Motivation of Students' Persistency for Online Learning Under Multiple Mediation Effect

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Abstract—This paper probed deep into the motivation of students' persistency for online learning from the perspective of user experience of online learning platforms, in the purpose of increasing user stickiness and formulating effective operation strategies in a targeted manner. Existing studies on the motivation of students' persistency for online learning mostly focus on theories, while few of them have talked about the problem with the multiple mediation effect taken into consideration, for this reason, this paper aims to fill in this research gap and explore the mechanism behind the motivation of students to carry out online learning persistently under the multiple mediation effect. At first, this paper built an improved support vector machine (SVM) classifier and used it to predict the duration of students' online learning; then, it adopted a structural equation model to analyze the data of students' willingness to continue online learning; after that, this paper gave a theoretical analysis on the motivation of students' persistency for online learning under multiple mediation effect, and constructed a basic regression model for the said matter; at last, this paper employed experimental results to verify the prediction accuracy of the constructed model, and gave the corresponding estimation results.

Keywords—support vector machine (SVM), multiple mediation effect, online learning, learning persistency, motivation, willingness

1 Introduction

The advances in mobile computing technology in recent years have greatly promoted the development of online learning platforms, and the conveniency of this novel learning method has become a new trend and is welcomed by students [1, 2]. For these emerging online learning platforms, user satisfaction and low utilization rate are common and urgent problems to be solved [3-5], however, few existing studies have concerned about the topic of the motivation of students' persistency for online learning [6-11]. In view of this situation, it is quite necessary to analyze the said topic from the perspectives of online learning platform and user experience [12-16] and figure out the influencing factors of the motivation of students' persistency for online learning; only in this way, could we achieve the ultimate purpose of increasing user stickiness in a more targeted manner, formulating effective operation strategies, stimulating users' willingness to use the platform continuously, and improving user satisfaction.

Affected by the COVID-19 epidemic, almost all students, both in urban areas and in rural areas, have to stay at home and learn online. Liang et al. [17] conducted a large-scale field survey on rural schools in four Chinese provinces, discussed the factors that affect students' persistency for online learning, and they found that perceived usefulness, perceived conveniency, behavior, and emotional engagement all have a positive impact on students' persistency for online learning. Machuca et al. [18] conducted a survey on 126 students in the engineering department of four private universities in Peru to understand their perceptions of virtual classroom operations and feelings about potential success, aiming to measure their willingness to continue online courses, and they discovered that user satisfaction, perceived usefulness, enjoyment, effort expectations, social influence, trust, shared norms, and connection strength can explain this variable to a great extent. Cui [19] tested the relationship between system quality, information quality, service quality, satisfaction degree and persistence intention in online learning, and the results verified the positive impact of system quality on satisfaction, and the significant positive impact of information quality and service quality on satisfaction degree and persistence intention; moreover, they also found that satisfaction can improve online learning persistency, so for providers of online learning service and educators, it's very important to keep the learners and urge them to be persistent in learning. Yang et al. [20] drew on the stimulus-organism-response framework and self-determination theory to investigate the factors affecting the continuity of mobile learning of college students from two aspects of self-determination requirement and learning input, the authors developed a research model and tested the data of 309 Chinese online learners collected from a few mobile online learning platforms. In the past decades, learning management systems have been widely used in colleges and universities to monitor and manage online learning and teaching. Zareravasan and Ashrafi [21] proposed a comprehensive model integrating the expected conformation theory with the technology acceptance model, and used the statistical data of students from an online university to test the model, then, the authors ran a partial least square structural equation to model and verify the proposed theoretical model, and the research findings suggested that perceived usefulness is the strongest predictor of students' persistence intention.

With the help of the effective prediction of students' online learning duration, online learning platforms can take targeted measures to constantly recommend learning resources to students to improve their learning continuity and effectiveness. After reviewing relevant literatures, it's found that there're many studies on students' learning motivation, however, the research on the motivation of students' persistency for online learning merely concentrated on theories, and few of them viewed the said matter with the effective prediction of online learning duration and the analysis of students' willingness to continue online learning under multiple mediation effect taken into consideration. For this reason, this paper aims to research the motivation of students' persistency for online learning under multiple meditation effect. In the second chapter, this paper constructed an improved SVM classifier to predict the duration of students' online learning. In the third chapter, this paper used a structural equation model to complete the data analysis of students' willingness to continue online learning. In the fourth chapter, this paper explored the theories of the motivation of students' persistency for online learning under multiple mediation effect, and constructed a basic regression model for the said matter. At last, experimental results proved the prediction accuracy of the constructed model, and the empirical estimation results were given in the text.

2 Prediction of online learning duration of students

2.1 Modelling principle and noise point analysis

This paper aims to predict students' online learning duration based on improved SVM. Different from the linear SVM that deals with linearly separable data in the feature space, the nonlinear SVM can realize the high-dimensional space mapping of original data *a*, namely to convert $\langle a_i,a\rangle$ into $\langle \Phi(a_i),\Phi(a)\rangle$, then there is hyperplane equation:

$$g(a)=q\cdot a+t=\sum_{i=1}^{k}\beta_i b_i\left\langle \Phi(a_i),\Phi(a)\right\rangle+t \tag{1}$$

The high-dimensional space mapping is completed by the kernel function. Assuming: $\Psi(a)$ represents the kernel function adopted by the SVM, then Formula 2 gives the equation for the hyperplane in the high-dimensional space:

$$g(a)=\sum_{i=1}^{k}\beta_i b_i\Psi\left\langle a_i,a\right\rangle+t \tag{2}$$

Based on the above formula and the calculation method of linear SVM, the optimal hyperplane in the high-dimensional space can be obtained. Usually, for the training samples of the data of students' online learning duration, they need to satisfy $b_i(a_i\cdot q+t)\geq 1$, that is, the distance between the support vector and the optimal hyperplane needs to satisfy $[1,+\infty]$; while for outlier sample points, this distance should be within [0,1], assuming for outlier sample points, δ_i represents the slack variable factor, this paper introduced the slack variable to achieve more intelligent model training performance:

$$\begin{cases} b_i\left(a_i\cdot q+t\right)\geq 1-\delta_i \\ \delta_i\geq 0 \end{cases} \tag{3}$$

After introducing δ_i, even if there are outlier sample points, still, a relatively ideal SVM hyperplane fault tolerance rate can be guaranteed, and Formula 4 gives the processing process after modification:

$$\begin{cases} min\chi(q) = \frac{1}{2}\|q\|^2 + Z\sum_{i=1}^{k}\delta_i \\ s.t. \quad b_i\left(a_i \cdot q + t\right) \geq 1 - \delta_i \\ \delta_i \geq 0 \end{cases} \tag{4}$$

Above formula is an optimization problem that satisfies correct classification and maximum interval, which can be solved using the Lagrangian algorithm. Assuming Z represents the penalty factor, then there is:

$$\begin{cases} \max_{\beta_i}\left\{\sum_{i=1}^{k}\beta_i - \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\beta_i\beta_j b_i b_j\left(a_i \cdot a_j\right)\right\} \\ s.t. \quad 0 \leq \beta_i \leq Z \\ \sum_{i=1}^{k}\beta_i b_i = 0 \end{cases} \tag{5}$$

The optimal hyperplane of the SVM could be obtained by solving the above formula.

2.2 Duration prediction

The constructed SVM classifier upgrades the dimension of the data of student's online learning duration to a higher dimensional space, and classifies these data using the optimal hyperplane function of the higher-dimensional space. The training and prediction steps of SVM are elaborated below:

Step 1: Select the preprocessed training data, assuming a_i represents the data of each group, k represents the number of samples, $b_i \in \{0,1,2,3\}$ represents the expected output, which are the divided range of students' online learning duration.

Step 2: Determine the penalty factor Z based on the following formula.

$$\begin{cases} \max_{\beta_i}\left\{\sum_{i=1}^{k}\beta_i - \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\beta_i\beta_j b_i b_j\left(a_i \cdot a_j\right)\right\} \\ s.t. \quad 0 \leq \beta_i \leq Z \\ \sum_{i=1}^{k}\beta_i b_i = 0 \end{cases} \tag{6}$$

Step 3: Determine the support vector of the online learning duration data of different type students, and solve the displacement of the hyperplane using $t=1/b_r-qa_r$.

Step 4: Select the appropriate $\Psi(a)$ to upgrade the dimension of original data, and use binary SVM to classify the online learning duration data of different type students; for each test sample point a, the hyperplane equation $g(a)=\Sigma^{k}_{i=1xi}b_i\Psi(a_i,a)+t$ can be used to determine the label of the category to which the sample belongs.

Assuming α represents the coefficient to be determined, the formula below shows the expression of the radial basis function (RBF).

$$\Psi\left(a_i,a\right)=exp\left(-\alpha\left\|a-a_i\right\|^2\right) \tag{7}$$

The Gaussian function-based kernel function has the ability to transform linearly inseparable data into linearly separable data based on high-dimensional space mapping.

2.3 Model parameter optimization

The basic idea of particle swarm optimization (PSO) is: update the position and speed of individuals through information interaction, and further update the two parameters (Z, Ψ) of penalty factor and kernel function to get the optimal values of position and speed, the specific steps are:

After the training samples of students' online learning duration data were read, the position and speed of particles in the population were initialized; then, the sample set was segmented into l subsets with the same size which were independent of each other. Then, the SVM was trained according to current (Z, Ψ), and the average value of the recognition accuracy of l times was obtained and taken as the fitness degree of individuals in the population, the optimal position P_B of individuals in the population and the position of optimal fitness of population G_B were memorized.

Assuming τ_1 and τ_2 represent learning factors, $P_{B\text{-}j}$ represents the optimal position of the j-th individual particle, N represents the total number of particles in the population, $G_{B\text{-}j}$ represents the current optimal position of all particles in the population; the random numbers between (0,1) can be generated by function RAND( ), K_j represents the current position of the j-th particle, U_j represents the corresponding speed of the j-th particle, then at last, update the position and speed of particles to search for better (Z,Ψ):

$$\begin{cases} U_j=U_j+\tau_1\times RAND(\ \ )\times\left(P_{B-j}-K_j\right)+\tau_2\times RAND(\ \ )\times\left(G_{B-j}-K_j\right) \\ K_j=K_j+U \end{cases} \tag{8}$$

Iteratively update the SVM until reaching the maximum number of iterations, and then output the optimization result of (Z, Ψ). Figure 1 shows the design of the model structure.

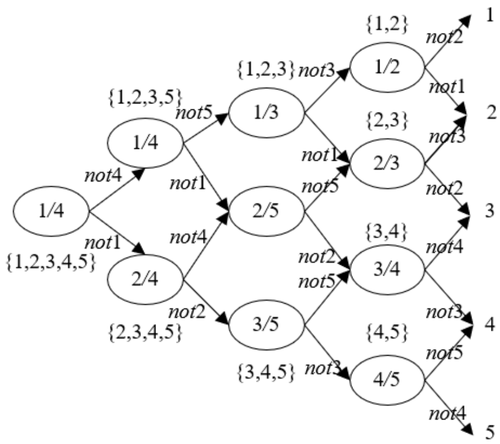

Fig. 1. Model structure

3 Analysis of students' willingness to continue online learning

This paper adopted a structural equation model to perform data analysis on students' willingness to continue online learning, aiming to research the direct or indirect impact of 3 endogenous variables (performance expectation, content quality, and satisfaction degree) and 3 exogenous variables (flow experience, perceived mobility, and service quality) on students' willingness to continue online learning. Figure 2 shows the theoretical model of the influencing factors of the motivation of students' persistency for online learning.

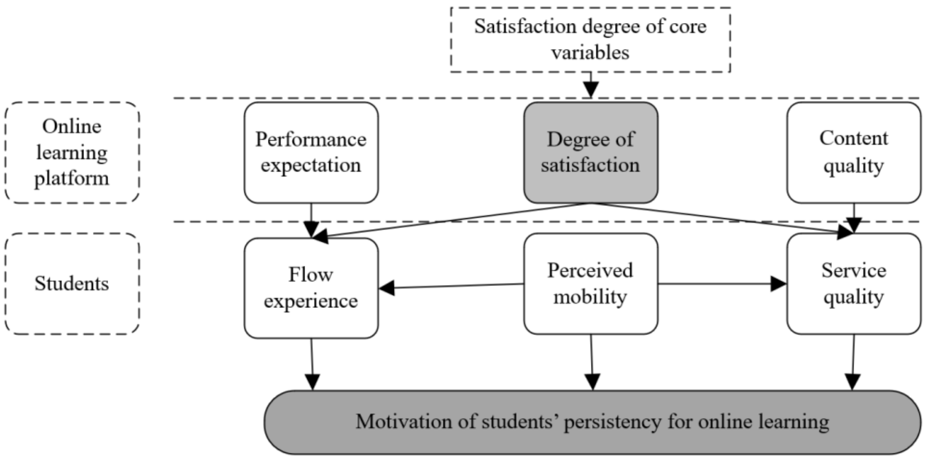

Fig. 2. Theoretical model of the influencing factors of the motivation of students' persistency for online learning

Assuming *a* and *b* respectively represent the endogenous and exogenous indicators of the motivation of students' persistency for online learning; *Γa* and *Γb* respectively represent the relationship between these indicators and the latent variable of the motivation of students' persistency for online learning; ψ and σ respectively represent the error of indicators *a* and *b*, then Formulas 9 and 10 give the measurement models of the structural equation model:

$$a = \Gamma_a \delta + \psi \tag{9}$$

$$b = \Gamma_b \gamma + \sigma \tag{10}$$

Assuming *Σa* and *Σb* represent the covariance matrices of observed indicator variables *a* and *b*; ^*a* and ^*b* represent their load matrices; ϕ and Ξ represent the covariance matrices of the latent variable and the error term, then, based on the basic measurement equation mentioned above, then for latent variables that are difficult to observe, there are:

$$\sum\nolimits_a = \left(\Gamma_a \varphi \Gamma_a ' + \Xi_\psi \right) \tag{11}$$

$$\sum\nolimits_b = \left(\Gamma_b \varphi \Gamma_b ' + \Xi_\sigma \right) \tag{12}$$

Assuming: γ and δ respectively represent the endogenous and exogenous latent indicator variables, *Y* represents the relationship between variables, *F* represents the impact of exogenous latent variables on endogenous latent variables, φ represents the residual term, then Formula 13 gives the expression of the structural model:

$$\gamma = Y\gamma + F\delta + \phi \tag{13}$$

Figure 3 shows a diagram of the structure of the structural equation model. The formula below gives the expression of indicator variables corresponding to the matrix equation in the figure:

$$A = \begin{bmatrix} a \\ a_2 \\ a_3 \\ a_4 \end{bmatrix}, B = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}, \Gamma_a = \begin{bmatrix} \mu_{11}^a & 0 \\ \mu_{12}^a & 0 \\ 0 & \mu_{32}^a \\ 0 & \mu_{32}^a \end{bmatrix}, \Gamma_b = \begin{bmatrix} \mu_{11}^b & 0 \\ \mu_{12}^b & 0 \\ 0 & \mu_{32}^b \\ 0 & \mu_{32}^b \end{bmatrix},$$

$$\psi = \begin{bmatrix} \psi_1 \\ \psi_2 \\ \psi_3 \\ \psi_4 \end{bmatrix}, \sigma = \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \sigma_3 \\ \sigma_4 \end{bmatrix}, F = \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix}, Y = \begin{bmatrix} \rho_{11} & 0 \\ 0 & 0 \end{bmatrix},$$

$$\delta = \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}, \phi = \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix}, \gamma = \begin{bmatrix} \gamma_1 \\ \gamma \end{bmatrix} \tag{14}$$

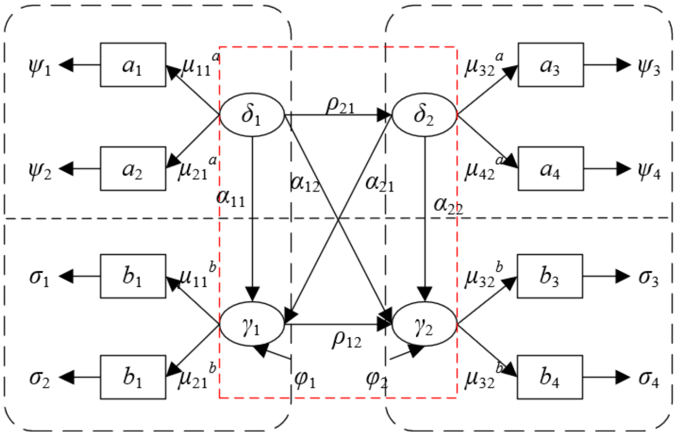

Fig. 3. Structure of the structural equation model

4 Analysis of the Motivation of Students' Persistency for Online Learning Under Multiple Mediation Effect

To conduct theoretical analysis on the motivation of students' persistency for online learning under multiple mediation effect, this paper constructed a basic regression model for the said matter:

$$LI = \beta_1 + \rho_{11} MZ + \lambda_1 \tag{15}$$

Assuming: *LI* represents the motivation level of students' persistency for online learning, *MZ* represents the satisfaction degree of online learning, β_1 represents the intercept term, ρ_1 represents regression coefficient, λ represents the error term.

The extended variables mainly included: flow experience *NJ*, perceived mobility *XJ*, and service quality *FZ*; assuming *n* represents the interaction term between the extended variables and online learning satisfaction, then the extended variables were introduced into the basic regression model to expand the model as:

$$\begin{aligned} LI &= \beta_I + \rho_{I1} JG + \rho_{I2} SR + \rho_{I3} MZ + \rho_{I4} FZ + \rho_{I5} NJ \\ &+ \rho_{I6} NJ^2 + \rho_{I7} XJ + \rho_{I8} n + \lambda_I \end{aligned} \tag{16}$$

In the above formula, at the economic level, the online learning satisfaction *MZ* affects the motivation of students' persistency for online learning via two ways: performance expectation *SR* and content quality *JG*, and this situation belongs to the phenomenon that multiple mediating variables exert multiple mediation effect between the multiple independent variables and the dependent variable (the motivation of students' persistency for online learning), and Formula 17 gives the further constructed multiple mediation model:

$$LI = \beta_1 + \rho_{11} MZ + \rho_{12} FZ + \rho_{13} NJ + \rho_{14} NJ^2 + \rho_{15} XJ + \rho_{16} n + \lambda_1 \tag{17}$$

$$JG = \beta_2 + \rho_{21}SR + \rho_{22}MZ + \rho_{23}FZ + \rho_{24}NJ + \rho_{25}NJ^2 + \rho_{26}XJ + \rho_{27}n + \lambda_2 \tag{18}$$

$$SR = \beta_3 + \rho_{31}JG + \rho_{32}MZ + \rho_{33}FZ + \rho_{34}NJ + \rho_{35}NJ^2 + \rho_{36}XJ + \rho_{37}n + \lambda_3 \tag{19}$$

$$\begin{aligned} LI &= \beta_4 + \rho_{41}JG + \rho_{42}SR + \rho_{43}MZ + \rho_{44}FZ + \rho_{45}NJ \\ &+ \rho_{46}NJ^2 + \rho_{47}XJ + \rho_{48}n + \lambda_4 \end{aligned} \tag{20}$$

The next step, calculate the total effect ς acted directly by online learning satisfaction *MZ* via mediating variables performance expectation *JG* and content quality *SR* on the motivation level of students' persistency for online learning *LI*:

$$\varsigma = \rho_{43} + \rho_{22}\rho_{41} + \rho_{32}\rho_{42} + \rho_{32}\rho_{21}\rho_{41} + \rho_{22}\rho_{31}\rho_{42} \tag{21}$$

The above formula describes the direct effect of online learning satisfaction *MZ* on the motivation of students' persistency for online learning. $\rho_{22}\rho_{41}+\rho_{32}\rho_{21}\rho_{41}$ represents the mediation effect acted by online learning satisfaction *MZ* on the motivation of students' persistency for online learning via content quality *JG*, namely the "online learning content quality effect"; $\rho_{32}\rho_{42}+\rho_{22}\rho_{31}\rho_{42}$ represents the mediation effect acted by online learning satisfaction *MZ* on the motivation of students' persistency for online learning via performance expectation *SR*, namely the "effect of effective improvement of learning performance".

5 Experimental results and analysis

Figure 4 shows the determination process of the two parameters (Z, Ψ) penalty factor and kernel function of PSO, it can be seen that, with the increase of the number of iterations, on the training samples of students' online learning duration data, the average fitness curve of the classifier showed a fluctuating change trend. In the experiment, the search range of Z was set to be within [0.1, 100], and Ψ was within [0.1, 100]. Figure 4 shows that, the searching stopped when the number of iterations reached 100, indicating that when the number of iterations reached the highest, the fitness degree hadn't met the termination condition, and the corresponding parameters (Z, Ψ)=(0.5781, 0.1) were the optimal parameters.

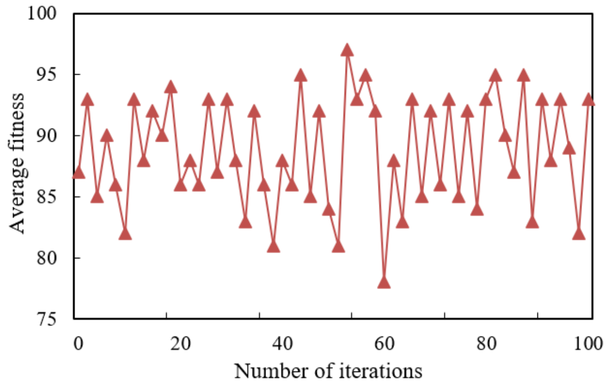

Fig. 4. The determination process of (Z, Ψ)

Using 2100 pieces of test sample data of students' online learning duration, this paper tested three optimal-searching algorithms, including the fruit fly algorithm, the genetic algorithm, and the proposed algorithm, and compared the prediction accuracy with the non-optimization state, the comparison results are shown in Figure 5.

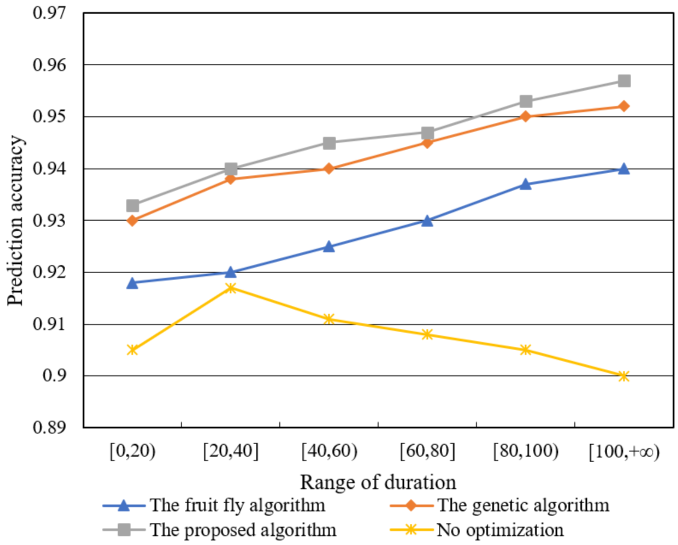

Fig. 5. Prediction accuracy of different algorithms

In this paper, the feature vector of SVM selected the preprocessed original data, and the entire prediction process adopted the PSO-optimized SVM model. The same 2100 pieces of training data of students' online learning duration were selected, but the deleted two-type attribute parameters of the data were supplemented, and the students' online learning duration was predicted again, then, the predicted range of online learning duration was compared with the actual time duration to get the absolute values of errors between the six predicted ranges and the actual online learning duration, which are given in Figure 6. The ordinate in the figure is the error value between the actual value and the predicted range, as can be seen in the figure, the average prediction error of the optimized model is smaller than that of the SVM model before optimization, and this proves that the prediction results of students' online learning duration given by the optimized model were closer to the real situations.

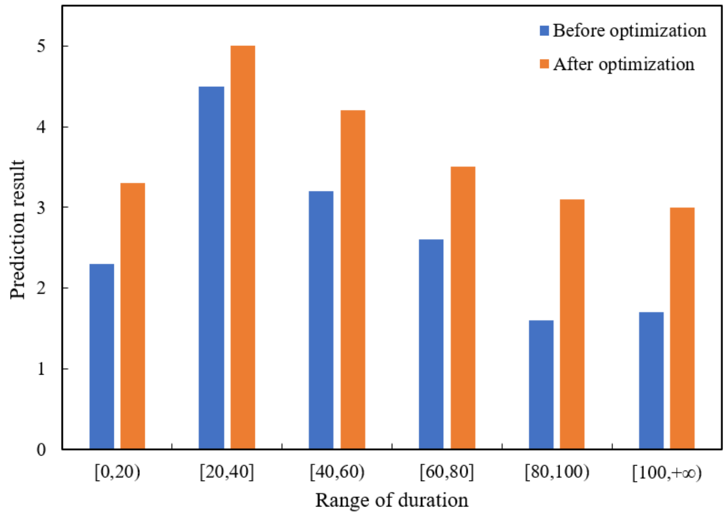

Fig. 6. The absolute errors of model prediction before and after optimization

In this paper, the least square method was employed to estimate the parameters of the multiple mediation effect one by one, and the estimation results are shown in Table 1. According to the data in the second to fourth columns in Table 1, the degree of students' satisfaction with online learning has a significant inhibitory effect on their motivation to continue online learning and the quality of learning content, and it has a significant promotive effect on the performance expectation of students. As can be seen from the fifth column in Table 1, after taking the two mediating variables of content quality and performance expectation under control, the inhibitory effect of the degree of students' satisfaction with online learning on their motivation to continue online learning had decreased, the coefficient of satisfaction degree changed from -0.015 in column 2 to -0.011, and it was still statistically significant at the 0.1 level. At the same time, the effect of two mediating variables, content quality and performance expectation, on the motivation of students' persistency for online learning, was statistically significant at the 0.1 level as well. The above analysis suggests that, at the 0.1 significance level, during the influencing process of online learning satisfaction on the motivation of students' persistency, content quality and performance expectation did have a significant partial mediating effect, which means that students' satisfaction with online learning not only indirectly inhibit their motivation of learning persistency via improving content quality and performance expectation, but also directly inhibit it as well.

Table 1. Estimation results of the influence of students' satisfaction degree with online learning on the motivation of their persistency for online learning

Independent variable	Before the multiple mediation effect	Content quality	Performance expectation	After the multiple mediation effect
Constant term	0.625	-742.482**	1.502	0.685***
	(2.58)	(-2.74)	(0.85)	(2.62)
Satisfaction degree with online learning	-0.015**	-53.715***	0.302**	-0.011***
	(-3.02)	(-4.25)	(2.85)	(-1.72)
Content quality	0.0005	-26.384***	0.312**	0.005
	(0.07)	(-6.58)	(9.48)	(1.27)
Flow experience	-0.042**	-5.274	0.148***	-0.04**
	(-3.51)	(-0.48)	(2.75)	(-2.88)
平方Squared flow experience	0.0003**	0.072	-0.002	0.0005***
	(3.25)	(0.42)	(-1.12)	(3.28)
Perceived mobility	0.002	2.954***	-0.002	0.0003
	(0.72)	(2.25)	(-0.05)	(0.35)
Interaction term	0.026**	37.485**	-0.085	0.018***
	(2.86)	(3.29)	(-0.92)	(1.74)
Content quality			0.005***	0.0003**
			(13.85)	(1.95)
Performance expectation		131.851***		-0.035
		(15.26)		(-1.79)
N	152	146	153	149
R^2	0.21	0.88	0.95	0.18

6 Conclusion

This paper studied students' persistency for online learning under multiple mediation effect. At first, this paper constructed an improved SVM classifier and used it to predict students' online learning duration. Then, it used a structural equation model to analyze the data of students' willingness to continue online learning. After that, this paper analyzed the theories of the motivation of students' persistency for online learning under the multiple mediation effect, and constructed a basic regression model for the said matter. After the theory part, this paper combined with experiment to give the selection process of two parameters of PSO, namely the penalty factor and kernel function (Z, Ψ), and determined the optimal parameters. The prediction accuracy of student's online learning duration of different algorithms was given, the absolute errors of the prediction of the model before and after optimization were compared, and the results showed that the predicted results of students' online learning duration obtained by the optimized model were closer to the real situations than the model results obtained before optimization. At last, the estimation results of the influence of students' satisfaction with online learning on their motivation to continue online learning were given, which had verified that students' satisfaction with online learning not only indirectly inhibit their motivation of learning persistency via improving content quality and performance expectation, but also directly inhibit it as well.

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