Influence of Self-efficacy Improvement on Online Learning Participation

https://doi.org/10.3991/ijet.v17i01.28719

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Abstract—More and more online learning apps are emerging, thanks to the development of Internet plus education and online learning platforms. Learning efficacy is the leading impactor of online learning participation. To avoid inefficiency and poor effect of online learning, it is necessary to explore the theory on the relationship between self-efficacy improvement and online learning participation. This paper examines the influence of self-efficacy improvement on online learning participation. Firstly, a general normal distribution map was drawn for self-efficacy. Then, a prediction model was established for participation based on the series of online learning behaviors. In addition, the k-means clustering (KMC) algorithm was optimized by information entropy, and the flow of the improved KMC was explained. The proposed model was proved valid through experiments.

Keywords—self-efficacy, online learning behaviors, learning participation, cluster analysis

1 Introduction

With the development of Internet plus education and online learning platforms, the dominance of classroom learning is being replaced with the combination between classroom learning and online learning [1-6]. Learning refers to the process that learners actively construct knowledge and experience [7-11]. To avoid inefficiency and poor effect of online learning, and to fully motivate the initiative of students, it is necessary to effectively improve their online learning participation [12-15]. Many factors could affect online learning participation. One of these factors is learning efficacy [16-20]. The theoretical research on the relationship between self-efficacy improvement and student online learning participation helps teachers to understand the status quo of teaching, and enhance the teaching effect.

Massive open online courses (MOOCs) have created a highly individualized and dynamic learning environment for higher education. However, the development of MOOCs is hindered by low completion rate. Susanti et al. [21] surveyed mediating role of online academic tenacity between online learning and self-efficacy, and discovered the significant mediating effect of commitment on the relationship between the behaviors, emotions, and cognitive participation of online learning. The outbreak of coronavirus COVID-19 brings new challenges to education, and presents a revolutionary opportunity for integrating the construction of information society. The resulting new learning model, i.e., family-based online learning, raises new requirements on college students. From the perspective of students' self-efficacy, Liu et al. [22] extended online learning to four dimensions, namely, sense of effort, sense of control, sense of participation, and sense of environment, and analyzed such five factors as learning attitude, learning strategy, learning interaction, learning evaluation, and learning environment, and put forward four strategies for improving learning effect.

Through literature review, surveys, and quasi-experiments, Krouska et al. [23] conducted theoretical analysis, scale preparation, experimental intervention, and effect testing to clarify the definition and structure of college students' self-efficacy of online learning, and explored some practical improvement strategies. Shi et al. [24] discussed how intelligent classroom teaching affects learning input, and online self-efficacy, and demonstrated that the students receiving intelligent classroom teaching have higher learning participation and online self-efficacy than those receiving traditional teaching. Peechapol et al. [25] reviewed the research in the past 12 years, which tackle the factors affecting self-efficacy in online learning environment, and the sources of self-efficacy in that environment. They further designed an online learning environment that guides learners to improve their self-efficacy.

Overall, the existing studies rarely talk about the correlations between self-efficacy and online learning participation. Only a few scholars have theoretically discussed the two factors independently. The few studies on their correlations are too general, without any detailed deliberation. Therefore, this paper examines the influence of self-efficacy improvement on online learning participation. The contents mainly evolve around two themes: (1) plotting a normal distribution map of self-efficacy in online learning, and building a prediction model for participation based on the series of online learning behaviors; (2) optimizing the k-means clustering (KMC) algorithm based on information entropy, and clarifying the flow of the improved algorithm. Experimental results demonstrate the effectiveness of our model.

2 Feature extraction

Self-efficacy, the sense of learning effectiveness, refers to students' cognition and belief of the degree of completion for learning goals. The self-efficacy of online learning can be understood as the manifestation of self-efficacy through the online learning process, that is, the students' belief of improving learning behavior control and learning quality during online learning. The online learning self-efficacy is closely related to most learning activities. The level of online learning self-efficacy directly affects the students' confidence in participating in online learning activities, and their degree of completion for learning tasks. Figure 1 shows the normal distribution map of online learning self-efficacy. It can be observed that the development level of online learning self-efficacy obeys normal distribution.

Based on the series of online learning behaviors, this paper predicts online learning participation by classifying the recent online learning behaviors, such as login, topic discussion, online test, and MOOC watching. Figure 2 shows the structure of the participation prediction model.

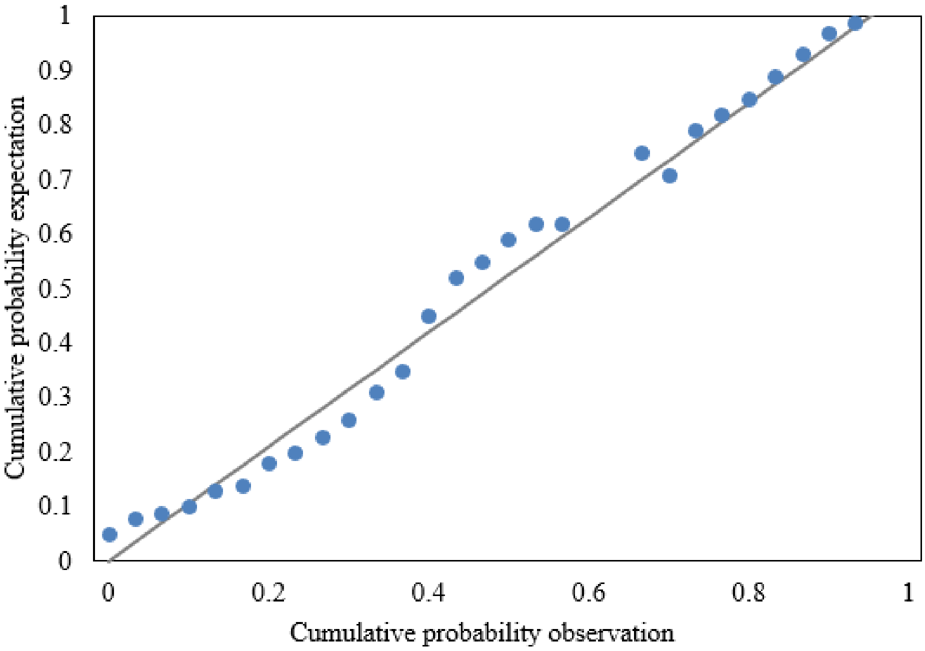

Fig. 1. Normal distribution map of online learning self-efficacy

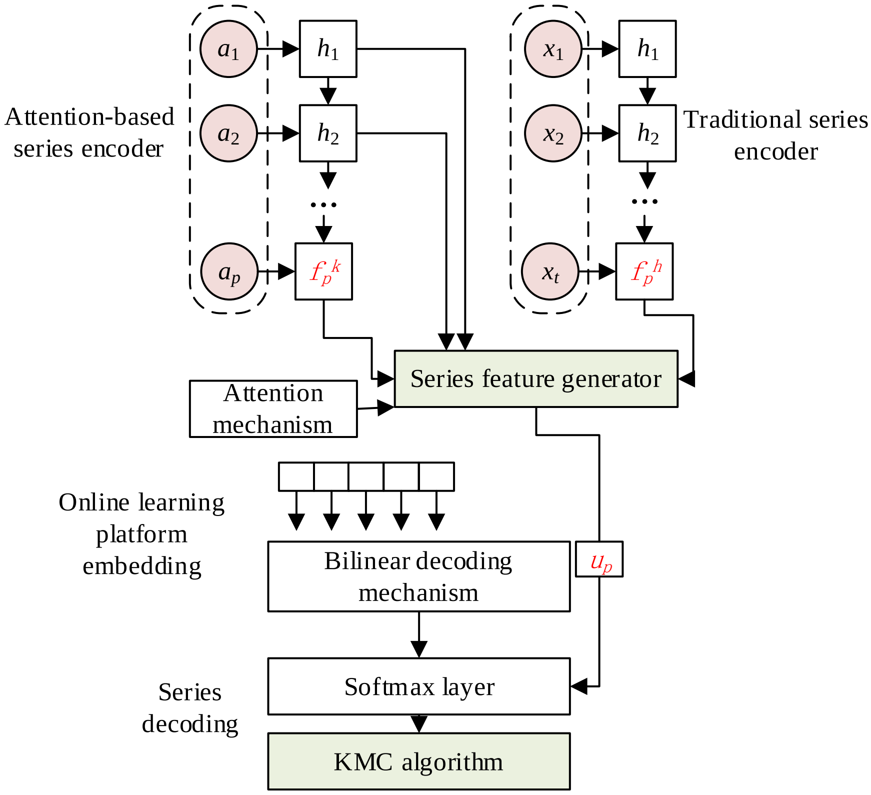

Fig. 2. Structure of participation prediction model

In the first phase of series-based prediction of learning participation, this paper constructs an attention-based hybrid encoder-decoder model, and uses the model to extract the features of the online learning behavior series under self-efficacy improvement. It is assumed that the upper and lower encoders receive the historical data of online learning behaviors a= [a_1, a_2,..., a_{p-1}, a_p], and output the hidden state f_i of the online learning behavior series.

The specific steps of the proposed algorithm are as follows: For each behavior series a_i, the gated unit of the model receives the historical online learning behavior series, and outputs the linear transform between the hidden state f'_p of the current online learning behavior series, and that f_{p-1} of the previous online learning behavior series. The update gate c_p controls how much information in f_{p-1} should be forgotten and how much information in f'_p should be memorized:

$$c_p = \tau\left(Q^{(c)} a_p + V^{(c)} f_{p-1}\right) \tag{1}$$

The reset gate s_p determines that the memory of the previous moment should be preserved:

$$s_p = \tau\left(Q^{(s)} a_p + V^{(s)} f_{p-1}\right) \tag{2}$$

The new network unit can be expressed as:

$$f_p^{'} = tan\left(Qa_p + s_p \oplus f_{p-1}\right) \tag{3}$$

The hidden state can be expressed as:

$$f_p = c_p \oplus f_{p-1} + \left(1 - c_p\right) \oplus f_p^{'} \tag{4}$$

The above analysis shows that the linear transform between f'_p and f_{p-1} is a linear interpolation between the hidden states of the current and previous online learning behavior series. The hidden state f_p finally outputted by the encoders carries most of the information in the initial online learning behavior series.

The features of online learning behavior series can be characterized by f_p, i.e., f^h_p as:

$$u_p^h = f_p = f_p^h \tag{5}$$

Not every recent online learning behavior is associated with the final learning effect. During participation prediction, the proposed model is expected to interact more with the behaviors related to learning quality and learning effect. Therefore, this paper extracts the above assumption based on the attention mechanism, and constructs an attention-based series encoder:

$$u_p^k = \sum^{p} \gamma_{pi} f_i \tag{6}$$

Where, u^k_p is the context vector; γ_{pi} is the weighting factor. The context factor can be calculated from γ_{pi} and hidden states f_1-f_p($1 \leq i \leq p$). Let φ be the sigmoid function that transforms f_p and f_i to a latent space. Then, the attention-based mechanism can be described as:

$$\gamma_{pi} = \phi\left(Q_\gamma \left[f_p ; f_i \right]\right) \tag{7}$$

Then, all hidden states are weighed and summarized. The sum is adopted to characterize the features of learning behavior series. To better understand u^k_p, this paper describes f_i as the final hidden state f_p at moment p, i.e., f^k_p. Hence, u^k_p can be optimized as:

$$u_p^k = \sum^{p} \gamma_{pi} f_i = \sum^{p} \gamma_{pi} f_p^k \tag{8}$$

It can be seen that f^h_p is incorporated into u^h_p, while f^k_p and γ_{pi} are incorporated into u^k_p. Together, u^h_p and u^k_p represent the online learning behavior series of the proposed model. The difference between the series-based encoder f^h_p and the attention-based encoder f^k_p lies in that: the final hidden state of the former is responsible for encoding the entire online learning behavior series, while the latter is responsible for computing the attention weight of the previous hidden state. In the hybrid scheme, the two encoders can be expressed as u_p, i.e., a series generator pieced up from u^h_p and u^k_p:

$$u_p = \left[u_p^h; u_p^k\right] = \left[f_p^h; \sum^p \gamma_{pi} f_p^k\right] \tag{9}$$

Let $|G|$ be the embedding dimension of online learning platform, which maps each behavior vector to the low-dimensional space; $|F|$ be the dimension of series state; ψ be a $|G|^*|F|$ matrix. To better predict online learning participation, this paper calculates the similarity score XZ_i by applying the selective bilinear decoding mechanism between the hidden state of the current online learning behavior series and the online learning platform:

$$XZ_i = emb_i^n \psi u_p \tag{10}$$

The softmax layer receives the similarity score of online learning platform, and decodes the proposed model with the probability of acquiring the deep behavior features of online learning.

3 Learning participation classification

For participation prediction, an important step is to establish the evaluation indices for behavior features by analyzing the online learning behavior series. The evaluation criteria, such as positivity, indifference, inactivity, and nonparticipation, can be determined based on the prediction goals. Based on the deep behavior features obtained in the preceding section, this section attempts to classify the students' learning participation with the improved KMC algorithm.

The m behavior features of sample set R of online learning behavior features, and K classes are imported to the algorithm. The sample set R can be expressed as:

$$R=\{a_1, a_2,...a_m\},K=\{u_1, u_2,...,u_k\}$$

The algorithm outputs K classes that satisfy the demand. The algorithm is realized in the following steps:

Step 1. Randomly choose K behavior features from R, and treat them as the initial cluster heads.

Step 2. Based on the mean of each behavior feature, compute the Euclidean distance ε from each sample to each initial cluster head, and re-classify the samples based on the minimum ε. The Euclidean distance $\varepsilon(a_i, a_j)$ between two T-dimensional behavior features $a_i=(a_{i1}, a_{i2},..., a_{it})$ and $a_j=(a_{j1}, a_{j2}, ..., a_{jt})$ can be defined as:

$$\varepsilon\left(a_i,a_j\right)=\sqrt{\left(a_{i1}-a_{j1}\right)^2+\left(a_{i2}-a_{j2}\right)^2+...\left(a_{it}-a_{jt}\right)^2} \tag{11}$$

The mean distance between all samples can be calculated by:

$$MEA\left(R\right)=\frac{2}{m\left(m-1\right)}\times\sum_{i\neq j,j,j=1}^{m}\varepsilon\left(a_i,a_j\right) \tag{12}$$

Step 3. Re-calculate the mean of each behavior feature.

Step 4. Repeat Steps 2 and 3 until the objective function value tends to be stable or falls below the preset threshold. Let u_i be the centroid of behavior features in the same class. Then, the objective function, i.e., the squared error criterion, can be given by:

$$\delta_i=\sqrt{\frac{\sum_{i=1}^{m_i}\left(a_i-u_i\right)^2}{\left|U_i\right|-1}} \tag{13}$$

The centroid u_i, i.e., the head of cluster i, can be calculated by:

$$u_i=\frac{1}{\left|U_i\right|}\sum_{a_j\in\psi_i}a_j \tag{14}$$

Where, c_iu_i is the center of cluster i; $|U_i|$ be the number of features in cluster U_i.

Step 5. End the algorithm and obtain K clusters.

Figure 3 shows the main steps of the KMC algorithm.

The traditional KMC algorithm has a large stochasticity and a high computing overhead. To solve these defects, this paper optimizes the KMC algorithm based on information entropy. Firstly, the information entropy was calculated for the behavior feature samples. Then, a weight was assigned to the Euclidean distance from each sample to each initial cluster head. After that, the criterion function value was computed, and the initial cluster heads were determined. On this basis, the behavior feature sample set was fully clustered.

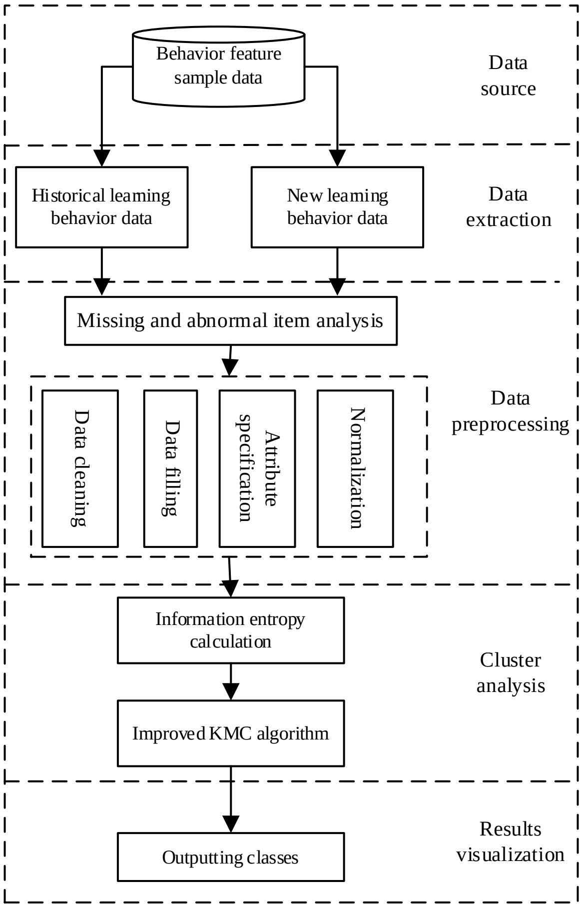

Fig. 3. Main steps of original KMC algorithm

The information entropy is calculated as follows: Let $r=\{a_1, a_2,....,a_m\}$ be the behavior feature sample set; $QG_i=QG[A=a_i]$ be the probability density. Then, the self-information volume of a behavior can be expressed as:

$$SF\left(a_i\right)=log\frac{1}{QG_i} \tag{15}$$

The information entropy of the behavior feature sample set can be expressed as:

$$SD\left(A\right)=\sum_i QG_i log\frac{1}{QG_i}\left(i=1,2,...,m\right) \tag{16}$$

The information entropy, as a measure of information volume, is positively correlated with uncertainty.

After analyzing the contribution of each behavior feature to the clustering of behavior feature samples, a weight is calculated for each behavior feature, and the Euclidean distance between samples is calculated again to complete clustering. The entropy-based feature weighting is implemented in the following steps:

Step 1. Let n be the dimensionality of behavior feature samples, and m be the number of samples. Then, the behavior feature matrix can be established as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{17}$$

Step 2. Compute the weight of each behavior feature, i.e., the ratio of the behavior feature in dimension j to the behavior feature of sample i. firstly, normalize sample data to the interval [0, 1]. Let x_{ij} be the value of behavior feature, with i=1, 2, …, n, and j=1, 2, …, m. Then, the behavior feature ratio Φ_{ij} can be calculated by:

$$\Phi_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij} \tag{18}$$

Step 3. The entropy of the behavior feature in dimension j can be calculated by:

$$SD_j = -\frac{1}{ln\ m} \sum_{i=1}^{m} \Phi_{ij} ln \Phi_{ij} \tag{19}$$

If Φ_{ij}=0, then $\Phi_{ij} 1n \Phi_{ij}$=0. If all behavior features are equal, for a given j. Then, we have:

$$\Phi_{ij} = x_{ij} / \sum_{i=1}^{\Phi} x_{ij} = 1/m \tag{20}$$

Step 4. The diversity factor for the behavior feature in dimension j can be calculated by:

$$\mu_j = 1 - SD_j \tag{21}$$

For a given j, the smaller the entropy SD_j of behavior feature, the greater the μ_j, and the more important the corresponding behavior feature. The inverse is also true. If SD_j=1, then μ_j=0, and the behavior feature has a negligeable contribution to clustering.

Step 5. The behavior feature in dimension j can be calculated by:

$$\alpha_j = \mu_j / \sum_{j=1}^{n} \mu_j \tag{22}$$

Step 6. Let α_t the weight of the behavior feature in dimension t. After the weighting, the Euclidean distance can be calculated by:

$$\varepsilon_{\alpha} = \left(a_i, a_j\right) = \sqrt{\sum_{t=1}^{n} \alpha_t \left(a_{it} - a_{jt}\right)^2} \tag{23}$$

The above formula essentially scales up or down behavior features properly according to their weights, such that the behavior features with a large weight contribute more to clustering, and those with a small weight contribute less to clustering.

Step 7. Let δ_i be the standard error of the weights assigned to class i; $|U_j|$ be the number of behavior features in U_j. Taking δ_i as the standard measuring function, the target value of each weighted class can be expressed as:

$$\delta_i = \sqrt{\frac{\sum_{x_i \in \psi_j} \varepsilon_{\alpha}\left(x_i, u\left(U_j\right)\right)}{\left|U_j\right| - 1}} \tag{24}$$

The greater the δ_i, the smaller the similarity between behavior features in the same class, and the more dispersed the behavior features. The smaller the δ_i, the more concentrated the samples. In the latter case, the centroid of the class of a sample can better reflect the classification plane for behavior features. Figure 4 shows the steps of information entropy-based KMC algorithm.

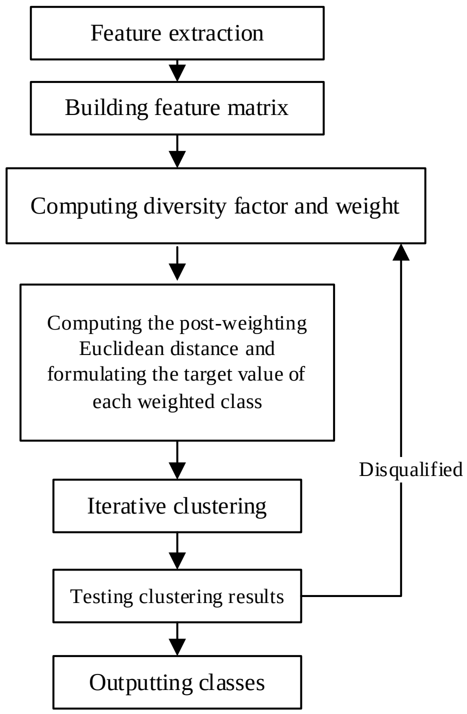

Fig. 4. Steps of information entropy-based KMC algorithm

4 Experiments and results analysis

Table 1 lists the online learning self-efficacy of students in different age groups. In the age group of 16-18, more than 91% have a relatively high self-efficacy, including 68% on the medium level, and 23% on the high level. In the age group of 19-21, more than 92% have a relatively high self-efficacy, including 56% on the medium level, and 36% on the high level. In the age group of 22-24, more than 93% have a relatively high self-efficacy, including 74% on the medium level, and 16% on the high level. In the age group of 25 and above, all students have a relatively high self-efficacy, including 41% on the medium level, and 56% on the high level. Therefore, older students are more capable of completing various learning tasks during online learning, and more confident in learning.

Table 2 shows the results of correlation analysis on online learning self-efficacy and classroom learning self-efficacy. The results show that the p-value of the correlations between the two self-efficacies was 0.001, smaller than 0.1. Hence, there is a significant correlation between online learning self-efficacy and classroom learning self-efficacy.

Table 1. Online learning self-efficacy of students in different age groups

Age group	16-18		19-21		22-24		25 and above	
	Number	***Proportion***	***Number***	***Proportion***	***Number***	***Proportion***	***Number***	***Proportion***
0-20 Low	5	6%	4	8%	2	1	/	/
20-40 Medium	32	68%	24	56%	8	74%	6	41%
40-60 High	12	23%	14	36%	5	16%	8	56%

Table 2. Correlation between online learning self-efficacy and classroom learning self-efficacy

	Online learning self-efficacy		Classroom learning self-efficacy	
	Correlation	***Significance***	***Correlation***	***Significance***
Online learning self-efficacy	1		0.618^{**}	0.001
Classroom learning self-efficacy	0.618^{**}	0.001	1	

Table 3 presents the descriptive statistics of different types of online learning participation. Five types of online learning participation were surveyed, including conventional participation, propelled participation, spontaneous participation, extended participation, and knowledge-centered participation. The statistics in Table 3 shows that the min, max, mean and SD of conventional participation were 5, 15, 35.25, and 2.582, respectively; the min, max, mean and SD of propelled participation were 2, 18, 26.35, and 6.258, respectively; the min, max, mean and SD of spontaneous participation were 4, 17, 21.38, and 4.296, respectively; the min, max, mean and SD of extended participation were 1, 12, 19.28, and 4.287, respectively; the min, max, mean and SD of knowledge-centered participation were 7, 16, 10.19, and 2.364, respectively.

Table 3. Descriptive statistics of different types of online learning participation

	Conventional participation	**Propelled participation**	**Spontaneous participation**	**Extended participation**	**Knowledge-centered participation**
Min	5	2	4	1	7
Max	15	18	17	12	16
Mean	35.25	26.35	21.38	19.28	10.19
SD	2.582	6.258	4.296	4.287	2.364

Note: Min, max, mean, and SD are short for minimum, maximum, mean value, and standard deviation, respectively.

By the mean values, conventional participation covers the greatest proportion of online learning students, followed in turn by propelled participation, spontaneous participation, extended participation, and knowledge-centered participation. Knowledge-centered participation involves the fewest number of online learning students. Overall, the five types of participation differ very slightly in mean value. According to the min values of different types of participation, some students very rarely engage in extended and propelled participation. Judging by the SDs, the students differ insignificantly between spontaneous participation and extended participation, but differ greatly between conventional participation and propelled participation.

The conventional and our improved KMCs were separated applied to cluster the sample set of online learning behavior features and the sample set of classroom learning behavior features. The clustering results are recorded in Table 4. The clustering effect was measured by the classification accuracy of participation, i.e., the number of correctly clustered instances as a percentage of the total number of instances. The classification accuracy of the sample set of classroom learning behavior features increased from 82.14% of the conventional KMC to 89.32% of the improved KMC; the classification accuracy of the sample set of online learning behavior features increased from 90.21% of the conventional KMC to 96.47% of the improved KMC. The comparison demonstrates the effectiveness of our improved algorithm.

Table 4. Results of different clustering algorithms on different sample sets

<table>
<tr><th>Sample set number</th><th colspan="2">Classes</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>Accuracy</th></tr>
<tr><td rowspan="2">1</td><td>Conventional KMC</td><td>Number of instances</td><td>111</td><td>113</td><td>114</td><td>111</td><td>112</td><td>82.14%</td></tr>
<tr><td>Improved KMC</td><td>Number of correctly clustered instances</td><td>95</td><td>94</td><td>97</td><td>96</td><td>102</td><td>89.32%</td></tr>
<tr><td rowspan="2">2</td><td>Conventional KMC</td><td>Number of instances</td><td>104</td><td>102</td><td>103</td><td>105</td><td>101</td><td>90.21%</td></tr>
<tr><td>Improved KMC</td><td>Number of correctly clustered instances</td><td>101</td><td>99</td><td>100</td><td>100</td><td>98</td><td>96.47%</td></tr>
</table>

5 Conclusions

To disclose the influence of self-efficacy improvement on online learning participation, this paper presents a general normal distribution map for self-efficacy, establishes a prediction model based on the series of online learning behaviors, optimizes the KMC algorithm, and specifies the flow of the improved KMC. Through experiments, the authors summarized the online learning self-efficacy of students in different age groups, analyzed the correlations between the online learning self-efficacy and classroom learning self-efficacy, collected the descriptive statistics on different types of participation, and compared the clustering results of different algorithms on different sample sets. The experimental results demonstrate the effectiveness of our improved algorithm.

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Article submitted 2021-10-08. Resubmitted 2021-12-15. Final acceptance 2021-12-16. Final version published as submitted by the author.