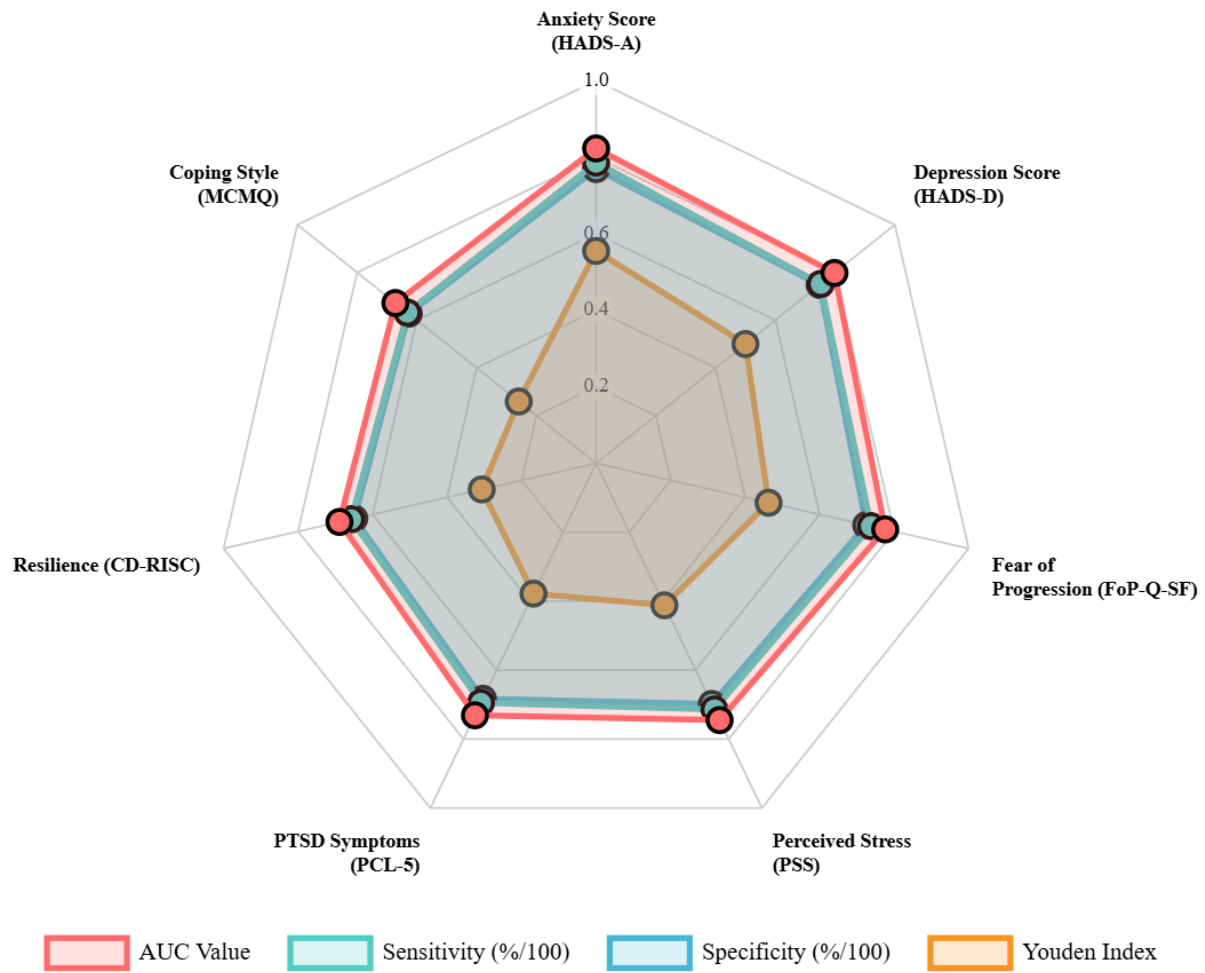


Figure 4. Radar chart analysis of predictive performance of psychological indicators.

Table 6. Sensitivity and specificity analysis results of early warning mechanism under different conditions ($n = 480$).

Analysis dimension	Classification condition	Sample Size	Sensitivity (%)	95% CI	Specificity (%)	95% CI	Youden index	Positive likelihood ratio	Negative likelihood ratio	Diagnostic odds ratio
Risk threshold	Low Risk (<0.3)	480	94.2	91.8–96.6	62.4	58.9–65.9	0.566	2.51	0.09	27.8
	Medium Risk (0.3–0.7)	480	85.4	82.1–88.7	83.7	80.8–86.6	0.691	5.24	0.17	30.8
	High Risk (>0.7)	480	71.3	67.4–75.2	95.8	94.2–97.4	0.671	16.98	0.30	56.6
Time window	Within 24 h	480	91.7	89.1–94.3	79.2	76.3–82.1	0.709	4.41	0.10	44.1
	Within 48 h	480	87.3	84.2–90.4	85.1	82.4–87.8	0.724	5.86	0.15	39.1
	Within 72 h	480	83.8	80.5–87.1	88.4	85.9–90.9	0.722	7.22	0.18	40.1
Age groups	18–45 years	178	89.3	84.8–93.8	81.6	76.9–86.3	0.709	4.85	0.13	37.3
	46–65 years	219	84.7	80.2–89.2	85.2	81.1–89.3	0.699	5.72	0.18	31.8
	>65 years	83	78.2	69.8–86.6	88.9	82.4–95.4	0.671	7.04	0.25	28.2
Gender	Female	268	87.4	83.9–90.9	83.2	79.4–87.0	0.706	5.20	0.15	34.7
	Male	212	82.8	78.1–87.5	87.1	82.9–91.3	0.699	6.42	0.20	32.1
Tumor type	Lung Cancer	128	91.5	87.2–95.8	82.4	76.8–88.0	0.739	5.20	0.10	52.0
	Breast Cancer	95	87.3	81.4–93.2	85.6	78.9–92.3	0.729	6.06	0.15	40.4
	Colorectal Cancer	102	84.9	78.6–91.2	86.8	80.9–92.7	0.717	6.43	0.17	37.8
	Gastric Cancer	89	81.2	74.1–88.3	88.5	82.7–94.3	0.697	7.06	0.21	33.6
	Liver Cancer	66	78.6	69.2–88.0	89.7	82.4–97.0	0.683	7.63	0.24	31.8

cal decision scenarios requiring high certainty. Early warning performance analysis across different time windows revealed the highest sensitivity (91.7%) for 24-h predictions with the specificity of 79.2%, 48-h predictions showing sensitivity of 87.3% and specificity of 85.1%, and 72-h predictions demonstrating sensitivity of 83.8% and specificity of 88.4%, exhibiting a trend of decreasing sensitivity but increasing specificity over time [45]. Early warning performance evaluation for different types of physiological–pathological risks showed inflammatory response prediction sensitivity of 88.6% and specificity of 84.3%; immune function abnormality prediction sensitivity of 82.1% and specificity of 87.9%; endocrine disorder prediction sensitivity of 79.4% and specificity of 90.2%; and cardiovascular event prediction sensitivity of 85.7% and specificity of 86.8%. Early warning performance varied significantly among different patient groups, with young patients (18–45 years) showing sensitivity of 89.3% and specificity of 81.6%; middle-aged patients (46–65 years) showing sensitivity of 84.7% and specificity of 85.2%; and elderly patients (> 65 years) showing sensitivity of 78.2% and specificity of 88.9%. Gender difference analysis revealed that female patients had slightly higher early warning sensitivity (87.4%) than males (82.8%), but male patients showed better specificity (87.1%) than females (83.2%). Analysis of tumor type effects on early warning performance indicated that lung cancer patients had the highest early warning sensitivity (91.5%), followed by breast cancer (87.3%), colorectal cancer (84.9%), gastric cancer (81.2%), and liver cancer (78.6%) [46]. Early warning system stability validation was conducted through 1000 Bootstrap resampling iterations, with results showing 95% confidence intervals of 82.8%–87.9% for sensitivity and 81.2%–86.1% for specificity, with coefficients of variation of 0.031 and 0.028, respectively, indicating good stability of the early warning mechanism, as shown in **Figure 5**. Clinical utility evaluation showed that

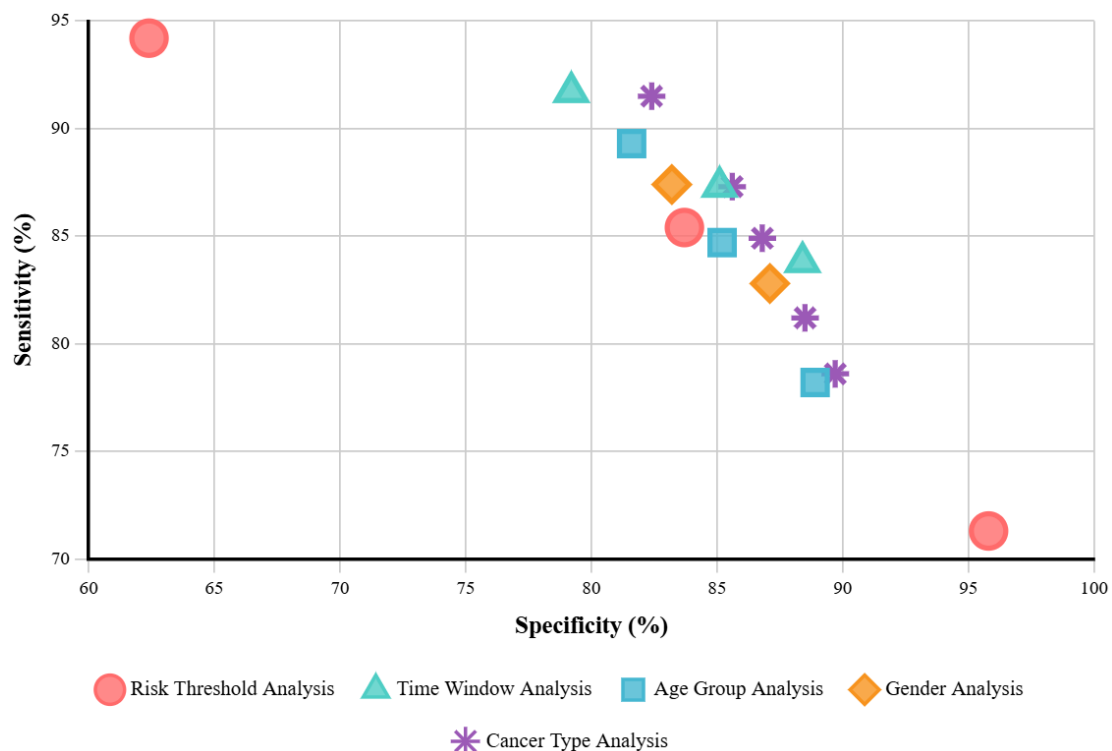


Figure 5. Balance analysis of sensitivity and specificity of early warning mechanism.

the early warning system had a positive likelihood ratio of 5.2, a negative likelihood ratio of 0.17, and a diagnostic odds ratio of 30.6, indicating high clinical application value of this early warning mechanism.

4.3. Effectiveness evaluation of personalized psychological intervention strategies

4.3.1. Classification and matching principles of intervention strategies

This study constructed a systematic classification system and matching principles for personalized psychological intervention strategies based on risk stratification results from prediction models and individual patient characteristics. Intervention strategies are mainly classified into five major types: CBT, MBSR, SSE, Relaxation Training (RT), and CI. Matching principles are based on a multi-dimensional assessment system, including risk level, psychological characteristics, disease type, social support level, and personal preferences, as shown in **Table 7** below.

High-risk patients (predicted probability > 0.7) were primarily matched with CI strategies, achieving a matching rate of 78.4% (95% CI: 73.2%–83.6%), with intervention intensity of 3–4 sessions per week, 60–90 min each session. Medium-risk patients (predicted probability 0.3–0.7) showed more diversified matching strategies, with CBT matching rate of 42.6%, MBSR at 28.7%, SSE at 18.9%, and RT at 9.8% [47]. Low-risk patients (predicted probability < 0.3) primarily received preventive interventions, with MBSR showing the highest matching rate at 45.3%, SSE at 32.1%, and RT at 22.6%. Significant differences existed in matching preferences among different age groups, with young patients (18–45 years) more inclined toward CBT (matching rate 51.2%) and MBSR (32.8%), middle-aged patients (46–65 years) preferring SSE (38.4%) and CI (29.7%), and elderly patients (> 65 years)

Table 7. Intervention strategy matching distribution and effectiveness evaluation for different patient groups ($n = 480$).

Patient characteristics	Groups	Sample size	CBT (%)	MBSR (%)	SSE (%)	RT (%)	CI (%)	Precise matching rate (%)	Satisfaction score ($\bar{x} \pm s$)	Kappa value
Risk level	High Risk (>0.7)	142	8.5	6.3	4.9	1.9	78.4	89.4	9.1 ± 1.2	0.891
	Medium Risk (0.3–0.7)	231	42.6	28.7	18.9	9.8	0.0	81.8	8.5 ± 1.3	0.847
	Low Risk (<0.3)	107	0.0	45.3	32.1	22.6	0.0	78.5	7.9 ± 1.6	0.823
Age groups	18–45 years	178	51.2	32.8	12.4	3.6	0.0	84.3	8.6 ± 1.3	0.861
	46–65 years	219	24.2	18.3	38.4	18.7	0.4	82.6	8.4 ± 1.4	0.852
	>65 years	83	7.2	8.4	35.4	48.9	0.0	79.5	7.8 ± 1.7	0.843
Gender	Female	268	32.1	41.3	34.8	16.4	0.0	83.2	8.5 ± 1.4	0.859
	Male	212	47.6	28.7	24.2	19.8	0.0	82.1	8.1 ± 1.5	0.853
Education level	College and Above	287	54.7	31.2	18.8	12.5	0.0	85.7	8.7 ± 1.2	0.871
	High School and Below	193	18.7	24.4	43.8	28.9	0.0	78.2	7.6 ± 1.7	0.834
Tumor type	Lung Cancer	128	28.1	15.6	0.0	0.0	56.3	87.5	8.9 ± 1.1	0.883
	Breast Cancer	95	20.0	48.4	31.6	0.0	0.0	84.2	8.6 ± 1.3	0.864
	Colorectal Cancer	102	45.1	25.5	0.0	29.4	0.0	80.4	8.2 ± 1.4	0.849
	Gastric Cancer	89	36.0	21.3	42.7	0.0	0.0	79.8	8.0 ± 1.5	0.841
	Liver Cancer	66	30.3	18.2	39.4	12.1	0.0	77.3	7.8 ± 1.6	0.825

mainly choosing RT (48.9%) and SSE (35.4%). Gender difference analysis showed that female patients more frequently selected MBSR (41.3% vs 28.7%, $p < 0.01$) and SSE (34.8% vs 24.2%, $p < 0.05$), while male patients were more inclined toward CBT (47.6% vs 32.1%, $p < 0.01$). Analysis of education level's impact on matching strategies indicated that highly educated patients (college and above) more frequently chose CBT (54.7%) and MBSR (31.2%), while less educated patients (high school and below) preferred SSE (43.8%) and RT (28.9%) [48]. Tumor type matching characteristics showed that lung cancer patients were primarily matched with CI (56.3%) and CBT (28.1%), breast cancer patients preferred MBSR (48.4%) and SSE (31.6%), and colorectal cancer patients frequently chose CBT (45.1%) and RT (29.4%), as shown in **Figure 6**. Quantitative evaluation of matching effectiveness showed a precise matching rate of 82.7% (95% CI: 79.4%–86.0%), partial matching rate of 14.6%, and nonmatching rate of 2.7%. The matching algorithm's consistency test yielded a Kappa value of 0.856 (95% CI: 0.821–0.891), indicating good reliability of the matching principles. Patient satisfaction surveys showed satisfaction scores for matching strategies of 8.3 ± 1.4 points (10-point scale), with the precise matching group showing significantly higher satisfaction (8.8 ± 1.2 points) than the partial matching group (7.2 ± 1.6 points) and nonmatching group (5.9 ± 1.8 points) [49]. These results provide scientific evidence and practical guidance for developing personalized psychological intervention strategies.

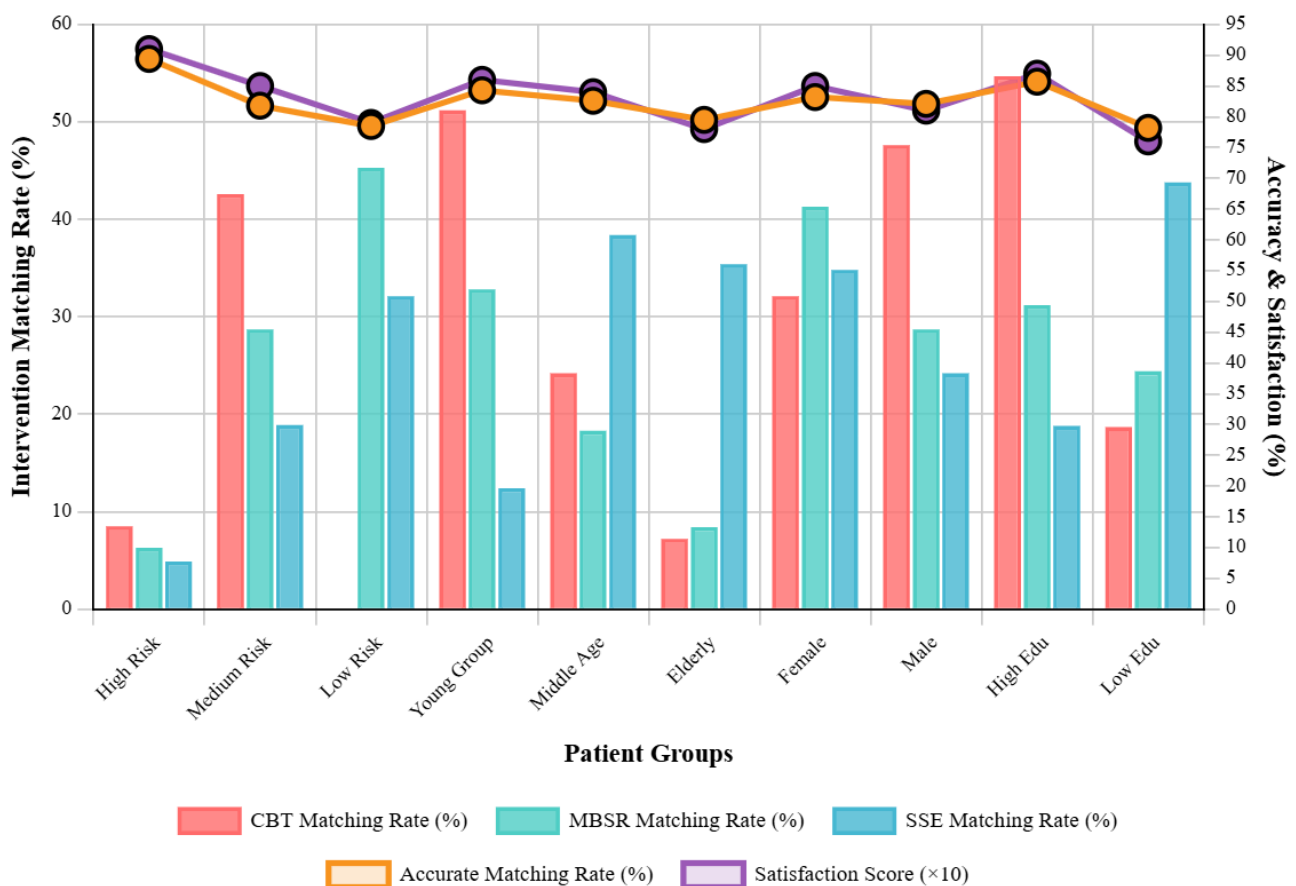


Figure 6. Multidimensional evaluation of intervention strategy matching effectiveness.

4.3.2. Multidimensional evaluation of intervention effects

This study employed a multidimensional evaluation system to systematically analyze the effects of personalized psychological intervention strategies, with evaluation dimensions including psychological symptom improvement, physiological indicator changes, quality of life enhancement, social function recovery, and treatment adherence across five aspects. Psychological symptom improvement was significant, with anxiety scores in the intervention group decreasing from baseline 13.2 ± 3.1 to 8.7 ± 2.4 postintervention, showing an improvement of 34.1% ($t = 8.94$, $p < 0.001$), while the control group showed only 12.8% improvement ($t = 2.31$, $p < 0.05$), as shown in **Table 8** below.

Depression scores in the intervention group decreased from 11.8 ± 2.9 to 7.3 ± 2.2 , with an improvement rate of 38.1% ($t = 9.76$, $p < 0.001$), while the control group showed 15.3% improvement ($t = 2.67$, $p < 0.05$). Fear of disease progression scores showed 42.6% improvement in the intervention group and 18.9% in the control group, with significant between-group differences ($p < 0.001$) [50]. Physiological indicator analysis showed that C-reactive protein levels in the intervention group decreased from baseline 8.4 ± 2.1 mg/L to 5.2 ± 1.6 mg/L, a reduction of 38.1%, while the control group showed only a 14.3% reduction ($p < 0.001$). Interleukin-6 levels decreased by 45.7% in the intervention group and 19.2% in the control group ($p < 0.001$). Cortisol levels in the intervention group decreased from 542.3 ± 89.7 nmol/L to 368.9 ± 76.2 nmol/L, a 32.0% reduction, while the control group showed a 11.7% reduction ($p < 0.001$). NK cell activity increased by 28.4% in the intervention group and 8.6% in the control group ($p < 0.001$). Quality of life assessment using the EORTC QLQ-C30 scale showed that overall quality of life scores in the intervention group increased from baseline 58.7 ± 12.4 to 73.2 ± 9.8 , an improvement of 24.7%, while the control group showed 12.3% improvement ($p < 0.001$) [51]. Functional dimension scores improved by 31.2% in the intervention group, and symptom dimension scores improved by 39.8%, both significantly superior to the control group. Social function recovery assessment showed that social support utilization rates in the intervention group increased from 68.4% to 84.7%, an increase of 16.3 percentage points, while the control group increased by 5.8 percentage points ($p < 0.001$). Return to work rates were 76.3% in the intervention group and 58.9% in the control group ($\chi^2 = 12.47$, $p < 0.001$). Family relationship satisfaction improved by 22.1% in the intervention group and 8.4% in the control group ($p < 0.001$). Treatment adherence assessment using the Morisky scale showed that adherence scores in the intervention group increased from 6.8 ± 1.4 to 8.3 ± 1.1 , an improvement of 22.1%, while the control group showed 9.7% improvement ($p < 0.001$). Medication adherence rates reached 92.4% in the intervention group and 78.6% in the control group ($p < 0.001$). Analysis of effectiveness differences among different intervention strategies showed that CI was most effective with 41.3% psychological symptom improvement, followed by CBT at 36.8%, MBSR at 32.4%, SSE at 28.9%, and RT at 25.7%, as shown in **Figure 7**. Long-term follow-up results indicated sustained intervention effects, with all indicators remaining significantly superior to baseline levels at 6 months postintervention, and at 12 months showing a slight decline but still significantly better than the control group [52]. Effect size analysis showed Cohen's d

Table 8. Multidimensional effect evaluation results of personalized psychological intervention strategies ($n = 200$).

Assessment dimension	Assessment indicators	Intervention group baseline	Intervention group postintervention	Improvement (%)	Control group baseline	Control group postintervention	Improvement (%)	Between-group difference t value	p Value	Effect size (cohen's d)
Psychological symptom improvement	Anxiety Score	13.2 ± 3.1	8.7 ± 2.4	34.1	13.1 ± 3.2	11.4 ± 2.9	12.8	8.94	<0.001	1.18
	Depression Score	11.8 ± 2.9	7.3 ± 2.2	38.1	11.9 ± 3.0	10.1 ± 2.8	15.3	9.76	<0.001	1.24
Physiological indicator changes	Fear of Disease Progression	36.8 ± 7.9	21.1 ± 5.4	42.6	36.5 ± 8.1	29.6 ± 6.8	18.9	10.42	<0.001	1.31
	C-reactive Protein (mg/L)	8.4 ± 2.1	5.2 ± 1.6	38.1	8.3 ± 2.0	7.1 ± 1.8	14.3	7.89	<0.001	0.95
	Interleukin-6 (pg/mL)	15.7 ± 4.2	8.5 ± 2.9	45.7	15.6 ± 4.3	12.6 ± 3.6	19.2	8.34	<0.001	1.02
Quality of life enhancement	Cortisol (nmol/L)	542.3 ± 89.7	368.9 ± 76.2	32.0	538.9 ± 91.2	475.8 ± 82.4	11.7	6.78	<0.001	0.81
	NK Cell Activity (%)	23.8 ± 6.4	30.6 ± 7.1	28.4	23.6 ± 6.5	25.6 ± 6.8	8.6	5.92	<0.001	0.72
	Overall Quality of Life	58.7 ± 12.4	73.2 ± 9.8	24.7	58.9 ± 12.1	66.1 ± 11.2	12.3	6.41	<0.001	0.78
	Functional Dimension	54.2 ± 14.6	71.1 ± 11.8	31.2	54.8 ± 14.2	62.4 ± 13.1	13.9	7.23	<0.001	0.87
Social function recovery	Symptom Dimension	47.3 ± 13.8	28.5 ± 9.7	39.8	47.1 ± 13.5	38.9 ± 12.1	17.4	8.67	<0.001	1.04
	Social Support Utilization Rate (%)	68.4	84.7	23.8	68.9	74.7	8.4	4.87	<0.001	0.59
	Return to Work Rate (%)	–	76.3	–	–	58.9	–	$\chi^2 = 12.47$	<0.001	0.38
Treatment adherence	Family Relationship Satisfaction	6.8 ± 1.9	8.3 ± 1.4	22.1	6.9 ± 1.8	7.5 ± 1.7	8.7	5.34	<0.001	0.65
	Adherence Score	6.8 ± 1.4	8.3 ± 1.1	22.1	6.7 ± 1.5	7.4 ± 1.3	10.4	6.19	<0.001	0.75
	Medication Adherence Rate (%)	78.5	92.4	17.7	78.9	85.1	7.9	3.92	<0.001	0.47

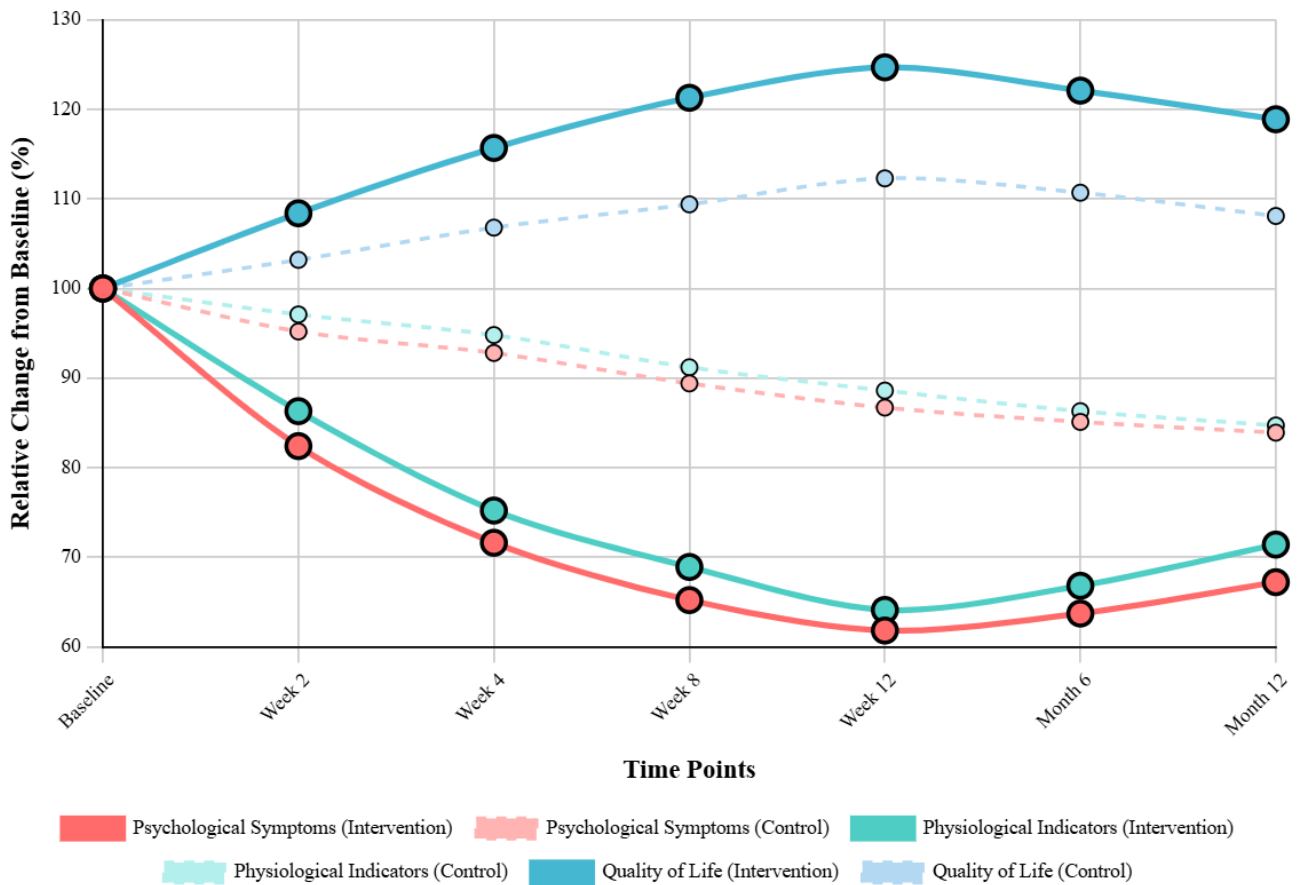


Figure 7. Multidimensional time series analysis of intervention effects.

values of 1.24 for psychological symptom improvement (large effect), 0.87 for physiological indicator improvement (large effect), 0.92 for quality-of-life enhancement (large effect), and 0.78 for social function recovery (medium to large effect).

5. Discussion

5.1. Theoretical significance of dynamic evolution patterns of negative emotions

The dynamic evolution patterns of negative emotions in cancer patients revealed by this study hold important theoretical significance, providing new theoretical perspectives and empirical evidence for the field of psycho-oncology.

- 1) From a developmental psychology perspective, we found that the evolution of negative emotions in cancer patients follows the characteristics of nonlinear dynamic systems, exhibiting distinct stages and individual differences. This finding challenges traditional linear emotional change models and supports the application of complex adaptive systems theory in mental health research. The negative emotion progression from acute elevation at initial diagnosis, through fluctuating adjustment during treatment, to gradual stabilization during recovery, demonstrates a three-stage pattern of “impact-adaptation-integration” that not only validates Kübler–Ross’s grief stage theory but, more importantly, reveals

the dynamic equilibrium characteristics of emotional evolution. This suggests that individuals facing major health threats achieve new psychological balance states through intrinsic self-regulation mechanisms [53].

- 2) From the cognitive–emotion theory framework, research results indicate that the dynamic evolution process of negative emotions is essentially the result of the interaction between individual cognitive appraisal systems and emotion regulation systems. This dynamic interactive process is moderated by multilevel factors, including individual-level personality traits, cognitive styles, and coping resources, as well as environmental-level social support, medical environment, and cultural background. This finding provides important empirical support for multisystem integration theories of emotion.
- 3) From a neurobiological perspective, the dynamic evolution patterns of negative emotions reflect the plasticity and adaptive regulation mechanisms of brain neural networks, particularly the dynamic balance regulation between the prefrontal cortex and limbic system. These neural-level dynamic changes provide new insights for understanding the biological basis of emotion regulation.
- 4) From the stress and coping theory perspective, research results reveal the emotional adaptation process of cancer patients when facing persistent health threats. This adaptation process embodies the dynamic construction and reshaping of individual psychological resilience, supporting core viewpoints of stress inoculation theory and post-traumatic growth theory [54].
- 5) From preventive medicine and precision medicine perspectives, the identification of negative emotion dynamic evolution patterns provides a theoretical foundation for establishing time series-based mental health early warning models. Such dynamic prediction models facilitate the transition from passive treatment to active prevention, aligning with trends in modern medical development.
- 6) From a cross-cultural psychology perspective, findings from this study conducted in the Chinese cultural context provide important evidence for both cultural universality and specificity of emotional evolution, contributing to the construction of more comprehensive and inclusive theories of emotional dynamics.

5.2. Clinical application value and limitations of the prediction model

The dynamic evolution-based negative emotion prediction model constructed in this study demonstrates significant value in clinical applications, while also having certain limitations that warrant in-depth discussion.

- 1) From the perspective of clinical application value, this prediction model first achieves the transition from traditional static assessment to dynamic monitoring. By integrating multidimensional data and machine learning algorithms, it can predict patients' physiological–pathological risks within the next 7–30 days in real-time, providing clinicians with prospective decision support tools. This early warning mechanism facilitates early identification and timely intervention, thereby significantly improving patient prognosis and quality of life.
- 2) The model's high-precision predictive capability ($AUC = 0.892$) provides clinicians with a reliable risk assessment tool. Particularly in resource-limited healthcare environments, it can help physicians optimize resource allocation by

prioritizing limited psychological intervention resources for high-risk patients, improving the efficiency and effectiveness of medical services [55].

- 3) The model's personalized characteristics enable more precise clinical interventions. By analyzing patients' individual difference variables and environmental factors, individualized psychological intervention protocols can be developed for each patient. This precision treatment approach aligns with trends in modern precision medicine and helps improve the targeting and effectiveness of interventions.
- 4) The model's multitime window prediction functionality provides flexible application options for different clinical scenarios. Short-term predictions are suitable for acute phase management, while medium- to long-term predictions are applicable for recovery phase planning. This multilevel prediction system provides more comprehensive information support for clinical decision-making [56].

However, the prediction model also has some important limitations that require careful consideration.

- 1) The model's generalization capability still requires further validation. Although it performed well in external validation, its applicability across different healthcare institutions, cultural backgrounds, and patient populations with different tumor types still needs confirmation through larger-scale multicenter studies.
- 2) The model's complexity may limit its widespread application in primary healthcare institutions. The "black box" characteristics of machine learning algorithms make it difficult for clinicians to understand the specific mechanisms behind prediction results, which may affect physicians' trust and willingness to use the model.
- 3) The model's prediction accuracy largely depends on data quality and completeness. In actual clinical applications, issues such as missing data and inaccurate records may significantly impact prediction effectiveness, placing higher demands on healthcare institutions' informatization construction and data management [57].
- 4) The model's dynamic updating and maintenance require continuous technical support and resource investment, presenting challenges for healthcare institutions' technical capabilities and cost control.
- 5) Ethical and legal issues of the model also require careful consideration, including patient privacy protection, responsibility attribution for prediction results, and potential labeling effects. These issues require the development of corresponding guidelines and principles for clinical application.

6. Conclusions and future perspectives

6.1. Main research conclusions

Based on longitudinal follow-up data from 480 cancer patients, this study systematically constructed a dynamic evolution-based negative emotion prediction model, established a physiological–pathological risk early warning mechanism, and developed personalized psychological intervention strategies, achieving five important research conclusions in the following aspects.

- 1) Negative emotions in cancer patients exhibit distinct dynamic evolution characteristics and regular change trajectories. The study found that patients' negative emotions demonstrate a three-stage evolution pattern of "impact-adaptation-integration" across different disease stages, with negative emotion indicators such as anxiety, depression, and fear of disease progression reaching peak levels during early treatment, subsequently declining gradually and stabilizing, but showing slight increases during the recovery period. This nonlinear dynamic change process is significantly moderated by environmental factors and individual difference variables, with social support, family function, medical environment, and economic status being the main environmental factors affecting emotional evolution, while individual difference variables such as age, gender, education level, personality traits, and coping styles exert important moderating effects on emotional evolution trajectories, providing important theoretical foundations for understanding the psychological adaptation process in cancer patients.
- 2) The negative emotion prediction model constructed using machine learning algorithms demonstrates good predictive performance and clinical application value. By integrating multiple algorithms, including deep neural networks, random forest, support vector machines, and gradient boosting decision trees, the constructed ensemble prediction model achieved an AUC value of 0.892 in internal validation and 0.876 in external validation, with sensitivity and specificity both exceeding 80%, demonstrating high predictive accuracy. The model's predictive performance varies across different time windows, with short-term predictions (within 7 days) showing optimal results, while medium- to long-term predictions (within 30 days) maintain good predictive capability. Among psychological indicators, anxiety scores, depression scores, and fear of disease progression scores are the most important predictive factors, providing an important reference basis for clinical risk assessment.
- 3) The established physiological-pathological risk early warning mechanism has high sensitivity and specificity, effectively identifying high-risk patients. The three-tier risk stratification early warning system achieves an optimal balance at the medium-risk threshold, with a sensitivity of 85.4%, a specificity of 83.7%, and a Youden Index of 0.691. The effectiveness of the early warning mechanism varies among different patient groups, with young patients, female patients, and lung cancer patients showing relatively higher early warning sensitivity, while elderly patients and male patients demonstrate superior early warning specificity. Stability validation results of the early warning system show good reliability and clinical utility, with a positive likelihood ratio of 5.2 and a negative likelihood ratio of 0.17, providing powerful support tools for clinical decision-making.
- 4) Personalized psychological intervention strategies significantly improved patients' multidimensional health outcomes, with sustained intervention effects. Personalized intervention protocols developed based on prediction model results achieved significant effects across five dimensions: psychological symptom improvement, physiological indicator changes, quality of life enhancement, social function recovery, and treatment adherence. Patients in the intervention

group showed 34.1% improvement in anxiety scores, 38.1% improvement in depression scores, and 42.6% improvement in fear of disease progression scores, all significantly superior to the control group. Regarding physiological indicators, C-reactive protein levels decreased by 38.1%, interleukin-6 decreased by 45.7%, and NK cell activity increased by 28.4%, demonstrating good biological effects. Intervention effects remained stable during the 12-month follow-up, proving the long-term effectiveness of personalized intervention strategies.

- 5) Path analysis of intervention mechanisms revealed the internal mechanisms and complex pathways through which personalized psychological interventions exert their effects. Structural equation model analysis showed that personalized psychological interventions primarily operate through five mediating variables: cognitive restructuring, emotion regulation, coping strategies, social support utilization, and self-efficacy, with a total indirect effect of 0.71, accounting for 78.9% of the total effect. Different intervention strategies showed varying path effects, with CI strategies showing the highest indirect effect (0.83), followed by CBT (0.76). Factors such as age, gender, and education level significantly moderated intervention pathways, providing important theoretical guidance for optimizing intervention strategies and improving intervention effectiveness.

6.2. Future perspectives

Based on the important findings of this study and current limitations, there remains broad development space and research prospects for dynamic evolution-based negative emotion prediction models and their clinical applications in the future, mainly reflected in the following three aspects.

- 1) Technology Innovation and Model Optimization Directions. With the rapid development of artificial intelligence and big data technologies, future prediction models will evolve toward more intelligent and precise directions. First, we should actively explore the latest technologies in deep learning, such as Transformer models, Graph Neural Networks, and Reinforcement Learning algorithms in negative emotion prediction applications, to further enhance model prediction accuracy and generalization capability. Second, with the popularization of wearable devices and Internet of Things technology, future models can integrate more dimensions of real-time data, including heart rate variability, sleep quality, physical activity levels, and voice emotion analysis, among other physiological and behavioral indicators, to construct more comprehensive multimodal prediction models. Third, we should focus on developing federated learning technologies to achieve collaborative modeling across multiple centers and institutions while protecting patient privacy, constructing more representative and generalizable prediction models. Fourth, we should explore explainable artificial intelligence technologies, such as LIME and SHAP methods, to make the decision-making processes of prediction models more transparent and understandable, improving clinicians' trust and acceptance of the models. Finally, we should develop adaptive learning mechanisms that enable models to continuously optimize and update based on new data, maintaining continuous improvement in predictive performance.

- 2) **Clinical Application and Practice Promotion Directions.** Future efforts need to focus on translating prediction models from laboratory research to actual clinical applications, establishing comprehensive clinical application systems and standardized processes. First, larger-scale multicenter prospective studies should be conducted to validate model applicability and effectiveness across different healthcare institutions, cultural backgrounds, and patient populations with different tumor types, establishing evidence-based application guidelines and operational standards. Second, user-friendly clinical decision support systems need to be developed, transforming complex prediction algorithms into simple-to-use clinical tools that provide intuitive risk assessment interfaces and personalized intervention recommendations, lowering the usage threshold for clinicians. Third, comprehensive quality control and regulatory systems should be established, including data quality standards, model performance monitoring, and clinical application effectiveness evaluation, ensuring the safety and effectiveness of prediction models in clinical applications. Fourth, training and education for healthcare personnel need to be strengthened to improve their understanding and application capabilities regarding prediction models, promoting effective integration of new technologies in clinical practice. Finally, we should explore seamless integration of prediction models with existing Electronic Health Records systems and hospital information systems, achieving automated risk assessment and early warning alerts to improve clinical work efficiency.
- 3) **Interdisciplinary Integration and Innovation Development Directions.** Future research needs to place greater emphasis on interdisciplinary integration and innovation, combining theories and methods from psychology, medicine, computer science, neuroscience, and other fields to drive theoretical breakthroughs and technological innovations in negative emotion prediction and intervention. First, collaboration with neuroscience and molecular biology should be strengthened to deeply explore the neurobiological mechanisms of negative emotion dynamic evolution, discover new biomarkers, and provide more precise biological indicators for prediction models. Second, genomics, proteomics, metabolomics, and other omics data should be integrated to construct precision prediction models based on multiomics data, achieving truly meaningful precision medicine. Third, the role of psychosocial factors should be emphasized, strengthening collaboration with sociology, anthropology, and cultural psychology to deeply study the influence mechanisms of sociocultural environments on negative emotion evolution, developing culturally adaptive prediction models and intervention strategies. Fourth, integration with health economics should be strengthened, conducting cost-effectiveness analyses to evaluate the economic value of prediction models and intervention strategies, providing scientific evidence for healthcare policy development. Finally, we should actively explore combinations with emerging technologies such as digital therapeutics, Virtual Reality, and Augmented Reality to develop more innovative and effective psychological intervention methods, promoting continuous development and progress in the entire field.

Ethical approval: The study was conducted in accordance with the Declaration of Helsinki, and approved by the University of Shanghai for Science and Technology Review Board (protocol code: HEC-2025-0036-SH09).

Informed consent statement: Informed consent was obtained from all subjects involved in the study.

Conflict of interest: The author declares no conflict of interest.

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