A Dynamic Learning Interest Model for a Personalized Learning Requirement Analysis of College Students

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Abstract—The randomness in college students' participation of online learning causes common problems such as improper learning resource allocation or unbalanced supply and demand to online education platforms, thus scientifically predicting college students' learning requirements, triggering their dynamic learning interest, and effectively improving their learning effect are important prerequisites for ensuring these platforms to develop stably, efficiently, and sustainably. Existing prediction models generally ignored the progressing process of learning and failed to comprehensively model or analyze from multiple dimensions such as resource utilization, learning behavior, learning pattern, teaching mode, and teaching management, etc. To fill in this research gap, this paper proposed a Dynamic Learning Interest (DLI) model for analyzing the personalized learning requirements of college students. Based on the college students' online learning cycles and the learning cycle division results, a time series DLI model was established for studying the prediction of college students' personalized learning requirements, and short-term prediction and comparative experiment were carried out accordingly. Then, the proposed model was subject to stability test and white noise test to determine the model structure and estimate it parameters. At last, significance test was performed on the proposed model and its parameters, and the results verified the effectiveness of the model.

Keywords—personalized learning, learning requirement, Dynamic Learning Interest (DLI), time series model

1 Introduction

Online learning is a novel learning pattern developing rapidly based on online education platforms in recent years, and it has been taken as a major development direction in the field of education [1–5]. This new style learning pattern can satisfy college students' personalized learning requirements in diverse directions, help improve their learning efficiency, and solve problems such as the time and space limits, as well as the unbalanced learning resource allocation [6, 7]. To urge college students to learn actively and satisfy their needs for modern education and lifelong learning, the online education platforms should formulate reasonable teaching strategies to improve users' learning effect [8–12]. However, the randomness in college students' participation of online learning causes common problems such as improper learning resource allocation or unbalanced supply and demand to online education platforms [13, 14], thus scientifically predicting college students' learning requirements, triggering their dynamic learning interest, and effectively improving their learning effect are important prerequisites for ensuring these platforms to develop stably, efficiently, and sustainably.

Multimedia are important information carriers in mobile learning, so how to design multimedia that could meet customer needs is a key task. Chen and Hsu [15] adopted the theory of attractive quality (Kano model) to analyze the needs of users for multimedia design in e-learning, so as to have a better under-standing of how customers evaluate a product, and help companies focus on the most important attributes that need to be improved. Capuano et al. [16] pointed out that designing personalized courses taking into account the needs and preferences of each learner is one of the most studied topics within the field of adap-tive learning systems, however, in real cases, learning needs are often latent and un-satisfied; to breakthrough this limitation, the authors proposed a methodology and a prototype system to trigger the latent learning needs, and automatically generate learning experiences capable of satisfying such needs. The proposed methodology conformed to the principles of recommending systems and depend on the semantic representations of topics to be taught. Lam et al. [17] studied the cognition, needs, and requirements of students at the Chinese University of Hong Kong for online learning, and their research results suggested that students generally hold a positive attitude towards various forms of online learning strategies. Volungeviciene et al. [18] theoretically and empirically studied a few dimensions of the online course quality of high education in a lifelong learning background, aiming to exploring cultural questions during the development process of e-learning courses, such as to figure out to what extent the development of e-learning courses may con-tribute to openness to a wider community of learners in higher education with respect to growing learner needs and demands. The authors viewed the quality of an e-learning course with emphasis laid on the perspective of learners, discussed the im-portance of learner requirement analysis, and introduced the results of an empirical study on experiences in an e-learning course.

With the development of online learning, more scholars began to pay attention to the research topic of personalized learning, but there're a few problems pending for solutions, such as when studying the features of college students' personalized learning, the factors considered in existing studies are too simple, moreover, in terms of the prediction of college students' requirements for personalized learning, the existing models generally ignored the progressing process of learning and failed to comprehensively model or analyze from multiple dimensions such as resource utilization, learning behavior, learning pattern, teaching mode, and teaching management, etc.; in terms of the measurement of dynamic interest, few of the existing models built for measuring the dynamic interest of college students have considered the short-term temporal and spatial requirements or the selection of personalized learning behaviors, they often neglected the dynamic changes of college students' personalized online learning and constructed static quantitative models, there're very few research results of using dynamic learning resource recommendation to meet college students' requirements for personalized online learning. Therefore, to fill in this research blank, this paper proposed a DLI model for analyzing the personalized learning requirements of college students. In the second chapter, this paper built a time series DLI model to predict college students' personalized learning requirements based on their online learning cycles and the learning cycle division results, gave short-term prediction and performed comparative experiment. In the third chapter, the proposed model was subject to stability test and white noise test to determine the model structure and estimate it parameters. At last, significance test was performed on the proposed model and its parameters, and the results verified the effectiveness of the model.

2 Construction of the time series DLI model

The prediction of college students' personalized learning requirements means to use relevant models or algorithms to forecast college students' requirements for online learning in the future based on the existing history data of college students' online learning behaviors. Prediction models with better prediction performance can find out the correlations between college students' personalized learning requirements and each influencing factor, thereby designing reasonable resource recommendation schemes for the online education platforms, allocate the learning resources and adjust the teaching assistance strategies. Based on college students' online learning cycles and the learning cycle division results, this paper built a time series DLI model which is usually used in the research on the prediction of college students' personalized learning requirements, and used the model to predict the short-term personalized learning requirements of college students and conduct comparative experiment.

Since the number of the online learning behaviors of college students showed significant time correlation feature, it can be used to describe college students' DLI for online learning to a certain extent. The time series DLI model can be used to study the correlation between the future sequence values and history sequence values of college students' personalized learning requirements, thereby deriving the amount of personalized learning requirements of college students. Therefore, this paper took the amount of history online learning requirements of college students as the influencing factor to establish the time series DLI model to predict college students' personalized learning requirements.

The time series of DLI refers to the data sequence formed by arranging the statistical index values of the personalized learning behaviors of a college student according to the occurrence time order. The DLI time series can be divided into stationary time series and non-stationary time series according to the degree of stationariness. This paper mainly analyzed the stationary DLI time series.

A stationary DLI time series $\{o_e\}$ needs to meet the following three conditions: 1) arbitrarily choose $e \in E$, which has variance and is not infinite, namely $TO_e^2 < \infty$; 2) arbitrarily choose $e \in E$ with a constant mean value, namely TO_e is equal to a constant λ; 3) arbitrarily choose $e, r, l \in E$, and $l + r - e \in E$, then the auto-covariance is only affected by the average value of the time moving length, namely $\alpha(e, r)$ is equal to $\alpha(l, l + r - e)$.

This paper built three types of stationary DLI time series models, including the autoregressive model, the moving average model, and the autoregressive moving average model. The principles and constraints of the three types of models are introduced in detail below.

The autoregressive model describes the correlation between the history observation values of college students' online learning behaviors and the random variables, assuming $AUR(y)$ represents the autoregressive model lagged for y-order; o_e represents the sequence value at time moment e; $o_{e-1}, o_{e-2}, ..., o_{e-y}$ represent the independent variables; $\psi_1, \psi_2, \ldots, \psi_y$ represent the coefficients of the independent variables in the autoregressive model; ρ_e represents the random disturbance term, then the model of the DLI time series $\{o_e\}$ could be expressed by the following formula:

$$\begin{cases} o_e = \psi_0 + \psi_1 o_{o-1} + \psi_2 o_{o-2} \cdots + \psi_y o_{e-y} + \rho_e \\ \psi_y \neq 0 \\ T(\rho_e) = 0, Var(\rho_e) = \varepsilon_r^2, T(\rho_e \rho_r) = 0, r \neq e \\ To_r \rho_e = 0, \forall r < e \end{cases} \tag{1}$$

The $AUR(y)$ model needs to meet the following three constraints: 1) let $T(\rho_e)$ be equal to 0, $VAUR(\rho_e)$ be equal to ε_ρ^2, $T(\rho_e \rho_r)$ be equal to 0, r is not equal to e, and make sure that $\{\rho_e\}$ is a white noise sequence with a mean value of 0; 2) let ψ_y be not equal to 0, and make sure that the highest order of the model is y; 3) let $To_r\, \rho_e$ be equal to 0, $\forall r < e$, and make sure that ρ_e is independent of the history sequence value, then the simplified $AUR(y)$ model is given by the following formula:

$$o_e = \psi_0 + \psi_1 o_{o-1} + \psi_2 o_{o-2} \cdots + \psi_y o_{e-y} + \rho_e \tag{2}$$

The moving average model describes the correlation between the random variables of college students' online learning behaviors and the random disturbance term. For the DLI time series $\{o_e\}$, the predicted value o_e of time moment e is independent of the history observation value of college students' online learning behaviors, and it can be represented by ρ_e; assuming $NB(w)$ represents the moving average model lagged for w-order; o_e represents the sequence value at time moment e; $\omega_1, \omega_2, \ldots, \omega_y$ represent the coefficients of independent variables in the autoregressive model; ρ_e represents the random disturbance term; $\rho_{e-1}, \rho_{e-2}, \ldots, \rho_1$ represent the prediction errors of each previous online learning cycle; then the model could be expressed as:

$$\begin{cases} o_e = \lambda + \rho_e - \omega_1 \rho_{e-1} - \omega_2 \rho_{e-2} \ldots - \omega_w \rho_{e-w} \\ \omega_w \neq 0 \\ T(\rho_e) = 0, Var(\rho_e) = \varepsilon_r^2, T(\rho_e \rho_r) = 0, r \neq e \end{cases} \tag{3}$$

The $NB(w)$ model needs to meet the following two constraints: 1) ω_w is not equal to 0, and make sure that the highest order of the model is w; 2) let $T(\rho_e)$ be equal to 0, $VAUR(\rho_e)$ be equal to ε_ρ^2, $T(\rho_e \rho_r)$ be equal to 0, r is not equal to e, and make sure $\{\rho_e\}$ is a white noise sequence with a mean value of 0. The simplified $NB(w)$ model is given by the following formula:

$$o_e = \lambda + \rho_e - \omega_1 \rho_{e-1} - \omega_2 \rho_{e-2} \ldots + -\omega_w \rho_{e-w} \tag{4}$$

By combining the $AUR(y)$ model with the $NB(w)$ model, the autoregressive moving average model could be built and denoted as $AURNB(y, w)$, and its expression is given by the following formula:

$$\begin{cases} o_e = \psi_0 + \psi_1 o_{e-1} + \ldots + \psi_y o_{e-y} + \rho_e - \omega_1 \rho_{e-1} - \ldots - \omega_w \rho_{e-w} \\ \psi_y \neq 0, \omega_y \neq 0 \\ T(\rho_e) = 0, Var(\rho_e) = \varepsilon_r^2, T(\rho_e \rho_r) = 0, r \neq e \\ To_r \rho_e = 0, \forall r < e \end{cases} \tag{5}$$

The simplified $AURNB(y, w)$ can be written as:

$$o_e = \psi_0 + \psi_1 o_{e-1} + \ldots + \psi_y o_{e-y} + \rho_e - \omega_1 \rho_{e-1} - \ldots - \omega_w \rho_{e-w} \tag{6}$$

When ψ_0 is equal to 0, the model is called the centralized $AURNB(y, w)$ model, and the simplified centralized $AURNB(y, w)$ model can be written as:

$$o_e = \psi_1 o_{e-1} + \ldots + \psi_y o_{e-y} + \rho_e - \omega_1 \rho_{e-1} - \ldots - \omega_w \rho_{e-w} \tag{7}$$

Assuming: A represents the delay operator, then there is:

$$o_{e-1} = Ao_e, o_{e-2} = A^2 o_e, \ldots, o_{e-y} = A^y o_e \tag{8}$$

Assuming: $\Psi(A)$ represents the auto-regression coefficient; $\Psi(A)$ is equal to $1 - \psi_1 A - \psi_y A^y$; $\Omega(A)$ represents the coefficient of average moving; $\Omega(A)$ is equal to $1 - \omega_1 A - \omega_y A^y$, then, by introducing A into the $AURNB(y, w)$ model, there is:

$$o_e = \frac{\Omega(A)}{\Psi(A)} \rho_e \tag{9}$$

3 Tests on the DLI time series model

The modeling process of the DLI time series model is introduced in detail below, Figure 1 gives the flow chart. At first, stability test was performed, if the model fails to pass the test, then difference operation is performed, and the test is carried out again. After the model had passed the stability test, it's subjected to the white noise test, if it passes the test, then the modeling terminates; if it fails to pass the test, then a stationary non-white noise sequence is constructed to further determine the model structure and complete the estimation of the model parameters; at last, significance test was performed on the model and its parameters.

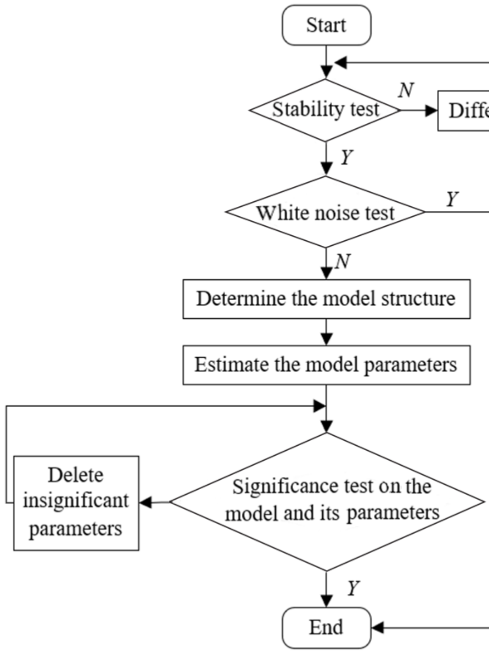

Fig. 1. Modeling process of the DLI time series model

Based on the unit root test, this paper tested the stability of the DLI time series; let $\sigma = \psi_1, \psi_2, \ldots, \psi_y - 1$; $R(\sigma^*)$ represents the sample standard deviation of parameter σ, then the constructed statistic π of the unit root test can be attained by calculating the following formula:

$$\phi = \frac{\sigma^*}{R(\sigma^*)} \tag{10}$$

The critical value of statistic φ can be attained based on the Monte Carlo method. If the p-value of statistic φ is less than 0.01, then the DLI time series is considered to be stationary; if the p-value is greater than 0.01, then it's considered to be non-stationary.

Not all non-stationary DLI time series need to be modeled, only those that can predict the future learning requirement trends based on college students' history online learning behavior data and are correlated with other series are worthy of modelling, the modeling of pure random DLI time series has no meaning, so before modeling, the stationary DLI time series need to be subject to white noise test.

In the white noise test, let the original assumption be F_0: $\sigma_1 = \sigma_1 = \ldots\sigma_n = 0$, $n \geq 1$, that is, the observation values of college students' online learning behaviors with a lag number less than or equal to n periods are independent of each other. The alternative assumption F_1: at least there is a σ_l that is not equal to 0, $n \geq 1$, $l \leq n$, that is, there're correlations between the observation values of college students' online learning behaviors lagged n or less than n periods; assuming m represents the number of observation periods of the series; n represents the number of delay periods; σ_l^* represents the autocorrelation coefficient of l-periods lag, then there is:

$$KA = m(m+2)\sum_{l=1}^{n}\left(\frac{\sigma^{*2}_{l}}{m-l}\right) \quad (11)$$

Assuming: y represents the order of auto-regression; w represents the moving average order; c represents the difference order; then, the determination of the model structure is to firstly determine the ranges of y, w, and c according to the tailing and truncation of the autocorrelation graph and the partial autocorrelation graph, and then determine the values and orders of y, w, and c based on the information criterion grading method and the Bayesian information criterion. Assuming: m represents the sample number; l represents the number of model parameters; SR represents the maximum likelihood function; $l\ ln(m)$ represents the penalty term, then there is:

$$AID = l\ ln(m) - 2ln(SR) \quad (12)$$

The least square method was adopted to estimate the model parameters. Assuming γ represents the parameter value to be estimated; ρ_e represents the residue; $W(\gamma)$ represents the sum of squares of the residue, then there are:

$$\gamma = (\psi_1, \psi_1, \ldots \psi_y, \omega_1, \omega_1, \ldots \omega_w)' \quad (13)$$

$$G_e(\gamma) = \psi_1 o_{e-1} + \ldots + \psi_y o_{e-y} - \omega_1 \rho_{e-1} - \ldots - \omega_w \rho_{e-w} \quad (14)$$

$$\rho_e = o_e - G_e(\gamma) \quad (15)$$

$$W(\gamma) = \sum_{e=1}^{m} \rho_e^2 = \sum_{e=1}^{m} (o_e - \psi_1 o_{e-1} - \ldots - \psi_y o_{e-y} + \omega_1 \rho_{e-1} + \ldots + \omega_w \rho_{e-w}) \quad (16)$$

After the model structure was determined and the model parameters were estimated, to ensure the effectiveness of the model analysis results of college students' personalized learning requirements, the constructed model and its parameters were subject to significance test further.

The significance test of the model is to verify whether the extracted DLI features have been fully and effectively tested. If the test is passed, then it means the extracted information of DLI features is relatively complete, and the residue doesn't contain valid information. If the test is failed, then it means the extracted information of DLI features is incomplete, and the residue containing valid information needs to be fitted further until the test is passed.

Set the original assumption of the model significance test as $\sigma_1 = \sigma_2 = \ldots \sigma_n = 0$, $n \geq 1$, and set the alternative assumption as at least there's a σ_l that is not equal to 0 and $n \geq 1$, $l \leq n$, then the calculation formula of the statistic is:

$$LB = m(m+2)\sum_{l=1}^{n}\left(\frac{\sigma^{*2}_{k}}{m-l}\right) \sim \varpi^2(n), \forall n > 0 \quad (17)$$

If the original assumption $\sigma_1 = \sigma_2 = \ldots\ \sigma_n = 0$ is accepted, then the model residue doesn't contain valid information, and the model is valid; if the original assumption $\sigma_1 = \sigma_2 = \ldots\ \sigma_n = 0$ is rejected, then the residue sequence contains valid information that has not been extracted, and the model is invalid.

The significance test of model parameters is to verify whether all parameters are significantly 0 or not. To ensure the simplicity of the model, if a parameter is significantly 0, then it's judged that the influence of this parameter on the changes of college students' online learning behaviors is not significant, and it needs to be deleted.

Set the original assumption of the model parameter significance test as: β_i is not equal to 0, γ_i is not equal to 0, and $1 \le i \le n$; and set the alternative assumption as at least there is a γ_i that is equal to 0, $1 \le i \le n$. Assuming: $W(\gamma)$ represents the sum of squares of the residue; γ_i^* represents the least square estimate of the i-th parameter, $\gamma_i^* \sim M(0, b_{ii}\varepsilon_l^2)$, $1 \le i \le n$; b_{ii} represents the input variable $(o_j^2)^{-1}$, then the calculation formula of the statistic is:

$$E = \sqrt{m-n}\,\frac{\gamma_i^*}{\sqrt{\beta_{jj}W(\gamma)}} \sim e(m-n) \tag{18}$$

If the original assumption that β_i is not equal to 0 and γ_i is not equal to 0 is rejected, then it's judged that the model parameter is significant. If this original assumption is accepted, then it's judged that the model parameter is not significant. Parameters that are not significant should to be eliminated.

4 Experimental results and analysis

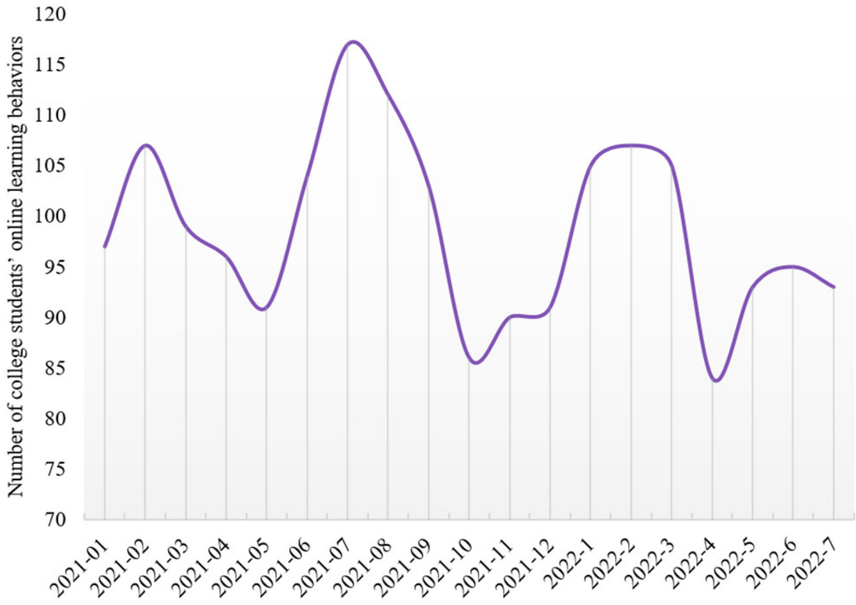

Fig. 2. The laws of college students' online learning during holidays and non-holidays

This paper studied the time features of college students' online learning and the laws of their online learning during non-workdays. When college students carry out online learning in different time periods, they will have different learning requirements and there're certain regularities in it. According to the laws of the time length college students spent on online learning, the online education platforms can adopt different resource recommendation methods, and satisfy students' learning requirements and improve their learning efficiency by adjusting the resource allocation schemes. Figure 2 shows the laws of college students' online learning during holidays and non-holidays. As can be seen from the figure, the number of the online learning behaviors of college students during holidays is significantly higher than that during non-holidays, indicating that the learning requirements of college students during holidays are higher.

Figure 3 shows the laws of college students' online learning during weekends and workdays. As can be seen from the figure, the number of online learning behaviors of college students during weekends and Fridays is significantly higher than that during workdays, indicating that their learning requirements during weekends are higher.

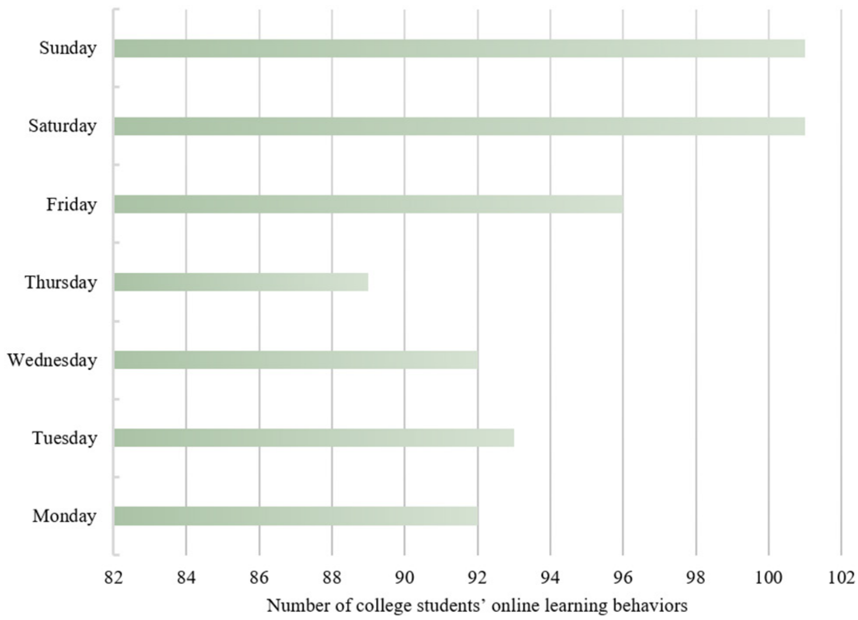

Fig. 3. The laws of college students' online learning during weekends and workdays

The distribution of each learning cycle and the number of online learning behaviors of college students are shown in Figure 4. There are obvious differences in the distribution density of learning cycles. In places with denser learning cycles, the bubbles representing the number of college students' online learning behaviors are bigger, indicating that the number of college students' online learning behaviors is higher, and the platform's setting of learning cycle is more reasonable; while the smaller the bubbles, the less the number of college students' online learning behaviors.

Figures 5 and 6 are respectively the auto-correlation graph and partial auto-correlation graph of the number of college students' online learning behaviors. As can be seen from the figures, when the auto-correlation coefficient and partial self-correlation coefficient of the DLI time series decreased gradually, the series didn't show obvious trend or periodicity. However, with the increase of the lag order, the DLI time series gradually converged to 0, indicating that the series tended to be stable.

To further verify the stability of the DLI time series, unit root test was performed and the results are given in Table 1, the P-value of the series is less than 0.05, which could verify the stability of the series, and it indicated that there's no need to perform difference operation processing on the series.

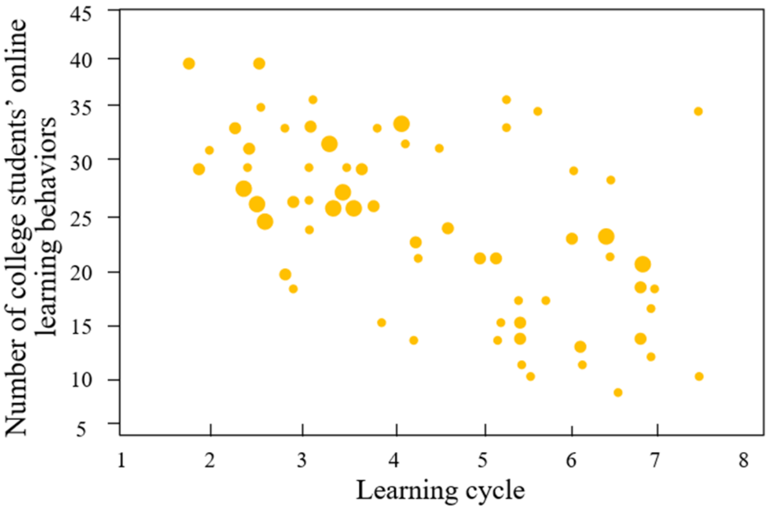

Fig. 4. Bubble diagram of the number of college students' online learning behaviors

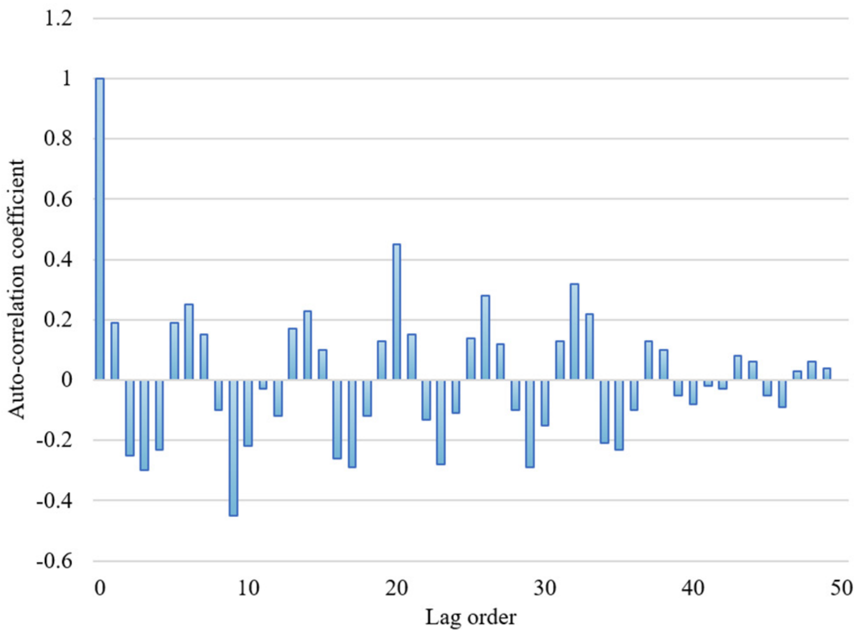

Fig. 5. Auto-correlation graph of the series

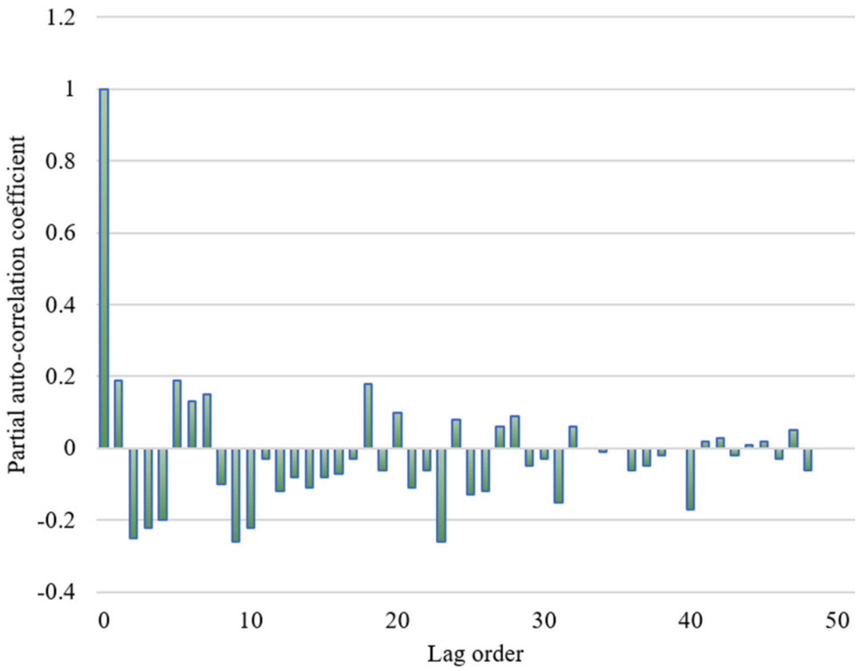

Fig. 6. Partial auto-correlation coefficient of the series

Table 1. Model parameter estimation results

Model Parameter Value	***AURNB*(6.2)**			
Parameter	**Estimated Value**	**Standard Deviation**	**Estimated *t*-Value**	***p*-Value**
Constant	25.169	0.327	62.351	0.047
AUR(1)	1.325	0.084	25.475	0.095
AUR(2)	–1.391	0.016	–22.693	0.017
AUR(3)	0.385	0.079	8.162	0.026
AUR(4)	–0.318	0.037	–8.374	0.014
AUR(5)	0.259	0.011	6.291	0.037
NB(1)	–0.047	0.067	–1.529	0.028
NB(2)	0.935	0.028	66.391	0.016
NB(3)	–0.91	0.036	–62.517	0.027

Table 1 shows the parameter values of the fitted *AURNB*(5, 3) time series model, as can be seen from the data in the table, the *p*-values of the time series model were all less than 0.05, thus it's judged that the model parameters had passed the test.

After the tests, the DLI time series model for predicting college students' personalized online learning requirements could be attained. Then, a test set was constructed based on the data of college students' online learning behaviors of 40 learning cycles, and was used to test the prediction accuracy of the constructed time series model. Figure 7 compares the prediction results of different learning cycles.

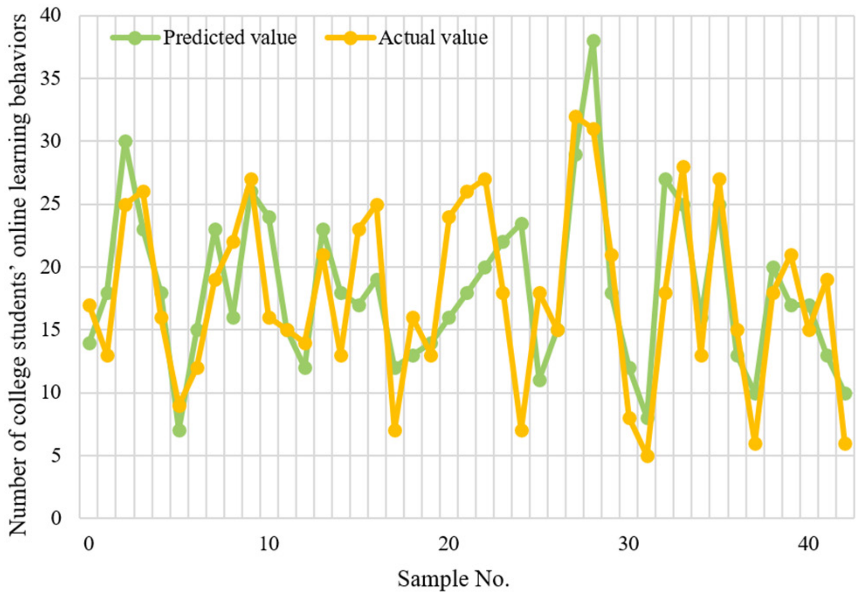

Fig. 7. Comparison of the prediction results of different learning cycles

Similarly, other learning cycle sets were predicted. Because there're great differences in the level of college students' personalized learning requirements of each learning cycle set, so the prediction errors are very different as well, and Table 2 lists the prediction errors of different learning cycle sets.

Table 2. Prediction errors of different learning cycle sets

Learning Cycle Set	Time Series Requirement Prediction	
	MAE	RMSE
Set 1	3.59	3.17
Set 2	3.47	3.95
Set 3	0.91	0.81
Set 4	0.84	0.96
Set 5	2.37	1.37
Set 6	1.19	1.29
Set 7	0.74	0.61
Set 8	1.49	2.57
Set 9	1.62	1.49
Set 10	1.05	0.95
Set 11	1.37	1.51
Set 12	1.62	1.49
Set 13	0.57	0.52
Set 14	2.32	2.17
Set 15	0.69	0.76

College students have different online learning habits in terms of learning time duration and learning difficulty level, etc. Based on the prediction results, Figure 8 gives the temporal and spatial analysis results of college students' online learning habits. By analyzing the data of college students' behaviors when participating in online learning, their unique online learning habits could be figured out, based on which the online education platforms could tag the student users so as to better understand their real learning requirements.

By analyzing college students' online learning time duration distribution based on their history behavior data, it's found that the student users tend to prefer mid-to-short online learning time length, as shown in Figure 8-1. Their preferred learning difficulty concentrated on the I and II levels, only 16.6% of college students chose the difficulty level lower than VI, and nearly half of them chose lower difficulty levels for their online learning, therefore, it can be seen that they generally prefer simpler and shorter online learning.

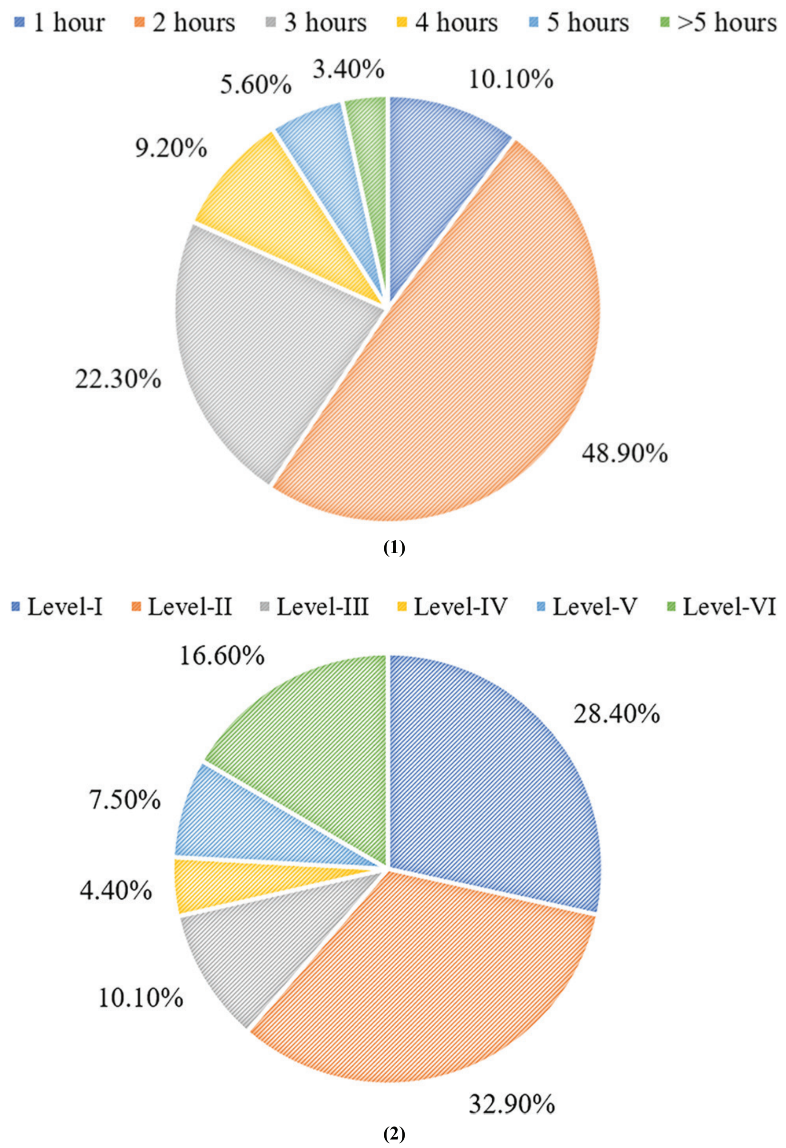

Fig. 8. Temporal and spatial distribution of college students' online learning habits

5 Conclusion

This paper proposed a DLI model to study the personalized learning requirements of college students. At first, based on the college students' on-line learning cycles and the learning cycle division results, a time series DLI model was constructed to predict college students' short-term personalized learning requirements and perform comparative experiment. Then, the proposed model was subjected to stability test and white noise test to determine the model structure and estimate it parameters. At last, significance test was performed on the proposed model and the model parameters. The attained experimental results gave the laws of college students' online learning during holidays and non-holidays, suggesting that the number of online learning behaviors of college students during holidays is significantly higher than that during non-holidays, and their learning requirements during holidays are higher. Then, the auto-correlation graph and partial auto-correlation graph of the number of college students' online learning behaviors were plotted, which verified that the series had certain stability. After that, the parameter values of the fitted $AURNB(5, 3)$ time series model were attained, and it's judged that the parameters of the constructed model had passed the test. At last, the prediction results of different learning cycles were compared, the prediction errors of different learning cycle sets were given, and the temporal and spatial distribution of college students' online learning behaviors was analyzed.

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