Evaluation of Comprehensive Services of an Online Learning Platform Based on Artificial Intelligence

https://doi.org/10.3991/ijet.v17i13.32797

Peifan Yang[1(✉)], Xia Liu[2]
[1] College of Music, Cangzhou Normal University, Cangzhou, China
[2] College of Qiyue Media, Cangzhou Normal University, Cangzhou, China
yangpeifan@caztc.edu.cn

Abstract—With the college students having increasing needs for learning diversified knowledge and skills, online learning platforms for essential qualities enhancement have emerged one by one. However, due to lack of feedbacks from students, the comprehensive service quality of these platforms varies greatly. Therefore, it has certain practical significance to study how to evaluate the comprehensive services of online learning platforms. The current evaluation models are not suitable for online learning platforms, nor have they fully considered the dynamic and subjective feedbacks of students about their experience. To this end, this paper takes an online music education platform as an example and studies the evaluation on the comprehensive services of the online learning platform. First, the overall architecture design of an online learning platform for essential qualities enhancement was displayed, and the teacher-student interaction mode for the comprehensive services of the online learning platform was identified and analyzed. Then, the derivation process of the evaluation model was presented, the evaluation indicator system for the comprehensive service quality of the online learning platform constructed, and the comprehensive service evaluation model for the online learning platform consisting of the hierarchical model and the rough set-neural network evaluation model established. The experimental results verified the effectiveness of the constructed indicator system and evaluation model.

Keywords—neural network, online learning, evaluation on comprehensive services

1 Introduction

Driven and catalyzed by the “Internet +” trend, online learning platforms have broken through the constraints of time and space, with the market size maintaining year-on-year growth in recent years [1-5]. Particularly in the post-COVID era, thanks to their advantages, online learning platforms integrating information technology have become an important direction of higher education in China and even in the world [6-14]. To meet the needs of the future society, high-level professional talents need to be well-rounded, that is, they have to have knowledge, abilities and also essential qualities, which is why college students have increasing demands for learning diversified knowledge and skills. Along with this trend, online learning platforms specialized in enhancement of essential qualities such as music and sports have developed rapidly within a short period of time. However, due to lack of feedbacks from students about their experience, the comprehensive service quality of these platforms varies greatly [15-19]. Therefore, it has certain practical significance to study how to evaluate the comprehensive services of online learning platforms.

Boko et al. [20] leveraged the powerful functions of a highly interactive online learning platform to improve its interactivity and service quality. The platform was built on FFmpeg, Tvheadend and Verto-FreeSwitch, allowing teachers to provide online courses with better service quality. The FFmpeg streaming server performs MPEG-TS encoding and allows teachers to unicast a multimedia (audio/video) stream from his webcam to the Tvheadend server, and the interactive IPTV server multicasts the stream to learners. Through a web browser or IPTV client, students can interact in real time as instructed by the teacher. Tsai et al. [21] discussed the construction and use of online learning platforms on the basis of total quality management and knowledge management. The data collection method was semi-structured interviews. The results consisted of three parts, which were the results respectively before, during and after use, analyzed from three perspectives - total quality management, knowledge innovation and knowledge sharing. Militaru et al. [22] proposed an expert system that can be used to build a web-based learning platform quality model to improve usability, reduce cost and facilitate services. The quality framework used was called SEEQUEL and the proposed expert system was built on CLIPS. The final conclusion of the experiment is that the expert system can successfully perform the assigned task in place of human experts. The online learning quality evaluation of learners is an important function of an online learning platform, and also an important means for teachers to remotely check the learning effect of learners. Wang et al. [23] discussed the importance and purpose of learning quality evaluation on online learning platforms, and proposed a content framework for online learning quality evaluation from five aspects - participation in learning activities, interactions, use of resources, acquisition of knowledge and contribution to the learning community. It also put forward two effective strategies for learning quality evaluation on online learning platforms, in order to provide some references for improving students' learning quality. Braccini et al. [24] investigated end users' perceptions of the quality of the Moodle open source e-learning platform in terms of usability, functionality, reliability, efficiency and use quality.

According to the existing research results, it is found that the current evaluation models are not suitable for online learning platforms, nor have they fully considered the dynamic and subjective feedbacks of students about their experience. To this end, this paper takes an online music education platform as an example and studies the evaluation on the comprehensive services of the online learning platform. The paper consists of the following sections. Section 2 presents the overall architecture design of an online learning platform for quality enhancement, and identifies and analyzes the teacher-student interaction mode for the comprehensive services of the online learning platform. Section 3 shows the derivation process of the evaluation model, constructs the evaluation indicator system for the comprehensive service quality of the online learning platform, and establishes the comprehensive service evaluation model for the online learning platform consisting of the hierarchical model and the rough set-neural network evaluation model. The experimental results prove the effectiveness of the constructed indicator system and evaluation model.

2 Identification of the teacher-student interaction mode

Online music education is different from general online education, as the learning of almost all musical instruments is mainly about practicing, mastering skills, practical tutoring and error correction, rather than theoretical learning. Since different students have different problems in learning, the traditional one-to-many teaching mode is often not quite effective. In order to obtain a more accurate evaluation result of the comprehensive services of an online learning platform, the teacher-student interaction mode in the comprehensive services of the online learning platform was first identified and analyzed. Figure 1 shows the overall architecture design of an online learning platform for essential-qualities enhancement (music education). As can be seen, the constructed platform consists of three layers – a presentation layer, a business logic layer, and a data service layer. The presentation layer consists of the client and the management system; the business logic layer contains such modules as music theory learning, musical instrument practicing, teacher-student interaction management, music appreciation and comment, Q&A and platform administration; and the data service layer has functions like platform access management, information transmission management and data storage management.

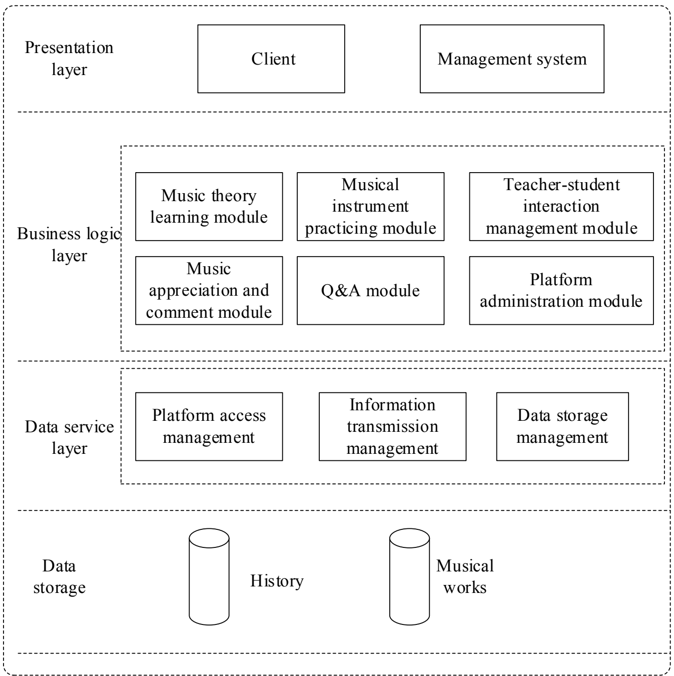

Fig. 1. Overall architecture design of an online music learning platform

During an online class, students will have interactive discussions with the teacher on some learning problems. To understand the question-based learning progress of all students, it is necessary to characterize the questions of each student. Therefore, in this paper, the interval between the question time and the start of an online class was used to generate the vector of students' question-based learning progress.

Assuming that the question-based learning progress vector of student s_1 is denoted as A, that the start time of the class as SD, that the end time of the class as ED, and that the time of the i-th question as PD, then the feature a_i represented by the question in A can be obtained according to Equation (1):

$$a_i = \frac{PD - SD}{ED - SD} \tag{1}$$

Suppose that there are n students studying this course X. The interactive behavior similarity was used in this paper to represent the behavior features of all students. Assuming that there are m behavior features of students, that the selection criteria is denoted as $A_1(a_1,a_2,a_3,a_4,a_5,a_6,a_7,a_8,a_9,\ldots a_m)$, calculate the similarity between $B1$, $B2$, .., B_n and the standard, and then $D_1,D_2...D_n$ are obtained. Calculate the number of students Ψ with D_i being greater than the behavior similarity threshold t, and then calculate the proportion of the students whose similarity with the standard is greater than δ in the total number of students:

$$\beta = \frac{\Psi}{n} * 100\% \tag{2}$$

If β is greater than x, it can be deemed that the teacher-student interaction mode of course X is task diving. If β is less than x, the teacher-student interaction mode is free learning. Since the students' questioning behavior data have no class reference, the *Calinski-Harabasz* clustering effect evaluation method was used in this paper to classify the teacher-student interaction modes. It is assumed that the data sample size is represented by N, that the number of data classes after clustering by l, that the covariance matrix between classes by Y_l, that the covariance matrix within each class of data by Q_l, and that the trace of the mean by Φ. Equation (3) gives the formula for calculating the fraction r:

$$r(l) = \frac{\Phi(Y_l)}{\Phi(Q_l)} * \frac{N-l}{l-1} \tag{3}$$

The larger the covariance between the teacher-student interaction modes and the smaller the covariance within each teacher-student interaction mode, the larger the value of r, that is, the better the clustering effect.

When the teacher-student interaction mode of a course is free learning, students's learning behaviors are active. In this paper, the teacher's interactivity was used to represent the course activity. Assuming that the total number of questions asked by students is represented by M, that the number of responses given by the teacher to the i-th question is represented by a_i, and that the total number of responses can be represented by $A(a_1,a_2...,a_m)$, then the teacher's response rate $\eta(A)$ to the students' questions can be calculated by Equation (4):

$$\eta(A)=\frac{\sum a_i}{M}*100\% \tag{4}$$

3 Construction of the evaluation model

3.1 Evaluation indicator system

The comprehensive service quality of an online learning platform targeting essential-qualities enhancement cannot be evaluated based solely on students' performance, but rather on multiple perspectives and criteria, including students' learning behavior data and skills acquisition level in the learning process. Aiming at the problems of the current essential-qualities-oriented online learning platforms, such as complicated content and poor functional experience, this paper made a comprehensive analysis from such aspects as students' experience feedbacks and intentions to continue use this platform. The derivation process of the evaluation model is shown in Figure 2. The constructed evaluation indicator system is presented as follows:

Layer 1 (evaluation objectives):

CS={CS_1, CS_2, CS_3, CS_4}={content experience, interaction experience, efficiency experience, process experience};

Layer 2 (evaluation criteria):

CS_1={CS_{11}, CS_{12}, CS_{13}, CS_{14}, CS_{15}}={frontier, practicality, comprehensiveness, generality, update progress};

CS_2={CS_{21}, CS_{22}, CS_{23}, CS_{24}, CS_{25}}={academic accomplishment, teaching organization ability, expression ability, patience, information-based teaching ability};

CS_2={CS_{21}, CS_{22}, CS_{23}, CS_{24}, CS_{25}}={Q&A effect, knowledge comprehension, skill acquisition, course completion, music appreciation ability};

CS_2={CS_{21}, CS_{22}, CS_{23}, CS_{24}, CS_{25}, CS_{26}, CS_{27}}={convenience, ease of operation, security, stability, response speed, resource abundance, functional completeness};

The evaluation model for the comprehensive services of online learning platforms constructed in this paper consists of two parts - the hierarchical model and the rough set-neural network evaluation model. The former is used to calculate the weights of the evaluation indicators on each layer, and the latter to calculate the actual efficacy value of online music learning by each student.

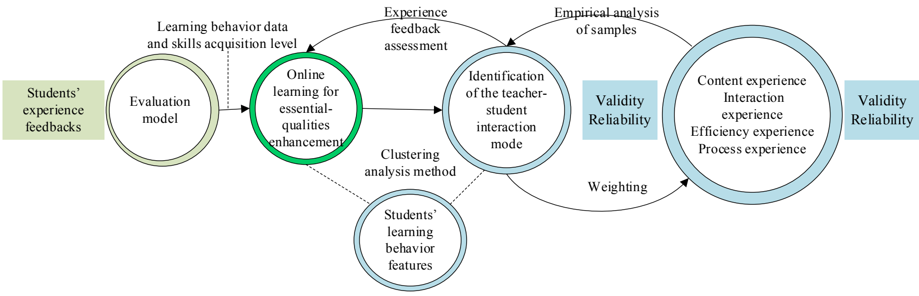

Fig. 2. Derivation process of the evaluation model

3.2 Hierarchical model

The first step is to carry out hierarchical single ranking for the hierarchical model, that is, to prioritize the evaluation criteria in the criteria layer corresponding to a certain evaluation indicator on the target layer. In order to obtain the composite weights of the evaluation indicators on each layer, the square root method was used to calculate the maximum eigenroot and eigenweight vector of the judgment matrix. Equation (5) shows how to calculate the product of the elements in each row of the judgment matrix *X*:

$$SN_i = \prod_{j=1}^{m} x_{ij}, i = 1, 2, ..., m \tag{5}$$

Equation (6) gives the formula for calculating the *m*-th root of SN_i:

$$\overline{SN_i} = \sqrt[m]{SN_i} \tag{6}$$

Normalize the required eigenweight vector Q_i based on Equation (7):

$$Q_i = \frac{\overline{Q_i}}{\sum_{j=1}^{m} \overline{Q_j}} \tag{7}$$

Suppose the *i*-th component of the vector *XQ* is represented by XQ_i, the maximum eigenvalue can be calculated as follows:

$$\mu_{max} = \sum_{i=1}^{m} \frac{(XQ)_i}{mQ_i} \tag{8}$$

Equation (9) shows how to calculate the consistency index of the judgment matrix:

$$SU = \frac{(\mu_{max} - m)}{m - 1} \tag{9}$$

Assuming that the value consistency index is represented by *TU*, and that the value of the consistency ratio by *ST*, based on *SU* and *TU*, the value *of ST* can be further calculated based on Equation (10):

$$ST = \frac{SU}{TU} \tag{10}$$

The next step is the hierarchical total ranking of the hierarchical model, that is, to rank the comprehensive weights of the evaluation indicators for the online learning platform on the objective layer. The calculation method is similar to that in hierarchical single ranking. And also like hierarchical single ranking, hierarchical total ranking requires consistency check. Equation (11) gives the calculation formula:

$$SU_T = \sum_{i=1}^{m} d_i SU_i TU_T = \sum_{i=1}^{m} d_i TU_i \tag{11}$$

The consistency index of the judgment matrix corresponding to D_i is represented by SU_i, and the consistency check value of the judgment matrix corresponding to D_i is represented by TU_i. Substitute SU_i and TU_i into the above equation to obtain ST_T. When the ST_T is less than 0.1, it can be considered that the consistency is satisfactory regarding the relative importance of all the comprehensive service evaluation indicators for the online learning platform in the hierarchical total ranking of the model.

3.3 Rough set-neural network evaluation model

A rough set-neural network model was constructed to evaluate the comprehensive service quality of the online teaching platform. The attribute reduction theory for the rough set was used to calculate the weights of the core evaluation indicators, and the calculation results were input into the BP neural network for training. The model can deal with the problem of insufficient prior information on evaluation indicators, and improve the training efficiency and calculation accuracy of BP neural network.

Figure 3 presents the architecture of the rough set model. First, discretize the collected comprehensive service evaluation data of the online teaching platform to further construct the two-dimensional decision table. Suppose that the conditional attributes in the decision table is represented by $D=(d_1,d_2,...,d_m)$, and that the decision attribute by *NCS*.

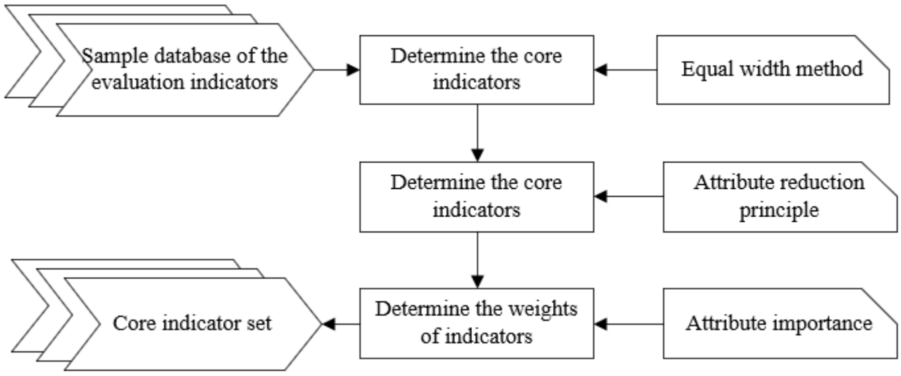

Fig. 3. Architecture of the rough set model

Equation (12) shows how to calculate the dependence of NA on the core attribute V_1:

$$\phi_{V1}(NA) = \frac{|\Gamma_{V1} NA|}{|RQ|} \tag{12}$$

After a certain core attribute V_i is removed, the dependence of NA on the core attribute set V_1-V_i can be calculated by the following formula:

$$\phi_{V_1-V_i}(NA) = \frac{|\Gamma_{V_1-V_i} NA|}{|RQ|} \tag{13}$$

The importance of each core attribute to NA can be calculated by Equation (14):

$$\chi_i = \phi_{V_1}(NA) - \phi_{V_1-V_i}(NA) \tag{14}$$

The weight coefficient of V_i can be obtained through normalization:

$$\varsigma_i = \frac{\phi_{V_1}(NA) - \phi_{V_1-V_i}(NA)}{\sum_{i=1}^{m}\left[\phi_{V_1}(NA) - \phi_{V_1-V_i}(NA)\right]} \tag{15}$$

Figure 4 shows the architecture of the neural network model. In the BP neural network, let the input of m evaluation indicator data be represented by $a=(a_1,a_2,\ldots,a_m)^T$, and the output of n units in the hidden layer be represented by $b=(b_1,b_2,\ldots,b_n)^T$, and the result of the output layer be denoted as c and the target output as o.

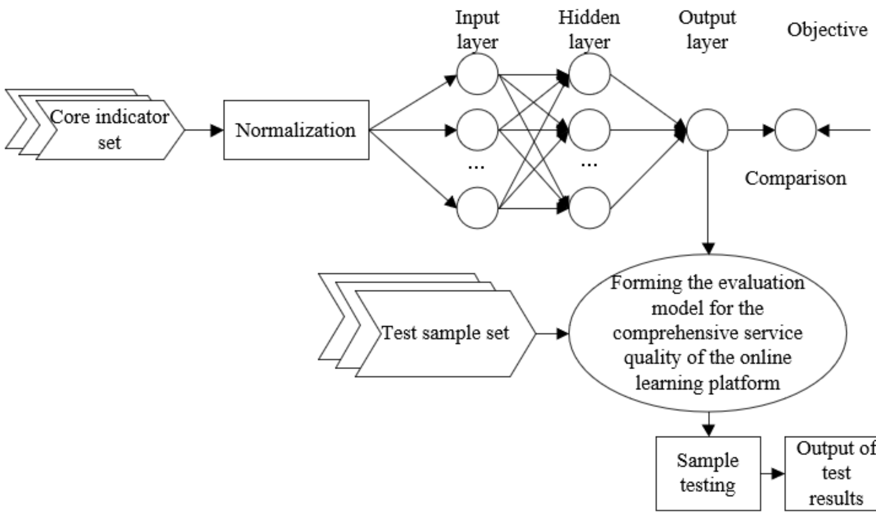

Fig. 4. Architecture of the neural network model

Suppose the transfer function of the hidden layer is denoted as e, and that the connection weight of neuron i in the input layer to neuron l in the hidden layer as Q_{il}. Equation (16) shows how to calculate the output result of the hidden layer of the network model:

$$b_l = e\left(\sum_{i=0}^{m} q_{il} a_i\right) \tag{16}$$

Assuming that the transfer function of the output layer is represented by h, and that the connection weight of neuron l in the hidden layer to neuron k in the output layer by Q_{lk}, Equation (17) shows how to calculate the result of the output layer of the network model:

$$c = h\left(\sum_{l=0}^{n} q_{lk} b_l\right) \tag{17}$$

The error between the output value and the target value of the network model can be calculated by the following formula:

$$E = \frac{1}{k}\sum_{k=1}^{1}\left(o_k - c_k\right)^2 \tag{18}$$

Through adjustment of Q_{lk} and Q_{il}, E is reduced until it meets the preset error requirement.

4 Experimental results and discussion

The statistical mean values of the overall teacher-student interaction behavior features are given in Table 1. It can be seen that the average number of responses from the teacher to students attending in a musical instrument training course was 4.15, and the maximum number of responses from the teacher 114; the average number of questions from a student was 0.25, and the number of questions raised by the student who asked the most questions 85. It can be found that the students of this musical instrument training course received a lot of responses from the teacher but raised fewer questions. The standard deviation of the number of questions raised by students was 1.52, indicating that there was little difference between the number of questions raised by each student attending the course and the average number. The standard deviation of the number of responses from the teacher was 3.69, indicating that the number of responses received by each student attending the course was significantly different from the average number.

Table 1. Statistical results of the features of interactions between teachers and students

Feature description	Mean	Median	Max	Min	Standard deviation
Number of questions	0.25	2	85	0.1	1.52
Number of responses	4.15	5	114	0.3	3.69
Interval between the date when the student asked the most questions and the start time of class	0.16	-0.3	36	-0.2	2.41
Number of questions on the date when the student asked the most questions	0.08	0.2	15	0.5	0.38
Interval between the date when the student received the most responses from the teacher and the start time of class	19.62	21	35	0.3	11.57
Number of responses on the date when the student received the most responses	1.84	3	42	-0.1	2.58

After the maximum eigenroot and eigenvector of the judgment matrix corresponding to the evaluation indicator system were calculated based on the square root method, the weights of all indicators were obtained. The comprehensive weights of the comprehensive service evaluation indicators for the online learning platform are shown in Table 2. It can be seen that the consistency ratio of the judgment matrix of the evaluation indicator system is less than 0.1, and the weight of the overall objective of the comprehensive service evaluation of the online learning platform is 1. The consistency ratios of the judgment matrix of CS_1, CS_2, CS_3, and CS_4 are all less than 0.1, and their weights to the overall objective are 0.174, 0.276, 0.336, and 0.241, respectively, indicating that the judgment matrix passes the consistency check.

Table 2. Comprehensive weights of the comprehensive service evaluation indicators for online learning platforms

	Weight		Weight	μ_{max}	*CI*	*C.R.*
Comprehensive service evaluation indicator for an online learning platform *CS*	1	*CS*1	0.174	4.528	0.016	0.084
		*CS*2	0.276			
		*CS*3	0.336			
		*CS*4	0.241			
Content experience CS_1	0.174	CS_{12}	0.034	4.915	0.063	0.074
		CS_{13}	0.047			
		CS_{14}	0.059			
		CS_{15}	0.034			
Interaction experience CS_2	0.276	CS_{21}	0.095	5.286	0.047	0.038
		CS_{22}	0.074			
		CS_{23}	0.032			
		CS_{24}	0.058			
		CS_{25}	0.017			
Efficiency experience CS_3	0.336	CS_{31}	0.036	5.738	0.141	0.068
		CS_{32}	0.041			
		CS_{33}	0.043			
		CS_{34}	0.084			
		CS_{35}	0.132			
Process experience CS_4	0.241	CS_{41}	0.089	5.926	0.173	0.081
		CS_{42}	0.064			
		CS_{43}	0.026			
		CS_{44}	0.017			
		CS_{45}	0.015			
		CS_{46}	0.012			
		CS_{47}	0.018			

Figure 5 shows the training error curve of the BP neural network. It can be seen that after 400 iterations, the training of the network was over. At this time, the prediction accuracy of the model reached the preset target and met the preset requirement. This proves that the model can be effectively applied to the simulation of the comprehensive service evaluation of an online learning platform for essential qualities enhancement.

Eight samples were selected from each of the five ratings of the comprehensive service quality of the online teaching platform - “very high”, “high”, “moderate”, “low” and “very low”, that is, a total of 40 sample data, to test the constructed evaluation model. It can be seen from the Figure 6 that the simulated values of the 40 samples almost completely coincided with the output values, proving that the model has high accuracy in predicting the comprehensive service quality of online teaching platforms.

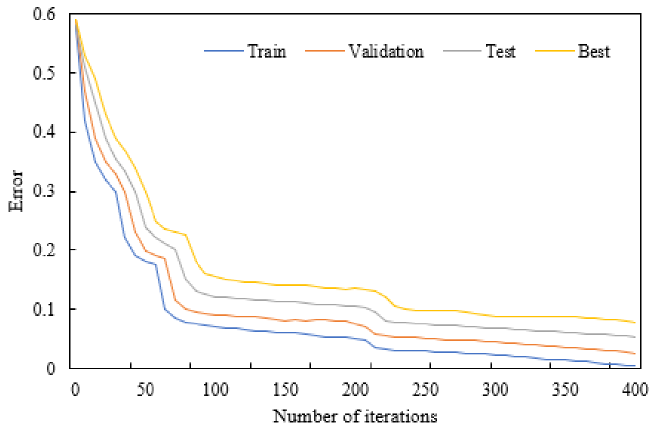

Fig. 5. Training error curve of the BP neural network

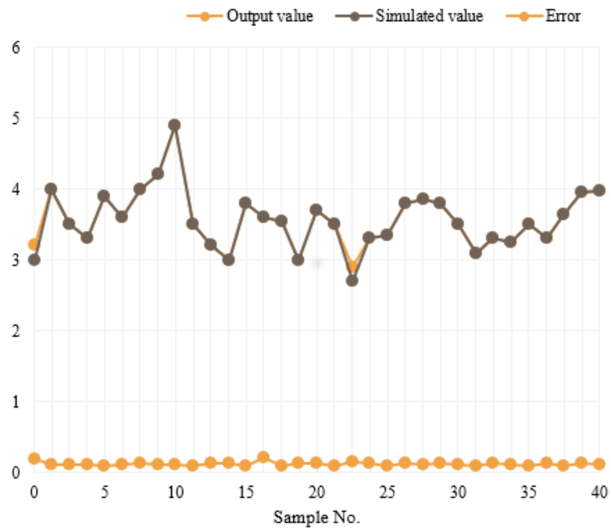

Fig. 6. Model test error comparison

5 Conclusions

This paper took an online music education platform as an example and studied the evaluation on the comprehensive services of the online learning platform. First, the overall architecture design of an online learning platform for essential qualities enhancement was displayed, and the teacher-student interaction mode for the comprehensive services of the online learning platform was identified and analyzed. Then, the derivation process of the evaluation model was presented, the evaluation indicator system for the comprehensive service quality of the online learning platform constructed, and the comprehensive service evaluation model for the online learning platform consisting of the hierarchical model and the rough set-neural network evaluation model established. The statistical results of the features of the teacher-student interactions in the course were given, from which it can be seen that the number of questions asked by each student attending the musical instrument training course was not much different from the average number, but there was a big difference between the number of responses from the teacher and the average number. Then, based on the square root method, the maximum eigenroot and eigenvector of the judgment matrix corresponding to the evaluation indicator system were calculated, and the comprehensive weights of the comprehensive service evaluation indicators for the online learning platform were obtained. The constructed judgment matrix also passed the consistency check. After that, the training error curve of the constructed BP neural network was presented, which verified the effectiveness of the model when applied to the simulation of the comprehensive service evaluation of online learning platforms. Finally, the errors of the model test were compared, which proves that the model has high accuracy in predicting the comprehensive service quality of online teaching platforms.

6 References

[1] Mingsiritham, K., Chanyawudhiwan, G. (2020). Experiment of the Prototype of Online Learning Resources on Massive Open Online Course (MOOC) to Develop Life Skills in Using Technology Media for Hearing Impaired Students, International Journal of Emerging Technologies in Learning, 15(3), 242-249.

[2] Yang, H. (2022). Online mathematics teaching reform based on network learning platform. In Innovative Computing, 1069-1075. https://doi.org/10.1007/978-981-16-4258-6_131

[3] Jin, D.M., Li, Y.P. (2020). A Teaching Model for College Learners of Japanese Based on Online Learning, International Journal of Emerging Technologies in Learning, 15(15), 162-175.

[4] Li, J. (2021). The application of big data analysis technology in the research of English online learning platform. In International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy, 169-176. https://doi.org/10.1007/978-3-030-89508-2_22

[5] Chen, G., Chen, P., Huang, W., Zhai, J. (2022). Continuance intention mechanism of middle school student users on online learning platform based on qualitative comparative analysis method. Mathematical Problems in Engineering, 2022: 3215337. https://doi.org/10.1155/2022/3215337

[6] Sun, Y., Chai, R.Q. (2020). An early-warning model for online learners based on user portrait. Ingénierie des Systèmes d'Information, 25(4), 535-541.

[7] Nobaew, B. (2021). Evaluation of self-directed learning through problem-based learning in the online class during Covid-19 epidemic. In 2021 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunication Engineering, 368-371. https://doi.org/10.1109/ECTIDAMTNCON51128.2021.9425713

[8] Ang, J., Wu, C. (2021). Research and thinking on online teaching and learning in secondary schools in China based on the background of epidemic prevention and control. In 2021 10th International Conference on Educational and Information Technology (ICEIT), 70-75. https://doi.org/10.1109/ICEIT51700.2021.9375602

[9] Wang, S.Y. (2021). Online learning behavior analysis based on image emotion recognition. Traitement du Signal, 38(3), 865-873.
[10] Cui, Y. (2021). The influence of quality factors on the satisfaction and continuance intention of Chinese college students' online learning during the COVID-19 epidemic. In 2021 12th International Conference on E-Education, E-Business, E-Management, and E-Learning, 145-150. https://doi.org/10.1145/3450148.3450168
[11] Wu, Y.Y., Li, K.Y., Qiu, Y.G., Zhou, Y.T. (2021). A study on the relationship between online learning and emotional quotient of college students during the period of epidemic prevention and control. In 2021 International Conference on Data Analytics for Business and Industry (ICDABI), 478-485. https://doi.org/10.1109/ICDABI53623.2021.9655787
[12] Ying, T., Mi, X. (2021). Analysis of online learning satisfaction and influencing factors of college students during epidemic period: based on probit model. In 2021 2nd International Conference on Big Data and Informatization Education (ICBDIE), 428-431. https://doi.org/10.1109/ICBDIE52740.2021.00103
[13] Wen, J., Wei, X.C., He, T., Zhang, S.S. (2020). Regression analysis on the influencing factors of the acceptance of online education platform among college students. Ingénierie des Systèmes d'Information, 25(5), 595-600.
[14] Wang, P., Chen, T., Liu, J., Luo, H. (2020). K-12 Teachers' attitude towards online learning platfoms during Covid-19 epidemic in China. In 2020 Ninth International Conference of Educational Innovation through Technology (EITT), 19-23. https://doi.org/10.1109/EITT50754.2020.00010
[15] Rohman, M., Wiyono, A., Baskoro, F. (2021). Combination of moodle online learning application (Vilearning UNESA) and google classroom to improve the quality of online learning. In 2021 Fourth International Conference on Vocational Education and Electrical Engineering (ICVEE), 1-6. https://doi.org/10.1109/ICVEE54186.2021.9649744
[16] Simaremare, A., Suyudi, A., Taqwa, M.R.A. (2021). Implementation management strategies for modern physics experiment with online systems approach to improve the quality of learning or physics students. In Journal of Physics: Conference Series, 2019(1): 012028.
[17] Thuy, D.T.M. (2020). Improving the quality of online learning at FUNiX. In Proceedings of the 2020 International Conference on Management of e-Commerce and e-Government, 61-65. https://doi.org/10.1145/3409891.3409904
[18] Wen, J., Wei, X.C., He, T., Zhang, S.S. (2020). Regression analysis on the influencing factors of the acceptance of online education platform among college students. Ingénierie des Systèmes d'Information, 25(5), 595-600.
[19] Liu, Y., Liu, M. (2015). An online learning approach to improving the quality of crowd-sourcing. ACM SIGMETRICS Performance Evaluation Review, 43(1): 217-230. https://doi.org/10.1145/2796314.2745874
[20] Boko, U.H.S., Dégboé, B.M., Ouya, S., Mendy, G. (2019). Proposal of an interactive IPTV platform to improve the quality of service of e-learning platforms. In International Conference on Interactive Collaborative Learning, 164-171. https://doi.org/10.1007/978-3-030-40274-7_17
[21] Tsai, M.S., Tsai, M.C., Chang, C.C. (2012). Analyzing the building and using situations of e-learning platform: From total quality management and knowledge management perspectives. In 2012 IEEE International Conference on Industrial Engineering and Engineering Management, 1815-1819. https://doi.org/10.1109/IEEM.2012.6838060
[22] Militaru, T.L., Suciu, G., Todoran, G. (2012). The use of expert systems in building the quality model of a web-based learning platform. In International Conference on Web-Based Learning, 318-327. https://doi.org/10.1007/978-3-642-33642-3_34

[23] Wang, Y., Cheng, Y., Zheng, Z. (2010). Evaluation design of learners' online learning quality in network learning platform. In 2010 International Conference on Artificial Intelligence and Education (ICAIE), 222-225. https://doi.org/10.1109/ICAIE.2010.5641449
[24] Braccini, A.M., Sivestri, C., Za, S., D'Atri, A. (2009). Users' perception of the quality of open source e-learning platform: The case of moodle. In IASTED International Conference on Web-based Education (WBE 2009), 343-348.

7 Authors

Peifan Yang, male, was born in Cangzhou, eastern China's Hebei Province, in December 1988. He is a Master of Arts, and lecturer at Department of Music, Cangzhou Normal College. His main research directions include music education and general education. He has published 2 academic books, and participated in the research of 1 humanities and social science project of Chinese Ministry of Education (email: yangpeifan@caztc.edu.cn).

Xia Liu, female, was born in Cangzhou, eastern China's Hebei Province, in November 1975. She is a Master of Engineering, and associate professor in Qiyue Media Department, Cangzhou Normal College. Her main research directions include computer application, Internet of things engineering, and multimedia software teaching. She has led the research of 2 departmental educational reform projects, and 4 municipal/department projects; co-edited 2 textbooks; published 6 academic papers on national core journals; won 2 invention patents (email: jsjxylxjsjxylx@163.com).

Article submitted 2022-04-26. Resubmitted 2022-05-27. Final acceptance 2022-05-30. Final version published as submitted by the authors.