ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Bayesian discriminant model driven educational planning design under optimistic psychological explanation style recognition

Jie Yu[1], *Yujia Peng*[2] *and Yuhua Li*[1,*]

[1] College of Elementary Education, Capital Normal University, Beijing 100048, Beijing, China

[2] Sino-Cuba Friendship Primary Schoo, Beijing 100044, Beijing, China

SUMMARY: *Aiming at the collaborative needs of optimistic psychological explanation style recognition and educational planning for senior primary school students, a Bayesian discriminant model integrating GB, G, B and six-dimensional explanation style features, student attribute features and stage response features is constructed, and a hierarchical educational planning and dynamic feedback optimization mechanism is designed accordingly. The identification experiment was carried out based on 534 valid samples of 560 questionnaires, and the experimental group-control group, pre-test-posttest-follow-up test certificates were implemented on 188 intervention samples. The results show that the Accuracy, Recall and F1-score of the model reach 88.7%, 87.9%and 88.1%respectively, which are better than logistic regression, decision tree and support vector machine. After the implementation of the plan, GB of the experimental class increased from -1.81 to -0.56, and reached 0.19 in the follow-up test stage, B decreased from 12.31 to 10.73, and PVB decreased from 3.72 to 2.72. The research showed that the Bayesian discriminant model could effectively identify students 'optimistic psychological explanation style, and the recognition results could support the generation of differentiated education planning, and had continuous application value for reducing pessimistic attribution and improving optimistic quality.*

KEYWORDS: *Bayesian discriminant model; Optimistic psychological explanation style; Educational planning and design; Dynamic feedback optimization*

1 Introduction

The senior stage of primary school is a critical period for individuals to transition from childhood to adolescence. The density of academic evaluation increases, peer comparison becomes more frequent, and the expectation of going to school is gradually strengthened. As an important part of positive psychological development, optimistic psychological quality can play a protective role in stressful situations, and explanatory style is an important cognitive representation of optimistic psychological quality. If students tend to attribute negative events to stable, universal and unchangeable reasons, they are more likely to form low sense of control, low expectation and low persistence. On the contrary, positive explanation style can enhance learning resilience, goal engagement, and self-regulation ability. At present, school education planning and design are mostly based on grades, classroom performance and general behavior records, and lack of attention is paid to the deep psychological variable of explanation style. As a result, planning schemes more stay at the group average level, and it is difficult to accurately

*liyuhua@cnu.edu.cn
https://doi.org/10.65102/is2026266

Published: 30 April, 2026

reflect students 'differentiated needs of "how to understand failure, how to adjust goals, and how to maintain positive expectations". Therefore, it has obvious theoretical significance and practical value to embed the identification of optimistic psychological explanation style into the process of educational planning and design, and construct an intelligent support path for psychological cognitive differences.

The existing research can be broadly summarized into three paths. First, the research on optimistic psychological quality and explanatory style has revealed that there is a close relationship between positive expectations, attribution style and academic adjustment. Baourda et al. (2024) found that positive psychological intervention at school can significantly improve children's optimism and hope[1]. Henss and Pinquart (2024) proposed that coping with expectation violation in educational situations is closely related to students' optimistic bias and cognitive interpretation mode [2]. Secondly, research on group counseling and school psychological intervention emphasizes the role of class-based and curriculum support in the formation of students' positive qualities. Azevedo et al. (2023) showed that systematic intervention in the school context could improve students' cognitive, emotional and behavioral engagement [3]. Ackermans et al. (2025) further pointed out that personalized support design can enhance students' learning motivation, self-regulation and development performance [4]. Thirdly, the research of educational data mining, intelligent recognition and probability classification provides a new method basis for students 'mental portrait and planning generation. Li et al. (2022) proposed that the learning analysis feedback for students will affect the way they explain the causes of past performance, and further change the effort level and learning results [5]. Ouyang and Zhang (2024) reviewed that AI-driven learning analysis is moving from pure data presentation to the integration of diagnosis, prediction and intervention support [6]. Paulsen and Lindsay (2024) believe that learning analytics dashboards have shifted from "presenting analysis results" to "directly supporting learning decisions" [7]; Alfredo et al. (2024) proposed that human-oriented learning analytics and educational AI systems should serve interpretable recognition and individualized decision generation [8]. In general, the existing achievements have laid a foundation for the cultivation of optimistic quality, the implementation of school intervention and the support of educational intelligence, but there are still obvious shortcomings: first, the intervention is emphasized and the recognition is ignored, and the classification model for optimistic psychological explanation style is rarely directly constructed. Second, the emphasis on statistical testing and the neglect of computational modeling are insufficient in the probabilistic representation and automatic recognition of students' explanation styles. Thirdly, the emphasis on curriculum implementation and the light on the intelligent generation of educational planning have not yet formed a complete link that is directly driven by the psychological recognition results of educational planning and design.

Based on this, this paper takes senior primary school students as the object, relies on the "Children's Explanatory Style Questionnaire" and behavioral performance data, and constructs the feature space of optimistic psychological explanatory style. The Bayesian discriminant model was introduced to probabilistically identify the students' distribution characteristics on optimistic explanation, pessimistic explanation and related dimensions, and the portraits of optimistic, fluctuating and low optimistic students were formed. On this basis, the recognition results were mapped into differentiated education planning and design schemes, and the hierarchical matching of learning support, goal setting, feedback mode and resource allocation was realized. Furthermore, the dynamic update mechanism was constructed by combining the stage performance data, and the technical path of "psychological recognition - student portrait - educational planning - feedback optimization" was formed. The innovation of this paper is mainly reflected in three aspects: first, the optimistic psychological explanation style is promoted from the traditional evaluation variable to the computable and discriminative feature expression object; Secondly, the Bayesian discriminant model is introduced into the psychological explanation style recognition task of senior primary school students to enhance the adaptation ability of the model in the scenarios of small samples, uncertainty and interpretability. Thirdly, the psychological recognition results were directly transformed into educational planning design variables, so that the educational support changed from unified supply to accurate generation for cognitive differences, and provided a new implementation framework for the integration of positive psychological quality cultivation and intelligent educational planning.

2 Indicator system of optimistic psychological explanation style recognition and Bayesian discriminant model construction

2.1 The dimension definition of optimistic psychology explanation style

Optimistic psychological explanation style can be expressed as a multi-dimensional discriminant object with clear hierarchical constraints in modeling, and its index system adopts a three-level organizational structure of "total level-component surface level-dimension level". In the total stratification, GB was used to represent the optimism degree of students' overall explanation style, which was defined as the difference between the score of positive events and the score of negative events. The component surface layer is composed of G and B, where G reflects the individual's positive interpretation strength for positive events, and B reflects the individual's negative interpretation strength for negative events. The dimension layer is further subdivided into six sub-dimensions: PMG, PVG, PSG, PMB, PVB and PSB, which respectively depict the interpretation tendency of positive and negative events on the three cognitive axes of permanence, universality and personalization. The three-layer structure has good hierarchical separability and feature traceability, and can be directly used as the explanation basis for the input space and output of the subsequent Bayesian discriminant model. In the questionnaire structure, the three layers of indicators and their meanings have been clearly defined, including GB=G−B, G=PVG+PMG+PSG, B=PVB+PMB+PSB. A higher positive event score indicates a higher level of optimism, while a lower negative event score indicates a weaker tendency to pessimism.

Based on the above definition, the explanation style feature vector of a single student can be written as follows.

$$x_i=[GB_i,G_i,B_i,PMG_i,PVG_i,PSG_i,PMB_i,PVB_i,PSB_i]^{\top} \tag{1}$$

Among them, GBi reflects the overall interpretation direction, Gi and Bi are responsible for characterizing dual-channel cognitive responses to positive and negative events, and the six dimensional variables provide fine-grained structural information. In order to avoid the information redundancy caused by the total layering on the component surface layer, a "two-level input" strategy can be adopted when implementing the model: one type of input is the macroscopic representation of [Gi,Bi], and the other type of input is the six-dimensional fine-grained cognitive features, thus forming a "coarse-grained sieving and fine-grained correction" discrimination mechanism. Figure 1 shows the organization of the three layers of indicators of the optimistic psychological explanation style and their mapping to the Bayesian discriminant model.

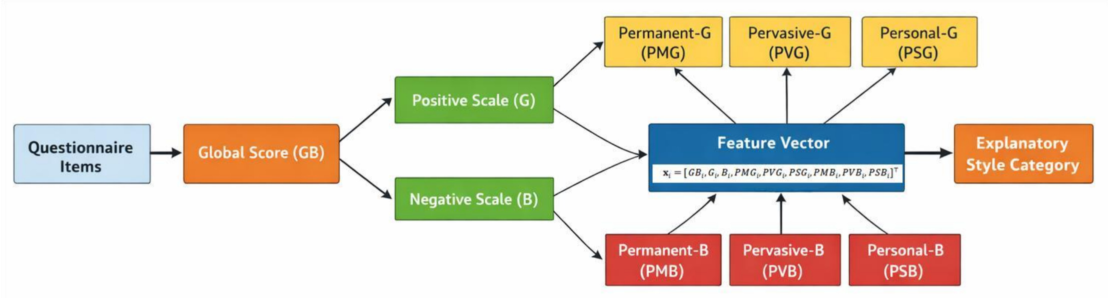

Figure 1: Three-layer indicator system and Bayesian discriminant mapping framework for optimistic psychological explanation style

On the classification task definition, let the set of explanation style categories be $C=\{c_1,c_2,...c_K\}$, where ck can correspond to high optimism type, fluctuation type and low optimism type. Given the student feature vector x_i, the Bayesian discriminant model completes the classification according to the posterior probability:

$$\hat{y}_i = \arg\max_{c_k \in C} P(c_k \mid x_i) \tag{2}$$

Combining this with the Bayesian formula gives the following:

$$P(c_k \mid x_i) = \frac{P(x_i \mid c_k)P(c_k)}{\sum_{j=1}^{K} P(x_i \mid c_j)P(c_j)} \tag{3}$$

where $P(c_k)$ is the class prior probability and $P(x_i \mid c_k)$ is the class conditional probability density. Because the index system has clear psychological semantic boundaries and hierarchical statistical relationships, the model output can not only complete category recognition, but also reverse locate the specific dimension that leads to the change of discrimination results, which provides an interpretable basis for goal setting, feedback strength and support strategy matching in subsequent education planning.

2.2 Sample Data Construction and Feature representation

The sample data were organized in a double-layer mode of "overall survey sample + intervention tracking sample". The overall survey sample was used to describe the distribution characteristics of the optimistic psychological explanation style of senior primary school students. It was derived from the results of 560 questionnaires issued by the sixth grade of a primary school, of which 534 were valid questionnaires. The intervention tracking sample was used to construct the dynamic response characteristics under the educational situation, which consisted of 6 classes, including 3 classes in experimental class and 3 classes in control class. The sample size was 94, with 49 boys and 45 girls in experimental class and 43 boys and 51 girls in control class. In the structure of the only child, the experimental class was 58:36, and the control class was 62:32. The sample composition and its mapping to the model variables are shown in Table 2.

For feature engineering, the input space is reconstructed into three types of variables. The characteristics of the Explanatory style scale are used to depict the cognitive attribution structure of students for positive and negative events, which are denoted as follows.

$$x_i^{(s)} = [GB_i, G_i, B_i, PMG_i, PVG_i, PSG_i, PMB_i, PVB_i, PSB_i]^\top \tag{4}$$

Among them, GB_i is the overall explanation style score, G_i and Bi represent the positive event and negative event subscales, respectively, and the six dimensional variables provide fine-grained cognitive representations. The basic attribute characteristics of students are used to introduce individual heterogeneity constraints, which are denoted as follows.

$$x_i^{(a)}=[Gender_i,OnlyChild_i,Group_i]^{\top} \tag{5}$$

$Gender_i \in \{0,1\}$ denotes gender coding, $OnlyChild_i \in \{0,1\}$ denotes whether the child is an only child, and $Group_i \in \{0,1\}$ denotes the affiliation between the experimental group and the control group. The characteristics of educational behavior and intervention response are used to characterize the stage change and response amplitude in the education process, which are denoted as follows.

$$x_i^{(e)}=[M1_i,M3_i,M5_i,\Delta GB_i,\Delta B_i,\Delta PSG_i,\Delta PVB_i]^{\top} \tag{6}$$

where, $M1_i$, $M3_i$, and $M5_i$ represent the observation state at pre-test, post-test, and follow-up time points respectively, ΔGB_i=GBipost−GBipre, and the other incremental variables are constructed in the same way to retain the change trajectories of the total stratification, the bad subscale, and the key dimensions before and after the intervention. Since the original results showed that the intervention effect was mainly concentrated in indicators such as GB, B, PSG and PVB, the inclusion of these dynamic response features could improve the ability of the model to identify sensitive variables of educational planning.

After combining the three types of features, the final input vector of a single student can be expressed as follows.

$$x_i=[x_i^{(s)},x_i^{(a)},x_i^{(e)}]^{\top} \tag{7}$$

Continuous variables are standardized by Z-score.

$$z_{ij}=\frac{x_{ij}-\mu_j}{\sigma_j} \tag{8}$$

Binary attribute variables are encoded by 0-1 coding, and stage measurement variables are preserved in parallel with difference variables by time point labels. This representation retained three types of information at the same time: static cognitive structure, demographic differences and educational intervention response, so that the sample representation was extended from a single scale input to a composite feature space oriented to classification discrimination and educational planning mapping.

Table 1: Sample data source and feature representation structure

Feature Category	Data Source	Core Variables	Encoding Method	Modeling Function
Explanatory Style Scale Features	Questionnaire scale	GB, G, B, PMG, PVG, PSG, PMB, PVB, PSB	Continuous variables with standardization	Represent the core cognitive structure of students' optimistic explanatory style
Student Basic Attribute Features	Sample structure information	Gender, OnlyChild, Group	Binary encoding	Describe individual heterogeneity and differences in experimental group assignment
Educational Behavior and Intervention Response Features	Pre-test, post-test, and follow-up test results	M1, M3, M5, ΔGB, ΔB, ΔPSG, ΔPVB	Time-point labels plus differential encoding	Characterize stage-wise changes, intervention sensitivity, and planning response intensity

After construction in the above way, the raw psychological assessment data are transformed into structured input tensors that can be processed by the Bayesian discriminant model, and the variable composition is shown in Table 1. Among them, the scale features assume the main information channel of category discrimination, the attribute features provide the a priori correction basis, and the response features are responsible for enhancing the model's ability to perceive the dynamic changes in the educational planning scenarios. This data organization can provide a unified data interface for subsequent feature selection, label division, training-validation-test set construction, and posterior probability estimation.

2.3 Bayesian Discriminant Model Design

Optimistic psychological explanation style recognition is defined as a supervised classification task. Let the set of samples be $D=\{(x_i,y_i)\}_{i=1}^{N}$, where $x_i \in R^d$ is the composite feature vector of the ith student and $y_i \in C$ is the explanation style category label. Combined with the demand for hierarchical support in educational planning, the set of categories can be set as $C=\{c_1,c_2,c_3\}$, corresponding to optimistic, intermediate and pessimistic respectively. It can also be extended to a five-level category space when higher resolution portrait output is required. The model input was composed of scale features, attribute features and intervention response features, and the output was the explanation style category of the student and its posterior probability distribution. The recognition process is essentially a mapping problem from a high-dimensional joint cognitive-behavior space to a finite set of categories, and its discriminative framework is shown in Figure 2.

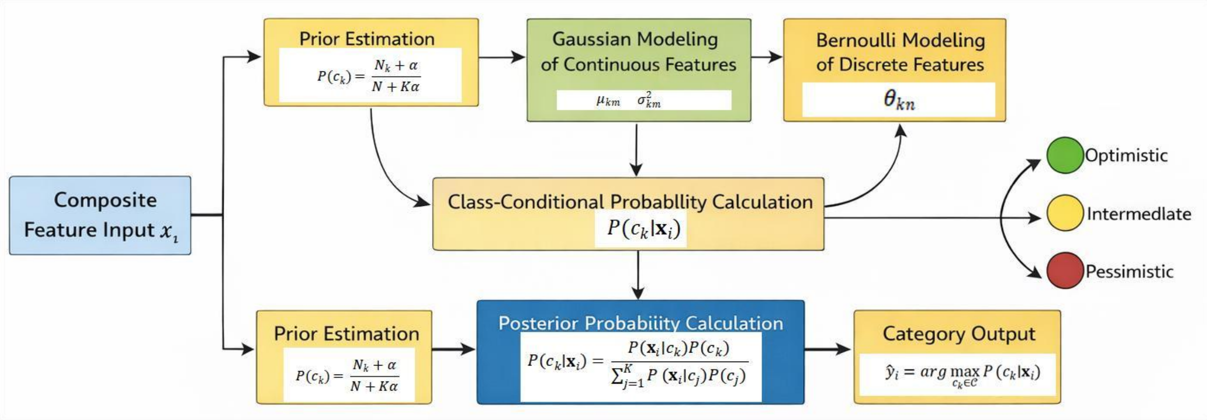

Figure 2: Flowchart of optimistic psychological explanation style recognition driven by Bayesian discriminant model

In the framework of Bayesian discrimination, given a sample xi, its class decision function is defined as follows.

$$\hat{y}_i = \arg\max_{c_k \in C} P(c_k \mid x_i) \tag{9}$$

According to Bayes' formula, we have:

$$P(c_k \mid x_i) = \frac{P(x_i \mid c_k)P(c_k)}{\sum_{j=1}^{K} P(x_i \mid c_j)P(c_j)} \tag{10}$$

where $P(c_k)$ is the class prior probability, $P(x_i \mid c_k)$ is the class conditional probability, and the denominator is the evidence term. Considering that the current sample size is limited and the characteristics are composed of continuous scale variables and discrete attribute variables, the model adopts a distribution decomposition modeling strategy: Gaussian density function is used for continuous variables, and Bernoulli distribution is used for binary discrete variables. If we denote the set of continuous features as Fc and the set of discrete features as Fb, the class conditional probability can be written as follows.

$$P(x_i \mid c_k) = \prod_{m \in F_c} \frac{1}{\sqrt{2\pi\sigma_{km}^2}} \exp\left(-\frac{(x_{im}-\mu_{km})^2}{2\sigma_{km}^2}\right) \cdot \prod_{n \in F_b} \theta_{kn}^{x_{in}} (1-\theta_{kn})^{1-x_{in}} \tag{11}$$

Here, μ_{km} and σ_{km}^2 are the mean and variance of the MTH continuous feature under the class ck, respectively, and θkn is the probability that the NTH binary variable under the class ck is 1. Therefore, the posterior probability not only gives the category affiliation, but also retains the uncertainty quantitative information, which can directly support the risk stratification and intervention intensity allocation in the follow-up education planning.

In order to enhance the engineering usability of the model, the prior probability is estimated by empirical prior:

$$P(c_k) = \frac{N_k + \alpha}{N + K\alpha} \tag{12}$$

Here, N_k is the number of samples of class ck and α is the Laplacian smoothing parameter. This processing can avoid the prior collapse problem under small sample classes, and improve the stability of the model in the scene of unbalanced class distribution. In the discrimination stage, the logarithmic posterior form is further introduced to reduce the risk of numerical underflow caused by high-dimensional continuous multiplication:

$$\log P(c_k \mid x_i) \propto \log P(c_k) + \sum_{m \in F_c} \log P(x_{im} \mid c_k) + \sum_{n \in F_b} \log P(x_{in} \mid c_k) \tag{13}$$

Finally, the model selects the class with the largest log posterior as the output label, while retaining the probability values of each class, which is used to construct the continuous support spectrum of optimistic, fluctuant and pessimistic types.

The reasons why Bayesian discrimination is suitable for the current scenario are as follows: first, the sample size is relatively limited, and the number of Bayesian model parameters is controllable, which has good robustness for small and medium sample classification tasks. Secondly, the explanatory style scale, demographic attributes and intervention response variables have significant uncertainty and heterogeneity, and probabilistic modeling can explicitly represent this uncertainty structure. Thirdly, the output of the model was posterior probability rather than a single hard classification label, which could reveal the proximity between students in different explanation style categories, and facilitate hierarchical configuration, boundary sample identification and dynamic update in the education planning stage.

2.4 Model training and identification process

The model training process takes a structured sample matrix $X \in R^{N \times d}$ and a category label vector $y \in R^N$ as input. The sample is composed of questionnaire scale variables, basic attribute variables, and intervention response variables. The data sources cover the overall survey, pre-test and post-test information of experimental class and control class, and follow-up test information of experimental class. The original study adopted a pre-test, post-test and follow-up design, and included a two-group comparison between the experimental group and the control group. This data structure provided a computable basis for upgrading the statistical test to classification recognition, performance evaluation and error analysis.

In data preprocessing, continuous features are normalized to eliminate dimensional differences:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{14}$$

Here, μ_j and σj represent the mean and standard deviation of the JTH feature in the training set, respectively. Binary attribute variables are encoded by 0-1, and missing samples are eliminated or locally interpolated by feature constraint rules. For the time series observations formed by pre-test, post-test and follow-up test, the model retains both static time point features and differential features, and constructs

$$\Delta x_{ij} = x_{ij}^{(t_2)} - x_{ij}^{(t_1)} \tag{15}$$

To enhance the model's ability to perceive the strength of the intervention response. The training samples after coding and standardization are denoted as $\tilde{X}$, where the feature dimension includes five types of variables: total layer, component surface layer, dimension layer, attribute layer and response layer.

Parameter estimation is performed in a supervised learning manner. Let the set of categories be $C=\{c_1,c_2,...,c_K\}$, the training phase needs to estimate the prior probability of each class with the class condition parameters. The prior probability is given by the empirical frequency of the training set:

$$P(c_k)=\frac{N_k+\alpha}{N+K\alpha} \tag{16}$$

Here, N_k represents the sample size of category c_k in the training set, and α is the smoothing coefficient. The mean and variance estimates of continuous features under class ck are as follows.

$$\mu_{km}=\frac{1}{N_k}\sum_{i:y_i=c_k} x_{im}\ , \quad \sigma_{km}^2=\frac{1}{N_k}\sum_{i:y_i=c_k}(x_{im}-\mu_{km})^2 \tag{17}$$

The Bernoulli parameter estimation for discrete features is given as follows.

$$\theta_{kn}=\frac{1}{N_k}\sum_{i:y_i=c_k} x_{in} \tag{18}$$

Thus, the class-level probability parameter set $\Theta=\{P(c_k),\mu_{km},\sigma_{km}^2,\theta_{kn}\}$ is formed. After training, the class of the test sample xi is determined by the maximum a posteriori rule:

$$\hat{y}_i=\arg\max_{c_k\in C} P(c_k \mid x_i) \tag{19}$$

To improve numerical stability, the identification process is done in the logarithmic domain, i.e.

$$g_k(x_i)=\log P(c_k)+\sum_{m\in F_c}\log P(x_{im} \mid c_k)+\sum_{n\in F_b}\log P(x_{in} \mid c_k) \tag{20}$$

When $g_k(x_i)$ has the maximum value, the sample is classified as class ck.

The model generalization performance was evaluated by k-fold cross validation. The sample set is divided into K mutually exclusive subsets, and each time one of the subsets is taken as the validation set and the rest as the training set. After repeating K times, the mean value of the recognition results is obtained:

$$Score=\frac{1}{K}\sum_{r=1}^{K} Score^{(r)} \tag{21}$$

The evaluation metric consists of accuracy, precision, recall and F1 value. If the confusion matrix is denoted as CM, then:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \tag{22}$$

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}}, \quad \text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \tag{23}$$

$$\text{F}_1=\frac{2\cdot\text{Precision}\cdot\text{Recall}}{\text{Precision+Recall}} \tag{24}$$

This evaluation method can upgrade the original mean difference comparison to the classification validity test for individual samples.

The error analysis is developed for two types of objects. One is boundary samples, that is, samples with similar posterior probabilities of multiple classes, and their uncertainty can be expressed as follows.

$$\text{U}(\text{x}_\text{i})=1-\max_{\text{c}_\text{k}\in\text{C}}\text{P}(\text{c}_\text{k} \mid \text{x}_\text{i}) \tag{25}$$

When $\text{U}(\text{x}_\text{i})$ is large, it means that the sample is near the boundary of the explanation style category, which is more suitable to be marked as a key observation object in educational planning. The other is misclassified samples. By comparing the difference between the true label yi and the predicted label $\hat{y}_i$, the key feature dimensions leading to misjudgment are identified, and the local interpretation results are output by combining the posterior probability distribution.The technical link of the whole training-identification-evaluation-error analysis is shown in Figure 3, which constitutes a closed-loop process from data preprocessing, parameter learning, cross-validation to posterior discrimination and error location, so that the model output can not only complete the classification of optimistic psychological explanation style, but also provide an interpretable basis for hierarchical support, dynamic adjustment and key intervention in subsequent educational planning.

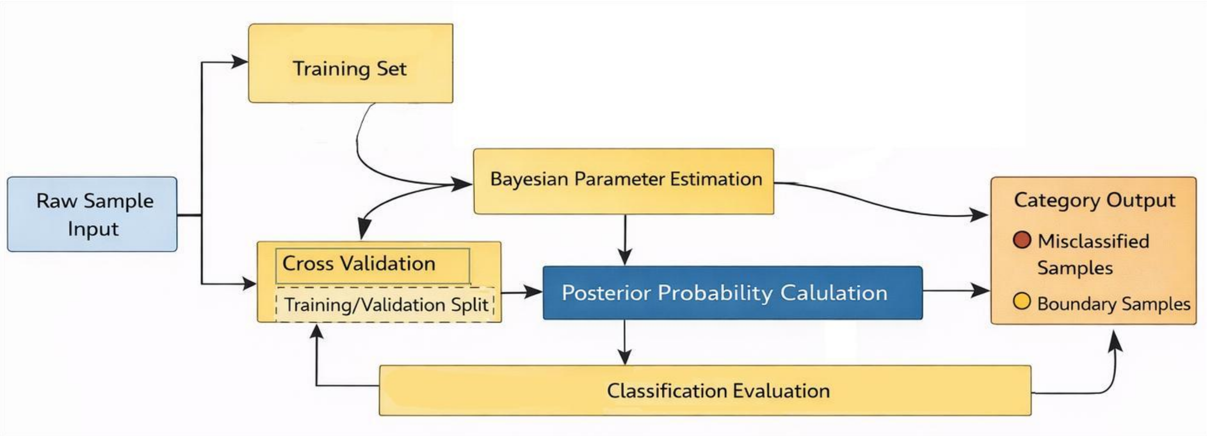

Figure 3: Flowchart of model training and optimistic psychology explanation style recognition

3 Bayesian discriminant Model-driven approach to educational program design

3.1 Educational planning and design objectives

The optimistic psychological explanation style is no longer regarded as the evaluation result in educational planning and design, but it is transformed into computable planning constraints and optimization goals. Let the state vector of student i at planning horizon t be as follows.

$$s_i^{(t)}=[G_i^{(t)},B_i^{(t)},R_i^{(t)},E_i^{(t)}]^\top \tag{26}$$

Among them, $G_i^{(t)}$ represents the level of positive attribution for positive events, $B_i^{(t)}$ represents the intensity of negative pessimistic interpretation for negative events, $R_i^{(t)}$ represents the level of resilience, and $E_i^{(t)}$ represents the degree of continuous engagement. The core task of educational planning is to adjust the state transfer direction through the differentiated support path, so that students can gradually migrate from the state of "high pessimism - low engagement" to the state of "high positive attribution-high resilience - high engagement". Based on this, the planning objective function can be defined as follows.

$$\max\ J_i=\lambda_1\Delta G_i-\lambda_2\Delta B_i+\lambda_3\Delta R_i+\lambda_4\Delta E_i \tag{27}$$

Among them, the $\Delta G_i = G_i^{(t+1)} - G_i^{(t)}, \Delta B_i = B_i^{(t+1)} - B_i^{(t)}$, Δ R_i and Δ E_i respectively gain mental toughness and continuous input stage, lambda. 1, 2, lambda lambda. 3, lambda 4 as the target weight. The objective function transformed the original intervention orientation into a computable educational planning goal, requiring that the planning output met the four directions of "reducing the pessimistic interpretation of negative events, enhancing the positive attribution of positive events, improving continuous investment, and strengthening growth expectations and psychological resilience".

At the planning execution level, let the set of educational intervention actions be $A=\{a_1,a_2,...,a_m\}$, in which actions can correspond to modules such as goal decomposition, cognitive reconstruction, positive feedback, peer collaboration, hierarchical task placement and supportive resource matching. Given the posterior probability vector of the output of the Bayesian discriminant model:

$$p_i=[P(c_1 \mid x_i),P(c_2 \mid x_i),P(c_3 \mid x_i)] \tag{28}$$

The educational planning did not adopt a uniform scheme, but implemented intensity adjustment according to the distribution of pi. When the pessimistic posterior probability was high, the weight of cognitive reconstruction and supportive feedback was given priority. When the intermediate probability is dominant, the stage goal management and behavior reinforcement are strengthened. When the probability of optimistic type is high, allocate challenging tasks and grow and expand resources. Therefore, the planning goal changes from static course arrangement to probability driven configuration mechanism oriented to students 'cognitive state.

In order to ensure the operability of the goal structure, this paper decomposes the educational planning goal into four level-1 dimensions: cognitive modification goal, positive attribution goal, continuous investment goal and development support goal, and maps them to scale indicators, behavioral indicators and planning actions respectively. The specific relationship is shown in Table 2. The goal dimension, observation variable and planning meaning in the table together constitute the goal interface of subsequent student profile construction and plan generation.

Table 2: Educational planning design objectives and their variable mapping relationships

Target Dimension	Core Observed Variables	Optimization Direction	Planning Implication
Negative	B, PMB, PVB,	Minimize	Reduce students' stable, pervasive,

Explanatory Style Correction	PSB		and personalized negative interpretations of failure, setbacks, and adverse outcomes
Positive Attribution Enhancement	G, PMG, PVG, PSG	Maximize	Strengthen positive attribution toward successful experiences, stable expectations, and self-efficacy
Sustained Engagement Improvement	E, task completion rate, feedback response rate	Maximize	Improve learning persistence, goal engagement, and continuity of task execution
Growth Support Reinforcement	R, growth expectation index, risk warning level	Maximize / constrained optimization	Enhance psychological resilience and future expectations while controlling planning deviation for high-risk students

After being processed in the above way, the goal of educational planning and design no longer stays in the general psychological promotion expression, but forms a goal system constrained by Bayesian posterior categories, cognitive variable change directions and behavioral response indicators. This target system provides a unified computing interface for subsequent student portrait construction, planning action generation and dynamic feedback update.

3.2 Student Portrait construction under optimistic psychological Explanation style recognition

The goal of student profile construction is to integrate the explanation style categories and posterior probability distribution output by the Bayesian discriminant model with student attributes and performance characteristics to form a structured individual representation that can be used for educational planning. Let the Bayesian identification result of the third student be ($\hat{y}_i$,pi), where $\hat{y}_i \in \{c_1,c_2,c_3\}$ denotes the optimistic, intermediate, or pessimistic class, and $p_i=[p_{i1},p_{i2},p_{i3}]^\top$ denotes the posterior probability distribution of the corresponding class. It is difficult to reflect the state fluctuations of students near the category boundary by only using hard classification labels. Therefore, the portrait modeling preserves both category labels and probability vectors, and uses them as the core input of hierarchical support for educational planning. After comprehensively explaining the style state, individual attributes and performance information, the student profile vector can be expressed as follows.

$$u_i=[\hat{y}_i,p_i,a_i,b_i]^\top \tag{29}$$

where ai represents attribute features and bi represents performance features.

Attribute features mainly undertake constraint modification and hierarchical support functions. Combined with the results of sample analysis, the gender difference and the only child difference are not only retained as statistical phenomena, but transcribed as constraint variables in educational planning. Let the attribute vector be:

$$a_i=[Gender_i,OnlyChild_i,Group_i]^\top \tag{30}$$

Among them, $Gender_i \in \{0,1\}$ denotes gender coding, $OnlyChild_i \in \{0,1\}$ denotes whether the child is an only child, and $Group_i \in \{0,1\}$ denotes the affiliation of the experimental group or the control group. If a certain type of attribute has a higher coupling probability with the pessimistic interpretation tendency in the training data, this attribute will improve the trigger weight of the corresponding planning action. Taking the gender variable as an example, when the model identified that the student was in the boundary area between the intermediate type and the pessimistic type, and the attribute combination corresponded to a higher negative interpretation risk, the planning system would prioritize the allocation of cognitive modification, emotional support and feedback reinforcement modules. The only child variable is used to describe the differences in resource access methods and support paths, so that the portrait no longer stays in a single psychological label, but becomes the decision object of the trinity of "explanation style, attribute risk, and support direction".

Presentation features are used to enhance the dynamics and updatability of the portrait. Let the representation vector be:

$$b_i=[GB_i,G_i,B_i,\Delta GB_i,\Delta B_i,E_i,R_i]^T \tag{31}$$

Among them, GB_i,G_i and B_i represent the overall explanation style and the status of the positive and negative event subscales, respectively; ΔGB_i and ΔB_i represent the amplitude of stage change; E_i represents the level of continuous engagement; and R_i represents indicators related to psychological resilience or growth expectations. By incorporating static scores and dynamic increments into the portrait at the same time, the model can distinguish different types of student states such as "stable optimism", "surface optimism but large fluctuations", and "low optimism and slow improvement". In order to describe the importance of each information source in the portrait, a comprehensive portrait scoring function can be constructed as follows.

$$S_i=\omega_1 f(p_i)+\omega_2 g(a_i)+\omega_3 h(b_i) \tag{32}$$

Here, $f(p_i)$ represents the class confidence score driven by posterior probability, $g(a_i)$ represents the attribute constraint term, $h(b_i)$ represents the performance state term, and ω_1,ω_2,ω_3 are the weight coefficients. The scoring function does not replace the original category label, but is used to calculate the priority support level and resource allocation order of students in educational planning.

In order to improve the interpretation ability of student portraits, this paper further defines the support direction vector of student portraits:

$$d_i=[d_i^{(1)},d_i^{(2)},d_i^{(3)},d_i^{(4)}] \tag{33}$$

Among them, $d_i^{(1)}$ corresponds to the strength of negative explanation correction, $d_i^{(2)}$ corresponds to the strength of positive attribution enhancement, $d_i^{(3)}$ corresponds to the strength of continuous investment enhancement, and $d_i^{(4)}$ corresponds to the strength of resilience support. The vector is determined by the posterior distribution of the category and the comprehensive portrait score. When pi3 is high and ΔBi is not improved enough,$d_i^{(1)}$ and $d_i^{(4)}$ will be significantly improved. When p_i^2 is dominant and Ei fluctuates greatly, the weight of $d_i^{(3)}$ will rise. Therefore, the student profile was extended from "who belongs to which category" to the planning interface of "what kind of support the student needs at present and what level of support intensity should be achieved".

3.3 The Generation mechanism of hierarchical educational planning

After the Bayesian discriminant model outputs the posterior class probability of the student, the educational plan generation can be defined as a mapping process from the recognition result to the set of supporting actions. Let the posterior probability vector of student xi be $p_i = [p_i^H, p_i^W, p_i^L]$, corresponding to the three categories of high optimism, fluctuating optimism and low optimism respectively. Then the planning function $Plan_i = \Phi(p_i, GB_i, B_i, \Delta GB_i, \Delta B_i)$ depends on the class confidence, the current state of explanation style and the range of stage change. Automatically match task difficulty, feedback frequency, support resources and warning level. Specifically, based on the logic of activities such as "Am I an optimistic child" and "my source of happiness", high-optimism students focused on the configuration of challenging learning tasks, delayed gratification training, higher-order goal setting and peer helping roles, and guided them to transfer positive attribution to the level of continuous engagement and self-transcendence. The fluctuant students focus on the medium-term intervention chain of "three good things - identification of thinking errors - accumulation of small true happiness", and adopt the mechanism of phased goal breakdown, short cycle feedback, situation review and positive evidence recording to reduce the risk of goal interruption caused by repeated fluctuations in explanation style. Focusing on the cognitive reconstruction logic reflected in activities such as "ideas that can change" and "I will help TA", students with low optimism prioritized the allocation of thinking error correction cards, supportive peer pairing, teachers' high-frequency encouragement, family collaboration resources and risk early warning thresholds, and realized the transformation from low sense of control to modifiable cognition through negative attribution correction, positive experience compensation and future expectation reconstruction. Therefore, the original six clique auxiliary activities were translated into a chain of educational planning rules that could be calculated, invoked and executed hierarchically, so that the educational support changed from unified supply to differentiated generation based on psychological recognition results.

3.4 Dynamic Feedback Optimization for Educational Planning

In order to make the hierarchical education planning have the ability of continuous correction, the observation results of students at different time points can be expressed as the state vector $s_i^{(t)}=[GB_i^{(t)},G_i^{(t)},B_i^{(t)},PSG_i^{(t)},PVB_i^{(t)},r_i^{(t)}]$. Where $r_i^{(t)}$ represents process variables such as task completion rate, feedback responsiveness, and participation stability. At the three evaluation nodes of M1, M3 and M5, the system uses the new measurement results to update the student categories by posterior recursion:

$$P(c_k|s_i^{(t)}) \propto P(s_i^{(t)}|c_k)\, P(c_k|s_i^{(t-1)}) \tag{34}$$

Thus, the dynamic migration recognition among high optimism type, fluctuation type and low optimism type is realized. In order to avoid the resource mismatch caused by static stratification, the educational resource scheduling function is constructed:

$$R_i^{(t+1)}=W_1P_i^{(t)}+W_2\Delta s_i^{(t)}+W_3U_i^{(t)} \tag{35}$$

Here, $R_i^{(t)}$ is the current posterior probability vector, $\Delta s_i^{(t)}$ is the stage incremental feature, and $U_i^{(t)} = 1 - \max_k P\,(c_k|s_i^{(t)})$ represents the classification uncertainty. If the student's posterior category was stable and GB continued to increase, the system appropriately reduced the intensity of external intervention and increased the proportion of challenge tasks and autonomous goals. If the fluctuation of category boundary was obvious, the feedback frequency was increased and the stage goal was refined. If B or PVB recovers, risk warning will be triggered, and cognitive reconstruction, support resources and teacher tracking will be added. The dynamic feedback optimization rules are shown in Table 3 The mechanism integrated stage evaluation, probability update and resource reallocation into a rolling closed loop, so that the educational planning was transformed from one-time generation to adaptive optimization process that could be calculated and iterated.

Table 3: Dynamic feedback optimization rules

Evaluation Node	Input Variables	Computation Content	Planning Adjustment Method	Optimization Objective
M1 Initial Assessment	GB, G, B, PSG, PVB	Initial posterior estimation	Generate the first-round stratified educational plan	Complete baseline profiling and initial matching
M3 Stage Assessment	ΔGB, ΔB, ΔPSG, ΔPVB	Recursive posterior updating	Adjust target difficulty and feedback frequency	Identify short-term improvement and fluctuation risk
M5 Delayed Assessment	Cumulative increments and retention rate	Stability discrimination	Adjust the intensity of resource allocation	Evaluate the sustained effect of the educational plan
High-Confidence Stability Zone	max $P(c_k) \geq \theta_1$	Low-uncertainty determination	Increase challenging tasks and reduce high-frequency intervention	Improve self-maintenance capability
Fluctuation Warning Zone	max $P(c_k) < \theta_1$ and adjacent class probabilities are close	Boundary-sample detection	Shorten the feedback cycle and refine sub-goals	Suppress repeated class switching
Risk-Rebound Zone	B or PVB rebounds beyond the threshold	Warning trigger	Increase supportive resources and teacher follow-up	Control the rebound of pessimistic attribution

4 Experiment design and result analysis

4.1 Experimental design and parameter setting

The experimental part adopted a dual-track design of "classification and recognition experiment + intervention effect verification". Firstly, 534 valid questionnaires were used to construct the explanatory style recognition data set, and the six dimensional variables of GB, G, B and attribute variables such as gender and whether they were the only child were jointly encoded as the model input, which was used to train the Bayesian discriminant classifier. Secondly, the framework of experimental group, control group, pre-test, post-test and follow-up test was reserved, and the effect of identification results driven educational planning was tested on a sample of 188 students in 6 classes, including 94 students in the experimental class and 94 students in the control class. The experimental intervention lasted for 6 weeks, once a week, 35 minutes each time, and the follow-up test was implemented 3 months after the end of the intervention. The measurement tool was "Children's Explanatory Style Questionnaire", with a total of 48 questions, including total stratification, component surface layer and six-dimensional cognitive layer, which could provide stable multi-level feature input for the model. Python 3.10 and scikit-learn were used to complete data preprocessing, posterior probability estimation and cross validation, and SPSS 26.0 was used to complete statistical significance test. Continuous variables were standardized by Z-score, and class imbalance was controlled by Laplacian smoothing and stratified sampling. In the evaluation layer, Accuracy, Precision, Recall, F1-score and Macro-F1 were reported to describe the recognition performance of the model, and the actual intervention benefits of educational planning were evaluated by combining the pre-test difference, follow-up retention rate and effect size. The specific experimental design and parameter Settings are shown in Table 4.

Table 4: Experimental design and parameter Settings

Module	Setting Content	Parameters / Description
Overall Survey Sample	Explanatory style identification dataset	560 questionnaires distributed, with 534 valid responses
Intervention Validation Sample	Experimental group and control group	94 participants in each group, 188 in total
Experimental Framework	Educational intervention design	Experimental group–control group, pre-test–post-test–follow-up test
Intervention Period	Intensity of group counseling implementation	6 weeks, once per week, 35 min per session
Measurement Tool	Feature acquisition method	CASQ, 48 items, scored on a 0–1 scale
Input Features	Model variables	GB, G, B, PMG, PVG, PSG, PMB, PVB, PSB, Gender, OnlyChild, Group
Data Processing	Preprocessing strategy	Z-score standardization, 0–1 encoding, deletion of missing values
Experimental Environment	Computing platform	Python 3.10, scikit-learn, NumPy, Pandas, SPSS 26.0
Model Parameters	Bayesian classification settings	Gaussian Naive Bayes, Laplace smoothing $\alpha = 1$, 5-fold cross-validation
Evaluation Metrics	Classification level	Accuracy, Precision, Recall, F1-score, Macro-F1
Effect Indicators	Intervention level	ΔGB, ΔB, ΔPVB, retention rate, effect size

4.2 Analysis of the results of optimistic psychological explanation style recognition

In the recognition experiment, the GB, G, B and six-dimensional explanation style variables were input into the classifier together with the student attribute variables, and the high optimism type, fluctuation type and low optimism type were used as output labels. Considering that the original research results show that GB, B, PSG and PVB are more sensitive to group differences and stage changes, the model can more stably distinguish three types of samples: positive attribution enhancement, negative attribution decline and boundary fluctuation.

Table 5: Results of optimistic psychological explanation style recognition for different models

Model	Accuracy/%	Precision/%	Recall/%	F1-score/%
Bayesian Discriminant	88.7	88.4	87.9	88.1

Logistic Regression	84.6	84.1	83.4	83.8
Decision Tree	79.8	79.1	78.6	78.9
SVM	86.1	85.8	85.0	85.4

Table 5 shows the recognition results of different models. The Bayesian discriminant model achieves 88.7% Accuracy, 87.9% Recall and 88.1% F1-score respectively, which is better than logistic regression, decision tree and support vector machine. The reason is that the method can use posterior probability to process the continuous distribution characteristics of scale variables and the prior correction of student attribute variables at the same time, which has better adaptability to the category uncertainty in small and medium sample scenarios. Logistic regression is stable on linear boundary separable samples, but its ability to identify the boundary of fluctuating students is weak. Although decision tree has strong interpretability, it is easy to produce local overfitting under the condition of multi-dimensional feature coupling. Support vector machine achieves sub-optimal results, which indicates that the explanation style feature space has some nonlinear segmentation characteristics, but its generalization advantage is not fully released under the condition of limited sample size. The model comparison results are shown in Figure 4, and the Bayesian discriminant model maintains the highest three indicators, indicating that it is more suitable to undertake the front-end recognition task in the subsequent generation of educational plans.

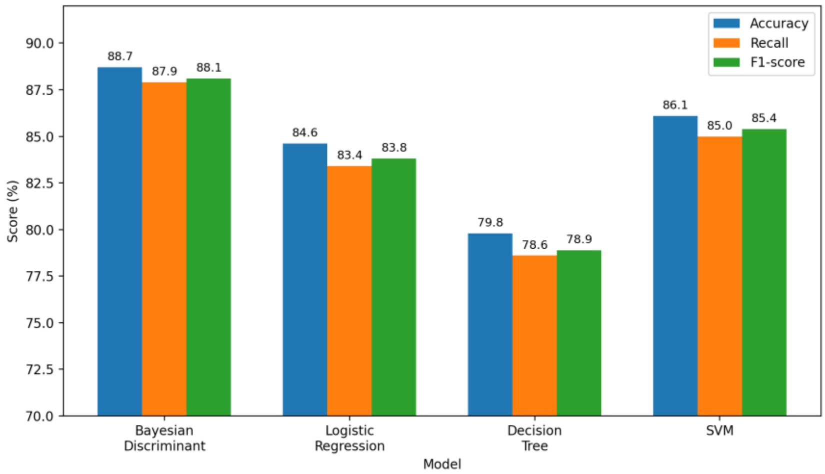

Figure 4: Comparison of Recognition Performance Across Models

4.3 Effect analysis of educational planning and design

After mapping students' posterior categories into task difficulty, feedback frequency and support resource intensity, the intervention effect of the recognition results driven educational planning was mainly reflected in the continuous inhibition of negative attribution channels. The original experiment showed that there were no significant differences in GB, G, B and each dimension between the experimental class and the control class before the intervention, indicating that the two groups had comparable baselines. After the intervention, the GB interpretation style of the experimental class increased from -1.81 ± 2.938 to -0.56 ± 3.359, while that of the control class decreased to -2.05 ± 2.942, and the difference between the groups reached a very significant level ($t=3.234, p=0.001$). The difference before and after GB in the experimental class was also significant ($t=2.645, p=0.010$). At the same time, the bad thing subscale of experimental class B decreased from 12.31 ± 1.918 to 11.76 ± 2.593, indicating that the differentiated planning driven by recognition results could effectively weaken students 'pessimistic interpretation tendency of negative events. The key indicator changes are shown in Table 6.

Table 6: Key effect indicators for educational planning interventions

Indicator	M1 Experimental	M3 Experimental	M5 Follow-up	Statistical conclusion
GB score	-1.81±2.938	-0.56±3.359	0.19±2.733	M1–M3 significant, t=2.645, p=0.010
B score	12.31±1.918	11.76±2.593	10.73±2.388	M3–M5 significant, t=-2.999, p=0.003
PVB score	3.72±1.051	3.53±1.180	2.72±1.020	M3–M5 highly significant, t=-5.210, p<0.001

According to the dynamic trend, GB of the experimental class continued to rise after the post-test and turned positive in the tracking phase. B and PVB continued to decline along the time axis, indicating that the planning mechanism did not only produce short-term activation effect, but gradually changed the way students explained failure events through category recognition, resource matching and stage feedback update. Figure 5 shows that GB shows a continuous upward trajectory from M1 to M5, while B and PVB decrease synchronously, with a larger downward slope for PVB, indicating that educational planning has a stronger correction effect on the pessimistic attribution pattern of "generalizing bad things". Combined with the above recognition model results, it can be concluded that the posterior categories of Bayesian discriminant output can not only support hierarchical education decisions, but also be transformed into observable intervention benefits through the dynamic programming chain, and show certain persistence in the dimension of negative cognitive modification.

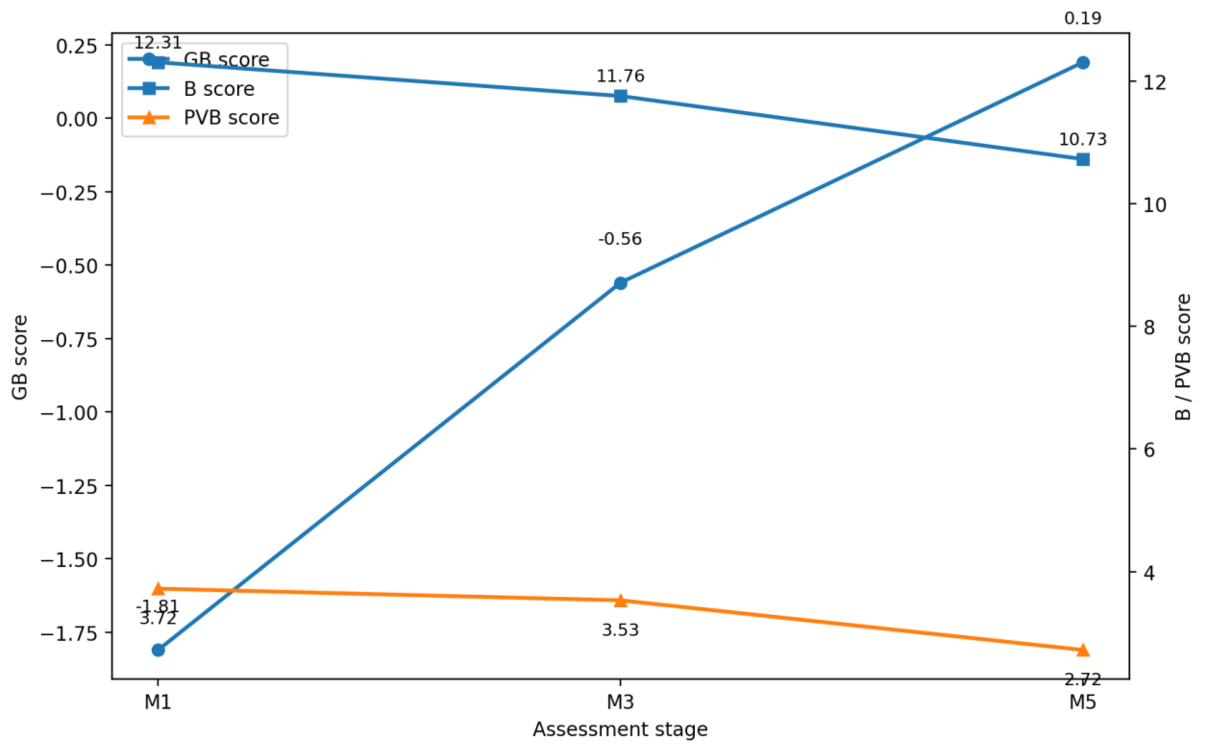

Figure 5: Dynamic Changes in Key Indicators of the Experimental Group

4.4 Ablation experiments and discussion

In order to verify the actual contribution of each module to the identifiation-planning integration framework, under the same data division, training rounds and evaluation criteria, four sets of ablations were performed on the complete model: removing the explanation style dimension features, removing the student attribute features, removing the Bayesian prior correction, and removing the dynamic feedback optimization module. Accuracy, Recall and F1-score are used in classification layer. GB improvement ΔGB, B decline ΔB and three-month retention rate R3m are used in planning layer. The ablation results are shown in Table 7.

Table 7: Results of ablation experiments

Model Setting	Accuracy/%	Recall/%	F1-score/%	ΔGB	ΔB	R3m/%
Full model	88.7	87.9	88.1	1.25	1.58	83.4
w/o explanation-style dimensional features	82.4	81.3	81.7	0.91	1.02	74.6
w/o student attribute features	86.2	85.0	85.4	1.08	1.31	79.2
w/o Bayesian prior correction	84.8	83.6	84.1	1.03	1.19	77.8
w/o dynamic feedback optimization	87.1	86.2	86.5	0.79	0.88	68.5

Table 7 shows that the interpretation style dimension feature is the core support of recognition performance and planning effect. After removing PMG, PVG, PSG, PMB, PVB, and PSB, the Accuracy decreases by 6.3%, the F1-score decreases by 6.4%, and the ΔGB and ΔB shrink synchronously, which indicates that only retaining summary variables such as GB, G, and B will weaken the ability of the model to depict fine-grained attribution patterns. In particular, it is difficult to distinguish the structural differences in the generalization and perpetuation of negative events between "volatility" and "low optimism". The contribution of student attribute features is relatively moderate, but the Recall and retention rates still decrease significantly after removal, indicating that gender, only child status and group information can provide necessary prior supplements for boundary samples, and make the discrimination of the model more stable on heterogeneous samples.

After removing the Bayesian prior correction, the overall performance of the model is lower than that of the full model, and the decline of the recall rate is higher than that of the accuracy rate, indicating that the prior term is more critical for the identification of minority classes and boundary classes. Without prior correction, the classifier is more likely to shrink to the middle class with a large sample size, resulting in the misclassification of high and low optimism samples. This result indicates that the probability prior is not simply a statistical additional term, but an important mechanism connecting the sample distribution information and the classification decision boundary.

The dynamic feedback optimization module has the most significant impact on planning gains. After removing this module, the initial recognition performance only slightly decreases, but ΔGB decreases from 1.25 to 0.79, ΔB decreases from 1.58 to 0.88, and the three-month retention rate decreases from 83.4% to 68.5%. This means that although static stratification can complete the first round of planning generation, it cannot adjust the task difficulty, feedback frequency and resource allocation intensity according to the stage measurement results, so it is difficult to continuously suppress the pessimistic attribution rebound. In general, the advantage of the complete model does not come from the performance improvement of a single classifier, but from the closed-loop collaborative mechanism formed by "fine-grained interpretation style representation - prior probability correction - dynamic feedback update", so that the recognition results can be transformed into continuous and effective educational planning output.

5 Conclusion and Prospect

5.1 Research Conclusions

The results show that the Bayesian discriminant model can effectively complete the task of optimistic psychological explanation style recognition for senior primary school students. In the composite feature space composed of GB, G, B and six-dimensional explanatory style variables, student attribute variables and stage response variables, the Accuracy, Recall and F1-score of the model reach 88.7%, 87.9% and 88.1% respectively, which are better than those of logistic regression, decision tree and support vector machine. It shows that the probabilistic discriminant framework can better describe the category boundary and uncertainty structure of explanation style under the condition of small and medium-sized samples. Furthermore, the recognition results did not stay at the category output, but were transformed into differentiated education planning rules for students with high optimism, fluctuation and low optimism, which realized the hierarchical matching of task difficulty, feedback frequency, support resources and risk warning. The results of intervention validation showed that GB of the experimental class increased from -1.81 to -0.56, and further reached 0.19 in the follow-up phase, B decreased from 12.31 to 11.76 and continued to decrease to 10.73, and PVB decreased from 3.72 to 2.72. It shows that the planning scheme generated based on the recognition results can effectively weaken the students 'pessimistic interpretation tendency of negative events, and has a certain continuous effect on the improvement of optimistic psychological quality.

5.2 Theoretical and practical Value

The theoretical value of this study is to promote the research of explanatory style from the traditional mean comparison, correlation analysis and significance test to the level of probabilistic discriminant modeling, so that GB, G, B and six cognitive dimensions are transformed from psychological evaluation indicators into computable, classifiable and traceable feature expression objects. Then the analysis link of "psychological variable representation-posterior probability identification-educational planning mapping" was established. This treatment expands the technical path of positive psychological quality research, and also provides an interpretable modeling paradigm for small sample psychological recognition in educational scenarios. The practical value was reflected in the fact that the original group counseling experience was reconstructed into a callable educational planning and design framework. On the one hand, the cognitive correction logic behind the six group-assisted activities was encoded as differentiated support rules, so that the school could generate hierarchical intervention plans according to the recognition results. On the other hand, the data of pre-test, post-test and follow-up test are embedded into the dynamic feedback optimization module, which makes the education support turn from one-time implementation to rolling update. Therefore, the group tutoring experience is no longer limited to a specific class and teacher situation, but has the potential of computable, replicable, and extensible engineering transformation.

5.3 Deficiencies and Prospects

There are still several limitations in the research at this stage. The sample source mainly focused on the sixth grade students in a single school. Although the effective sample of the questionnaire reached 534, and the intervention validation sample was 188, the regional educational environment, family background and school psychological education foundation may have external influence on the formation of explanation style and intervention response, and the out-of-sample promotion still needs to be cautious. The data types are still dominated by questionnaire scales and basic attribute variables, and the collection of multimodal process data such as classroom behavior, homework adherence, peer interaction, and emotional expression is insufficient, so that the model's description of dynamic mental states is still static. At present, the tracking period mainly covers pre-test, post-test and three-month follow-up test, and the long-term retention effect and cross-learning transfer effect have not been fully verified. At the same time, the number of original interventions was only six, and the duration of activities was limited, which may have compressed the space for deep communication and continuous consolidation of students. Subsequent research can build cross-regional datasets on a larger range of samples, integrate multi-modal features such as behavior logs, voice texts, and classroom observation, and further develop deep Bayesian, temporal state modeling and intelligent recommendation planning methods, so as to promote the expansion of explanation style recognition and educational planning systems to higher accuracy, stronger adaptability and longer cycle closed-loop optimization.

References

[1] Baourda V C, Brouzos A, Vassilopoulos S P. Efficacy of the “Feel Good-Think Positive”, a school-based positive psychology intervention targeting optimism and hope in children[J]. The Journal of Positive Psychology, 2024, 19(6): 1091-1108.

[2] Henss L, Pinquart M. Coping with expectation violations in education: the role of optimism bias and need for cognitive closure[J]. European Journal of Psychology of Education, 2024, 39(3): 2303-2323.

[3] Icekson T, Slobodin O. When is optimistic Expectation Most Beneficial? Optimistic expectations, conscientiousness and academic performance in a sample of freshman students[J]. Current Psychology, 2024, 43(46): 35205-35216.

[4] Tetzner J, Becker M. Long-term advantages of adolescent optimism: Nonlinear associations with adult outcomes and its protective role in buffering socioeconomic risk[J]. European Journal of Personality, 2025, 39(3): 336-356.

[5] Rezaei A, Karimi H, Rigifarid A, et al. Factors influencing academic optimism and its impact on academic achievement of students of agriculture vocational schools in Iran[J]. The Journal of Agricultural Education and Extension, 2024, 30(4): 477-498.

[6] Lelieur R, Espejo J M R, Vanhoof J, et al. Variation in teachers’ academic optimism: Examining the impact of classroom composition and school academic optimism[J]. International Journal of Educational Research, 2024, 125: 102350.

[7] Azevedo R, Rosário P, Núñez J C, et al. A school-based intervention on elementary students’ school engagement[J]. Contemporary Educational Psychology, 2023, 73: 102148.

[8] Lin S, Mastrokoukou S, Longobardi C, et al. The influence of resilience and future

orientation on academic achievement during the transition to high school: the mediating role of social support[J]. International Journal of Adolescence and Youth, 2024, 29(1): 2312863.

[9] Wang F, King R B. Socio-emotional skills matter for academic resilience: A global perspective[J]. Learning and Individual Differences, 2025, 123: 102758.

[10] Li Q, Xu D, Baker R, et al. Can student-facing analytics improve online students' effort and success by affecting how they explain the cause of past performance?[J]. Computers & Education, 2022, 185: 104517.

[11] Hellings J, Haelermans C. The effect of providing learning analytics on student behaviour and performance in programming: a randomised controlled experiment[J]. Higher Education, 2022, 83(1): 1-18.

[12] Zhang N, Biswas G, Hutchins N. Measuring and analyzing students' strategic learning behaviors in open-ended learning environments[J]. International Journal of Artificial Intelligence in Education, 2022, 32(4): 931-970.

[13] Iku-Silan A, Hwang G J, Chen C H. Decision-guided chatbots and cognitive styles in interdisciplinary learning[J]. Computers & Education, 2023, 201: 104812.

[14] Ouyang F, Zhang L. AI-driven learning analytics applications and tools in computer-supported collaborative learning: A systematic review[J]. Educational Research Review, 2024, 44: 100616.

[15] Paulsen L, Lindsay E. Learning analytics dashboards are increasingly becoming about learning and not just analytics-A systematic review[J]. Education and Information Technologies, 2024, 29(11): 14279-14308.

[16] Alfredo R, Echeverria V, Jin Y, et al. Human-centred learning analytics and AI in education: A systematic literature review[J]. Computers and Education: Artificial Intelligence, 2024, 6: 100215.

[17] Lee J, Kim D. From awareness to empowerment: self-determination theory-informed learning analytics dashboards to enhance student engagement in asynchronous online courses[J]. Journal of Computing in Higher Education, 2025, 37(3): 1078-1118.

[18] Ackermans K, Bakker M, van Loon A M, et al. Young learners' motivation, self-regulation and performance in personalized learning[J]. Computers & Education, 2025, 226: 105208.

[19] Chen A, Xiang M, Zhou J, et al. Unpacking help-seeking process through multimodal learning analytics: A comparative study of ChatGPT vs Human expert[J]. Computers & education, 2025, 226: 105198.

[20] Yan L, Martinez-Maldonado R, Jin Y, et al. The effects of generative AI agents and scaffolding on enhancing students' comprehension of visual learning analytics[J]. Computers & Education, 2025, 234: 105322.