Requirement Analysis of Student Individual Learning Based on the Idea of Lifelong Learning

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Abstract—We are currently experiencing a knowledge-chasing society in which acquiring new knowledge and solving new problems are necessary and required skills for people to survive in human society in the future. Therefore, in such a circumstance, it is of certain research value to analyze the requirement satisfaction of Student Individual Learning (SIL) based on the idea of lifelong learning and discover problems in the process of SIL. However, existing studies generally have a few shortcomings such as the too narrow scope of study groups and the undiversified research objects. To this end, this paper took English learning as an example to research the requirement analysis of SIL based on the idea of lifelong learning. In the texts, the paper constructed a requirement satisfaction (RS) model of SIL, gave the calculation method of the learning benefit of SIL, and elaborated on the strategy optimization and selection method of SIL. The effectiveness of the proposed model was verified by experimental results attained in the study.

Keywords—lifelong learning, student individual learning (SIL), requirement satisfaction degree (RS-degree), learning requirement, learning benefit

1 Introduction

The current era values knowledge very much. Only through constant learning can people learn to know, adapt to, and transform the society. Learning will run through modern people's entire lives, and acquiring new knowledge and solving new problems are necessary and required skills for people to survive in human society in the future [1-7]. Since lifelong learning has been advocated in modern society, more emphasis should be laid on the cultivation of SIL. For students, in order to realize their ideals, they should perform individual learning based on their own conditions, and the requirement satisfaction of SIL plays a key role in lifelong learning and the realization of personal values [8-14]. Individual learning can motivate students' learning initiative and urge them to choose the learning plans and strategies that are suitable for their current cognition level. During the process of individual learning, students can control their learning progress in real time and perceive their own progress status; moreover, the positive self-evaluation results can further promote students' learning initiative, in this way, a virtuous circle of SIL could be formed [15-19]. Thus, it is of certain research value to analyze the requirement satisfaction of SIL based on lifelong learning and discover problems in the process of SIL.

Rapid technological advancement requires people to master new skills, knowledge, and competencies to succeed in engineering profession. In order to cultivate students' abilities to meet desired needs, Mazumder et al. [20] proposed to set an engineering baccalaureate program that satisfies different engineering criteria and hold seminars to increase their knowledge and enhance their professional abilities; also, students are required to select research topic related to the engineering courses they've taken and write research papers about it, so that their professional knowledge could be increased and their professional skills could be strengthened. Castaneda and Cheng [21] used a statistical model to better interpret factors that can affect the participation of lifelong learning, and applied the statistical software package R to generate a multinomial logistic regression model, their research results showed that student attribute has a decisive role in determining the participation of lifelong learning. Dietrich et al. [22] investigated the influence of learning design on students' motivation (self-concept, self-efficacy, intrinsic and utility task values) and performance, they employed the structural equation modeling method to discover that intervention can positively affect the self-concepts of effort avoidant students and their attitudes and self-efficacy towards inclusive education, but it showed no effect on course performance, course-related self-efficacy, and task values. During the COVID-19 pandemic in 2019, these influences may be exacerbated which had resulted in the sudden transformation to online education. To figure out the individual variability in stress and learning, Hobert [23] discussed three different techniques of dense longitudinal data analysis, including regression analysis, multi-layer models, and individual-specific network models, briefly introduced the research background of each technique, and employed the data of college students to give illustrative analysis. Developing effective teaching processes for students suitable for their respective learning pace is a challenging task for teachers, so it's necessary to identify the difficulties of each student so that proper instructional measures could be adopted to help them one by one, to solve this problem, Santos et al. [24] proposed a web-based assisted learning tool which can monitor and report students' individual learning behavior to teachers, and the evaluation results proved that the proposed tool had promoted student assistance and helped teachers to get closer to students.

After carefully reviewing related literatures, we discovered a few limitations in existing research results, such as the too narrow scope of study groups and the undiversified research objects. Numerous field scholars have discussed the connotation of lifelong learning, but few of them have concerned about the requirement dimensions of individual learning, the influencing factors of requirement satisfaction, or the related applications. Hence, to fill in this research blank, this paper took English learning as an example to research the requirement analysis of SIL based on the idea of lifelong learning. The second chapter built a RS model of SIL; the third chapter gave the calculation method of the learning benefit of SIL; the fourth chapter elaborated on the strategy optimization and selection method of SIL. At last, the effectiveness of the proposed model was verified by experimental results.

2 The RS model of SIL

Figure 1 summarizes the manifestations of students' lifelong learning ability. The 8 aspects include: the general learning idea, a high life goal, flexible thinking, scientific time management method, scientific learning method, strong adaptability, creativity, and hands-on ability. In order to realize their ideals, students need to carry out individual learning based on their own conditions; for students in different life stages, they would have different learning requirements.

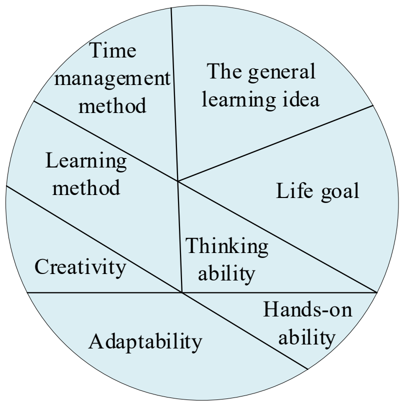

Fig. 1. Manifestations of lifelong learning ability

The degree of requirement satisfaction of SIL (hereinafter referred to as the RS-degree and RS model) is the evaluation of the status of satisfying students' requirements for individual learning, and it is also the evaluation of the degree of matching between students' educational status and their individual learning requirement. This paper introduced the psychological curve function to attain more accurate evaluation results of RS-degree. The psychological curve function can quantitatively describe the RS-degree based on expected benefit and current benefit of SIL. Assuming: Φ represents the RS-degree of SIL; β represents the expected benefit; ψ represents the current benefit; then, the psychological curve function can be expressed as:

$$\Phi = 1 - d^{-\left(\frac{\beta}{\psi}\right)^2} \tag{1}$$

Based on the above formula, this paper built the RS model. Assuming: $\alpha_{pc}\beta_{zd}$ represents the expected benefit of learning input cost zd; β_{ξ} represents the expected benefit of ξ (the efficacy and sustainability attributes of SIL); $\psi_{i,\,zd}$ represents the current benefit of the learning input cost zd of the i-th candidate SIL strategy; $\psi_{i,\xi}$ represents the current benefit corresponding to ξ (attributes of the i-th candidate SIL strategy); $\Phi_{i,\,zd}$ represents the satisfaction degree of the learning input cost zd of the i-th candidate SIL strategy; Φ_i, ξ represents the satisfaction degree of ξ (attributes of the i-th candidate SIL strategy), then Formula 2 gives the learning input cost satisfaction model:

$$\Phi_{i,zd} = \begin{cases} 1, \beta_{zd} >= \psi_{i,zp} \\ 1 - d^{-\left|\frac{\beta_{zp}}{\psi_{i,zp}}\right|}, \beta_{zd} < \psi_{i,zp} \end{cases} \tag{2}$$

The satisfaction model of SIL efficacy and sustainability attributes is given by Formula 3:

$$\Phi_{i,\xi} = \begin{cases} 1, \beta_{\xi} <= \psi_{i,\xi} \\ 1 - d^{-\left|\frac{\beta_{\xi}}{\psi_{i,\xi}}\right|}, \beta_{\xi} > \psi_{i,\xi} \end{cases} \tag{3}$$

3 Calculation of learning benefit of SIL

In this paper, the involved benefit contains two aspects: the expected benefit, and the current benefit. The former can be attained based on the history learning behavior data of students; the latter can be calculated based the real-time collected learning behavior data according to the new SIL strategy. This paper adopted the fuzzy analytic hierarchy process (AHP) to attain the weights of related parameters and used them to characterize the requirement of SIL.

AT first, parameters in the RS model were divided into two groups, which respectively represent the importance of SIL efficacy and the importance of SIL sustainability. Figure 2 shows the parameter structure of the RS model and gives all the parameters. Quantitative scale values could be attained by comparing the two groups of parameters in pairs, wherein $s_{x,y}$ represents the scale value of the y-th column of the x-th row, then the corresponding fuzzy complementary judgment matrix could be attained, which is denoted as S=$s_{x,y}$*(d*d). Moreover, by substituting S=$s_{x,y}$*(d*d) into the two major attributes of SIL (namely efficacy and sustainability), the corresponding fuzzy complementary judgment matrices could be attained, which are represented by S_{rz} and S_{ro} respectively.

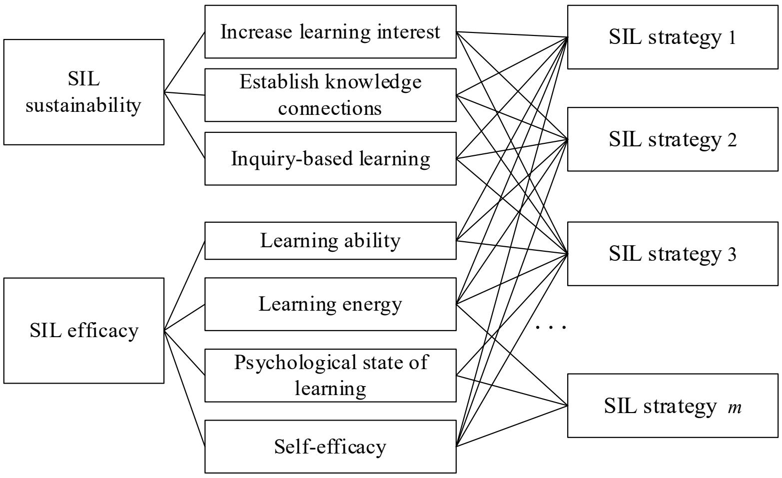

Fig. 2. Parameter structure of the RS model

Assuming: d represents the number of rows in the matrix; x and y represent the x-th row and the y-th column; $\sum^{m}_{x=1}q_x=1$, $q_x \geq 0$, $x=1,2,...,d$; then the weights of the parameters in the RS model can be calculated by the following formula:

$$q_x = \frac{\sum_{y=1}^{m} s_{x,y} + \frac{m}{2} - 1}{d\left(d-1\right)}, x = 1,2,...,d \tag{4}$$

To verify the consistency of fuzzy matrix $S=s_{x,y}*(d*d)$, at first, a feature matrix with d rows and d columns of the weight $q_{x,y}$ of the y-th column of the x-th row was constructed, and $q_{x,y}$ can be calculated by the following formula:

$$q_{x,y} = \frac{q_x}{q_x + q_y}, \forall x, y = 1,2,...,d \tag{5}$$

The normalized value of the duration of SIL was defined as the composite value of its learning input cost attribute. Assuming: $\psi_{i,zp}$ represents the value of the learning input cost attribute of the i-th SIL strategy; D represents the duration of SIL; $\psi_{i,zd}$, $\psi_{i,xz}$, $\psi_{i,xo}$ respectively represent the learning input cost zd of the i-th SIL strategy; rz represents the SIL efficacy; ro represents the composite value of the sustainability of SIL; then, by substituting the parameters of current candidate SIL strategy, the composite value of learning input cost, SIL efficacy, and SIL sustainability of the current candidate SIL strategy could be attained, in this paper, this composite value was defined as the current benefit of SIL; wherein $\psi_{i,zp}$ represents the current benefit of learning input cost; $\psi_{i,xz}$ represents the current benefit of SIL efficacy; $\psi_{i,xy}$ represents the current benefit of SIL sustainability, then, the composite value of SIL efficacy attribute and SIL sustainability attribute could be attained by accumulating the products $\Gamma\alpha_{i,z}$, see below:

$$\psi_{i,zp} = \Gamma \ \alpha_{i,d} \tag{6}$$

$$\psi_{i,x\alpha} = q_{SRR} \times \Gamma \alpha_{i,SRR} + q_Y \times \Gamma \alpha_{i,Y} \tag{7}$$

$$\times \Gamma \alpha \psi_{i,xz} = q_{Ei,N} + q_C \times \Gamma \alpha_{i,C} + q_G \times \Gamma \alpha_{i,G} \tag{8}$$

Assuming: m groups of parameter data of RS model and SIL strategy selection results are attained when student selecting SIL strategy for m times from the history learning behavior data, by substituting the m groups of data into above formulas, the set of the composite value of learning input cost, SIL efficacy and SIL sustainability of m groups of SIL strategy in the history learning behavior data could be attained, that is:

$$\Psi_w = \{\psi_{1,w}, \psi_{2,w}, \ldots, \psi_{m,o}\} \tag{9}$$

However, in the history learning behavior data, under the condition that the SIL strategy has been executed for f times, inevitably there are data anomalies in the collected student attribute data values, so this paper took the average value of the composite value of each attribute under the condition that the SIL strategy has been executed for f times, that is:

$$\beta_w = \frac{1}{f} \sum_{i=1}^{f} \psi_{i,w} \tag{10}$$

Assuming: $\beta_{i,w}$ represents the composite value of learning input cost, SIL efficacy and SIL sustainability under the condition that a same SIL strategy has been executed for Z times; β_w represents the average value of the composite value of SIL strategy attribute requirement, which was defined as the expected benefit of SIL in this paper, then, the values of set Ψ_w were substituted into the above formula to attain the expected benefit of learning input cost, the expected benefit of SIL efficacy, and the expected benefit of SIL sustainability.

4 The searching for optimal SIL strategy and selection

In order to comprehensively evaluate the RS-degree of SIL, this paper introduced the radar chart analysis to describe changes in the composite value of the parameters of the RS model by analyzing the changes of the area in the chart.

Assuming: $\Phi_{i,zp}$ represents the satisfaction degree of learning input cost of candidate SIL strategy C attained by the radar chart analysis method; $\Phi_{i,xz}$ represents the satisfaction degree of SIL efficacy; $\Phi_{i,xy}$ represents the satisfaction degree of SIL sustainability; θ_1 represents the central angle of the enclosed equilateral triangle, then its area R_1 can be calculated by the following formula:

$$R_1 = \frac{1}{2}\Big(\Phi_{i,zp}\Phi_{i,xz} + \Phi_{i,zp} \\ \Phi_{i,ro}\Phi_{i,ro}\Phi_{i,rz}\Big) sin\theta_1 \tag{11}$$

After subjected to area linear growth processing, R_1 was converted into R_2:

$$R_2 = h \times x^{y \times R_1} + u \tag{12}$$

Assuming: θ_2 represents the interior angle of the equilateral triangle; v represents its side length, then the formula for calculating the largest equilateral triangle area R_2 is:

$$R_c = \frac{1}{2} \quad v \times v \quad sin\theta_2 \tag{13}$$

Assuming: PRR_i represents the total satisfaction degree of students for candidate SIL strategy i, then the ratio of R_2 to the total area R_c can be calculated by the following formula:

$$PRR_i = \frac{R_2}{R_c} \tag{14}$$

Based on the history learning behavior data, the expected benefits of learning input cost, SIL efficacy, and SIL sustainability were obtained; then, through the calculation of the data of current candidate SIL strategy, the current benefits of learning input cost, SIL efficacy, and SIL sustainability were obtained as well. By substituting them into the RS model, the total satisfaction degree set PRR_i of student j for the i-th candidate SIL strategy could be attained. Assuming: m represents the number of SIL strategy candidates; the strategy with the highest satisfaction degree was selected from the candidate SIL strategy set of student j, then, the total satisfaction degree set PRR_i can be constructed as follows:

$$PRR_j=\{prr_{1,j}, prr_{2,j},\ldots,prr_{m,j}\} \tag{15}$$

Since in the history learning behavior data, for each student, the expected benefits of learning input cost, SIL efficacy, and SIL sustainability were different, the algorithm proposed in this paper chose the SIL strategy with the highest satisfaction degree of each student from SIL strategy candidates to satisfy students' requirement for SIL.

Recommendation algorithms have been successfully applied in various research fields. Conventional recommendation algorithms use scores collected from students' history learning behavior data to judge their learning preferences and predict the SIL items that they may be interested in. This paper introduced the collaborative filtering recommendation algorithm to process students' history learning behavior data and get SIL strategies with higher student satisfaction degree, thereby assisting students to select SIL strategies. Figure 3 shows the process of SIL strategy selection.

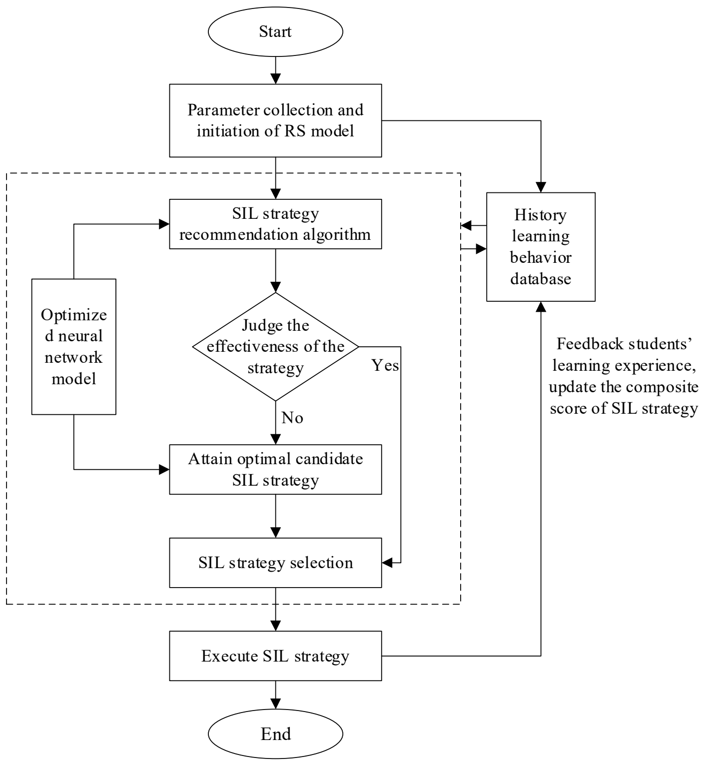

Fig. 3. The process of SIL strategy selection

Parameters of received signal strength, SIL duration, bandwidth, and load rate in the history learning behavior data were substituted into the raccoon optimization algorithm neural network model of SIL strategy to get the composite value of each candidate SIL strategy, which was taken as the similarity score of students for each SIL strategy. Then, the similarity scores of students for each SIL strategy were converted into a similarity score matrix $S(m,n)$, wherein m represents the student set and n represents the SIL strategy set.

Based on the Pearson correlation coefficient, the similarity of students' learning preferences was calculated, and students with similar learning preferences were found through the similarity score matrix. Assuming: $M_{i',i''}$ represents the set of SIL strategies to which both students i' and i'' have given composite scores; $vr_{i',j}$ represents the score given by student i' for SIL strategy j; $vr_{i'',j}$ represents the score given by student i'' for SIL strategy j; vr_z^* represents the average score given by student z; vr_w^* represents the average score given by student w, then the coefficient could be expressed as:

$$spd_{i',i''} = \frac{\sum_{j \in M_{i',i''}} \left(vr_{i',j} - vr_{i'}^*\right)\left(vr_{i'',j} - vr_{i''}^*\right)}{\sqrt{\sum_{j \in M_{i',i''}} \left(vr_{i',j} - vr_{i'}^*\right)^2 \left(vr_{i'',j} - vr_{i''}^*\right)^2}} \tag{16}$$

This paper adopted the artificial neural network for the selection of optimal SIL strategy, and the output value of each candidate SIL strategy was taken as the score of each candidate SIL strategy. The execution principle of the constructed neural network model can be regarded as to iteratively search for the optimal weight assignment scheme so that the output error is lower than the preset minimum value. Assuming BT represents the expected output; BT represents the actual output; T represents the number of neurons, then the error function of the network model could be expressed as:

$$g = 1/2\sum_{T}\left(b_T - B_T\right)^2 \tag{17}$$

Based on the raccoon optimization algorithm, the constructed neural network was optimized, that is, to get the weight assignment scheme H_{pzo} with the smallest initialization error:

$$H_{pzo} = AP_0 \tag{18}$$

Assuming: APl-1 represents the weight assignment scheme with the smallest model error in the current iteration; SDl-1 represents the local optimal weight assignment scheme in the previous iteration; UD_{l-1} represents the overall optimal weight assignment scheme in the previous iteration, then the optimal scheme among AP_{l-1}, SD_{l-1}, UD_{l-1} was selected. The optimization of the artificial neural network could be taken as a problem of network error minimization, then the fitness function g to be optimized could be expressed as:

$$\begin{aligned}
&AP_l = k_v \\
&where \\
&k_v \in \left\{AP_{l-1}, S_{l-1}, U_{l-1}\right\} \\
&g\left(k_v\right) = max\left\{g\left(fo\right) \mid fo \in \left\{AP_{l-1}, SD_{l-1}, UD_{l-1}\right\}\right\}
\end{aligned} \tag{19}$$

The optimal fitness function value attained through iterations was the optimal weight assignment scheme of the artificial neural network after repeated iterations and error corrections.

After attaining the new weight assignment scheme, based on the corrected model, AP_l and H_{pzo} were further evaluated, and the D_{pzo} got the smallest error, that is:

$$\begin{aligned}
&H_{pzo} = \left(g\left(H_{pzo}\right) > g\left(AP_l\right)\right) \to \left(H_{pzo}\right) \\
&\wedge\neg\left(g\left(H_{pzo}\right) > g\left(AP_l\right)\right) \to \left(AP_l\right)
\end{aligned} \tag{20}$$

Judge whether the total satisfaction degree PRR of students for the recommended SIL strategy, the SIL duration of students PR, and other parameters could meet the minimum threshold for accepting the recommended SIL strategy or not, if the minimum threshold is met, then the strategy is accepted. Assuming: MUO represents the SIL strategy selected by student; i' represents the SIL strategy recommended for students with similar learning preferences; i'' represents the optimal candidate SIL strategy selected by the model; $\Omega_{i,z'}$ represents the normalized value of parameter z' in SIL strategy i; Ω_p^* represents the minimum threshold of parameter z; F(u') represents the output value of the model, then there are:

$$\begin{aligned} & MUO = i' \\ & when \\ & \Omega\alpha_{i,z'} > \Omega_{z'}^{*}, z' \in \{PR, SRR, Y, G\} \end{aligned} \tag{21}$$

If the minimum threshold is not met, then the optimized neural network model is run to get the composite value of each candidate SIL strategy, the SIL strategy with greater composite value is selected for execution, and the composite values given by students for each candidate SIL strategy are updated into student similarity table in the history learning behavior database.

$$\begin{aligned} & MUO = i' \\ & where \\ & i'' \in \{0,1,...,m\} \\ & and \\ & g(i'') = max\{F(u') \mid i \in \{0,1,...,m\}\} \end{aligned} \tag{22}$$

5 Experimental results and analysis

This paper took English learning as an example to build RS model of SIL, based on the idea of lifelong learning, two dimensions of SIL efficacy and SIL sustainability and seven parameters were selected, including: increase learning interest, establish knowledge connections, inquiry-based learning, learning ability, learning energy, psychological state of learning, and self-efficacy. Table 1 lists the average score and standard deviation of each parameter of the RS model. According to the data shown in the table, the average score of SIL sustainability is 3.52, and the average score of SIL efficacy is 3.29, indicating that under the influence of the idea of lifelong learning, students have certain awareness and motivation of SIL, but there's still room for improvement in terms of learning ability and self-efficacy. Judging from the seven parameters, the average scores of "establish knowledge connections", "increase learning interest", "psychological state of learning", and "self-efficacy" are respectively 3.69, 3.25, 3.85, and 3.56, indicating that students' satisfaction with these aspects is relatively high, while their satisfaction with other aspects is lower; moreover, during the process of SIL, students' learning ability improvement is not significant, their ability of inquiry-based learning is relatively weak, and their learning energy is insufficient.

Table 1. Average score and standard deviation of each parameter

Dimension	**SIL sustainability**			**SIL efficacy**			
Average score	3.52			3.29			
Parameter	Increase learning interest	Establish knowledge connections	Inquiry-based learning	Learning ability	Learning energy	Psychological state of learning	Self-efficacy
Minimum	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Maximum	5.7	5.7	5.7	5.7	5.7	5.7	5.7
Mean	3.25	3.69	3.15	3.24	3.15	3.85	3.56
Standard deviation	0.835	0.985	0.962	0.913	0.947	0.885	0.835

Table 2 gives the RS-degree of SIL. In order to investigate student satisfaction with each aspect of the recommend SIL strategy comprehensively and objectively, this paper divided the RS-degree into five levels: very satisfied, satisfied, average, not very satisfied, and not satisfied at all. According to the table, overall speaking, the RS-degree of students was average level or satisfied level, indicating that students generally satisfy with the current SIL status, but there's still room for improvement. According to the data in Table 2, the RS-degree of students with inquiry-based learning and psychological state of learning is lower than the overall level, so the recommended SIL strategy should work on these two aspects in a targeted manner. As for the rest 5 aspects, the current status should be maintained and the existing advantages should be exerted.

Table 2. RS-degree of SIL

Option	**Increase learning interest**	**Establish knowledge connections**	**Inquiry-based learning**	**Learning ability**	**Learning energy**	**Psychological state of learning**	**Self-efficacy**
Very satisfied	9.52%	7.41%	8.62%	7.84%	12.68%	14.68%	13.48%
Satisfied	9.47%	45.16%	40.39%	47.62%	40.63%	47.51%	49.68%
Average	36.59%	41.59%	36.95%	37.42%	39.27%	39.58%	37.49%
Not very satisfied	7.62%	5.48%	8.69%	12.47%	13.69%	7.36%	8.69%
Not satisfied at all	1.39%	1.41%	2.65%	0.58%	0.62%	0.36%	1.85%

To verify the effectiveness of the proposed model, this paper designed a comparative experiment, and Figure 4 compares the changes of average RS-degree of different models with the number of students. Reference model A is the conventional BP neural network, and the reference model B is the BP neural network improved by particle swarm optimization (PSO). According to the Figure 5, the change trends of the curves of the three models are basically the same, the RS-degree of the proposed model is slightly higher than that of the other two models; under the condition that the number of students was fixed, the models were run for 82 times respectively and the RS-degree of each user was averaged. Among the three models, the average RS-degree of the proposed model is the highest, indicating that the proposed model not only ensured the effectiveness of the recommended SIL strategy, but also enhanced students' life-long learning ability.

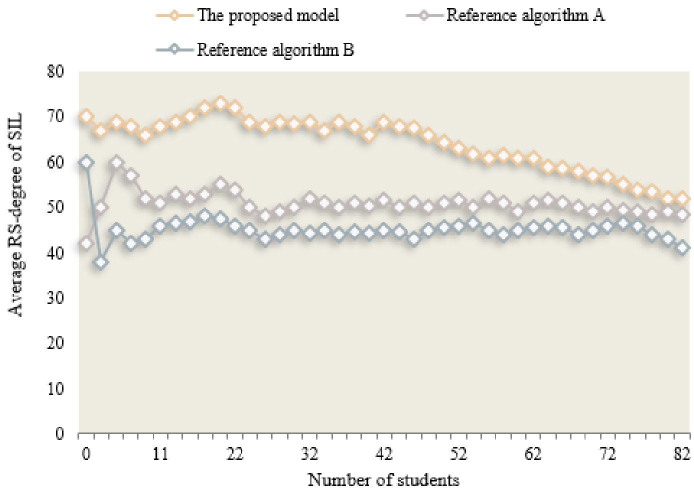

Fig. 4. The change of average RS-degree of SIL with the number of students

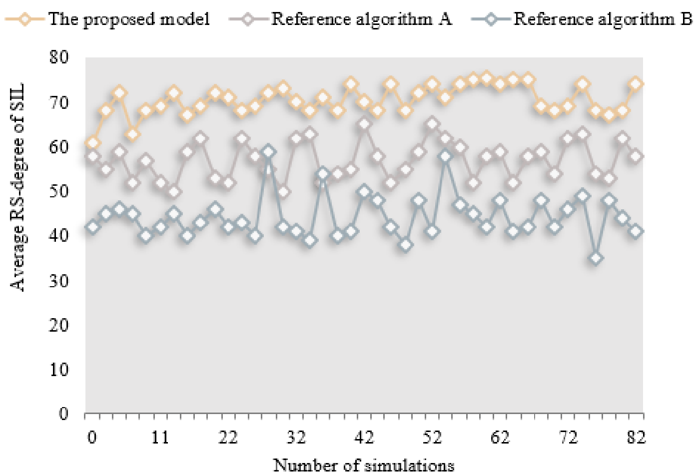

Fig. 5. The change of average RS-degree of SIL with the number of simulations

At last, this paper performed cross analysis on students' willingness to participate in individual SIL and group SIL. Figures 6 and 7 show the corresponding analysis results. As can be seen from the results, for both individual SIL and group SIL, there is a significant positive correlation between student willingness and their behavior, students who had experience SIL in the past are more willingness to participate in the next SIL stage. In contrast, students who hadn't participated in SIL before have lower willingness to participate in individual SIL and their satisfaction degree is generally lower; but their willingness to participate in group SIL is higher and their satisfaction degree is higher as well.

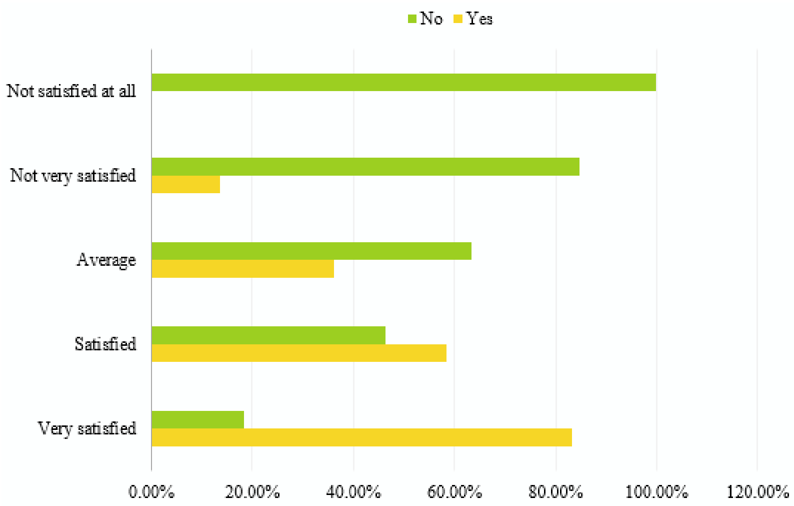

Fig. 6. Cross analysis of individual SIL participation willingness

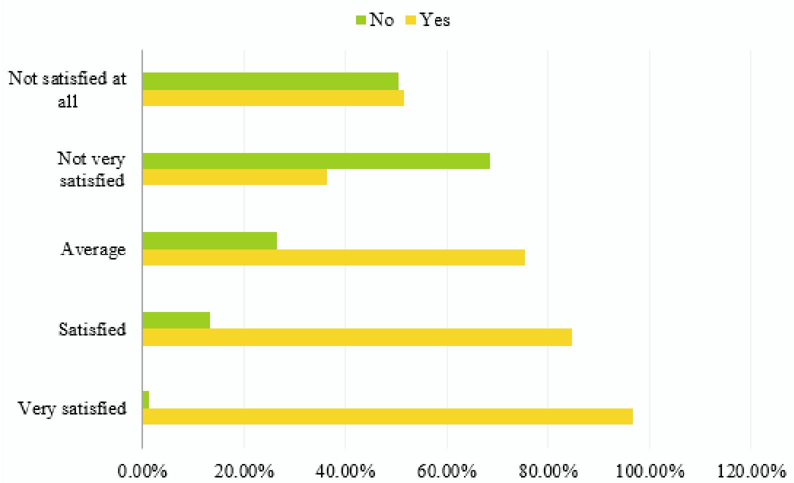

Fig. 7. Cross analysis of group SIL participation willingness

6 Conclusion

This paper took English learning as an example to research the requirement analysis of SIL based on the idea of lifelong learning. In the texts, the paper constructed a RS model of SIL, gave the calculation method of the learning benefit of SIL, and elaborated on the strategy optimization and selection method of SIL. Through the experiment, at first, this paper gave the average score and standard deviation of each parameter of the RS model, and the results suggested that, during the process of SIL, students' learning ability improvement is not significant, their ability of inquiry-based learning is relatively weak, and their learning energy is insufficient; secondly, this paper gave the RS-degree of students with SIL, and the results suggested that, the RS-degree of students with inquiry-based learning and psychological state of learning is lower than the overall level, so the recommended SIL strategy should work on these two aspects in a targeted manner, as for the rest 5 aspects, the current status should be maintained and the existing advantages should be exerted; thirdly, this paper gave the trend of the average RS-degree of each model with the changes of the number of students and the number of simulations, and verified the effectiveness of the proposed model; at last, this paper performed cross analysis on students' willingness to participate in individual SIL and group SIL and gave the corresponding analysis results.

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