Evaluation and Measurement of Student Satisfaction with Online Learning Under Integration of Teaching Resources

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Abstract—The effective organization and integration of educational resources can solve the information confusion in online learning, and assist online teaching platforms in recommending multisource personalized learning resources. After the integration of teaching resources, the student satisfaction with online learning should be evaluated, setting the stage for the management and application of teaching resources, as well as the improvement of online teaching quality. Therefore, this paper evaluates and measures student satisfaction with online learning under the integration of teaching resources. Specifically, the name and descriptive features of the Japanese teaching resource library were extracted by the linguistic model, the class structure features and relationship attribute features of the library were learned by graph convolutional neural network (GCNN), and the corresponding eigenvectors were obtained. Next, the similarity of different features was calculated, the teaching resources were sorted, and the matching resources were selected, completing resource integration. After feature integration, the student satisfaction with online learning was evaluated, and a structural equation model (SEM) was established for the student satisfaction with online learning under the integration of teaching resources. The effectiveness of our model was proved through experiments.

Keywords—integration of teaching resources, online learning, learning satisfaction

1 Introduction

With the boom of education information technology, educational resources are shifting gradually from offline to online [1-5]. Due to online teaching activities, a huge amount of disorderly, scattered online educational resources have accumulated, resulting in information overload [6-8]. To solve the information confusion in online learning, it is necessary to clarify the distribution and form of educational resources, and organize and integrate educational resources effectively. This would also assist online teaching platforms in recommending multisource personalized learning resources [9-11], and provide a good way information organization for enhancing the correlations between educational resources [12-15]. The integration of teaching resources can effectively improve the utilization efficiency of online educational resources. After the integration of teaching resources, the student satisfaction with online learning should be evaluated, setting the stage for the management and application of teaching resources, as well as the improvement of online teaching quality [16-19].

With the development of science and technology, multimedia auxiliary teaching is increasingly important in practical teaching. The integration between multimedia technology and teaching is not only needed by current teaching, but also a demand by education development and reform. Lin [20] explored the integration of multimedia resources in college English teaching from the angle of artificial intelligence (AI). Firstly, the teaching features in the context of AI were analyzed, and the AI applications in college teaching were summarized. The traditional integration technology for online educational resources has errors in assessing educational resources, because it overlooks the variance contribution rate of online educational resource features. Zhao [21] proposed an online educational resource integration technology based on the scheduling of distance teaching information. According to the theory on the scheduling of distance teaching information, the value of online educational resource integration was quantified. In the era of the big data, the informatization of college English education calls for a simulated learning environment supported by massive information resources, which provides students with information and the chance of language practices. After analyzing the relevant concepts, Luo [22] expounded on the new problems of college English teaching in the background of big data, and presented strategies for integrating and optimizing the information resources of college English teaching in the context of big data, with the aim to enhance the efficiency and effect of college English education. Yuen et al. [23] put forward a growth model for belief and utilization to capture the dynamic changes in the belief and utilization of learning management system, and measure the influence of these changes over the system satisfaction. Their model adopts three longitudinal survey datasets, which cover random samples with different academic abilities from 25 junior high schools in Hong Kong. Chen et al. [24] extensively analyzed a large dataset containing more than 15,000 tutorial dialogs, which were generated by human tutors and students in the counseling services based on mobile apps. The dataset was analyzed to identify the factors related to student satisfaction in the online counseling system.

There are several problems with the research paradigm for the evaluation of student satisfaction with online learning: the satisfaction model is built by unscientific methods, the model is not widely applicable or highly adaptive, the students' self-expression and individualized development are often neglected, and the variation in student satisfaction with online learning after the integration of teaching resources is not fully considered. Taking Japanese teaching for example, this paper evaluates and measures student satisfaction with online learning under the integration of teaching resources. The main contents are as follows: (1) The linguistic model was adopted to extract the name and descriptive features of the Japanese teaching resource library, and trained iteratively to obtain the corresponding eigenvectors. (2) The graph convolutional neural network (GCNN) was employed to learn the class structure features and relationship attribute features of the library, and further acquire the corresponding eigenvectors. (3) The similarity of different features was calculated for Japanese teaching resources before sorting the resources, and the matching resources were selected to complete resource integration. (4) The student satisfaction with online learning was evaluated after integrating the features of Japanese teaching resources, and a structural equation model (SEM) was established for the student satisfaction with online learning under the integration of Japanese teaching resources. The effectiveness of our model was proved through experiments.

2 Feature extraction and integration

2.1 Feature extraction

In this paper, the term library refers to a database of various kinds of Japanese teaching resources. It mainly consists of the name, description, class, relationship, relationship attribute, and volume of Japanese teaching resources. The integration of teaching resources is premised on the matching between teaching resources. The purpose is to find the correlations of new teaching resources, according to the node information and correlations of the existing online teaching resources, and then match the teaching resources.

This paper firstly acquires the necessary information like the name, description, class, relationship, and volume from the Japanese teaching resources to be integrated. The acquired text information characterizes the relationship between teaching resources, and stores the class, relationship attribute, and volume of teaching resources in the teaching resource network. Then, multiple eigenvectors of the teaching resources were obtained, and the similarity between features was solved. After that, the weights corresponding to the similarity of different features of teaching resources were calculated by the learning to rank (LTR) algorithm. Finally, the teaching resources were integrated, and the similarity ranking and resource matching of the target teaching resources were obtained. In this paper, the linguistic model is adopted to extract the names and descriptive features of Japanese teaching resource library, and iterative model training was carried out to generate the corresponding eigenvectors. The name and descriptive feature extraction model is illustrated in Figure 1, where r is a teaching resource, and BI is the name and descriptive text of that resource.

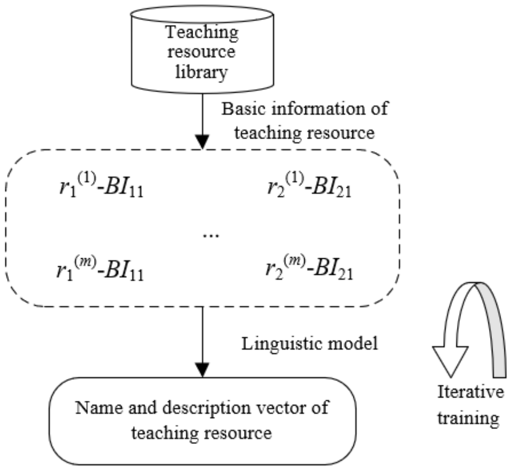

Fig. 1. The name and descriptive feature extraction model

This paper employs the GCNN to learn the class structure features and relationship attribute features of Japanese teaching resource library, and further derives the corresponding eigenvectors.

Figure 2 shows the class structure feature extraction model for teaching resources. During the acquisition of class-based structural feature, it is assumed that the connections between teaching resources are directional. In the teaching resource network, the diversity of relationship increases with the number of resource classes. When two teaching resources are connected to another teaching resource via different relationships, there will be a difference between the matching probabilities of the two teaching resources. Let HE be the number of initial teaching resources belonging to relationship s; TA be the number of final teaching resources belonging to relationship s; TR be the total number of resources belonging to relationship s. Then, two independent functions can be established to characterize the importance of each relationship:

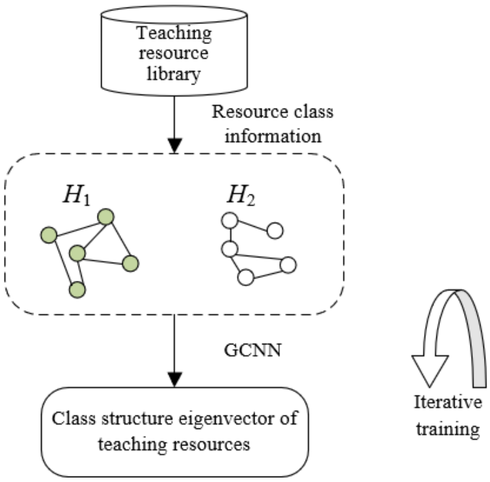

Fig. 2. Class structure feature extraction model

$$FU\left(s\right)=\frac{HE}{TR} \tag{1}$$

$$IF\left(s\right)=\frac{TA}{TR} \tag{2}$$

Under relationship s, two teaching resources r_i and r_j can be expressed as two triples $<r_i, s, r_j>$ and $<r_j, s, r_i>$, respectively. Let x_{ij} be the influence of the i-th teaching resource over the j-th teaching resource. Then, the relationship matrix X can be established as:

$$x_{ij}=\sum_{\langle r_i,s,r_j\rangle} IF\left(s\right)+\sum_{\langle r_j,s,r_i\rangle} FU\left(s\right) \tag{3}$$

Figure 3 shows the relationship attribute feature extraction model for teaching resources. During the acquisition of relationship attribute feature, it is assumed that the connections between teaching resources are non-directional. The relationship attributes of different teaching resources play different roles in the matching between teaching resources. To match teaching resources with a specific relationship attribute, this paper establishes a function to characterize the importance of the relationship attribute. Let x be a relationship attribute of a teaching resource r; RPV be the relationship attribute corresponding to attribute x of r. Then, we have:

$$Q\left(\beta,VA\right)=\frac{1}{\left|\left\{r:x\left(r,RPV\right)\right\}\right|} \tag{4}$$

A local weight needs to be assigned to any relationship attribute of the acquired teaching resource. Let y_{ij} be an element in the adjacency matrix Y, which represents the degree of correlation between the i-th teaching resource and the j-th attribute. Then, the discriminability of teaching resources by each relationship attribute in the teaching resource network can be calculated by:

$$y_{ij} = \frac{1}{\left|\left\{r_i : y_j\left(r_i, RPV\right)\right\}\right|} \tag{5}$$

The loss functions of the GCNN training model are defined as follows: The eigenvectors obtained by GCNN learning of two teaching resource networks correspond to two different spaces. To optimize the representation of eigenvectors, the model must be trained by the matched teaching resources. On this basis, the loss functions can be defined as formulas (5)-(7).

Based on a pair E of known teaching resources, the initial or final resource was replaced with a random resource, producing the set of negative samples E'. Let $u_{re}(r_1)$ and $u_{rx}(r_1)$ be the class structure eigenvector and relationship attribute eigenvector of teaching resource r_1, respectively; t_{re} and t_{rx} be the edge parameters of the samples matched with positive and negative teaching resources, respectively. Then, the loss functions for the class structure feature training and relationship attribute training can be respectively expressed as:

$$K_{re} = \sum_{(r_1,r_2)\in E}\sum_{(r'_1,r'_2)\in E'}\left(g\left(u_{re}\left(r_1\right),u_{re}\left(r_2\right)\right) - g\left(u_{re}\left(r'_1\right),u_{re}\left(r'_2\right)\right) + t_{re}\right) \tag{6}$$

$$K_{rx} = \sum_{(r_1,r_2)\in E}\sum_{(r'_1,r'_2)\in E'_{(r_1,r_2)}}\left(g\left(u_{rx}\left(r_1\right),u_{rx}\left(r_2\right)\right) - g\left(u_{rx}\left(r'_1\right),u_{rx}\left(r'_2\right)\right) + t_{rx}\right) \tag{7}$$

The distance between the two vectors can be calculated by:

$$g\left(a,b\right) = \left\|a-b\right\|_{K1} \tag{8}$$

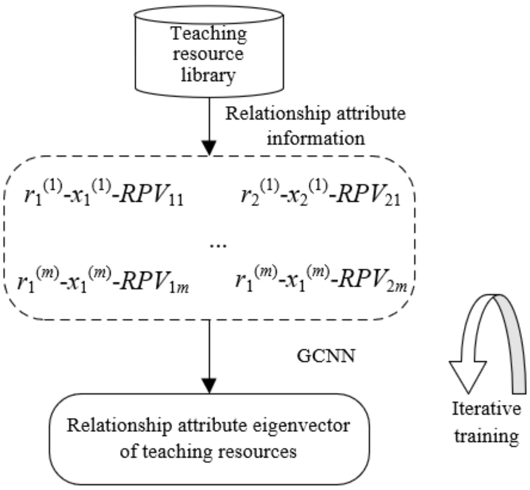

Fig. 3. Relationship attribute feature extraction model

Figure 4 explains the matching and integration steps of teaching resources. For the class structure features and relationship attribute features of teaching resources, this paper adopts cosine similarity to measure the resemblance of eigenvectors between different teaching vectors. In this way, the necessary eigenmatrix of teaching resources can be obtained.

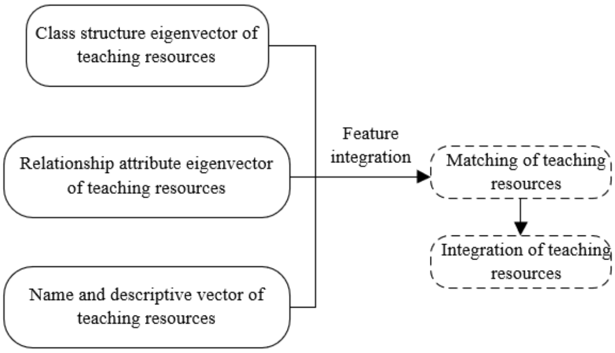

Fig. 4. Matching and integration steps of teaching resources

2.2 Feature integration

For the similarity integration of multiple teaching resource features, the manual assignment of feature weights lacks generalizability, and consumes too much time and efforts. Capable of multifeatured integration, common classifiers like support vector machine (SVM) and Bayesian classifier merely consider the relationship between independent pairs of teaching resources, without taking account of the relationship between teaching resources in a candidate set of teaching resources. Therefore, this paper chooses to compute the similarity of each feature of teaching resources, rank the said teaching resources, and select the matchable resources.

Let r be a teaching resource to be matched; m be the number of teaching resource pairs; c be the number of teaching resource features to be integrated. Then, the input of the LTR algorithm can be viewed as a c-dimensional space vector $u \in R^{m \times c}$. The classifier is constrained by the condition that: the evaluation score of the correct teaching resource containing r should be higher than that of any other teaching resource containing r. Let $g(q, t)$ be the loss function of the weight characterizing the feature to be integrated; θ be the slack variable of a teaching resource; D be the penalty factor; r_1 be the teaching resource to be matched in teaching resource network H_1; r_2 be the teaching resource in teaching resource network H_2, which can be matched with r_1; r_2' be the other candidate resources in teaching resource network H_2 for matching with r_1. Then, the optimization function can be established as:

$$Min: g\left(q,\theta\right) = \frac{1}{2} q * q + D\theta_{r_1,r_2'} \tag{9}$$

The corresponding constraint can be expressed as:

$$s.t: q\left(u\left(r_1,r_2\right)-u\left(r_1,r_2'\right)\right)\geq 1-\theta_{r_1,r_2'} \quad (10)$$

$$\theta_{r_1,r_2'}\geq 0 \quad (11)$$

3 Satisfaction evaluation and measurement

Based on multisource online educational resources, this paper extracts the characteristic information and relationships from various kinds of educational resources, and integrates the resources into a resource network. Online learning platforms should collect, analyze, and organize massive educational resources, such that the students can learn all knowledge units of the curriculum system independently and methodically, and select learning resources with a clear purpose. Owing to the fast update of online educational resources, the effective integration of teaching resources provides students with the latest knowledge of the selected disciplines, which improves the experience and satisfaction of online learning.

This paper evaluates the online learning satisfaction after the integration of teaching resources. Figure 5 shows the student satisfaction evaluation and measurement model after the integration of teaching resources. Six variables were selected for the evaluation, namely, diversity of teaching resources, innovativeness of teaching resources, novelty of teaching resources, selectivity of teaching resources, quality of teaching resources, and gap between learning effect and ideal level. Based on the selected variables, the authors built up the SEM for student satisfaction with online learning, facing the integration of teaching resources.

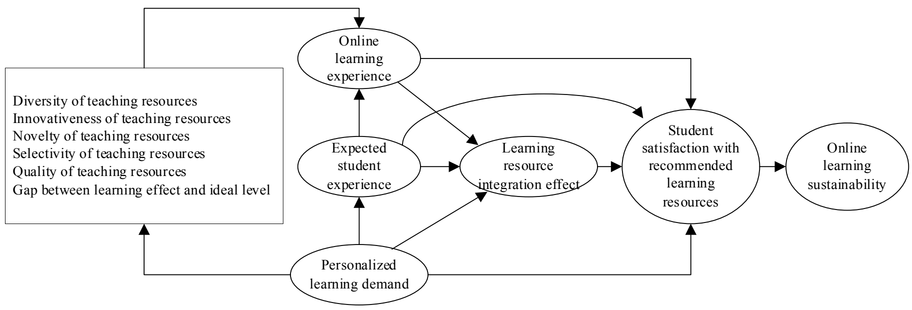

Fig. 5. Student satisfaction evaluation and measurement model after the integration of teaching resources

The exponent of evaluation index refers to the score of a student against an evaluation index. The exponent value reflects the student satisfaction with that index. There are two exponents of student satisfaction index: latent variable exponent and explicit variable exponent. Let λ be the overall score of exogenous latent variables; μ_i be the loading coefficient corresponding to these variables; a_{1i} be the mean of the latent variables; u_σ be the overall score of students given for the σ-th endogenous latent variable;

σ be the σ-th endogenous latent variable; $\xi_{\sigma i}$ be the loading coefficient corresponding to the σ-th endogenous latent variable; $b_{\sigma i}$ be the explicit variable corresponding to $t\sigma$ endogenous latent variables; l be the number of explicit variables corresponding to endogenous variables. The latent variable of an evaluation index can be calculated by:

$$\lambda = \sum_{i=1}^{l} \mu_i a_{1i}, u_\sigma = \sum_{i=1}^{l} \xi_{\sigma i} b_{\sigma i} \tag{12}$$

Let QH_η and QH_α be the exponents of exogenous and endogenous latent variables, respectively; $R[\lambda]$ and $R[u_\sigma]$ be the mean overall scores of exogenous and endogenous latent variables, respectively; $min[\lambda]$ and $min[u_\sigma]$ be the minimum overall scores of exogenous and endogenous latent variables, respectively; $max[\lambda]$ and $max[u_\sigma]$ be the maximum overall scores of exogenous and endogenous latent variables, respectively. The variable exponents can be calculated by:

$$\begin{aligned} QH_\eta &= \frac{R[\lambda] - min[\lambda]}{max[\lambda] - min[\lambda]} \times 100 \\ QH_\alpha &= \frac{R[u_\sigma] - min[u_\sigma]}{max[u_\sigma] - min[u_\sigma]} \times 100 \end{aligned} \tag{13}$$

$min[\lambda]$ and $max[\lambda]$ can be calculated by:

$$min[\lambda] = \sum_{i=1}^{l} \mu_i min(a_{1i}), max[\lambda] = \sum_{i=1}^{l} \mu_i max(a_{1i}) \tag{14}$$

$min[u_\sigma]$ and $max[u_\sigma]$ calculated by:

$$min[u_\sigma] = \sum_{i=1}^{l} \xi_{\sigma i} min(b_{\sigma i}), max[u_\sigma] = \sum_{i=1}^{l} \xi_{\sigma i} max(a_{\sigma i}) \tag{15}$$

The exponents of exogenous and endogenous latent variables can be simplified as:

$$\begin{aligned} QH_\eta &= \frac{\sum_{i=1}^{l} \mu_i A_{1i} - \sum_{i=1}^{l} \mu_i}{4\sum_{i=1}^{l} \mu_i} \times 100 \\ QH_\alpha &= \frac{\sum_{i=1}^{l} \xi_{\sigma i} b_{\sigma i} - \sum_{i=1}^{l} \xi_{\sigma i}}{4\sum_{i=1}^{l} \xi_{\sigma i}} \times 100 \end{aligned} \tag{16}$$

Let a_{1i} be the i-th exogenous explicit variable; μ_i be the loading coefficient corresponding to the exogenous explicit variable; $b_{\sigma i}$ be the i-th explicit variable corresponding to the σ-th endogenous latent variable; $\xi_{\sigma i}$ be the loading coefficient corresponding to the endogenous latent variable. Then, the explicit variable exponents can be calculated by:

$$QH_{a_{1i}} = \frac{\mu_i a_{1i} - \mu_i}{4\mu_i} \times 100$$
$$QH_{b_{\sigma i}} = \frac{\xi_{\sigma i} b_{\sigma i} - \xi_{\sigma i}}{4\xi_{\sigma i}} \times 100 \tag{16}$$

4 Experiments and results analysis

Table 1 presents the reliability test results on student satisfaction indices after the integration of teaching resources. The reliability was tested by Cronbach's alpha and split-half reliability. It can be seen that the reliability coefficients of all factors, including diversity of teaching resources, innovativeness of teaching resources, novelty of teaching resources, selectivity of teaching resources, quality of teaching resources, and gap between learning effect and ideal level, were greater than 0.82. Thus, the proposed evaluation index system is reliable enough for further analysis.

Table 2 displays the total variance explained by the measurement and evaluation system for student satisfaction after the integration of teaching resources. The initial eigenvalues of the six indices were 36.185, 8.192, 8.374, 5.629, 3.281, and 2.936, all of which was greater than 1. In addition, after the integration of teaching resources, the six indices of the measurement and evaluation system cumulatively explained 68.419% of the total variance. The percentage was greater than 60%, the threshold for scientific education and teaching. Therefore, after the integration of teaching resources, the measurement and evaluation system for student satisfaction has an overall good explanatory power of the relevant data.

Table 1. Reliability test results on student satisfaction indices after the integration of teaching resources

Variable	Cronbach's alpha	Split-half reliability
Diversity of teaching resources	0.917	0.935
Innovativeness of teaching resources	0.973	0.968
Novelty of teaching resources	0.958	0.908
Selectivity of teaching resources	0.961	0.913
Quality of teaching resources	0.829	0.846
Gap between learning effect and ideal level	0.975	0.933

Table 2. Total variance explained by the measurement and evaluation system

Compo-	**Initial variance**			**Extraction sums of squared loadings**			**Rotation sums of squared loadings**		
	Total	***% of variance***	***Cumulative %***	***Total***	***% of variance***	***Cumulative %***	***Total***	***% of variance***	***Cumulative %***
1	18.246	36.185	34.528	18.158	37.126	38.415	8.629	15.269	13.427
2	4.205	8.192	45.636	4.627	8.936	45.128	7.158	12.085	32.528
3	4.369	8.374	55.907	4.824	8.742	53.629	7.052	10.062	46.057
4	2.741	5.629	56.127	2.618	5.281	58.152	5.139	9.158	55.169
5	2.306	3.281	63.174	2.041	3.905	62.157	2.751	4.329	57.421
6	1.846	2.936	68.419	1.294	2.738	67.362	1.862	3.749	68.293

This paper adopts two datasets of teaching resources, none of which contain many long-tail resources. Table 3 shows the statistical features of the two teaching resources datasets. To verify its effectiveness, our feature extraction algorithm was compared with four classic entity matching algorithms, including TransH (1), TransR (2), TransD (3), and TransSpare (4). The performance was measured by the percentage of the matchable resources whose ranking is no greater than 1, the percentage of the matchable resources whose ranking is no greater than 10, and the reciprocal of mean ranking.

As shown in Table 4, the traditional entity matching algorithms are limited. Our algorithm fully utilizes the name and description feature, class structure feature, and relationship attribute feature of teaching resources, and carries out weighted fusion between the three kinds of features. Then, the linguistic model and GCNN are adopted to enhance the matching and integration effects of teaching resources through iterative training. That is why our algorithm outperformed the traditional entity matching algorithms in all three performance metrics.

Table 3. Statistical features of the integrated teaching resources datasets

Dataset	Number of resources	Class structure	Class structure triple	Relationship attribute	Relationship attribute triple
1	16025	261	36298	352	72153
	14528	153	42153	664	152456
2	13629	224	35084	332	68592
	16284	36	33291	214	23157

Table 4. Experimental results on different datasets

Algorithm	Dataset 1			Dataset 2		
	Ranking ≤ 1	*Ranking ≤ 10*	*Reciprocal of mean ranking*	*Ranking ≤ 1*	*Ranking ≤ 10*	*Reciprocal of mean ranking*
Algorithm 1	0.251	0.528	0.336	0.284	0.512	0.361
Algorithm 2	0.294	0.562	0.384	0.249	0.574	0.382
Algorithm 3	0.236	0.597	0.352	0.277	0.539	0.348
Algorithm 4	0.148	0.301	0.241	0.183	0.427	0.281
Our algorithm	0.816	0.864	0.862	0.926	0.974	0.964

Next, the effectiveness of our iterative model training was verified through an experiment on the prior data percentage, using 10%-90% of known matched teaching resources. The results in Table 5 show that the three performance indices of the linguistic model and GCNN increased continuously, with the rising proportion of prior data. That is, the matching effect of teaching resources became better and better. Therefore, more known matched teaching resources help the proposed model acquire the features of teaching resources, which in turn improves the matching effect of teaching resources.

Table 5. Test results on the effectiveness of iterative model training

Prior data proportion		10%	20%	30%	40%	50%	60%	70%	80%	90%
Linguistic model	Ranking≤1	0.728	0.715	0.762	0.784	0.815	0.843	0.859	0.805	0.926
	Ranking≤10	0.802	0.836	0.847	0.869	0.937	0.963	0.918	0.985	0.973
	Reciprocal of mean ranking	0.862	0.892	0.815	0.847	0.836	0.829	0.861	0.842	0.869
GCNN	Ranking≤1	0.715	0.769	0.825	0.862	0.819	0.847	0.836	0.829	0.872
	Ranking≤10	0.862	0.816	0.872	0.884	0.895	0.952	0.961	0.968	0.974
	Reciprocal of mean ranking	0.813	0.828	0.809	0.836	0.817	0.829	0.816	0.889	0.861

Table 6 compares the satisfaction of students in different grades for each evaluation index. It can be seen that the student learning satisfaction with diversity of teaching resources, innovativeness of teaching resources, novelty of teaching resources, selectivity of teaching resources, quality of teaching resources, and gap between learning effect and ideal level was higher among grade 1 and grade 2 students than that among grade 3 and grade 4 students. On the selectivity of teaching contents, the difference between the satisfaction of students in different grades widened with the F-score.

Table 6. Satisfaction of students in different grades with each evaluation index

Index	Grade	Mean	Standard deviation	F-score	Significance
Diversity of teaching resources	Grade 1	2.5	1.30258	4.85	0.025
	Grade 2	2.4853	0.91842		
	Grade 3	1.8517	0.74851		
	Grade 4	1.962	1.26359		
Innovativeness of teaching resources	Grade 1	2.748	0.68521	4.97	0.026
	Grade 2	2.3628	0.91847		
	Grade 3	1.7482	0.74812		
	Grade 4	1.92	1.06258		
Novelty of teaching resources	Grade 1	2.6851	0.91847	4.58	0.036
	Grade 2	2.36248	0.96285		
	Grade 3	1.8459	0.75182		
	Grade 4	1.748	0.81547		
Selectivity of teaching resources	Grade 1	2.8	1.30625	6.35	0.028
	Grade 2	2.3262	0.91487		
	Grade 3	1.8459	0.62854		
	Grade 4	1.6258	0.92847		
Quality of teaching resources	Grade 1	2.215	0.5774	5.12	0.025
	Grade 2	2.625	0.68451		
	Grade 3	1.589	0.59748		
	Grade 4	1.516	1.0594		
Gap between learning effect and ideal level	Grade 1	2.544	1.3542	4.65	0.019
	Grade 2	2.3691	0.9644		
	Grade 3	1.6482	0.7587		
	Grade 4	1.5614	1.2455		

5 Conclusions

This paper mainly explores the evaluation and measurement of student satisfaction with online learning under the integration of teaching resources. Based on the linguistic model, the authors extracted the name and descriptive features of the Japanese teaching resource library. Then, the GCNN was adopted to learn the class structure features and relationship attribute features of the library. The corresponding eigenvectors were further obtained. Next, the similarity of each kind of features was computed, and the teaching resources were thus ranked. The matchable resources were then selected to complete resource integration. After integrating the features of teaching resources, the authors evaluated the student satisfaction with online learning, and built an SEM for student satisfaction with online learning, facing the integration of teaching resources. Through experiments, the reliability of the evaluation and measurement indices for student satisfaction was tested after the integration of teaching resources. The total variance explained by the evaluation and measurement system was obtained, revealing that the measurement and evaluation system for student satisfaction has an overall good explanatory power of the relevant data. Further, the proposed feature extraction algorithm was proved effective through experiments on different datasets. In addition, the effectiveness of our iterative model training was verified through an experiment on the prior data percentage, using 10%-90% of known matched teaching resources. The results show that our algorithm outperformed the traditional entity matching algorithms in all three performance metrics. Finally, the authors compared the satisfaction of students in different grades for each evaluation index.

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