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PAPER

Using Autonomous Learning Mode to Improve Students' Learning Willingness and Resilience

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ABSTRACT

In China, English teaching has become a key part of the education system at all levels. However, despite the significant resources invested in the education system, many students lack the necessary motivation and perseverance to learn. The interactive autonomous learning mode is a newly emerged educational approach that aims to enhance students' motivation and resilience in learning through interaction and self-motivation. Existing works mostly focus on qualitative analysis and case studies; however, few have comprehensively considered the multiple factors or the future trend. To address this research gap, this paper proposes three novel research methods: predicting future learning willingness using a grey prediction model, evaluating the effectiveness of a learning resilience enhancement strategy using the TOPSIS analysis method, and analyzing the relationship between learning willingness and learning resilience enhancement using an improved grey relation projection method. These methods not only provide a comprehensive and accurate analytical framework, but they also contribute to educational reform and teaching practice.

KEYWORDS

learning willingness, learning resilience, interactive autonomous learning mode, grey prediction model, TOPSIS analysis method, grey relation projection method

1 INTRODUCTION

As the pace of globalization accelerates in modern society, English teaching is widely regarded as a key factor in opening the door to the global stage [1, 2]. In China, English skills have been considered an important criterion for assessing individuals' qualifications, from elementary schools to universities and colleges, and even in the workplace after graduation [3, 4]. However, despite the large number of resources invested in English teaching, including teaching equipment, professional faculties, and rich course resources for students, many of them still lack sufficient learning initiative and persistent motivation, which has greatly limited their academic achievements and affected their competitiveness in the workplace [5]. In recent years, there

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has been an increasing focus on the interactive autonomous learning mode among educators and scholars. Its objective is to improve students' willingness and resilience to learn through interaction and self-motivation.

Figuring out students' willingness and resilience to learn in the interactive autonomous learning mode has profound implications for the field of education [6–9]. Firstly, understanding the intrinsic relationship between these two variables can help educators design courses and teaching activities more effectively, thereby enhancing students' learning experience and academic performance [10, 11]. Secondly, policymakers can optimize the allocation of educational resources based on these research findings. This can be done by adjusting teaching methods, updating teaching materials, or improving the educational environment. These measures aim to promote more comprehensive and effective teaching [12–15]. Thirdly, for individual students, enhancing their learning willingness and resilience not only contributes to their short-term academic success but also affects their long-term career and life plans.

Although topics related to learning willingness and learning resilience are popular research areas in educational psychology and educational management, the existing studies primarily focus on qualitative analysis and case studies. As a result, it is challenging to draw universal conclusions [16, 17]. More importantly, currently available methods often fail to consider the interactive effects and time factors of multiple variables, and there are few predictions of future development trends [18–22]. So, there is an obvious gap in the research area, namely how to quantify and analyze multiple related factors and how to predict future trends based on these analyses.

To address these gaps, this paper aims to make innovations from three perspectives. Firstly, a grey prediction model was utilized to forecast the future trends of students' learning willingness under interactive autonomous learning modes. This provides valuable insights for educational institutions and decision-makers. Secondly, the TOPSIS analysis method was employed to conduct comprehensive evaluations of students' learning resilience. Through multidimensional analysis, the factors that have the most significant impact on students' learning resilience were determined. Lastly, an improved grey relation projection method was applied to analyze the correlation between students' learning willingness and their learning resilience. This helps to identify potential influencing factors and the internal mechanisms at play. Through these three sections, this paper not only proposes a comprehensive and accurate analytical framework but also formulates practical strategies and suggestions for educational reform and practice. In summary, this paper has both theoretical and practical value and is expected to make substantial contributions to promoting students' willingness to learn and resilience.

2 PREDICTION OF STUDENTS' FUTURE LEARNING WILLINGNESS

When predicting students' future learning willingness using the grey prediction model, the first step is to select the variables that can influence their learning willingness. Figure 1 presents a diagram illustrating the selection of variables that influence students' willingness to learn. In this study, several variables were chosen from five aspects.

1. Academic variables: a) Past grades: students' past performance is often correlated with their future learning intentions; b) Participation: involvement in classroom

discussions, projects, or assignments; c) Learning duration: the amount of time dedicated to learning each day or each week.

2. Social and environmental variables: a) Teacher support: the teaching methods of teachers and the support given by teachers to students; b) Peer influence: learning attitudes and grades of friends and classmates; c) Family support: the importance attached by family to learning and their support.
3. Psychological variables: a) Self-efficacy: students' self-confidence of successfully completing the learning tasks by themselves; b) Internal and external control: does a student believe that success is determined by their own efforts or external factors; c) Learning motivation: internal or external learning motives.
4. Technology and resource variables: a) Available resources: such as books, online courses, experimental materials, etc.; b) Acceptance of technology: the degree to which students are willing to use technologies or tools in learning.
5. Life situation variables: a) Health status: the mental and physical health conditions that can affect learning willingness; b) Economic conditions: burdens such as tuition fees, expenses on books, and other learning resources.

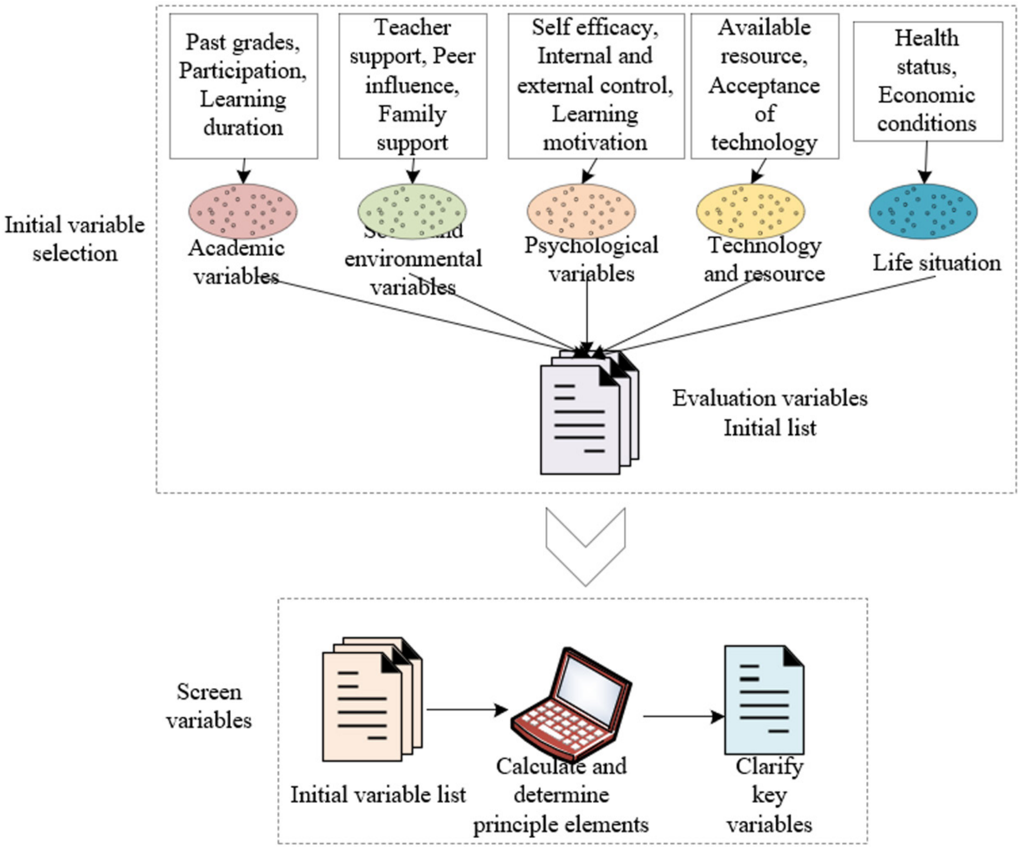

Fig. 1. Idea of influence variables of students' learning willingness

Before applying the grey prediction model, it is necessary to ensure the quality and reliability of the data in order to obtain accurate predictions. The grey prediction model needs to be regularly calibrated in order to adapt to potential new trends or changes in educational policies. In the grey prediction model, the independent variables should be selected carefully to accurately reflect the characteristics of the interactive autonomous learning mode.

Based on the collected data, a time series related to learning intentions can be constructed. Assuming that $Z^{(0)}$ represents a non-negative series, then there is:

$$Z^{(0)} = (z^{(0)}(1), z^{(0)}(2), \ldots, z^{(0)}(b)) \tag{1}$$

Assuming: $Z^{(1)}$ represents the first-order accumulated series of $Z^{(0)}$, $z^{(1)}(j) = \sum_{u=1}^{j} z^{(0)}(u)$, $j = 1, 2, \ldots b$, then an Accumulated Generating Operator (AGO) series was generated:

$$Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), \ldots, z^{(1)}(b)) \tag{2}$$

Assuming: $X^{(1)}$ represents the nearest neighbor generating series, then there is:

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(b)) \tag{3}$$

where,

$$x^{(1)}(j) = \frac{1}{2}(z^{(1)}(j) + z^{(1)}(j-1)) \tag{4}$$

Then, a grey model of first-order differential equation was established based on the AGO series and mean value, namely the GM (1, 1).

$$\frac{dz^{(1)}}{dy} + sz^{(1)} = n \tag{5}$$

By solving the whitening equation $z^{(0)}(j) + sz^{(1)}(j) = n$, we have

$$\hat{s} = \begin{pmatrix} s \\ n \end{pmatrix} = (N^{Y} N)^{-1} N^{Y} T_{B} \tag{6}$$

where,

$$N = \begin{bmatrix} -X^{(1)}(2) & 1 \\ -X^{(1)}(3) & 1 \\ \vdots & 1 \\ -X^{(1)}(b) & 1 \end{bmatrix}, T_{B} = \begin{bmatrix} z^{(0)}(2) \\ z^{(0)}(3) \\ \vdots \\ z^{(0)}(b) \end{bmatrix} \tag{7}$$

Then the solution is:

$$z^{(1)}(y) = \left(z^{(1)}(0) - \frac{n}{s} \right) r^{-sy} + \frac{n}{s} \tag{8}$$

By discretizing above formula, the time response series of the $GM(1, 1)$ mode is:

$$\hat{z}^{(1)}(j+1) = \left(z^{(0)}(1) - \frac{n}{s} \right) r^{-sj} + \frac{n}{s} \tag{9}$$

Through consecutive subtraction, the final predicted value of students' learning willingness was determined.

$$\hat{z}^{(0)}(j+1) = \hat{z}^{(1)}(j+1) - \hat{z}^{(1)}(j) = (1 - r^{s}) \left(z^{(0)}(1) - \frac{n}{s} \right) r^{-sj} \tag{10}$$

3 COMPREHENSIVE EVALUATION OF LEARNING RESILIENCE ENHANCEMENT STRATEGIES UNDER INTERACTIVE AUTONOMOUS LEARNING MODE

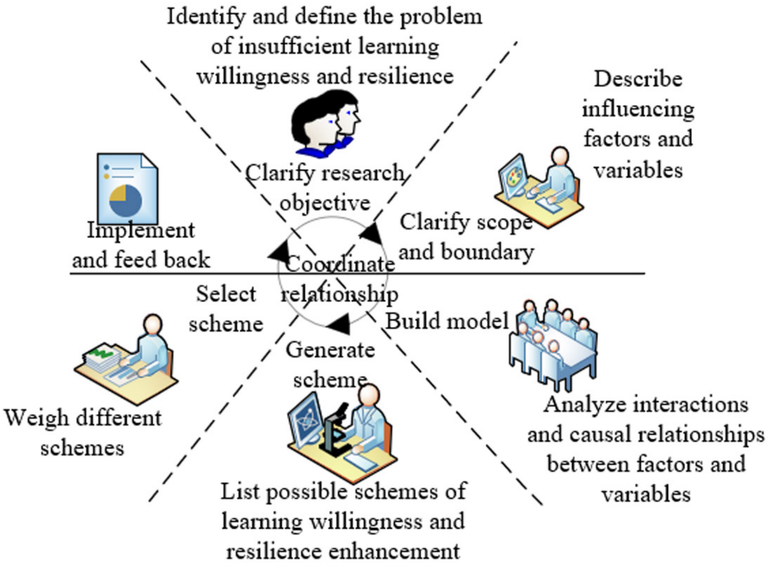

Fig. 2. Generation process of learning resilience enhancement plan

Figure 2 illustrates the process of developing a framework to enhance students' learning resilience. Specifically, this process includes six steps, which will be introduced in detail below.

Step 1: Build an evaluation series. At first, determine evaluation indicators based on various aspects of learning resilience. Obtain the raw data for these indicators through methods such as questionnaire surveys, interviews, and teacher evaluation. Then, standardize or normalize the collected data to eliminate the influence of different units or dimensions of indicators. The specific evaluation indicators are as follows:

1. Psychological adaptability: a) Stress tolerance: the stability of students when facing difficulties and setbacks; b) Emotional regulation: the ability of students to regulate their own emotions, especially negative emotions.
2. Academic performance: a) Performance stability: the stability of students' academic performance over a period of time; b) Subject interest: students' interest and enthusiasm for main subjects.
3. Self-efficacy: a) Learning confidence: students' self-confidence in their learning abilities; b) Problem-solving ability: the ability of students to independently solve learning and life problems.
4. Social skills: a) Teamwork: students' performance in team projects or activities; b) Interpersonal skills: the quality of relationships between students, classmates, and teachers.
5. Goal setting and achievement: a) Goal clarity: whether the learning goals set by students are clear and measurable; b) Goal achievement rate: the frequency and efficiency at which students achieve the learning goals they set.
6. Time management: a) Learning plan: whether students have a clear learning plan and time schedule; b) Deferred gratification: can students delay immediate pleasure and satisfaction to complete more important tasks.

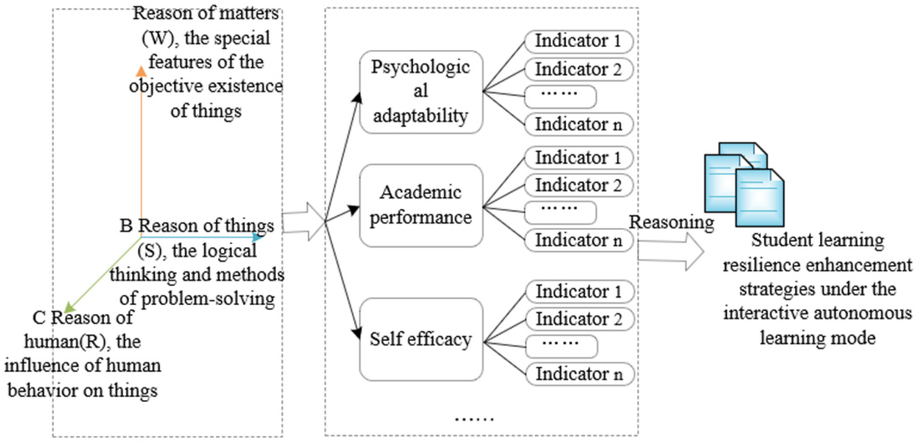

Fig. 3. Idea of evaluation indicator selection of learning resilience

Figure 3 illustrates the concept of selecting evaluation indicator for learning resilience. Assuming that $A = \{A_j\}(j = 1, 2, ..., u)$ represents the series of strategies to be evaluated, and $L = \{l_e\}(e = 1, 2, ..., b)$ represents the series of evaluation indicators, the evaluation series consisting of u learning resilience enhancement strategies for the e-th indicator can be expressed as:

$$Z_j = \{Z_1(e), Z_2(e), \ldots, Z_j(e)\} \quad (j = 1, 2, \ldots, u) \tag{11}$$

By combining the data from all evaluation indicators, it is possible to achieve the formulation of an ideal series of strategies for enhancing learning resilience.

$$Z_j^* = \{Z_1^*(e), Z_2^*(e), \ldots, Z_j^*(e)\} \quad (j = 1, 2, \ldots, u) \tag{12}$$

The formula for the negative ideal learning resilience enhancement strategy series is as follows:

$$Z_j^0 = \{Z_1^0(e), Z_2^0(e), \ldots, Z_j^0(e)\} \quad (j = 1, 2, ..., u) \tag{13}$$

Step 2: Use the entropy method to determine indicator weights.

$$Q = \{q_e\}(e = 1, 2, \ldots, b) \tag{14}$$

Step 3: Calculate the degree of grey relation. Convert the preprocessed data into a standardized matrix, and calculate the positive and negative ideal solutions for each indicator using the standardized matrix and weights. Then, the Euclidean distance or other similar metrics can be used to calculate the distance from each sample to the ideal solution and the negative ideal solution. This calculation determines the grey relation degree (E_1 and E_2) between the evaluation object and the ideal learning resilience enhancement strategy series, as well as the negative ideal learning resilience enhancement strategy series. The formula for calculating the grey relation coefficient of the e-th indicator is as follows:

$$E^*(e) = \frac{\underset{u}{MIN}\, MIN \left|Z_j^*(e) - Z_j(e)\right| + 0.5 \underset{u}{MAX}\, MAX \left|Z_j^*(e) - Z_j(e)\right|}{\left|Z_j^*(e) - Z_j(e)\right| + 0.5 \underset{u}{MAX}\, MAX \left|Z_j^*(e) - Z_j(e)\right|} \tag{15}$$

$$E^0(e) = \frac{\underset{u}{MIN}\,MIN\left|Z_j^0(e) - Z_j(e)\right| + 0.5\,\underset{u}{MAX}\,MAX\left|Z_j^0(e) - Z_j(e)\right|}{\left|Z_j^0(e) - Z_j(e)\right| + 0.5\,\underset{i}{MAX}\,MAX\left|Z_j^0(e) - Z_j(e)\right|} \tag{16}$$

Next, the grey relation degree between the evaluation sequence and the series of ideal learning resilience enhancement strategies, as well as the series of negative ideal learning resilience enhancement strategies, can be calculated using the following formula:

$$E_1 = \sum_e^b q_e E^*(e), E_2 = \sum_e^b q_e E^0(e) \tag{17}$$

Step 4: Calculate the degree of nearness in grey relation using the TOPSIS formula for nearness degree calculation. This will help determine the nearest degree index for each sample (or student). By sorting the students based on their nearness degree index, we can obtain a comprehensive evaluation of their learning resilience. Assuming that W represents the degree of nearness of grey relation of the evaluation object:

$$W = \frac{E_1}{E_1 + E_2} \tag{18}$$

Then, interpret the learning resilience performance of each student or student group based on the nearness degree index and the sorting results. Based on the evaluation results, propose specific intervention measures or policy suggestions to enhance students' learning resilience.

4 ANALYSIS OF CORRELATION BETWEEN LEARNING WILLINGNESS AND LEARNING RESILIENCE ENHANCEMENT

In this paper, an improved grey relation projection method was used to establish a correlation analysis model of student learning willingness and resilience enhancement. The basic steps are as follows:

Step 1: Determine the decision matrix. Assuming that O represents the set of learning resilience enhancement strategies and Z represents the set of variables affecting students' learning willingness, X_{0k} represents the evaluation indicators of the optimal learning resilience enhancement strategy O_0. Therefore, X_{0k} needs to satisfy the following formulas:

$$\begin{aligned}&When\ evaluation\ indicator\ Z_k\ is\ an\ efficiency-type\ indicator:\\&X_{0k} = MAX(X_{1k}, X_{2k}, \dots, X_{bk})\end{aligned} \tag{19}$$

$$\begin{aligned}&When\ evaluation\ indicator\ Z_k\ is\ an\ input-type\ indicator:\\&Z_{0k} = MIN(X_{1k}, X_{2k}, \dots, X_{bk})\end{aligned} \tag{20}$$

The matrix $X = (X_{uk})_{(b+1)\times l}$ can be considered as the decision matrix for the student learning resilience enhancement strategy set O, in relation to the influencing factors of student learning willingness Z, wherein $u = 0, 1, 2, \dots, b$; $k = 1, 2, \dots, l$.

Step 2: Build the standardized decision matrix. To address the discrepancies arising from the varying dimensions and units of evaluation indicators mentioned earlier, a standardization method was employed to normalize the decision matrix. Assuming: $X' = (X'_{uk})_{(b+1)\times l}$ represents the standardized decision matrix, the formula is:

$$X'_{uk} = X_{uk} / X_{0k}\ ,wherein\ u = 1, 2, \dots, b; k = 1, 2, \dots, l \tag{21}$$

Step 3: Calculate the Euclidean correlation degree e_{uk} between X'_{uk} and X'_{0k}. Assuming that η represents the coefficient of distinction, according to X', the correlation degree e_{uk} between X'_{uk} and X'_{0k} was calculated using the following formula:

$$e_{uk} = \frac{\underset{b}{MIN}\,\underset{l}{MIN}\left|X'_{0k} - X'_{uk}\right| + \eta\,\underset{b}{MAX}\,\underset{l}{MAX}\left|X'_{0k} - X'_{uk}\right|}{\left|X'_{0k} - X'_{uk}\right| + \eta\,\underset{b}{MAX}\,\underset{l}{MAX}\left|X'_{0k} - X'_{uk}\right|} \tag{22}$$

Step 4: Construct the grey relation decision matrix. Based on the correlation degree obtained in Step 3, determine the grey relation decision matrix. The expression is as follows:

$$B = \begin{bmatrix} B_{01} & B_{02} \cdots B_{0l} \\ B_{11} & B_{12} \cdots B_{1l} \\ B_{21} & B_{22} \cdots B_{2l} \\ \vdots & \vdots \cdots \vdots \\ B_{b1} & B_{b2} \cdots B_{bl} \end{bmatrix} \tag{23}$$

Step 5: Construct the weighted grey relation decision matrix. Determine the weights of each indicator using the *C-OWA* operator weighting method, where the weights are represented by $\phi = (\phi_1, \phi_2, \ldots, \phi_l)^Y$; based on ϕ and B, a weighted grey relation decision matrix B' was established.

$$B' = \begin{bmatrix} \varphi_1 & \varphi_1 & \cdots & \varphi_l \\ \varphi_1 B_{11} & \iota_2 B_{12} & \cdots & \varphi_l B_{1l} \\ \varphi_1 B_{21} & \varphi_2 B_{22} & \cdots & \varphi_l B_{2l} \\ \vdots & \vdots & \cdots & \vdots \\ \varphi_1 B_{b1} & \varphi_2 B_{b2} & \cdots \varphi_l Bbl \end{bmatrix} \tag{24}$$

Step 6: Determine the value of the gray relation projection. Use the weighted grey relation decision matrix to calculate the grey relation projection values for each sample (student) across different indicators. Specific steps are as follows:

1. Each candidate learning resilience enhancement strategy is considered as a row vector. The gray relation projection angle is defined as the angle π between each candidate learning resilience enhancement strategy O_u and the optimal learning resilience enhancement strategy O_0. The cosine value of the angle can be calculated using the following formula:

$$COS\pi = \frac{\sum_{k=1}^{l} \varphi_k B_{uk} \cdot \varphi_k}{\sqrt{\sum_{k=1}^{l} [\varphi_k B_{uk}]^2 \cdot \sum_{k=1}^{l} \varphi_k^2}}, k = 1, 2, \ldots, l \tag{25}$$

2. Calculate the modulus f_u of O_u using the following formula:

$$f_u = \sum_{k=1}^{l} [\varphi_k B_{uk}]^2 \tag{26}$$

3. The grey relation projection value of O_u and O_0 can be calculated using the following formula:

$$F_u = f_u \cdot COS\pi = \sum_{k=1}^{l}[\varphi_k B_{uk}]^2 \cdot \frac{\sum_{k=1}^{l}\varphi_k B_{uk} \cdot \varphi_k}{\sum_{k=1}^{l}[\varphi_k B_{uk}]^2 \cdot \sum_{k=1}^{l}\varphi_k{}^2} = \sum_{k=1}^{l} B_{uk}\left[\varphi_k^2 \Big/ \sum_{k=1}^{l}(\varphi_k)^2\right] \tag{27}$$

$$denoted\ as\ \overline{\varphi_k} = \varphi_k^2 \Big/ \sum_{k=1}^{l}(\varphi_k)^2 \tag{28}$$

The calculation formula of grey relation projection value is:

$$F_u = \sum_{k=1}^{l} B_{uk}\overline{\varphi_k}, u = 1, 2, \ldots, b \tag{29}$$

A higher projection value indicates a stronger correlation between students' willingness to learn and the enhancement of learning resilience under the interactive autonomous learning mode, and vice versa.

5 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1 lists indicators for evaluating students' learning resilience and their corresponding weights. The weights values were obtained through expert review, historical data analysis, and other methods. Different indicators reflect various aspects of students' learning resilience, and the weight values indicate their relative importance in the evaluation. The highest weights were assigned to two indicators: goal achievement (0.109) and learning plan (0.099). This indicates that in the evaluation of learning resilience, the most important factors are realizing one's goals and having a clear learning plan. The weight values of stress tolerance (0.091) and clear goals (0.089) are relatively high, indicating that psychological quality and goal orientation also play important roles in learning resilience. The average weight values of interest in subjects (0.088) and interpersonal skills (0.084) reflect that these two indicators are also important for developing resilience in learning. The weight values of performance stability (0.062) and confidence in learning (0.069) are lower. However, these two indicators are still important, albeit less important, in evaluating learning resilience compared to other indicators.

Table 1. Weight values of grey relation projection

Indicator	Weight	Indicator	Weight
Stress tolerance	0.091	Emotional regulation	0.079
Performance stability	0.062	Interest in subject	0.088
Confidence in learning	0.069	Problem-solving ability	0.077
Teamwork	0.072	Interpersonal skills	0.084
Clear goals	0.089	Goal achievement	0.109
Learning plan	0.099	Deferred gratification	0.081

According to the above analysis, it can be concluded that goal achievement and learning plans are the most critical factors for learning resilience. Stress tolerance and goal-setting are indispensable factors. Interest in the subject and interpersonal skills cannot be ignored either, but their weights in the comprehensive evaluation are relatively low.

Under the interactive autonomous learning mode, students' willingness to learn and their resilience in learning are both very important. In this paper, four different strategies for enhancing students' learning resilience are proposed. Scheme 1 is an enhancement program that utilizes goal orientation and self-monitoring techniques. Its objective is to enhance students' ability to establish learning goals and effectively achieve them, thereby increasing their motivation to learn. Scheme 2 is a program focused on stress management and psychological support. Its objective is to improve students' psychological resilience and ability to manage stress. Scheme 3 is based on a variety of learning resources and personalized learning paths. Its goal is to enhance students' interest in learning by providing a wide range of resources and tailored learning paths. Scheme 4 is an enhancement program based on social interaction and cooperative learning. Its aim is to improve students' teamwork abilities and interpersonal skills by providing more opportunities for social interaction and cooperative learning. These schemes aim to comprehensively enhance students' learning resilience and willingness to learn from various perspectives. With the help of these programs, educators can effectively enhance students' learning outcomes and accelerate their enthusiasm for ongoing learning and personal growth.

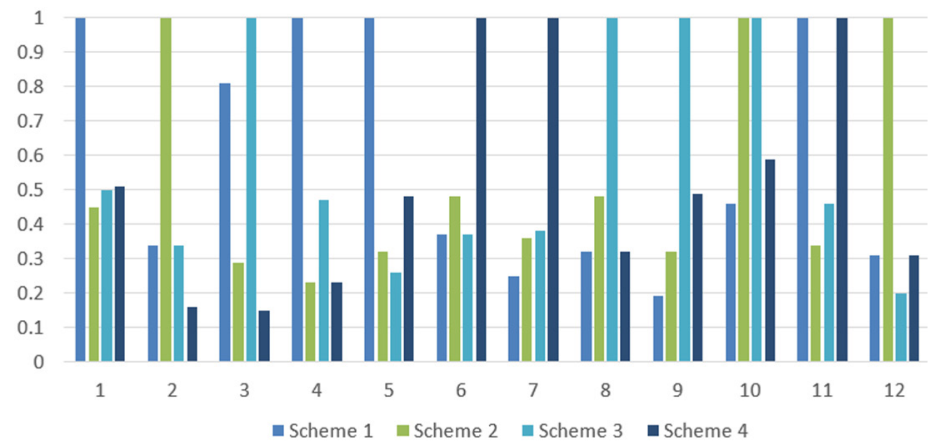

Fig. 4. Comparison of evaluation index data of learning resilience enhancement schemes

According to Figure 4, these four schemes exhibited varying performance in terms of different indicators of learning resilience. Scheme 1 highly emphasizes clear goals (Indicator 9), a learning plan (Indicator 11), stress tolerance (Indicator 1), and teamwork (Indicator 4), while placing less emphasis on problem-solving ability (Indicator 6), emotional regulation (Indicator 7), and interpersonal skills (Indicator 8). Scheme 2 performed well in emotional regulation (Indicator 7), interpersonal skills (Indicator 8), and goal achievement (Indicator 12), but performed poorly in problem-solving ability (Indicator 3), teamwork (Indicator 4), and interest in the subject (Indicator 5). Scheme 3 performed excellently in problem-solving ability (Indicator 3), interpersonal skills (Indicator 8), and interest in the subject (Indicator 9), but performed poorly in terms of clear goals (Indicator 9), learning plan (Indicator t1), and deferred gratification (Indicator 2). Scheme 3 performed satisfactorily in teamwork (Indicator 4), problem-solving ability (Indicator 6), and goal achievement (Indicator 12), but performed inadequately in stress tolerance (Indicator 1), performance stability (Indicator 2), and interest in the subject (Indicator 5).

According to the above analysis, it can be concluded that students' ability to achieve goals and make learning plans is the most critical factor affecting their learning resilience. If the ultimate goal is to enhance students' capacity to establish learning objectives, learning strategies, and manage psychological stress, then Schemes 1 and 2 are more appropriate. If the ultimate purpose is to increase students' interest in a subject and enhance their problem-solving and interpersonal skills, then Scheme 3 is a better choice. Scheme 4 is a comprehensive but average program that is more suitable for students with average performance in multiple areas. However, it is particularly beneficial for those who need to enhance their teamwork and problem-solving skills.

Table 2. Descriptive statistics of continuous learning willingness of students with different levels of learning resilience

Test Variable	Level of Learning Resilience	Number	Average	Standard Deviation
Continuous learning willingness	Negative learner	25	1.5248	0.15245
	Result-orientated learner	87	3.4168	0.55263
	Positive learner	47	3.7752	0.57412
	Average learner	35	3.6268	0.63592

According to the descriptive statistics presented in Table 2, it is evident that there is a significant correlation between the level of learning resilience and the willingness to engage in continuous learning. Students in the negative learner group obtained the lowest scores in the willingness to engage in continuous learning. The average score was 1.5248, with a standard deviation of 0.15245. These results suggest that these students lack long-term motivation and interest in learning, and there is relatively little variation within the group. Students in the result-oriented learner group obtained significantly higher scores compared to those in the negative learner group. The average score was 3.4168, with a standard deviation of 0.55263. These results indicate that students in the result-oriented group generally have a positive attitude towards learning, although they may prioritize short-term outcomes. Students in the positive learner group achieved the highest scores in terms of their willingness to engage in continuous learning. The average score was 3.7752, with a standard deviation of 0.57412. These results indicate that these students actively participate in learning activities and have a preference for continuous learning. Students in the average learner group obtained an average score of 3.6268 and a standard deviation of 0.63592 in terms of their willingness to engage in continuous learning. This indicates that while students in this group are generally open to continuous learning, there are significant differences among them, as evidenced by the relatively large standard deviation.

Then, the following conclusions can be drawn from the above analysis: there is a significant positive correlation between the level of learning resilience and the willingness to engage in continuous learning. For reluctant learners, special attention and intervention are needed to increase their motivation to learn. Result-oriented learners and average learners performed well in terms of their willingness to engage in continuous learning, but there is still room for improvement. Positive learners performed the best among all groups of learners. However, educators should ensure that students in this group can maintain their enthusiasm for learning and continue to enhance their learning outcomes.

According to the data in Table 3, various interactive autonomous learning modes have a significant impact on students' willingness to engage in continuous learning. Under the single-resource interaction mode, students' scores for continuous learning willingness are the lowest, with an average score of 1.5143 and a standard deviation of 0.15548. This suggests that students lack long-term motivation and willingness to learn in this mode. The small standard deviation indicates that students in this group have relatively consistent levels of continuous learning willingness. Students in the multi-resource interaction group obtained an average score of 3.1167, with a standard deviation of 0.55135. These results suggest that multi-resource interaction can enhance students' motivation for continuous learning, although there is still potential for further improvement. Students in the team interaction group achieved the highest scores, with an average score of 3.7527 and a standard deviation of 0.37451. These results indicate that team interaction can stimulate students' desire for continuous learning, and students in this group consistently demonstrate a willingness to engage in continuous learning. Students in the teacher-instructed interaction group obtained an average score of 3.4281 with a standard deviation of 0.92315. Although the average score is relatively high, the standard deviation is the largest, indicating significant variations among students within this group.

Table 3. Descriptive statistics of continuous learning willingness of students under different interactive autonomous learning modes

Test Variable	Type of Interactive Autonomous Learning Mode	Number	Average	Standard Deviation
Continuous learning willingness	Single-resource interaction	25	1.5143	0.15548
	Multi-resource interaction	87	3.1167	0.55135
	Team interaction	47	3.7527	0.37451
	Teacher-instructed interaction	35	3.4281	0.92315

Based on the above analysis, it can be concluded that there is a significant correlation between the willingness to engage in continuous learning and the adoption of an interactive autonomous learning mode. The single-resource interaction mode is the least favorable for cultivating students' willingness to engage in continuous learning, while the team interaction mode is the most effective mode for increasing students' willingness of continuous learning. Although the teacher-instructed interaction mode performed well, there are significant differences within the group that necessitate a more personalized teaching method. This information is of great value to educators and policymakers, as it can be used to improve teaching methods and educational policies, thereby effectively enhancing students' willingness to learn.

6 CONCLUSION

This study analyzed the future trend of students' learning willingness under an interactive autonomous learning mode based on a grey prediction model. Additionally, the study employed the TOPSIS analysis method to provide comprehensive evaluations of students' learning resilience and determine the weights of evaluation indicators. Furthermore, this study employed an enhanced grey correlation projection method to examine the correlation between students' learning willingness and their learning resilience. Descriptive statistics were also utilized to analyze the impact of various factors such as learning resilience level, interactive autonomous learning mode, gender, major, and online learning experience on students' continuous learning willingness.

In this paper, experimental analysis demonstrated that the constructed grey prediction model can accurately predict students' future learning willingness under an interactive autonomous learning mode. Additionally, the application of TOPSIS analysis and grey relation projection methods has shown a correlation between learning resilience and learning intention. Descriptive statistics have revealed that the level of learning resilience and the use of interactive autonomous learning modes significantly influence students' continuous learning willingness. However, gender, major, and online learning experience only have a limited impact on it.

Based on a comprehensive analysis and various research methods, this paper thoroughly discusses multiple aspects of students' willingness to learn and their resilience in the context of interactive autonomous learning. The research findings offer substantial data support and theoretical guidance for educational practices.

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