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Research on the ecosystem design of "Artificial Intelligence+" empowering the cultivation of positive mental qualities in adolescents

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SUMMARY: *One of the important goals of mental health education is positive psychological quality. The current paper explores the characteristics of adolescents positive psychological quality using a survey of high school students and uses the XGBoost algorithm to determine what factors contribute to it. It is on this that ecosystem theory as an analytical model is presented and combined with artificial intelligence technology to create an ecological intervention design that would help develop positive psychological qualities in adolescents, which is then evaluated based on intervention experiments. Parenting style, academic performance, family economic situation, campus climate, and week-long time spent exercising are all characteristic important predictors of positive psychological quality development, with all having characteristic importance values of more than 0.12. Also, the intervention group showed better results, namely, the increases in five dimensions of positive psychological quality were between 15.60% and 19.97%, as compared to the pre-experiment levels. There was also a statistically significant difference between the two groups (P<0.01) and the score of each dimension was at least 15.18% higher than the control group. The results indicate that the ecological design of developing the positive psychological quality of adolescents has a high level of practical effectiveness.*

KEYWORDS: *artificial intelligence; XGBoost algorithm; intervention experiment; positive psychological quality*

1 Introduction

Currently, adolescent mental health has been taken as a matter of growing concern in society. Information published by reputable organizations show that almost 20 percent of adolescents around the world suffer from mental health issues whereas depression rates among Chinese adolescents are at the level of 17.5 percent [1-3]. Such numbers indicate the emergence of such issues as an immediate social problem. Adolescence is a critical period in the development of intelligence, self-awareness, and socialization of personality and the formation of positive psychological qualities at this age promotes academic performance, successful adaptation, and normal growth [4-6]. However, traditional methods of ensuring adolescent mental health continue to be based mostly on educating about mental health, psychological consultation and psychotherapy. Though they can also help adolescents with their mental status to a certain degree, they do not have as much impact on enhancing positive psychological qualities [7-9]. The rapid development of information technology is seeing the rise of artificial intelligence as one of the emerging technologies that is progressively making

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its way into education. In specific terms, the AI-enabled ecosystem to nurture positive psychological qualities among the adolescent population has expanded the opportunities of mental health protection [10-12].

Compared with traditional strategies, the AI ecosystem shows significant application advantages in adolescent mental health protection, which are mainly reflected in the following aspects. Accuracy, the system utilizes AI to diagnose adolescent mental problems more accurately, which not only helps healthcare professionals to identify potential mental health problems in adolescents at an early stage, but also improves the diagnostic process [13-15]. Personalization, AI can provide personalized mental health intervention programs for adolescents, and intelligent chatbots and virtual psychologists can provide customized psychological counseling and intervention services according to adolescents' specific situations [16-18]. Flexibility, AI psychological counseling system is not limited by time and place, and can provide 24/7 services [19, 20]. Efficient, AI can efficiently collect, organize and analyze a large amount of mental health data, which not only helps to track the psychological changes of adolescents, but also provides valuable data support for research and treatment [21-23]. Therefore, it is very important to design an ecosystem for the cultivation of positive psychological qualities in adolescents, to provide psychological support for adolescents in a comprehensive and timely manner, and to escort their psychological health growth.

The data on the level of positive psychological qualities and the factors that influence it among high school students was measured through a standardized scale and a sample database was created to analyze positive psychological quality profiles of adolescents. The next step involved the use of the XGBoost algorithm to construct a predictive model, which was subsequently compared to decision tree, SVM model, and random forest. This led to the ranking of the features found by XGBoost in terms of their contribution weights in order to identify the main factors that impact positive psychological qualities of adolescents. An ecological cultivation strategy was then created based on ecosystem theory and artificial intelligence technology, and with focus on the viewpoint of multi-subject collaboration and AI-based assistance. The students in the sample were divided into an intervention group and a control group, who were given the comparative study. The utility of this ecological design was evaluated by analyzing the alteration of five aspects of adolescent positive psychological qualities prior to and following the intervention. These results lead to the conclusion that the study has offered practical measures to enhance the process of developing positive psychological qualities in adolescents, which will be helpful as a reference in future studies.

2 Analysis of factors affecting positive psychological qualities of adolescents

In this chapter, we collect data related to positive psychological quality through the scale, establish a positive psychological quality prediction model for adolescents based on the XgBoost algorithm, predict the positive psychological quality of adolescents, and also analyze their influencing factors.

2.1 Data collection and analysis

2.1.1 Data collection

Adopt the whole group sampling method, select students from a high school as the test object, through the paper questionnaire and network questionnaires issued by the way of the scale, the test object a total of 400 people, the effective recovery of scale data 384 people, the effective rate of 96%. The effective questionnaire using SPSS26.0 raw data into the entry, analysis, resulting in an Alpha value of 0.927, according to the internal consistency reliability coefficient Alpha value is greater than 0.7, proving that the questionnaire has a good reliability can be analyzed in the next step.

The administered scale consists of the following two parts:

(1) Questionnaire on factors influencing positive psychological qualities of adolescents

The recorded variables were gender (male or female), grade level (freshman, sophomore, or junior), academic track (arts or science), place of origin (rural or urban), only-child status (yes or no), parental rearing style (democratic, authoritarian, or indulgent), parents educational background (elementary school and below, middle school, high school, college and above), academic achievement (top 30 percent of class rank, 70th to 30th percentile, or lower than 30), class ranking after 30, campus climate (good, average, or poor), length of exercise per week (0-2 hours, 2-5 hours, or over 5 hours), family economic status (poor, average, or good), and involvement in social club activities (never, rarely, moderately, or often) with a total of 12 factors recorded as X1~X12.

(2) Positive Psychological Character Scale for Adolescents

Table 1 presents the dimensions and the detailed indicators of the Positive Psychological Quality Scale. It has 60 items and spans across six subscales and 15 positive psychological characteristics, with the qualities measured by each subscale being different. The ratings were made on a five-point scale with 1 meaning very un-like me and 5 meaning very much like me. Any given subscale high score indicates higher positive psychological quality in that dimension.

Table 1: The dimensions and specific qualities of the positive psychological quality scale

Dimensions	Specific qualities
Cognitive dimension A1	Creativity B1
	Knowledge B2
	Thinking and insight B3
Brave dimension A2	Sincerity B4
	Clinging B5
Interpersonal dimension A3	Love B6
	Amicability B7
Fair dimension A4	Leadership B8
	Cooperative force B9
Moderation dimension A5	Tolerance B10
	Modesty B11
	Sedate B12
Transcendental dimension A6	Psychic touch B13
	Humor B14
	Faith and hope B15

2.1.2 Correlation analysis

The Pearson correlation analysis was carried out in SPSS 26.0 to analyze the correlations between general score of positive psychological quality and its different dimensions. The relevant findings are shown in Fig. 1 where PPQ is used to refer to positive psychological quality. The findings show strong two-way correlations between the sum of PPQ scores and every dimension, where all correlation coefficients were over 0.60 ($p<0.05$). Besides, the six dimensions also have a significant positive correlation with each other, and correlation coefficients are over 0.25 (p<0.05).

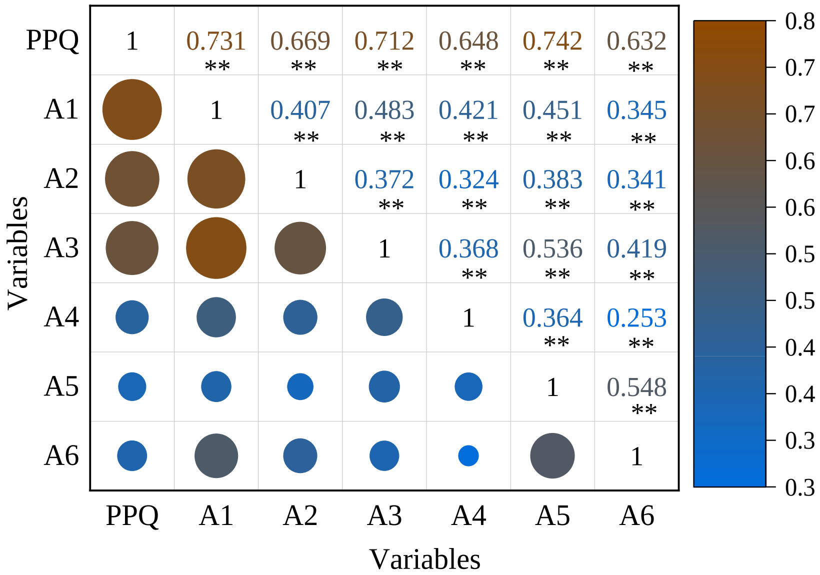

Figure 1: Correlation analysis result

2.1.3 Analysis of positive psychological qualities

The survey data on positive psychological quality were processed using SPSS 26.0 by applying descriptive statistics in order to get a comprehensive view of the positive psychological attributes of the sample students. Figure 2 gives us the overview of the positive psychological qualities of adolescents. The results show that the overall level is still within the range of medium to high with the average scores in all dimensions being greater than 3. However, there are five qualities that demonstrated relatively low and poor performance, including Leadership B8, Friendliness B7, Thinking Power B3, Tolerance B10, and Creativity B1, with all of them scoring less than 3.25. Of the 15 positive psychological qualities, Humility B11 had the highest value, and Leadership B8 had the lowest value, 3.714 and 3.018 respectively.

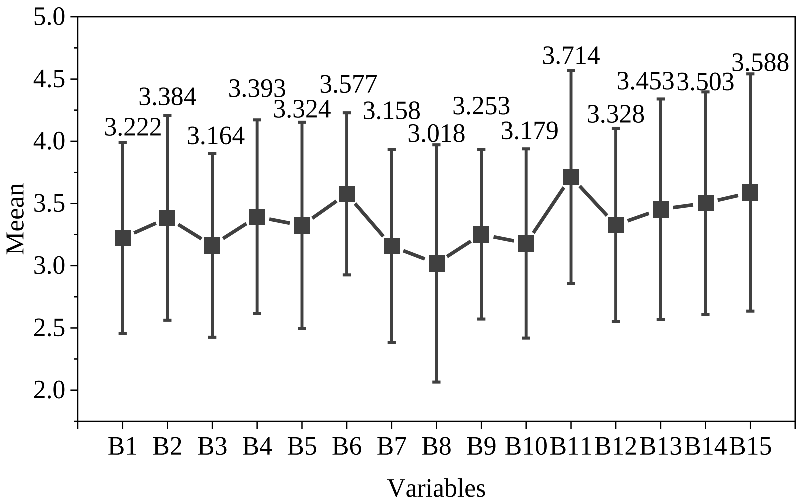

Figure 2: Overall situation of the positive psychological quality

2.2 Model construction and experiments

2.2.1 XGBoost Algorithm

Extreme Boosting Tree XGBoost is a new generation of algorithms based on the gradient boosting tree algorithm GBDT, and the optimized distributed gradient boosting library makes it efficient, flexible and portable. It uses CART regression tree as the base learner for gradient boosting, and boosting integrated learning as the core. Through the process of multiple rounds of iteration, it generates weak classifiers round by round, and in each round, each newly generated classifier will be trained based on the gradient computed in the previous round of classifiers, so as to continuously improve the classification performance. The requirements for weak classifiers-typically simple enough and with low variance and high bias-allow the loss function to continuously decrease, thus continuously improving the model.

The XGBoost algorithm is an additive model formed by forward stepwise addition on top of multiple base learners with the mathematical expression:

$$\hat{y} = \sum_{k=1}^{K} f_i\left(x_i\right) \tag{1}$$

where f_t is the t th base model and $\hat{y}_i$ is the predicted value of the i th sample. Assuming that the tree model to be trained in the t iteration is $f_t(x)$, we have:

$$\hat{y}_i^t = \sum_{t=1}^{k} f_i\left(x_i\right) = \hat{y}_i^{t-1} + f_i\left(x_i\right) \tag{2}$$

$\hat{y}_i^t$ is the prediction of the sample i after the t th iteration, $\hat{y}_i^{t-1}$ is the prediction of the previous $t-1$ tree, and $f_i\left(x_i\right)$ is the model for the first t tree. The loss function corresponding to the constructed model can be represented by $\hat{y}_i$ with the true value y_i:

$$L = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i\right) \tag{3}$$

where n is the sample size.

The predictive performance of a model is also affected by two fundamental factors, which include bias and variance. Bias refers to the mean difference between the expected output and actual value, and it is usually used in conjunction with the loss function to measure this difference and to characterize the behavior of the model in the training set. Simpler models are often preferable when the aim is to constrain variance, reduce overfitting to the training data, and achieve better generalization to out-of-sample data. This is why simultaneous optimization of bias and variance needs an objective function that is not simply minimizing losses. To control variation in practice, another regularization term is added to restrict model complexity. The resulting objective function has two terms: the loss term and the regularization term. It can be expressed as:

$$O(\theta) = \sum_{i=1}^{I} l\left(y_i, \hat{y}_i\right) + \sum_{t=1}^{T} \Omega\left(f_t\right) \tag{4}$$

where $\sum_{t=1}^{T}\Omega\left(f_t\right)$ denotes the complexity summation of the generated T tree, which then acts as the regularization term of the objective function, so as to solve the overfitting problem of the model.

(1) XGBoost regularization term

Where the regularization term is defined as follows:

$$\Omega\left(f_i\right)=\gamma T+1/2\lambda\sum_{q=1}^{T}\omega_j^2 \tag{5}$$

where f_i denotes the t th tree, T denotes the number of leaf nodes, ω_j represents the leaf node weights, γ and λ are the penalization factors, and the magnitude of the value of the sum determines the magnitude of the penalty on the complexity of the tree, and γT is the number of leaf nodes complexity The $L2$ regular term of a flat leaf node is the sum-of-squares term.

The base model of XGBoost has excellent flexibility, not only compatible with the decision tree as the base learner, but also able to support the linear model, the base model used in this paper is the decision tree, then the main introduction to determine the mapping function of the decision tree:

$$f_i(x)=w_{q_{(x)}},\omega\in R^T,q:R^d\rightarrow\{1,2,3\ldots,T\} \tag{6}$$

where ω is a one-dimensional vector of length T, corresponding to T leaf node score weights, and q is a mapping, representing the structure of a tree that maps the input $x_i\in R^d$ to some leaf node, assuming the tree has T leaf nodes.

(2) Loss function

The XGBoost algorithm obeys the forward division addition rule of its family Boosting algorithm, and the model's prediction for i samples x_i at step t, for example, is:

$$\hat{y}_i^t=\hat{y}_i^{t-1}+f_i\left(x_i\right) \tag{7}$$

y_i^{t-1} is the prediction given by the model at step $t-1$, a known constant, and $f_t\left(x_i\right)$ is the new model prediction that needs to be added to carry out the prediction at step t. The objective function at this point is:

$$\begin{aligned}O\left(\theta^t\right)&=\sum_{i=1}^{n}l\left(y_i,\hat{y}_i^t\right)+\sum_{t=1}^{k}\Omega\left(f_t\right)\\&=\sum_{i=1}^{n}l\left(y_i,\hat{y}_i^{t-1}+f_t\left(x_i\right)\right)+\sum_{t=1}^{k}\Omega\left(f_t\right)\\&=\sum_{i=1}^{n}l\left(y_i,\hat{y}_i^{t-1}+f_t\left(x_i\right)\right)+\sum_{t=1}^{k}\Omega\left(f_t\right)+constant\end{aligned} \tag{8}$$

Among them:

$$\begin{aligned}\sum_{t=1}^{k}\Omega\left(f_t\right)&=\Omega\left(f_t\right)+\sum_{i=1}^{t-1}\Omega\left(f_i\right)\\&=\Omega\left(f_i\right)+constant\end{aligned} \tag{9}$$

At this point, the optimization objective function, is to solve for the only variable in the above equation, the first t tree $f_i\left(x_i\right)$, the other variables in the equation are known quantities or can be calculated.

(3) Objective function

Then in then use Taylor's formula for the objective function for the second-order expansion to get the approximate error term, which is also a highlight of the XGBoost algorithm, then the objective function is expanded as:

$$O\left(\theta^t\right)\approx\sum_{i=1}^{n}\left[l\left(y_i,\hat{y}_i^t\right)+g_i f_t\left(x_i\right)+\frac{1}{2}h_i f_t^2\left(x_i\right)\right]+\Omega\left(f_t\right)+constant \tag{10}$$

$$g_i=\partial_{\hat{y}^{t-1}}l\left(y_i,\hat{y}_i^{t-1}\right) \tag{11}$$

$$h_i=\partial_{\hat{y}^{t-1}}^2 l\left(y_i,\hat{y}_i^{t-1}\right) \tag{12}$$

g_i and h_i are the first-order and second-order partial derivatives of the loss function $l\left(y_i,\hat{y}_i\right)$ with respect to $\hat{y}_i$, respectively, and by bringing the f_t and $\Omega\left(f_t\right)$ equations into the approximate objective function by removing the constant part:

$$\begin{aligned}O\left(\theta^t\right)&\approx\sum_{i=1}^{n}\left[l\left(y_i,\hat{y}_i^t\right)+g_i f_t\left(x_i\right)+\frac{1}{2}h_i f_t^2\left(x_i\right)\right]+\Omega\left(f_t\right)\\&=\sum_{i=1}^{n}\left[g_i w_q\left(x_i\right)+\frac{1}{2}h_i w_q^2\left(x_i\right)\right]+\gamma T+\frac{1}{2}\lambda\sum_{j=1}^{T}w_j^2\\&=\sum_{j=1}^{T}\left[\left(\sum_{i\in I(j)}g_i\right)w_j+\frac{1}{2}\left(\sum_{i\in I(j)}h_i+\lambda\right)w_j^2\right]+\gamma T\\&=\sum_{j=1}^{T}\left[G_j w_j+\frac{1}{2}\left(H_j+\lambda\right)\omega_j^2\right]+\gamma T\end{aligned} \tag{13}$$

The G_j and H_j in Eq. are defined as:

$$G_j=\sum_{i\in I(j)}g_i \tag{14}$$

$$H_j=\sum_{i\in I(j)}h_i \tag{15}$$

After the tree structure has been finalized, the samples $\left(x_i,y_i,g_i,h_i\right)$ assigned to each node can be specified accordingly; that is, G_j,H_j,T can then be obtained.In this environment, the regression score of every leaf node is chosen such that the previous equation has the least value, and the lowest point of the quadratic equation is expressed as:

$$w_j^* = -\frac{G_i}{H_j + \lambda} \tag{16}$$

The associated objective function may be stated as follows:

$$O\left(\theta^*\right) = \sum_{j=1}^{T} \left(-\frac{1}{2} \frac{G_j^2}{H_j + \lambda} + \gamma \right) \tag{17}$$

The value achieved by the objective function is used as the tree score, and the lower the score, the better the tree structure.

2.2.2 Evaluation indicators

The experiment adopts the coefficient of determination R^2 as the evaluation index, and the formula of R^2 is shown in equation (18):

$$R^2 = 1 - \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2 / \sum_{i=1}^{n} \left(y_i - \bar{y} \right)^2 \tag{18}$$

where n is the number of samples, y_i is the label value of the first sample point, $\hat{y}_i$ is the predicted value of the label of the i th sample point, and $\bar{y}$ is the average value of the label of all sample points. The more the value of R^2 tends to 1, the higher its prediction accuracy.

2.2.3 Model parameters

The experiment was carried out in Python 3.7 and the data were trained by XGBRegressor module of the xgboost.sklearn package. In the experiment, 70 percent of the 384 mental health records gathered were chosen at random as the training set, whereas the rest of them (30 percent or 115 records) were used as the test set. With R^2 taken as the performance indicator, GridSearchCV was used to optimize parameters and find the best model. The research was focused on the following parameters: learning rate, number of estimators and maximum depth. The primary function of GridSearchCV is to automatically change the combination of parameters, define their proper values, and find the maximum result along with the corresponding configuration that is why it can be applied to relatively small data sets. Following multiple adjustments based on the given sample data and the ranges of parameters, the optimal parameters were identified as learning_rate=0.10, n_estimators=316, and max_depth=4.

2.2.4 Experimental results

In order to forecast positive psychological quality among adolescents, this paper will compare XGBoost with various widely-used methods of psychological data analysis, such as decision tree, support vector machine (SVM) and random forest. Prior to comparing the models, GridSearchCV was used to select the parameter of the decision tree and the rest three methods. Each method was repeated 15 times, and in each repetition, 70% of all samples were randomly allocated into the training set and the remaining 30 percent were kept aside to use as an evaluation sample. Maximum and mean values of the R^2 metric were measured and the results of these four models are depicted in Figure 3. Decision tree, support vector machine, random forest, and XGBoost models have average values of 0.789, 0.817, 0.850, and 0.874, respectively, and their maximum R^2 values are 0.869, 0.899, 0.918, and 0.933. These findings suggest that the best-performing model is XGBoost because it achieves the best overall average and peak R^2 performance of the four methods.

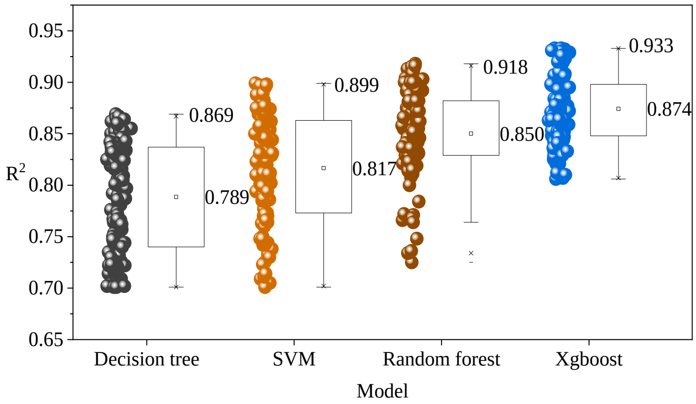

Figure 3: The maximum and mean value of the four models

2.3 Analysis of Impact Factors

The weight values of the XGBoost model were investigated using the built-in method get_booster().get_fscore() to determine the main variables that can affect adolescents positive mental qualities and assist in the development of appropriate cultivation strategies. Depending on these weights, the contributions of individual variables were arranged and the results of the ranking are shown in Figure 4. The five most influential factors were parental style (X6), school performance (X8), economic situation at home (X11), climate of the campus (X9) and time spent on weekly exercise (X10), and all the respective importance scores were higher than 0.12. It indicates that the influences of the formation of positive psychological qualities of adolescents are primarily focused on the family and school developmental situations. Family-related variables are parenting style (1 st rank), household economic status (3 rd rank), parents education level (6 th rank), and only-child status (9 th rank). These results suggest that the adolescent positive psychological qualities are more influenced by the family environment.

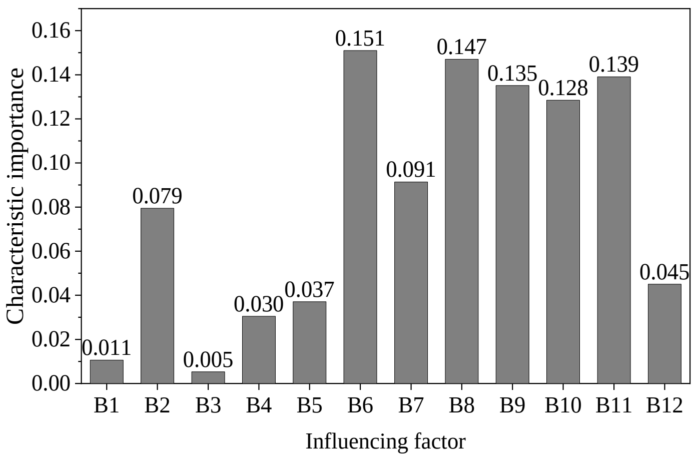

Figure 4: The results of the ranking of characteristics

The ecological systems theory provides a theoretical framework to study and understand the determinants of adolescent mental health. The theory states that social factors may be ordered into a hierarchical structure based on the individual. At the center of it is the human being who has physical attributes as well as psychological features. The closest surroundings that have the biggest influence on the individual are the microsystems, i.e., family, peers, and school. Relations between these immediate environments are the mesosystems. Outside of this level, there are outside conditions that also do not directly influence the individual but rather through their impact on the microsystem, like the status of the parents in their occupations; these are the exosystem. At a more macroscopic level, the macrosystem constitutes the cultural values, social norms, customs, and legal frameworks of a particular society. In the outermost layer, the chronosystem is the representation of change over time and its impact on other systems. As per the XGBoost-based analysis of the factors related to the development of positive psychological qualities in adolescents, the family, school, and community settings are all significant factors in their development. That is why ecological systems theory is presented below as an analytical basis of the implementation of positive psychological qualities in adolescents.

3 Ecosystem Design for Positive Mental Character Cultivation

Artificial intelligence, as one of the highest achievements of the current stage of Internet technology, has been applied in a wider and wider range of fields and plays an increasingly important role. This paper combines artificial intelligence technology to design an ecosystem for the cultivation of positive psychological qualities in adolescents, the framework of which is shown in Fig. 5, reconstructing the synergistic mechanism from the three dimensions of family, school, and community, and utilizing artificial intelligence interaction technology to promote the ecosystem for the cultivation of positive psychological qualities to change from fragmented operation to systematic collaboration.

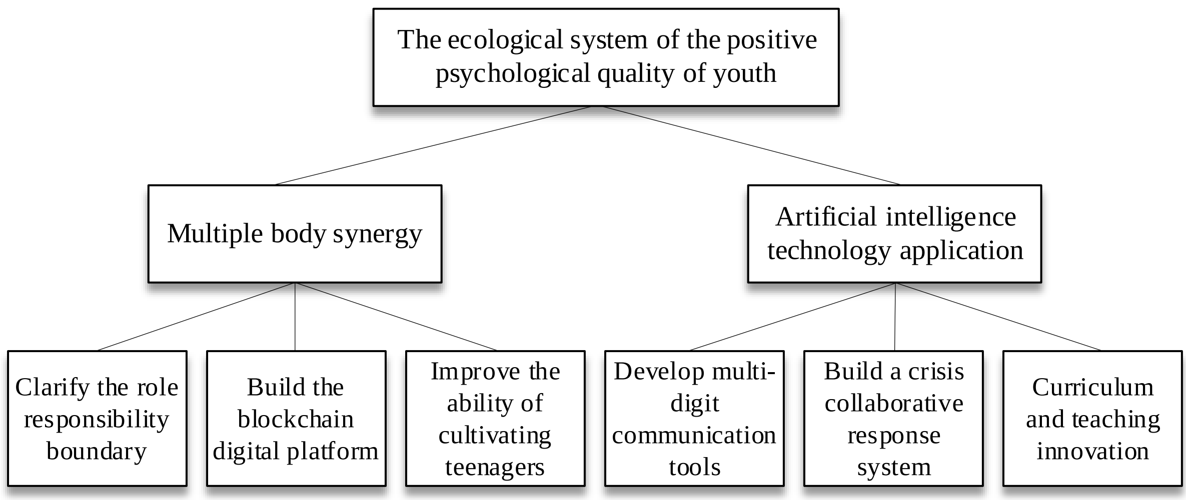

Figure 5: The ecological system of the positive psychological quality of youth

3.1 Synergy among multiple actors

3.1.1 Clarify role responsibility boundaries

The family focuses on emotional support and character building, the school focuses on knowledge transfer and moral education, and society provides a practical platform and an environment for the cultivation of positive mental qualities. The three parties work together to build a solid foundation for the cultivation of positive mental qualities among young people. Through the establishment of a list of responsibilities for each main body, the boundaries of responsibilities in the three major areas of mental health, academic support and social practice are clearly defined, so as to avoid unauthorized functions or shifting of responsibilities by each party, and joint meetings of the three parties are held on a regular basis to discuss educational issues and formulate educational plans, so as to ensure the consistency of educational actions. By giving full play to their respective professional strengths, families, schools and communities are able to find their place in the education chain.

3.1.2 Building a blockchain digital platform

Digitize educational resources to achieve full traceability of educational behaviors. Relying on blockchain technology, build an education depository platform, register students, guardians, teachers, community service workers and other relevant identity information into the blockchain, carry out sub-ledger-style management, and dynamically record and store students' growth trajectories, teachers' teaching and research achievements, and home-school-society communication and collaboration, so as to improve the transparency of the education process and timely deal with the trust crisis caused by information asymmetry, and at the same time, allow pluralistic evaluation subjects to At the same time, it allows multiple evaluation subjects to participate in the evaluation process, introduces a monitoring mechanism, eliminates unfairness in the evaluation process, and improves the credibility of the evaluation results.

3.1.3 Improved tripartite parenting capacity

First, at the family level, as the nurturing ground for the development of mentalization, families need to focus on enhancing parents' emotional perception and response abilities. Schools and communities can offer courses such as "Parent-Child Communication" and "Emotional Management" for parents, helping them regulate their own emotions and improve intimate relationships, thereby creating a warm and pleasant family atmosphere for children. Secondly, at the school level, as schools are the main focus of education, emphasis should be placed on the cultivation of teachers' empathic ability, through workshops on home-school communication and emotional insight, and teaching seminars with the help of real cases, so as to enhance their ability to empathize with the psychological state of students and parents, and to provide more humanistic educational services for students. Thirdly, at the community level, psychological guidance training courses are provided to community service personnel, guiding them to learn basic mental health knowledge and communication skills, and encouraging them to obtain social worker qualifications for self-improvement, so as to provide favorable conditions for the cultivation of positive psychological qualities in young people.

3.2 Artificial Intelligence Technology Enablement

The cultivation of positive psychological qualities of youth cannot be separated from the empowerment of artificial intelligence technology, which can be used to crack the real problems of information silos, delayed response, and insufficient incentives, and to promote the paradigm shift of the cultivation of positive psychological qualities of youth from experience-driven to data-driven.

3.2.1 Development of digital communication tools

A special home-school-society collaborative APP can be developed that integrates information dissemination, communication and sharing functions, sets up resource sharing boards, publishes educational documents and online courses to meet the learning needs of all parties, as well as opens up the communication field so that the three parties can communicate one-on-one or through groups, and improves the efficiency of communication through a distributed ledger to record the interaction process, which corresponds to the blockchain.

3.2.2 Building a coordinated crisis response system

On the basis of the establishment of an efficient communication platform, based on big data and the integration of information on academic fluctuations, attendance behavior, physiological indices, etc., a psychological risk prediction and assessment model is constructed through arithmetic, a response mechanism is set up, and a responsibility-tracing system is imported. Once an early warning is triggered, the system automatically links the response to notify parents, teachers and third-party social stakeholders.

3.2.3 Curricular and pedagogical innovations

In the mental health education course, artificial intelligence technology can be used to create a good classroom teaching situation for students, using a diversified teaching mode, allowing students to explore the situation constructed by virtual technology, carry out cooperative exchanges, and stimulate students' interest in learning. For example, in the classroom teaching session, teachers can use VR and other technologies to allow students to build virtual environments in advance through convenient wearable devices for interactive and immersive learning, realizing multi-screen synchronous teaching and multi-person collaborative learning, so as to build a new structured teaching mode of a two-way cycle of teachers, students, scientific content, and intelligent environments. In addition, through artificial intelligence technology, teachers can build realistic psychological group counseling scenarios for students, and utilize the immersive psychological training system to strengthen psychological counseling and treatment for college students.

In order to cultivate students' positive psychological qualities more effectively, the school-based program adopts the teaching mode of “experience-reflection- transfer”, which allows students to learn through practical experience, grow through reflection, and apply what they have learned in their daily lives. Positive psychology is integrated into the teaching of various subjects. For example, in Chinese language teaching, teachers analyze the psychological growth paths of characters in literary works to guide students to understand and learn how to grow in adversity. For example, in physics teaching, teachers use “frustration experiments” (such as spring force analysis) as a metaphor for the cultivation of stress resistance, so that students can learn how to face and overcome the frustrations and difficulties in life while learning physics, and realize the organic integration of knowledge transfer and psychological development.

4 Effectiveness of fostering positive psychological qualities in adolescents

Based on the above ecosystem design for positive mental character cultivation, the five weak positive mental qualities with the lowest scores of adolescents were intervened to improve the positive mental qualities of adolescents.

4.1 Research methodology

4.1.1 Objects of study

Based on the results of the scale survey in Chapter 2, two classes with comparable levels of positive psychological qualities were selected and divided into an intervention group and a control group with 40 students in each group. The consent of each student was obtained for this educational intervention process, and all of them pledged to voluntarily participate in this educational intervention activity.

4.1.2 Research tools

The same Positive Mental Character Scale as above was used, through which pre- and post-intervention measurements were taken for the intervention and control groups. The independent variable is the application of the ecosystem of positive psychological qualities cultivation and the dependent variable is the change in the positive psychological qualities of the adolescents.

4.1.3 Research procedures

The initial step was to conduct a pre-intervention assessment to determine the level of positive psychological qualities among the students in both the intervention group and the control group. Following these premises, an educational intervention project was created based on an ecological perspective of promoting positive psychological qualities and subsequently applied to students within the intervention group. Once the program had ended, a post-intervention assessment was performed to determine the changes in their positive psychology qualities of the adolescents.

4.2 Findings

4.2.1 Comparison of differences in pre-tests

A between-subjects t-test was conducted on the pre-test scores of the Positive Psychological Qualities Survey of the five lowest-scoring dimensions of the intervention and control groups and the comparative findings are given in Table 2. Creativity ($P > 0.05$), insightfulness ($P > 0.05$), friendliness ($P > 0.05$), leadership ($P > 0.05$)and forgiveness ($P > 0.05$) had no significant difference between the two groups. It means that the chosen samples of the research demonstrated similar general performance in creativity, insightfulness, friendliness, leadership, and tolerance prior to the intervention.

Table 2: Comparison of pretests with the lowest scores

	Intervention group(n=40)		Control group (n=40)		*t*	*p*
	Mean	*SD*	*Mean*	*SD*		
Leadership	2.848	1.048	2.919	0.834	-0.688	0.394
Amicability	3.068	0.726	3.025	1.053	0.321	0.535
Thinking and insight	3.166	1.116	3.145	1.006	-0.425	0.671
Tolerance	3.075	0.906	3.153	0.933	-0.599	0.596
Creativity	2.911	1.136	3.079	0.988	-0.379	0.755

4.2.2 Comparison of post-test differences

The posttest results of the five lowest scoring weak positive psychological qualities surveyed in the intervention and control groups were subjected to independent samples t-tests, and the results of the posttest comparison of the positive psychological qualities are shown in Table 3. For the five weak positive psychological qualities of creativity ($P < 0.01$), think-dong power ($P < 0.01$), friendliness ($P < 0.01$), leadership ($P < 0.01$), and tolerance ($P < 0.01$). There was a significant difference between students in the intervention and control groups on the posttest, indicating that the positive psychological qualities nurturing ecosystem design of this study was effective. In particular, the scores of the 5 weak positive psychological qualities in the control group were not significantly different from the pre-intervention period, with the difference in scores within 2%, while the scores of the 5 weak positive psychological qualities in the intervention group increased by 19.39%, 15.60%, 19.97%, 16.24%, and 16.53%, in order of magnitude, from the pre-intervention period. After the intervention, students in the intervention group increased their scores on the five weak positive psychological qualities by 23.41%, 15.18%, 20.66%, 19.97%, and 21.01%, respectively, compared to the control group.

Table 3: Comparison of posttests with the lowest scores

	Intervention group (n=40)		Control group (n=40)		*t*	*p*
	Mean	*SD*	*Mean*	*SD*		
Leadership	2.824	0.929	3.485	3.575	-3.738	0.004
Amicability	3.036	0.854	3.497	3.465	-2.625	0.001
Thinking and insight	3.127	0.854	3.773	3.489	-3.354	0.003
Tolerance	3.055	0.972	3.665	3.851	-2.298	0.006
Creativity	2.965	1.076	3.588	3.085	-3.585	0.005

5 Conclusion

This paper investigates the positive psychological qualities of students in a high school, uses the XGBoost algorithm to construct a model to analyze the influencing factors of positive psychological qualities of adolescents, introduces the ecosystem theory to explore the ecosystem design for the cultivation of positive psychological qualities of adolescents, and carries out intervention experiments in this way. The mean scores of the positive psychological qualities of the sample students were all above 3, which was in the middle to upper level, and modesty and leadership were the qualities with the highest and lowest scores, respectively. The five factors that have the greatest influence on the positive psychological attributes of adolescents are: parenting style, academic performance, family economic status, school atmosphere, and weekly exercise time, and the importance values of the characteristics are all greater than 0.12, so that the influence of the family, school, and community environments on the cultivation of positive psychological attributes of adolescents is very significant.

The ecological model of developing positive psychological traits of adolescents involves various groups (family, school, and community) and is additionally enhanced by artificial intelligence technology. Through the use of digital means to enhance the track record of educational behaviors and communication between various parties, it creates a collaborative process on addressing crises and revives the teaching style of the mental health curriculum as well as school-based courses, thus promoting the growth of positive psychological characteristics of adolescents. After the intervention experiment, there were critical differences between the two groups of students based on the five weakest dimensions of positive psychological qualities ($P < 0.01$). The intervention group scored better by 15.18% to 23.41% compared to the control group and by 15.60% to 19.97% compared to the pre-intervention level. These results also reveal that the enhancement of positive psychological qualities in students of the intervention group was significantly related to the educational intervention. To put it differently, this ecological design is one of the key factors in the promotion of the development of adolescents positive psychological qualities.

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