Machine Learning-Based Evaluation of Information Literacy Enhancement among College Teachers

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Abstract—To enhance the information literacy among college teachers, it is necessary to evaluate their existing information awareness, information ethics, information techniques and information competence. Existing studies qualitatively analysed the effective means of enhancing information literacy among college teachers, and the dimensions were too homogeneous. In response, this paper studies the machine learning-based evaluation of college teachers' information literacy enhancement. Firstly, the paper presents a framework of predictive model on information literacy enhancement evaluation of college teachers, and the influencing factors of college teachers' information technology usage behaviour (ITUB) from the authors' viewpoint. Then the paper presents a framework diagram for extracting ITUB features, along with a detailed introduction to specific influencing factors. After that, the paper extracts the potential information in the content of information technology behaviour to be predicted. The content features of ITUB are characterised by two aspects: content similarity and data form features. Next, the paper shows a method for calculating the affective polarity of ITUB. It also constructs a predictive model for enhancing ITUB and shows the objective function of the model. The experimental results verify the validity of the constructed model.

Keywords—college teachers, information literacy, machine learning, classifier, literacy enhancement

1 Introduction

With the rapid development of information technology, the vast amount of fragmented knowledge, advanced teaching equipment and methods have brought opportunities and challenges to the teaching of college teachers [1–4]. Information literacy refers to the retrieval and use of various information sources through skilled use of information techniques, so as to obtain necessary knowledge information and make sound decisions [5–11]. An information-literate college teacher recognises the benefits of access to cutting-edge web-based information and the use of information technology to improve his or her teaching skills [12–17]. Such teachers are able to integrate valuable teaching materials, learning resources, assessment information, and teacher-student interaction information, which are obtained from computers and other information sources, with the existing knowledge system about teaching in specialized courses. They also flexibly use various information during the process of reflective thinking, critical thinking and blended teaching practices [18–22]. To enhance the information literacy among college teachers, it is necessary to evaluate their existing information awareness, information ethics, information techniques and information competence for their educational and teaching quality improvement.

Danping [23] discussed the evaluation function of college teacher's ability of using information technology including oriented function, inspiring function and ensuring function, and established the evaluation index system including information ideals, information circumstances, basic knowledge, using ability and effects. Libbrecht et al. [24] presented the concept of an intelligent tutoring system which combines web search for learning purposes and state-of-the-art natural language processing techniques. The concept is described for the case of teaching information literacy, but has the potential to be applied to other courses or for independent acquisition of knowledge through web search. The main focus of Pinto et al. [25] was to analyse the relation between information literacy and the use of mobile devices in the process of learning-teaching in university students, specifically, teachers-in-training. Both results (qualitative and quantitative) were compared in order to check the consistency of the information offered by the students. Grigas et al. [26] presented the results of a questionnaire study in three countries on teachers' awareness of and attitudes towards information literacy instruction in secondary schools. The authors summarised the results of a survey they administered to the top 250 secondary school teachers (9–12 classes) in Hungary, Lithuania, and Poland (total 801 teachers) at the start of 2019. The study shows that teachers need to be able to locate, assess and use internet resources in the teaching and learning process. Ntuli et al. [27] reported the results of a study that sought to examine strategies used by teacher candidates when using Internet search engines, their ability to integrate the information they find into their own assignments, and use the acquired skills for future classroom use.

From the existing domestic and foreign research, we saw that most of the studies analyzed the influencing factors of information literacy enhancement of college teachers from multiple dimensions, or qualitatively analysed the effective means of enhancing information literacy among college teachers. The dimensions were too homogeneous. On the basis of building an appropriate model of the influencing factors on information literacy enhancement of college teachers, the existing studies manifested too monotonous extraction of behavioural features of information technology usage among college teachers to improve their own information literacy. In response, this paper studies the machine learning-based evaluation of college teachers' information literacy enhancement. Its main contents are as follows: 1) presenting a framework of predictive model on information literacy enhancement evaluation of college teachers, and the influencing factors of college teachers' information technology usage behaviour (ITUB) from the authors' viewpoint; 2) presenting a framework diagram for extracting ITUB features, along with a detailed introduction to specific influencing factors; 3) extracting the potential information in the content of information technology behaviour to be predicted. The content features of ITUB are characterised by two aspects: content similarity and data form features; 4) showing a method for calculating the affective polarity of ITUB; 5) constructing a predictive model for enhancing ITUB and showing the objective function of the model. The experimental results verify the validity of the constructed model.

2 Structure of the predictive model for information literacy enhancement among college teachers

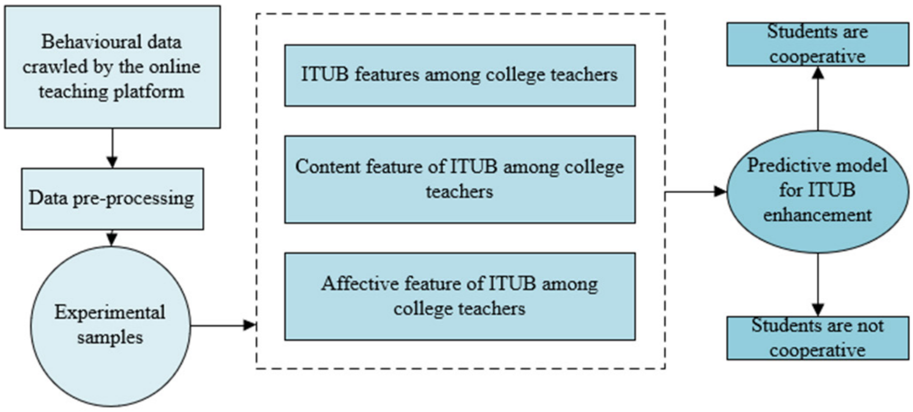

Fig. 1. Predictive model framework diagram

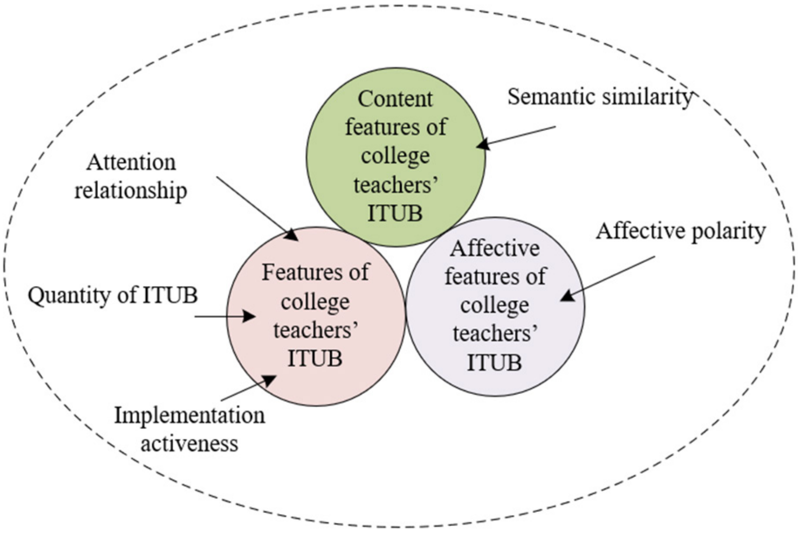

Fig. 2. Schematic diagram of the relationship among influencing factors

In response to the existing problem of monotonous dimension when thinking over factors influencing the implementation of ITUB by college teachers, this paper constructs an optimized system of factors influencing such implementation with reference to the existing research results. Accordingly, the paper selects the features of relevant ITUB influencing the implementation by college teachers from multiple dimensions, so that the predictive model is more accurate for evaluating information literacy enhancement of college teachers.

Figure 1 illustrates the framework diagram of the predictive model. The factors influencing such implementation in this paper contain three dimensions: features of college teachers' ITUB, content features of college teachers' ITUB, and affective features of college teachers' ITUB. The following five different statistical indicators are identified in this paper: the attention relationship between college teachers and the object of implementing ITUB, represented by *RE*; the quantity of college teachers' ITUB, represented by *AC*; the implementation activeness of college teachers' ITUB, represented by *EA*; the semantic similarity with historical ITUB, represented by *SI*; and the affective polarity of informatization behaviour to be implemented, represented by *SP*. A schematic diagram of the relationships among the influencing factors is given in Figure 2.

3 Feature extraction of ITUB

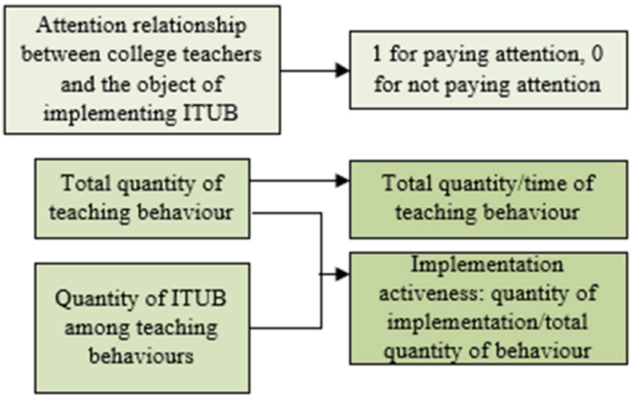

Fig. 3. Framework diagram for feature extraction of information technology usage behavior

Figure 3 gives a framework diagram for feature extraction of ITUB, with the specific influencing factors detailed below.

3.1 Attention relationship

Attention relationship reflects to some extent the degree of ITUB objects' preference for college teachers' ITUB content. When the ITUB objects pay attention to the teachers, there will be a greater probability of the ITUB objects cooperating with the teachers to implement ITUB, hence the attention relationship between the teachers and the ITUB objects is a distinguishing factor. In this paper, the attention relationship between college teachers and the ITUB objects is a differentiating factor. In this paper, the attention relationship among college teachers in the experimental sample set was obtained by correlating the data crawled by the online teaching platform. The attention relationship was made to be 1 if the ITUB objects paid attention to college teachers, and 0 otherwise.

$$RE = \begin{cases} 1, & \text{Paying attention} \\ 0, & \text{Not paying attention} \end{cases} \tag{1}$$

3.2 ITUB quantity

The quantity of ITUB implemented by college teachers on the online teaching platform reflects to some extent whether college teachers have the habit of implementing ITUB on the online teaching platform. In order to obtain accurate parameters of the ITUB quantity and to solve the problem that there is a certain gap between the quantity of ITUB implemented by different college teachers, this paper takes the logarithmic operation of the ITUB quantity implemented by college teachers in a fixed period of time. Assuming that M represents the total quantity of ITUB implemented by college teachers in a fixed period of time, the calculation formula is

$$AC = \ln M \tag{2}$$

3.3 Implementation activeness

Implementation activeness refers to the percentage of ITUB in all teaching behaviours performed by college teachers in a fixed period of time. In this paper, the ratio of the ITUB quantity implemented by college teachers to the total quantity of behaviours within a fixed period of time represents the implementation activeness of college teachers' ITUB, and characterizes the degree of willingness of college teachers to implement ITUB. Assuming that M represents the total quantity of teaching behaviours of college teachers in a fixed period, and m represents the total quantity of ITUB implemented by college teachers in a fixed period, the calculation formula is

$$EA = \frac{n}{N} \tag{3}$$

4 Content feature extraction of ITUB

The ITUB content is a key factor when determining whether ITUB involving textual information is accepted by the target objects. The target objects will be willing to cooperate if the content is of interest to them, and the willingness of the target objects to cooperate will increase if ITUB involving textual information is presented in a topic or other more attractive form. Considering the above factors, this paper focuses on extracting the potential information contained in the ITUB content to be predicted, and characterising the content features of ITUB through both content similarity and data form features. Figure 4 shows the framework for extracting the content features of ITUB.

The content of ITUB performed by a college teacher during a fixed period of time can often be characterised by the focus of that college teacher's teaching during that fixed period. If you want to determine whether or not a teacher has carried out a ITUB involving specific textual information, the prediction accuracy can be improved to some extent by knowing the teacher's recent teaching focus.

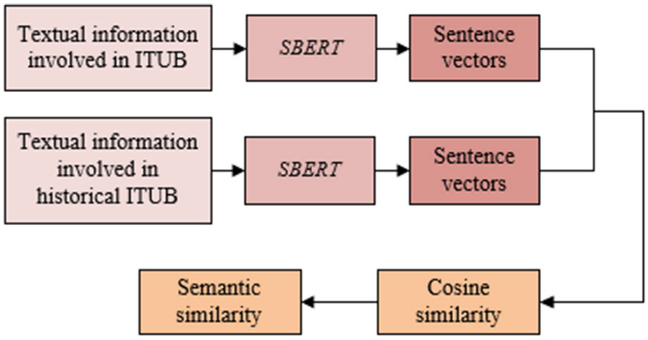

Fig. 4. Framework for extracting content features of ITUB

Assume that M represents the entire vocabulary of textual information and N represents the number of occurrences of a keyword. The keyword's word frequency can be calculated based on the formula $TF = N/M$. Assume that en (E) represents the total number of strings in the corpus, and $m(i)$ represents the number of occurrences of a keyword in the strings. To reduce the influence of high-frequency words, the inverse document frequency *ID is* introduced in this paper, and the calculation formula is given by the following equation.

$$IDF = log\left(\frac{len(E)}{m(i)}\right) \tag{4}$$

Deep learning-based estimation of ITUB similarity involving textual information means that the current textual information and the textual information to be predicted are first transformed into vectors and then compared for similarity. The twin network *SBERT* has a higher computational accuracy than the traditional semantic similarity model *BERT*.

Assume that v and u respectively represent the sentence vectors of the two sentences for the current textual information and the textual information to be predicted, the sentence vector dimension is represented by m, the number of categories is represented by a, and the weights are represented by $Q_p \in S^{3m*a}$. The *SBERT* model can splice the difference vectors of the two vectors v and u and multiply them by Q_p. The following equation gives the final output expression:

$$z = softmax(Q_p(v, u\, |v - u|)) \tag{5}$$

Since the teaching focus of college teachers may change within a short period of time, this paper still chooses to calculate the similarity based on all ITUBs implemented by college teachers within a fixed period of time. f_i denotes the vector of textual information sentences involved in the ITUB to be implemented, which is obtained using *SBERT*. $f_j^m (m \in NU)$ denotes the vector of ITUBs implemented by college teachers within a fixed period of time. NU denotes the quantity of ITUBs implemented by college teachers in a fixed period. $cos(f_i, f_j^a)$ denotes the cosine similarity between the two sentences. Then the similarity between each ITUB and the textual information involved in the ITUB to be predicted can be calculated using cosine similarity based on the following equation:

$$SI = \frac{\sum_{a \in NU} cos(f_i, f_j^a)}{NU} \tag{6}$$

When the two textual information vectors are $k^* = (k_1, k_2, k_3, \ldots, k_m)$ and $l^* = (l_1, l_2, l_3, \ldots, l_m)$, then the following equations are available:

$$\cos\omega = \frac{k^* \cdot l^*}{k^* * l^*} = \frac{k_1 * l_1 + k_2 * l_2 + \ldots + k_m * l_m}{\sqrt{k_1^2 + k_2^2 + \cdots k_m^2} * \sqrt{l_1^2 + l_2^2 + \cdots l_m^2}} \tag{7}$$

5 Affective feature extraction of ITUB

The affective features of ITUB implemented by teachers in this paper have two parts: on the one hand, they are the affective tendencies of college teachers obtained through the affective analysis of their ITUB implemented in a short period of time; on the other hand, they refer to the prediction of the affective intensity shown by college teachers when implementing ITUB, the latter can be quantified through the number of affective symbols in the textual information involved in their ITUB.

If there is a high degree of similarity between the affective polarity of the current informational behaviour and the affective polarity expressed in the predicted ITUB, then the higher the probability that the college teachers will implement the current informational behaviour again. In this paper, we use the "*sentiments*" attribute r of the *SnowNLP* class to extract the sentiment polarity. When the value of the attribute is greater than or equal to 0.5 and less than 1, it can be judged that the affective polarity of the current ITUB is positive. When the value of the attribute is less than 0.5 and greater than 0, it can be judged that the affective polarity of the current informational behaviour is negative. The following equation gives the calculation formula.

$$SP = \begin{cases} |r_1 - r_2|, r_1 \geq 0.5, r_2 \geq 0.5, r_1 < 0.5, r_2 < 0.5, \\ 0, other \end{cases} \tag{8}$$

6 Predictive model for ITUB enhancement

According to the previous sections, this paper obtained five different statistical indicators: the attention relationship between college teachers and the object of implementing ITUB *RE*, the ITUB quantity of college teachers *AC*, the implementation activeness of college teachers' ITUB *EA*, the semantic similarity with historical ITUB *SI*, and the affective polarity of ITUB to be implemented *SP*. Due to the data quantitative level of *AC* and *SI* is not consistent with other indicators, this paper normalizes the two based on sigmoid function, and the processing formula is:

$$AC = 2 \times Sigmoid\,(AC) - 1 \tag{9}$$

$$SI = 2 \times Sigmoid\,(SI) - 1 \tag{10}$$

The following equation gives the expression for the sigmoid function used:

$$R(k) = \frac{1}{1+f^{-k}} = \frac{f^{k}}{f^{k}+1} \tag{11}$$

Based on the calculation results of equations 9 and 10 for training the classification model, this paper combines several S4VMs *to* build a high-precision predictive model for ITUB enhancement using the AdaBoost algorithm. The following equation gives the expression of the AdaBoost algorithm:

$$H(k) = sign\left(\sum_{n=1}^{N} \gamma_n h_n(k)\right) \tag{12}$$

Assume that several basic weak classifiers S4VM are denoted by $h_n(k)$ and the corresponding weights of each basic weak classifier S4VM are denoted by γ_n (n=1…,N), defined as $\sum_{n=1}^{N}\gamma_n = b$, $0 \le \gamma_n \le b$, and the total number of basic weak classifiers is denoted by N. Assuming that the computation on the training set is represented by f_n and the error rate is represented by h_n, we have $f_n = Z(H_n(k_i) \neq l_i) = \sum_{i=1}^{N}\theta_{ni}\, I(H_n(k_i) \neq l_i)$. The following equation gives the formula for the weight coefficient γ_n *of* $h_n(k)$:

$$\gamma_n = \frac{1}{2} log \frac{1-f_n}{f_n} \tag{13}$$

Assuming that the low density separator is represented by $\{g_p\}_{p-1}^{P}$ and the corresponding label assignment is represented by $\{l_p^*\}_{p=1}^{P}$, the following equation gives the objective function $o(g, l^*)$ that needs to be optimized for the basic weak classifier S4VM *as* follows:

$$o(g,l^*) = \frac{\|g\|_F}{2} + D_1\sum_{i=1}^{b} b(l_i, g(k_i)) + D_2\sum_{j=1}^{v} b(l_j^*, g(l_j^*, g(k_i))) \tag{14}$$

According to the above equation, the l^* objective is to find multiple large $\{g_p\}_{p-1}^{P}$ and $\{l_p^*\}_{p=1}^{P}$ such that the objective function of the following equation satisfies minimization. Assuming that the number of separators is denoted by P, the penalty quantity with respect to separator diversity is denoted by R_2, and a large constant that enhances the diversity is denoted by N, we have:

$$\min_{\{g_p, \hat{b}\in L\}_{p=1}^{P}} \sum_{p=1}^{P} o(g_p, l_p^*) + M\Gamma(\{l_p^*\}_{p=1}^{P}) \tag{15}$$

$\Gamma(\{l^*_p\}^P_{p=1})$ is the sum of pairs of terms, defined here as $\Gamma(\{l^*_p\}^P_{p=1}) = \Sigma_{1\le p\ne p\sim\le P}\psi((l^{*\prime}_p \times l^*_{p\sim}/v) \ge 1-\sigma$ where ψ is a constant function and $\sigma \in [0,1]$ is a constant. Without loss of generality constraints, the linear model is assumed to be defined as $g(a) = \theta'\upsilon(k) + \phi$, with a feature mapping induced by the kernel a denoted by $\upsilon(k)$ and the j-th term of l_p denoted by $b_{p,j}$. The following equation gives an expression for the optimization problem to be solved by the predictive model for ITUB enhancement:

$$\begin{aligned}
&\min_{\{\theta_p, l_p, \hat{l}\in Y\}^P_p} \sum_{p=1}^{P}\left(\frac{1}{2}\left\|\theta_p\right\|^2 + D_1\sum_{i=1}^{b}\vartheta_i + D_2\sum_{j=1}^{v}\hat{\vartheta}_j\right) + N\sum_{1\le p\ne\tilde{p}\le P} I\left(\frac{l^{*\prime}_p l^*_{\tilde{p}}}{v} \ge 1-\sigma\right)\\
&s.t \qquad l_i(\theta_p\upsilon(k_i)+\varphi_p) \ge 1-\vartheta_i, \quad \vartheta_i \ge 0\\
&\qquad\quad \hat{l}_{p,j}(\theta'_p\upsilon(\hat{k}_i)+\varphi_p) \ge 1-\hat{\vartheta}_i, \quad \hat{\vartheta}_i \ge 0,\\
&\qquad\quad \forall i = 1,\dots b, \quad \forall j = 1,\dots v, \quad \forall p = 1,\dots P,
\end{aligned} \tag{16}$$

Assume that the weights corresponding to several basic weak classifiers are denoted by γ_n (n=1,...,N), defined as $\sum_{n=1}^{N}\gamma_n = 1$, $0 \le \gamma_n \le 1$, and the total number of basic classifiers is denoted by N. The following equation gives the objective function of the improved ITUB enhancement predictive model obtained by combining several basic weak classifiers.

$$H(k) = \sum_{n=1}^{N}\gamma_n \left\{ \begin{array}{l} \min\limits_{\{\theta_p,\varphi_p,\hat{l}\in Y\}^P_p} \sum\limits_{p=1}^{P}\left(\begin{array}{l} \frac{1}{2}\left\|\theta_p\right\|^2 + \\ D_1\sum\limits_{i=1}^{k}\vartheta_i + D_2\sum\limits_{j=1}^{v}\hat{\vartheta}_j \end{array}\right) + N \\ \sum\limits_{1\le p\ne\tilde{p}\le P} I\left(\frac{\hat{l}_p{}'\hat{l}_{\tilde{p}}}{v} \ge 1-\sigma\right) \end{array} \right\} \tag{17}$$

7 Experimental results and analysis

The prediction performance of four classification models, namely, support vector machine, random forest, expectation maximisation and Fuzzy C-means clustering, was selected for comparison with the model in this paper, and the comparison results are shown in Table 1. According to the table, the prediction accuracy of the model proposed in this paper is over 90%, and its performance advantage is higher than the other four models.

Table 1. Comparison of the performance of different predictive models

	Accuracy	*F*1	Precision	Recall Rate
Support vector machines	0.817	0.869	0.841	0.842
Random Forest	0.835	0.837	0.819	0.839
Expectation maximisation	0.829	0.824	0.855	0.837
Fuzzy C-means clustering	0.83	0.818	0.81	0.759
Model in this paper	0.915	0.803	0.826	0.927

Table 2. Scores in each dimension of the influencing factor

Dimensionality	Average Value	Standard Deviation
RE	4.385	0.638
AC	3.169	0.827
EA	4.125	0.695
SI	3.297	0.841
SP	3.417	0.829
Comprehensive forecast	3.629	0.605

Table 3. Results of correlation analysis

		RE	*AC*	*EA*	*SI*	*SP*
RE	*Pearson* correlation	1.251	0.758**	0.718**	0.558**	0.811**
	Significance (bilateral)	0.02	0.06	0.02	0.07	0.04
	N	126	159	162	139	184
AC	*Pearson* correlation	0.748**	1.205	0.847**	0.648**	0.936**
	Significance (bilateral)	0.26	0.03	0.07	0.04	0.01
	N	125	141	169	117	137
EA	*Pearson* correlation	0.749**	0.857**	1.16	0.728**	0.918**
	Significance (bilateral)	0.07	0.02	0.05	0.01	0.04
	N	126	169	195	161	184
SI	*Pearson* correlation	0.528**	0.615**	0.748**	1.025	0.849**
	Significance (bilateral)	0.03	0.05	0.01	0.09	0.01
	N	162	137	158	135	127
SP	*Pearson* correlation	0.817**	0.958**	0.911**	0.869**	1.041
	Significance (bilateral)	0.06	0.04	0.01	0.03	0.01
	N	174	129	136	171	169

Note: **, significantly correlated at the 0.1 level (bilateral).

Descriptive statistics were conducted on the scores in each dimension of the factors influencing the implementation of ITUB by college teachers, i.e., the following five evaluation dimensions: the attention relationship between college teachers and the object of implementing ITUB *RE*, the ITUB quantity of college teachers *AC*, the implementation activeness of college teachers' ITUB *EA*, the semantic similarity with historical ITUB *SI*, and the affective polarity of ITUB to be implemented *SP*. Specific statistical results are given in Table 2. According to the table, the overall mean score of the predicted status of ITUB enhancement was above the moderate threshold of 3, and the mean scores of all five evaluation dimensions were also above 3. This indicates that the overall effectiveness of teachers' ITUB enhancement was moderate to high. Teachers scored the highest mean value on the attention relationship with students *RE*, indicating that teachers pay more attention to students and have a more positive attitude towards the implementation of ITUB.

To further explore the correlation between the five evaluation dimensions, this paper will conduct a correlation analysis using the five evaluation dimensions as dependent variables. The analysis results are given by Table 3.

According to the table above, there are significant differences between all five evaluation dimensions, which means that teachers' scores on any of the five evaluation dimensions are influenced by their scores on the other evaluation dimensions and are mutually reinforcing.

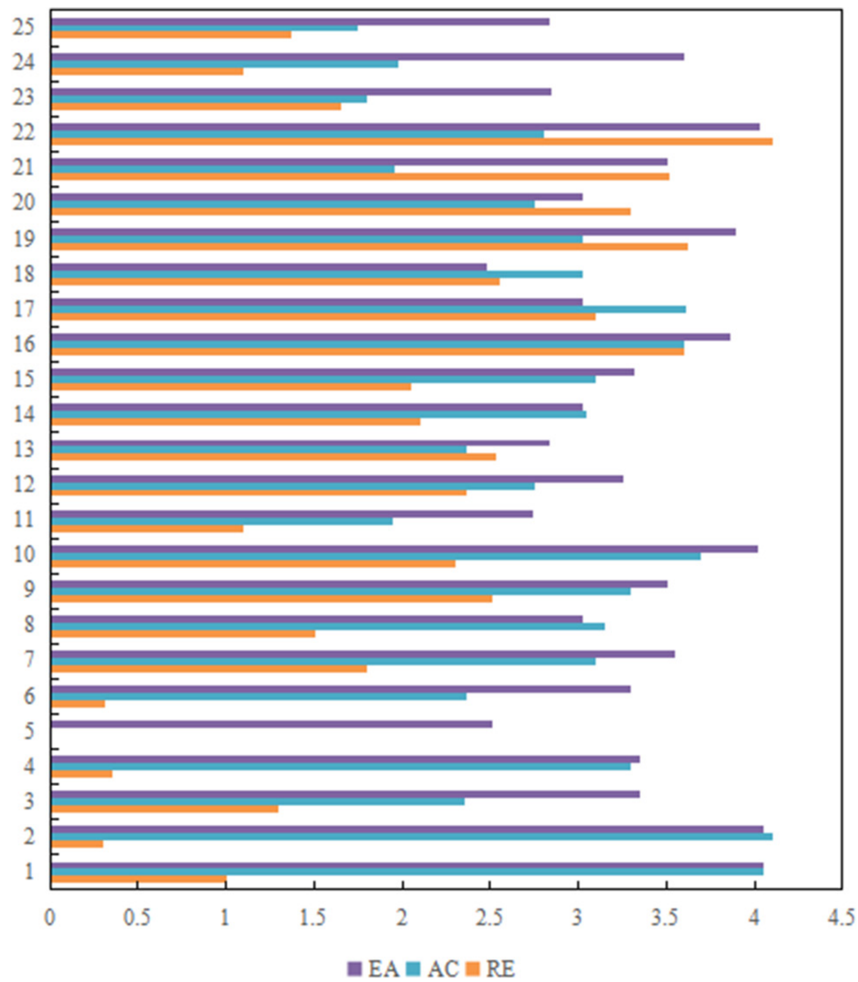

Fig. 5. Graph of ITUB feature scores for a sample of 25 teachers

Figure 5 gives a graph of the ITUB feature scores of the 25 sampled teachers. According to the figure, scores on the three indicators *RE*, *AC* and *EA* among the 25 sampled teachers have almost all improved. Some teachers made concrete progress from nothing in terms of ITUB feature score characterized by the three indicators.

When it comes to the individual variability of a sample of 400 teachers, this paper divides the total rating scale for the effectiveness of teachers' ITUB enhancement into four levels: [0,1], [1,2], [2,3] and [3,5]. Figure 6 gives the overall rating scale for the effectiveness of teachers' ITUB. Figure 7 gives the rating scale for each indicator of the effectiveness of teachers' ITUB enhancement. According to the two figures, the majority of teachers scored below 1 on the overall effectiveness of ITUB enhancement, with very few scoring greater than 3. The number of teachers who met and didn't meet the criteria for each of the five evaluation dimensions also varied greatly. The number of teachers who met the criterion for *RE* scores was the biggest one out of the five indicators. The reason for this is the increasing attention of teachers to students.

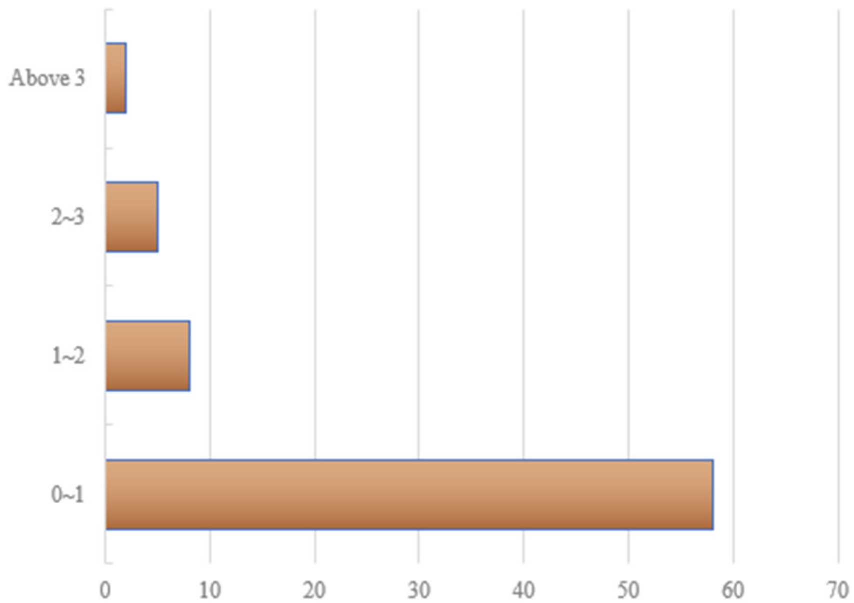

Fig. 6. Overall rating scale for the effectiveness of teachers' ITUB enhancement

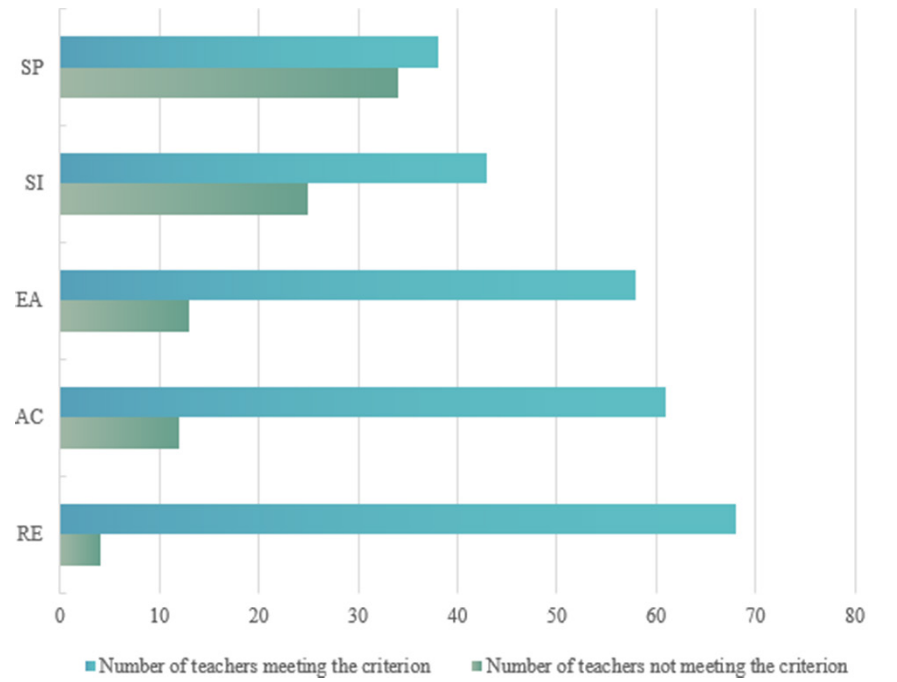

Fig. 7. Rating scale for each indicator of the effectiveness of teachers' ITUB enhancement

8 Conclusion

This paper studies the machine learning-based evaluation of college teachers' information literacy enhancement. Firstly, the paper presents a framework of predictive model on information literacy enhancement evaluation of college teachers, and the influencing factors of college teachers' ITUB from the authors' viewpoint. Then the paper presents a framework diagram for extracting ITUB features, along with a detailed introduction to specific influencing factors. After that, the paper extracts the potential information in the content of information technology behaviour to be predicted. The content features of ITUB are characterised by two aspects: content similarity and data form features. Next, the paper shows a method for calculating the affective polarity of ITUB. It also constructs a predictive model for enhancing ITUB and shows the objective function of the model. The prediction performance of four classification models, namely, support vector machine, random forest, expectation maximisation and Fuzzy C-means clustering, was selected in experiments for comparison with the model in this paper. Results show that the performance advantage of the model proposed in this paper is higher than the other four models. Descriptive statistics were conducted on the scores in each dimension of the factors influencing the implementation of ITUB by college teachers, using the 5 evaluation dimensions as dependent variables. It was verified that teachers' scores on any of the five evaluation dimensions are influenced by their scores on the other evaluation dimensions and are mutually reinforcing. We also presented two figures: overall rating scale for the effectiveness of teachers' ITUB enhancement; rating scale for each indicator of the effectiveness of teachers' ITUB enhancement. Experimental results indicate that the effectiveness of teachers' ITUB can be further improved.

9 References

[1] Kamaghe, J.S., Luhanga, E.T., Kisangiri, M. (2020). The Challenges of Adopting M-Learning Assistive Technologies for Visually Impaired Learners in Higher Learning Institution in Tanzania, International Journal of Emerging Technologies in Learning, 15(1): 140–151. https://doi.org/10.3991/ijet.v15i01.11453

[2] Metruk, R. (2020). Confronting the Challenges of MALL: Distraction, Cheating, and Teacher Readiness, International Journal of Emerging Technologies in Learning, 15(2): 4–14. https://doi.org/10.3991/ijet.v15i02.11325

[3] Guo-rong, S. (2018). Effect of Macro Environment on the Development of College English Teachers' Information-Based Teaching Ability, International Journal of Emerging Technologies in Learning, 13(12): 201–210. https://doi.org/10.3991/ijet.v13i12.8278

[4] Zhong, D., Yan, X. (2018). Research on the Strategy of Improving the Teaching Ability of Teachers' Information in Higher Education. In Proceedings of the 2018 International Conference on Distance Education and Learning, 127–130. https://doi.org/10.1145/3231848.3231861

[5] Zhen-Yong, L., Dong, L., Zheng-Pei, W. (2011). How to Improve the Teacher-Students' Educational Technique Ability in the Information Society. In 2011 International Conference on E-Business and E-Government (ICEE), 1–4. https://doi.org/10.1109/ICEBEG.2011.5887103

[6] De-Mei, S., Zheng-Pei, W., Lu, Z. (2011). How to Improve University Teacher's Educational Technique Ability in the Information Society. In 2011 International Conference on E-Business and E-Government (ICEE), 1–4. https://doi.org/10.1109/ICEBEG.2011.5887104

[7] Qingwen, X., Yi, L. (2011). Build Knowledge-Ability Curriculum for Information Technology Curriculum and Teaching in Higher Teacher Education. In 2011 International Conference on Electrical and Control Engineering, 6400–6403. https://doi.org/10.1109/ICECENG.2011.6056973

[8] Arfandi, A. (2020). The Development of a Thurstone Scale for Identifying Teacher Ability in using Information and Communication Technology. In Journal of Physics: Conference Series, 1456(1): 012038. https://doi.org/10.1088/1742-6596/1456/1/012038

[9] Wu, B. (2017). Analysis of Teacher Training Mode and Technical Ability in Information Network Age Based on AHP Model. Boletin Tecnico/Technical Bulletin, 55(18): 253–259.

[10] Li, W. (2021). Information-Based Teaching Ability Training of PE Teachers and Information-Based Teaching Practice Paths. Proceedings – 2021 International Conference on Information Technology and Contemporary Sports, 152–155. https://doi.org/10.1109/TCS52929.2021.00040

[11] Lili, C. (2021). Research on the Countermeasures of Improving Teachers' Information Teaching Ability in Higher Vocational Colleges Based on Big Data. In 2021 2nd International Conference on Education, Knowledge and Information Management (ICEKIM), 553–556. https://doi.org/10.1109/ICEKIM52309.2021.00127

[12] Jiqiong, Y., Yue, Q. (2021). Based on "MOOC+ SPOC" Customized Regional Primary and Secondary School Teachers' Information Technology Application Ability Training Strategy. In Journal of Physics: Conference Series, 1931(1): 012005. https://doi.org/10.1088/1742-6596/1931/1/012005

[13] Yan, Q., Zhao, X., Chen, M. (2021). The Research Community under Technical Support Improves Primary School Teachers Case Study of Information Teaching Ability. In 2021 4th International Conference on Education Technology Management, 189–194. https://doi.org/10.1145/3510309.3510339
[14] Lin, B. (2021). A Study on College English Teachers' Informatization Teaching Ability in Private Colleges Based on Information Technology in Blended Teaching Mode. In 2021 2nd International Conference on Information Science and Education (ICISE-IE), 259–263. https://doi.org/10.1109/ICISE-IE53922.2021.00067
[15] Bao, X., Xu, C. (2021). Research on the Influencing Factors of Teaching Ability of Textile University Professional Teachers under the Combination of Teaching and Big Data Information – Taking Dalian Polytechnic University as an Example. In 2021 2nd International Conference on Big Data and Informatization Education (ICBDIE), 135–138. https://doi.org/10.1109/ICBDIE52740.2021.00038
[16] Zeng, W. (2020). Information Teaching Ability of EFL Teachers in Application-Oriented College. In Journal of Physics: Conference Series, 1533(4): 042076. https://doi.org/10.1088/1742-6596/1533/4/042076
[17] Zhang, Y. (2020). Cultivation Methods of Information Technology Educational Ability of English Teachers in Higher Vocational Colleges. In Journal of Physics: Conference Series, 1533(2): 022102. https://doi.org/10.1088/1742-6596/1533/2/022102
[18] Žufić, J., Žufić, A. (2020). Ability of the Information Science Teachers to Teach Programing in the Lower Grades of Primary School. In 2020 43rd International Convention on Information, Communication and Electronic Technology (MIPRO), 899–904. https://doi.org/10.23919/MIPRO48935.2020.9245284
[19] Chen, M., Zhou, C., Wu, Y. (2020). Research on the Model and Development Status of Information Literacy Self-Improvement Ability of Primary and Secondary School Teachers. In 2020 Ninth International Conference of Educational Innovation through Technology (EITT), 87–91. https://doi.org/10.1109/EITT50754.2020.00021
[20] Pu, X.C. (2014). Research on Improving the Teacher's Ability of Transmitting Teaching Information Based on the Horizon of Mobile Platform Technology. In Applied Mechanics and Materials, 687: 2470–2473. https://doi.org/10.4028/www.scientific.net/AMM.687-691.2470
[21] Sun, Y., Li, F., Zhang, Z. (2019). Promotion of Information Technology Teaching Ability of Food Specialty Teachers. In International Conference on Application of Intelligent Systems in Multi-modal Information Analytics, 1397–1402. https://doi.org/10.1007/978-3-030-15740-1_176
[22] Fang, J., Ge, S., Hu, X., Lu, X. (2019). A Study on the Dilemma and Countermeasures of Rural Teachers' Information-Based Teaching Ability in Guangxi. In 2019 International Conference on Information Technology and Computer Application (ITCA), 134–140. https://doi.org/10.1109/ITCA49981.2019.00037
[23] Danping, L. (2009). The Evaluation of College Teacher's Ability of Using Information Technology Based on Analytic Hierarchy Process Method. In 2009 International Forum on Computer Science-Technology and Applications, 3: 74–77. https://doi.org/10.1109/IFCSTA.2009.256
[24] Libbrecht, P., Declerck, T., Schlippe, T., Mandl, T., Schiffner, D. (2020). NLP for Student and Teacher: Concept for an AI based Information Literacy Tutoring System. In CIKM (Workshops).
[25] Pinto, M., Caballero-Mariscal, D., Fernández-Pascual, R., Sales, D., Guerrero-Quesada, D. (2018). The Attitudes of Teachers-in-Training towards Information Literacy Skills and the Inclusion of Mobile Devices in the Process of Teacher Education. In European Conference on Information Literacy, 597–606. https://doi.org/10.1007/978-3-030-13472-3_56

[26] Grigas, V., Mierzecka, A., Tomori, T., Koltay, T. (2022). Secondary School Teachers' Attitudes to Information Literacy in Hungary, Lithuania and Poland. In European Conference on Information Literacy, 688–697. https://doi.org/10.1007/978-3-030-99885-1_57
[27] Ntuli, E., Kyei-Blankson, L. (2016). Improving K-12 Online Learning: Information Literacy Skills for Teacher Candidates. International Journal of Information and Communication Technology Education (IJICTE), 12(3): 38–50. https://doi.org/10.4018/IJICTE.2016070104

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