Online-Journals.org

iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 23 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i23.45635

PAPER

AI-Based Collaborative Teaching: Strategies and Analysis in Visual Communication Design

Songhua Liu, Jing Li(✉), Jiannan Zheng

Yanching Institute of Technology, Langfang, China

lijing@yit.edu.cn

ABSTRACT

With the rapid development of technology, AI has been widely applied in multiple fields, especially the field of education. As a discipline involving art, technology and creativity, visual communication design is facing the challenge of keeping up with the times and combining new technologies for innovation. Collaborative teaching model emphasizes multi-party participation and collaborative learning, and its proposal has injected new vitality into traditional educational patterns. However, existing studies, which combine collaborative teaching model with artificial intelligence, still have limitations in application and practice, and most of them remain in the theoretical discussion stage and lack empirical support. This study aimed to make up for this deficiency. After in-depth analysis of educational data, a forecasting model of collaborative teaching demand based on AI was proposed. Course content suitable for the collaborative teaching model was further planned for the education in visual communication design.

KEYWORDS

AI, collaborative teaching, visual communication design, teaching model, demand forecasting

1 INTRODUCTION

With the rapid development of technology, AI technology has penetrated into various fields, leaving deep marks ranging from traditional industrial applications to modern digital life [1, 2]. Especially in the field of education, AI application has brought unprecedented opportunities for changes [3–6]. As a discipline integrating art and technology into creativity, visual communication design faces the challenge of keeping up with the times and combining new technologies for innovation [7, 8]. In this context, the proposal of a collaborative teaching model has injected new vitality into traditional educational patterns, which emphasizes multi-party participation and collaborative learning, aiming to provide students with broader and interactive learning space [9–12].

Liu, S., Li, J., Zheng, J. (2023). AI-Based Collaborative Teaching: Strategies and Analysis in Visual Communication Design. *International Journal of Emerging Technologies in Learning (iJET)*, 18(23), pp. 182–196. https://doi.org/10.3991/ijet.v18i23.45635

Article submitted 2023-08-12. Revision uploaded 2023-10-14. Final acceptance 2023-10-16.

In past educational practices, teaching was often seen as a one-way fixed process, with students often being passive learners. But modern educational concepts increasingly emphasize individual differences and initiative [13, 14]. The research on the AI-based collaborative teaching model of visual communication design not only provides educators with a brand-new teaching strategy that deeply integrates technology into education, but also helps students better adapt to future career needs, thereby cultivating their teamwork, innovative thinking and practical ability [15, 16].

Although more studies of the teaching model combining collaborative teaching with AI have been conducted, most of them still have significant limitations in application and practice [17–24], because they usually focus on theoretical discussions and lack empirical support in real-world teaching scenarios. In addition, they have not deeply discussed the application methods and potential value of AI technology in the collaborative teaching model. Traditional educational patterns are still being used in many teaching practices, without fully utilizing the advantages brought by AI.

Aiming to supplement and improve the above research deficiencies, this study analyzed the AI-based collaborative teaching demand forecasting in detail. After deeply mining lots of educational data, a more robust and accurate demand forecasting model was established. Based on the forecasting, course content suitable for the collaborative teaching model was further planned. This new teaching strategy that combines AI technology not only helps promote continuous innovation in the education in visual communication design, but also opens up new research directions and application prospects in educational research and practice.

2 AI-BASED COLLABORATIVE TEACHING DEMAND FORECASTING

With the rapid progress of technology, traditional educational patterns are facing challenges and changes. To better adapt to the needs of modern society, the field of education is shifting towards a more collaborative, interactive and innovative direction. As a representative of this transformation, the collaborative teaching model needs to be combined with modern technology to realize its maximum potential. AI provides customized learning paths for each student by analyzing a large amount of learning data. The AI-based forecasting of collaborative teaching demand helps educational institutions judge students' demand more accurately, thereby providing them with more suitable resources and teaching content.

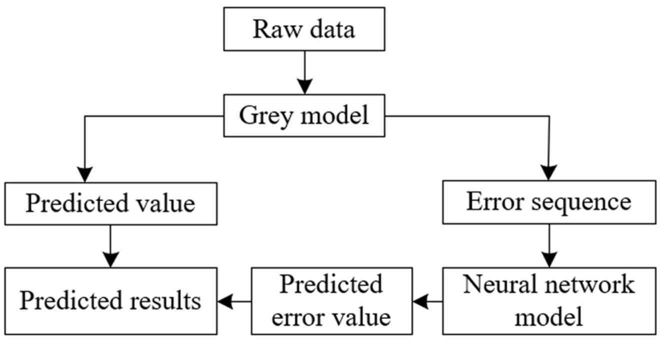

Fig. 1. Forecasting principle of the combination model

This study forecast the collaborative teaching demand using a grey-neural combination model based on weight allocation. Both the DI-GM model (a grey model) and the LM-BP model (a neural network model) have their unique modeling and forecasting capabilities. They complement each other after being combined, which obtains more accurate and stable forecasting results. Through weight allocation, the weights of both models can be dynamically adjusted based on the characteristics of actual data and the forecasting performance of both models, thereby achieving the best forecasting effect. Figure 1 shows the forecasting principle of the combination model.

The DI-GM model is a type of grey model, which is used to handle forecasting problems with small samples and incomplete information. It mainly captures the growth trend of data by constructing a differential equation, thereby forecasting the future. The LM-BP model is a neural network model based on the backpropagation algorithm, which is suitable for dealing with nonlinear problems. Composed of an input layer, a hidden layer and an output layer, data is modeled and forecast by the model through multi-layer neural connections and weight adjustments. Different weights are assigned to both models based on their forecasting performance. Let S_y be the accuracy sequence predicted by the model, z_y be the real value, and $\hat{z}_y$ be the reducing value of the model. The weighting coefficient was determined using the following equation:

$$S_y = 1 - \left| \frac{z_y - \hat{z}_y}{z_y} \right|, y = 1,2,\ldots,Y \tag{1}$$

Let R be the mean value of the precision sequence, and δ be the standard deviation, then there were the following equations:

$$R = \frac{1}{B}\sum_{y=1}^{B} S_y \tag{2}$$

$$\delta = \sqrt{\frac{1}{B}\sum_{y=1}^{B}(S_y - R)^2} \tag{3}$$

The effectiveness of a single forecasting model was given as follows:

$$A = R(1 - \delta) \tag{4}$$

Let A_1 and A_2 be the effectiveness of the DI-GM model and the LM-BP model, respectively. After normalization processing of A_1 and A_2, the weighted coefficients η_1 and η_2 were calculated using the following equation:

$$\eta_u = \frac{A_u}{\sum_{k=1}^{2} A_k}, u = 1,2 \tag{5}$$

Let w_1 and w_2 be the predicted values of both models, then the equation for collaborative teaching demand forecasting was given as follows:

$$V_w = \eta_1 w_1 + \eta_2 w_2 \tag{6}$$

In the forecasting of collaborative teaching demand, high forecasting accuracy means that teaching resources can be allocated more effectively to better meet the demand of students. Each forecasting model has its unique advantages and disadvantages. Although the DI-GM model, which is a grey forecasting model, is suitable for forecasting scenarios with small samples and incomplete information, predicted deviations may occur in certain situations. However, neural network models, especially the LM-BP model, are likely to correct the predicted deviations of the DI-GM model due to their nonlinear fitting ability.

This study used the DI-GM model for forecasting for the first time based on historical data. The equation derived from the DI-GM model was used for future forecasting. Based on the known true values and the predicted results of the DI-GM model, the predicted error for each step was calculated, which was obtained from the difference between the real and predicted values. The LM-BP model was trained, with the predicted error of DI-GM as the input and the real teaching demand data as the target output. Appropriate network structure, number of hidden layers and neurons, and activation function were selected to ensure that the model accurately captured error patterns.

Part of the data was further used as the training set, and the other part as the validation set, thereby determining the optimal parameters of the model. With the predicted value of the DI-GM model as the input, the trained LM-BP model was used for error correction. The LM-BP model output an error value, which represented the difference between the predicted and real situations of the DI-GM model. Finally, the preliminary predicted value of DI-GM was added to the corrected error value forecast by the LM-BP model, which obtained the final predicted results.

In a traditional LM-BP model, direct input of raw data may limit the forecasting accuracy of the model. The addition of a greying layer transforms multivariate data into single data, thereby simplifying the data structure and highlighting its key features. In this way, the model processes data more efficiently, and the forecasting accuracy can be improved. Figure 2 shows the structure optimization principle of the combination model.

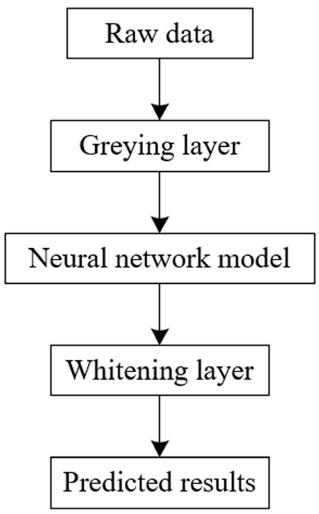

Fig. 2. Structure optimization principle of the combination model

Modification of the formula or differential equation in the DI-GM model was considered in order to better describe the data behavior. Additional parameters or variables may be introduced to enhance the model's descriptive power as needed. This study mapped the solution of the grey differential equation to the LM-BP neural network. Let s and n be the optimal parameters of the grey differential equation; $t(y)$ be the one-time accumulative generation sequence $z^{(1)}(y)$. The expression for the time response function of the model was given as follows:

$$t(y) = \left(z^{(0)}(1) - \frac{n}{s} \right) e^{-sy} + \frac{n}{s} \tag{7}$$

Let $t(y)$ be the predicted value of the network; q_{11}, q_{21}, q_{22}, q_{31} and q_{32} be the network inputs; y be the network weight; φ be the threshold of the output nodes; $H1$, $H2$, $H3$ and $H4$ be four layers of the network. The above equation was transformed as follows:

$$t(y)=\left[\left(z^{(0)}(1)-\frac{n}{s}\right)-\frac{z^{(0)}(1)}{1+e^{-sy}}+\frac{2n}{s(1+e^{-sy})}\right](1+e^{-sy}) \tag{8}$$

The network weight was calculated using the following equation:

$$q_{11}=s, q_{21}=-z^{(0)}(1), q_{22}=\frac{2n}{s}, q_{31}=q_{32}=1+e^{-sy} \tag{9}$$

The threshold of $H4$-layer output nodes was derived using the following equation:

$$\varphi=\left(z^{(0)}(1)-\frac{n}{s}\right)(1+e^{-sy}) \tag{10}$$

In the constructed model, the weight was adjusted and optimized, which aimed to find the parameter value that minimized the predicted error using the mathematical optimization method.

3 COURSE CONTENT IDEATION AND PLANNING BASED ON COLLABORATIVE TEACHING DEMAND

The design of the collaborative teaching model is inseparable from the ideation and planning of course content. Taking the courses of visual communication design as an example, the actual collaborative teaching demand can be elaborated in the following five aspects:

First, the integration demand for technology and creativity. Visual communication design involves not only technical aspects, such as operation of design software and graphic processing, but also artistic and creative thinking. Therefore, apart from mastery of relevant technical knowledge, the creative thinking and artistic perception ability of students need to be cultivated. The courses should combine technical operation with creative practice, and encourage students to constantly try and innovate on the basis of technology mastery, thereby forming their own design language and style.

Second, the demand for interdisciplinary cooperation. Visual communication design not only is an independent field, but also is closely related to other disciplines, such as marketing, psychology, cultural research, etc. The courses should encourage students to cooperate with students or experts from other disciplines in order to engage in interdisciplinary project practice, thereby cultivating their interdisciplinary cooperation and communication ability.

Third, the demand for practical application and practice. The learning of visual communication design should not be limited to theoretical knowledge. Instead, greater emphasis should be placed on practical application and practice. The courses should combine practical design projects or cases, and enable students to apply their knowledge in practical environments, thereby cultivating their practical and problem-solving ability.

Fourth, the demand for team collaboration and communication. Every designer should possess the essential team collaboration and communication ability, because a design project usually requires cooperation of several people. The courses should organize team projects, and enable students to work together in the team, thereby cultivating their team spirit and communication ability.

Finally, the demand for critical thinking and self-directed learning. In the rapidly changing design field, students not only need to master current knowledge and skills, but also should possess critical thinking and self-directed learning ability to cope with future challenges. The courses should encourage students to critically think about existing design concepts and methods, thereby cultivating their ability to think and learn independently.

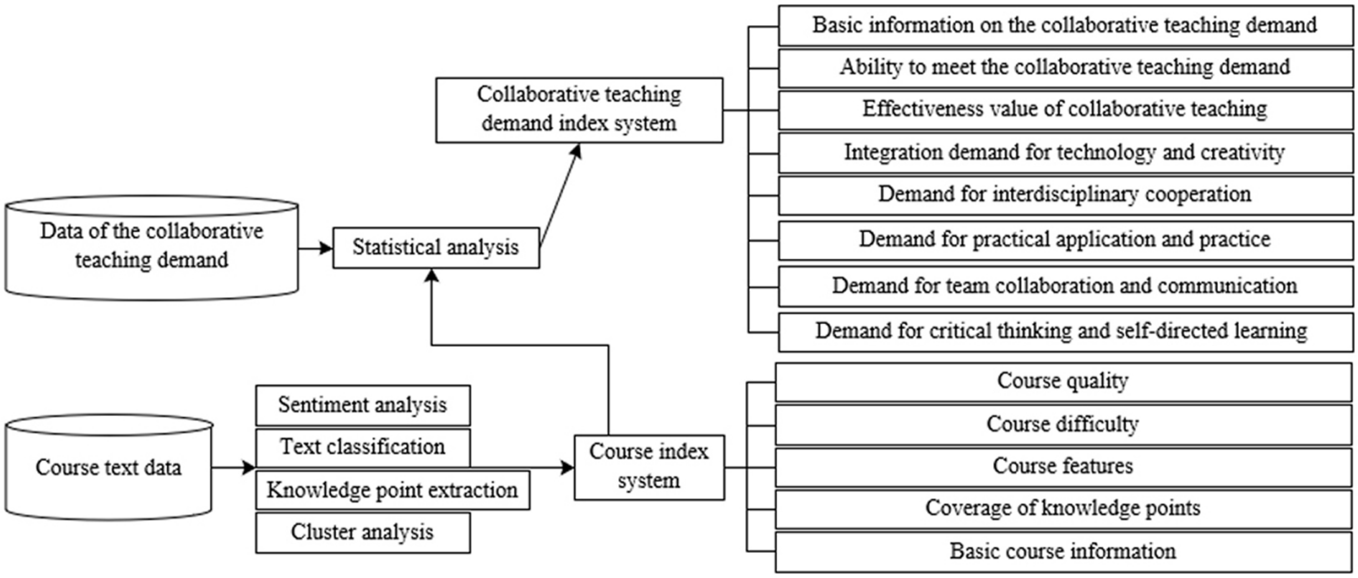

Fig. 3. Flowchart of constructing the course and collaborative teaching demand index system

This study mainly relies on two types of core educational data: course data and data of the collaborative teaching demand. To extract useful information from these data, several methods were adopted in this study, such as natural language processing technology, cluster analysis and feature engineering, which helped identify key course features and the collaborative teaching demand, and transformed them into actionable indexes. Furthermore, this study constructed a course and collaborative teaching demand index system. Figure 3 shows the flowchart for constructing the system, which provides a clear and systematic framework for subsequent course content recommendation and planning. Considering that different users (e.g. students and teachers) may have different demands and purposes, two course content recommendation methods were proposed: a method based on course similarity, and a method based on Deep Belief Network (DBN), aiming to provide users with course content that best met their demand. Figures 4 and 5 show the similarity-based and DBN-based course content recommendation flowcharts.

Let X be the basic course information, Y be the course features, V be the course quality, F be the course difficulty, R be the coverage of course knowledge points, D be the basic information on the course collaborative teaching demand, with $D = \{SI, SM, ED\}$, SI be the linear mapping of learner Uf, SM be the course type, ED be the academic qualifications of students, and H be the ability of current teaching model to meet the collaborative teaching demand. MIN-MAX was used to normalize the effectiveness value of collaborative teaching. Let z be the raw data, z_{NO} be the normalized data, z_{MIN} and z_{MAX} be the minimum and maximum values of the dataset. The normalization equation was given as follows:

$$z_{NO} = (z - z_{MIN})/(z_{MAX} - z_{MIN}) \tag{11}$$

Let G be the integration demand for technology and creativity, U be the demand for interdisciplinary cooperation, K be the demand for practical application and practice, B be the demand for team collaboration and communication, and A be the demand for critical thinking and self-directed learning.

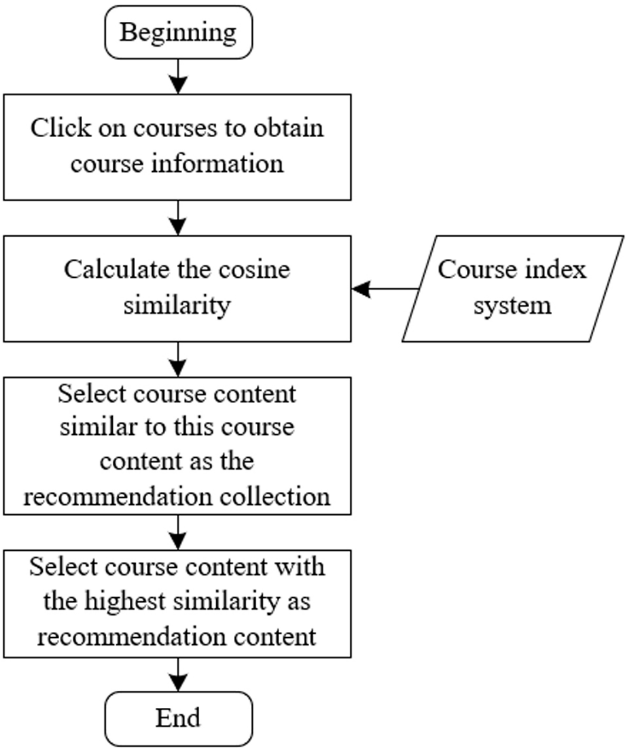

Fig. 4. Flowchart of similarity-based course content recommendation

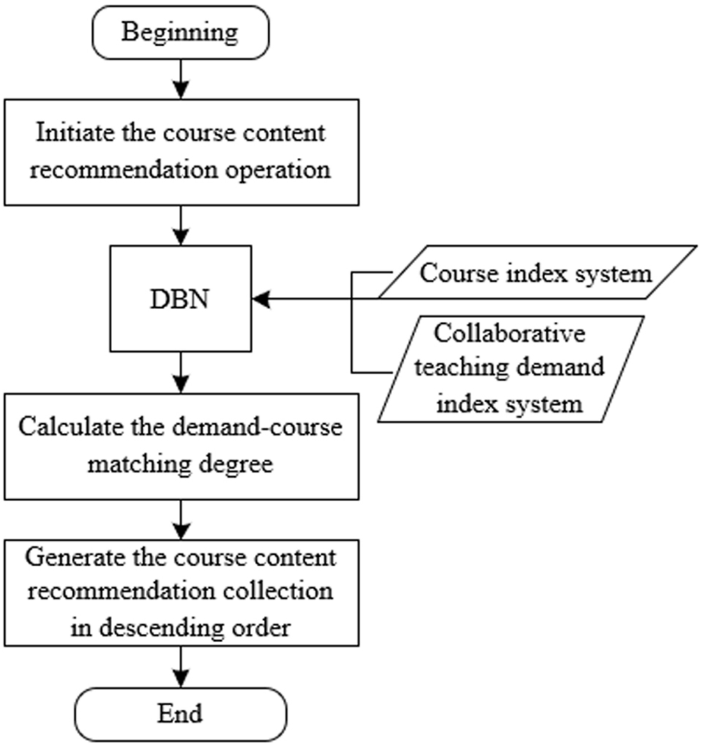

Fig. 5. Flowchart of DBN-based course content recommendation

Let v_u and v_k be the feature vectors of the course system, then cosine similarity was used to calculate the similarity of the method based on course similarity:

$$SL_{u,k} = (v_u, v_k) \Big/ \left(\|v_u\| * \|v_k\| \right) \tag{12}$$

For the DBN-based course content recommendation method proposed in this study, a sparse matrix was constructed to capture the relationship between learners and course features, which aimed to quantify and represent basic information on learners, correlation between learning ability and courses, difficulty and specific requirements. This sparse matrix not only recorded the correlation between learners' basic information and courses, but also captured the matching degree between learners' learning ability and course difficulty, as well as the relationship between specific course requirements and internal characteristics. These merged features of learners and courses were used as the input to the course recommendation algorithm, which meant that the recommendation process comprehensively considered the attributes of both learners and courses, thereby improving the recommendation accuracy and pertinence. A probability generative model was used to generate predicted scores for each course, which represented the matching likelihood or suitability degree between learners and the course.

DBN is a deep learning model, which captures advanced features and patterns in data. In this study, it was used to extract and learn features from the above sparse matrix, and generate predicted course scores. The specific steps for the DBN-based course content recommendation method were described as follows:

Step 1: Collecting data of learners and courses from educational platforms or other relevant sources. These data may include basic information on learners, their learning habits and previous learning records, as well as descriptions, difficulty and requirements of courses and other information. The collected data was used to construct a sparse matrix Z, which captured various relationships between learners and courses, such as learners' learning ability and course difficulty, basic information on learners, correlation of courses, etc.

Step 2: Determining the appropriate network structure and randomly initializing the weight. Raw data Z from the sparse matrix was used for unsupervised pretraining. Then the backpropagation algorithm was used for training, which obtained the weight $q(1)$ and the bias $n(1)$. Z was further multiplied by $q(1)$, and was added to the bias $n(1)$. Then the sigmoid function was used for processing. The first-layer output was calculated using the following equation:

$$s(1) = sigmoid(Z * q(1) + n(1)) \tag{13}$$

Step 3: Obtaining the first-layer output by passing the raw data through the pretrained first layer. The output was viewed as high-level features or representations of raw data. The data output by the first layer was used for unsupervised pretraining of the second layer, which once again involved weight adjustment to make the network better capture patterns and relationships in the data. The backpropagation algorithm was used for training, which obtained the weight $q(2)$ and the bias $n(2)$. Furthermore, $s(1)$ was multiplied by $q(2)$, and then was added to $n(2)$. The sigmoid function was used for processing. The second-layer output was calculated using the following equation:

$$s(2) = sigmoid(s(1) * q(2) + n(2)) \tag{14}$$

Step 4: Labeled data (e.g. whether learners chose a particular course) was used for supervised learning to train the top-level classifier, after two-layer unsupervised pretraining was conducted in previous steps. After the supervised learning, the entire network was fine-tuned to better predict the course choices of learners. Specifically, after the obtained feature representation $g(M)$ was multiplied by the weight matrix Q, it was added to the bias vector n. Then the softmax function was used for processing. Let J be the number of types, then there were:

$$soft\max(z\_u) = e^{z\_u} / SUM(e^{z\_k}), k = 1, \ldots, J \tag{15}$$

To obtain a scientific strategy for course content ideation and planning, course content should be first deeply analyzed based on the recommendation results. Considering factors, such as learning ability, backgrounds and interests of learners, the information needed to be integrated for refined course content planning for different learner groups. Visual communication design requires both technical ability, such as proficient operation of design software and understanding of graphic processing techniques, and creative thinking. These two aspects should be integrated into courses on this basis, thereby providing technical training while encouraging and cultivating the creative thinking of students. Personalized learning paths were designed for students based on their learning ability and interests, including selection of appropriate courses, learning materials and pace, thereby making their learning more efficient and interesting. To enable students to better understand and apply their knowledge, course content should be combined with real-life scenarios, such as real design projects, on-site inspections, and practical opportunities of cooperating with enterprises.

In terms of interdisciplinary and team cooperation, students were encouraged to participate in interdisciplinary projects and cooperate with students or experts from other disciplines to gain broader knowledge and skills. For example, cooperating with students in marketing or advertising to design advertisements or publicity materials for real clients. Teamwork and communication ability of students was cultivated through group discussions, team projects and other activities, which not only promoted students to help each other in learning and cooperate in completing tasks, but also cultivated their team spirit and leadership ability. Given that visual communication design is a global field, students may need to cooperate with people from different cultural backgrounds. The courses should include cross-cultural communication training to help students understand and respect different cultures, and effectively communicate with people from different cultural backgrounds. Students were encouraged to apply their knowledge and skills to practical projects, and receive feedback from clients or other team members, which not only helped them test and consolidate their knowledge, but also improved their ability in practical operation and dealing with real problems.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Predicted results of single models

Serial Number	Real Demand Value	Grey Model		Neural Network Model	
		Predicted Value	Error	Predicted Value	Error
1	4.856	4.522	–0.334	4.528	–0.328
2	4.632	5.147	0.515	4.722	0.09
3	5.485	5.639	0.154	5.639	0.154
4	5.783	6.239	0.456	5.413	–0.37
5	6.418	6.899	0.481	6.742	0.324

It can be seen from Table 1 that the predicted error of the grey model ranges from –0.334 to 0.515 for the given five real demand values, which indicates that some slight deviations may exist in the model's forecasting, but the error is relatively small in some cases. The predicted error of the neural network model ranges from –0.37 to 0.154. Compared with the grey model, the neural network model forecasts more accurately in certain situations, especially in the case of serial numbers 2 and 4. It can be seen from Table 2 that the predicted error of the grey-neural combination model ranges from –0.315 to 0.311. The combination model has a relatively small error in most cases, especially compared with the single grey model. The error range of the combination model after error correction is between –0.304 and 0.302. Compared with the previous combination model, its forecasting is slightly more accurate in certain situations. The predicted error of the combination model after structure optimization ranges from –0.285 to 0.246, which means that structure optimization helps further reduce the predicted error. Based on the above analysis, it can be concluded that the structurally optimized combination model may be the best choice to obtain the most accurate forecasting of the collaborative teaching demand.

Table 2. Predicted results of combination models

Serial Number	Real Value	Grey-Neural Combination Model		Combination Model After Error Correction		Combination Model After Structure Optimization	
		Predicted Value	Error	Predicted Value	Error	Predicted Value	Error
13	4.856	4.541	–0.315	4.552	–0.304	4.571	–0.285
14	4.692	4.712	0.08	4.682	0.05	4.642	0.01
15	5.413	5.634	0.149	5.616	0.131	5.603	0.118
16	5.796	5.503	–0.28	5.533	–0.25	5.576	–0.207
17	6.499	6.729	0.311	6.72	0.302	6.664	0.246

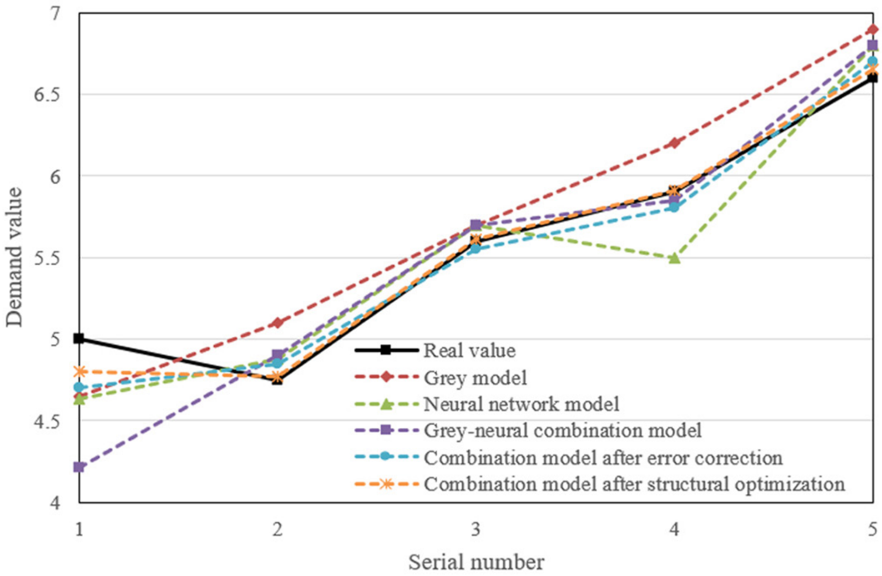

Fig. 6. Predicted result trends of five models

As shown in Figure 6, the grey model may not be the best choice in certain scenarios, because it overestimates the demand in certain situations. The neural network model forecasts relatively accurately in most cases, but there may be some deviations in certain specific situations. Combination models are obviously superior to single ones, especially the structurally optimized combination model, whose forecasting is very close to the actual value in all cases. Overall, it is more appropriate to use the structurally optimized combination model to obtain the most accurate forecasting.

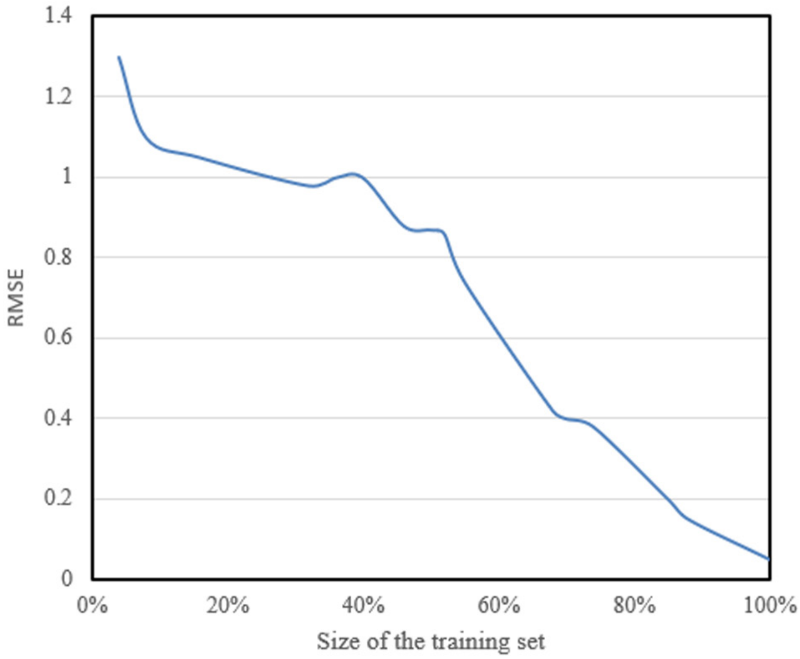

Fig. 7. Training situation of the course content recommendation model

As shown in Figure 7, the root mean square error (RMSE) shows a downward trend on the whole as the size of training set increases, which means that the predicted error of the model gradually decreases and the predicted accuracy increases as more data is added to the training process. When the size of training set is from 4% to 32%, RMSE of the model gradually decreases, but the decrease is not significant. This indicates that the model may face overfitting problems when the data volume is small in the early stage, which makes the model perform well on training data, but its generalization ability is limited on unknown data. As the size of training set is from 36% to 40%, an increase in RMSE can be observed, maybe because the model encounters some noisy data or other abnormal data points. RMSE rapidly decreases when the size of training set is and more than 55%, and decreases significantly when the size is from 85% to 100%, which indicates that the model captures more useful features and improves its forecasting accuracy when the training data is sufficient.

Table 3. Similarity matching results of the index system

Experiment No.	Accuracy	Recall	F1
1	0.8145	0.6239	0.7326
2	0.8462	0.6124	0.7789
3	0.7562	0.6699	0.7144
4	0.8122	0.7125	0.7415
5	0.8159	0.7759	0.7629
6	0.7456	0.7316	0.7598
7	0.7643	0.7458	0.7514
Average	0.8259	0.7155	0.7655

Table 3 shows the matching results of course content recommendation based on the course similarity method. The accuracy in the table fluctuates slightly in experiments, but remains above 0.75 on the whole, with an average value of 0.8259, which means that the recommendation method accurately provides users with the course content in which they are truly interested in most cases. The average recall is 0.7155, which means that the model captures and recommends the course content in which users are truly interested approximately 71.55% of the time. The average F1-score is 0.7655, indicating that the model reaches a relatively balanced state between accuracy and recall. Therefore, the recommendation method based on course similarity performs well in the experiments. It provides users with the course content in which they are truly interested in most cases, which has been verified with high accuracy and recall.

Table 4. Matching results of the DBN model

Experiment No.	Accuracy	Recall	F1
1	0.8425	0.9210	0.8741
2	0.8369	0.8459	0.8326
3	0.8147	0.8563	0.8452
4	0.7144	0.8514	0.7789
5	0.8415	0.9125	0.8741
6	0.8126	0.8745	0.8426
7	0.8626	0.9123	0.8633
Average	0.8320	0.8412	0.8326

Table 4 shows the matching results of course content recommendation based on the DBN method. The average accuracy is 0.8320 in the table, which means that DBN accurately provides users with the course content in which they are truly interested in most cases. The average recall is 0.8412, which means that the model captures and recommends the course content in which users are truly interested approximately 84.12% of the time. The average F1-score is 0.8326, indicating that the model reaches a relatively balanced state between accuracy and recall. Therefore, the DBN-based recommendation method has good performance in the experiments. Its accuracy, recall and F1-score are relatively high, indicating that the model effectively matches the demand of users.

5 CONCLUSION

This research mainly studied the AI-based collaborative teaching model of visual communication design. A more robust and accurate forecasting model for the collaborative teaching demand was established. In addition, course content planning methods based on the demand were proposed. In terms of experiments, the forecasting effect of the grey model and the neural network model was first studied. A grey-neural combination model was further proposed for error correction and structural optimization. The experimental results showed that the structurally optimized combination model exhibited higher forecasting accuracy compared with other models. The proposed methods based on both course similarity and DBN showed superior performance in course content recommendation. These research results provide powerful tools and methods for practical teaching environments, which helps improve the teaching effect and meet the collaborative teaching demand.

6 ACKNOWLEDGMENT

This paper was funded by Hebei Province Education Science Research 14th Five Year Plan Project (Exploration on the Teaching Mode of Ideological and Political Education in Visual communication), (Grant No.: 2103307).

7 REFERENCES

[1] Julhadi and M. Ritonga, "Human resource management in Islamic educational institutions to improve competitiveness in society 5.0 era," *International Journal of Sustainable Development and Planning*, vol. 18, no. 2, pp. 611–619, 2023. https://doi.org/10.18280/ijsdp.180231

[2] L. Zhou and J. J. Li, "The impact of chatGPT on learning motivation: A study based on self-determination theory," *Education Science and Management*, vol. 1, no. 1, pp. 19–29, 2023. https://doi.org/10.56578/esm010103

[3] J. Kwon, "A study on ethical awareness changes and education in artificial intelligence society," *Revue d'Intelligence Artificielle,* vol. 37, no. 2, pp. 341–345, 2023. https://doi.org/10.18280/ria.370212

[4] R. M. Ramo, A. A. Alshaher, and N. A. Al-Fakhry, "The effect of using artificial intelligence on learning performance in Iraq: The dual factor theory perspective," Ingénierie des Systèmes d'Information, vol. 27, no. 2, pp. 255–265, 2022. https://doi.org/10.18280/isi.270209

[5] L. M. Liu, "Analysis on class participation based on artificial intelligence," *Revue d'Intelligence Artificielle,* vol. 34, no. 3, pp. 369–375, 2020. https://doi.org/10.18280/ria.340316

[6] S. Z. Kolidakis, K. M. A. Kotoula, and G. N. Botzoris, "School mode choice classification model exploitation though artificial intelligence classification application," *Mathematical Modelling of Engineering Problems*, vol. 9, no. 6, pp. 1441–1450, 2022. https://doi.org/10.18280/mmep.090601

[7] D. Xiong, T. M. Soikun, and J. Wang, "Teaching mode design and effect evaluation method of visual communication design course from the perspective of big data," *Mathematical Problems in Engineering*, vol. 2022, Article ID 2768336. https://doi.org/10.1155/2022/2768336

[8] X. Liu, "Research on the teaching mode of information visualization course for visual communication design major based on artificial intelligence technology," in *2022 IEEE Conference on Telecommunications, Optics and Computer Science (TOCS)*, Dalian, China, 2022, pp. 227–230. https://doi.org/10.1109/TOCS56154.2022.10016125

[9] K. Zhampeissova, I. Kosareva, and U. Borisova, "Collaborative mobile learning with smartphones in higher education," *International Journal of Interactive Mobile Technologies*, vol. 14, no. 21, pp. 4–18, 2020. https://doi.org/10.3991/ijim.v14i21.18461

[10] S. S. Mallampalli and S. Goyal, "Mobile applications for developing second language collaborative writing," *International Journal of Interactive Mobile Technologies*, vol. 15, no. 7, pp. 185–193, 2021. https://doi.org/10.3991/ijim.v15i07.19885

[11] S. Zhang, "A novel teaching approach for mobile internet-based collaborative knowledge construction in 'teaching management'," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 12, pp. 51–64, 2021. https://doi.org/10.3991/ijet.v16i12.23223

[12] T. Wang, "A blended collaborative teaching mode in language learning based on recommendation algorithm," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 23, pp. 111–126, 2021. https://doi.org/10.3991/ijet.v16i23.27253

[13] J. X. Wang and A. Mangmeechai, "Impact of entrepreneurship knowledge literacy curriculum on college graduates' sustainable entrepreneurial competence based on entrepreneurial learning theory," *International Journal of Sustainable Development and Planning*, vol. 17, no. 4, pp. 1309–1316, 2022. https://doi.org/10.18280/ijsdp.170428

[14] M. Zotova, T. Likhouzova, L. Shegai, and E. Korobeynikova, "The use of MOOCS in online engineering education," *International Journal of Engineering Pedagogy*, vol. 11, no. 3, pp. 157–173, 2021. https://doi.org/10.3991/ijep.v11i3.20411

[15] P. Pandita, S. Verma, S. Kumar, R. Bakshi, and Aman, "Recent innovations of computing in education: Emerging collaborative blended learning models in India," in *Proceedings of International Conference on Recent Innovations in Computing: ICRIC 2022*, Jammu, India, vol. 1, 2023, pp. 649–656. https://doi.org/10.1007/978-981-19-9876-8_49

[16] E. Jones and T. Palmer, "A review of group-based methods for teaching statistics in higher education," *Teaching Mathematics and its Applications: An International Journal of the IMA*, vol. 41, no. 1, pp. 69–86, 2022. https://doi.org/10.1093/teamat/hrab002

[17] R. Kandakatla, E. J. Berger, J. F. Rhoads, and J. DeBoer, "Student perspectives on the learning resources in an active, blended, and collaborative (ABC) pedagogical environment," *International Journal of Engineering Pedagogy*, vol. 10, no. 2, pp. 7–31, 2020. https://doi.org/10.3991/ijep.v10i2.11606

[18] B. Standl, T. Kühn, and N. Schlomske-Bodenstein, "Student-collaboration in online computer science courses—an explorative case study," *International Journal of Engineering Pedagogy*, vol. 11, no. 5, pp. 87–104, 2021. https://doi.org/10.3991/ijep.v11i5.22413

[19] T. Wang, "A blended collaborative teaching mode in language learning based on recommendation algorithm," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 23, pp. 111–126, 2021. https://doi.org/10.3991/ijet.v16i23.27253

[20] C. Khentout, K. Harbouche, and M. Djo udi, "Learner to learner fuzzy profiles similarity using a hybrid interaction analysis grid," *Ingénierie des Systèmes d'Information,* vol. 26, no. 4, pp. 375–386, 2021. https://doi.org/10.18280/isi.260405

[21] P. Wang, P. Li, and M. C. Cuntapay, "Recognition of student emotions in classroom learning based on image processing," *Traitement du Signal,* vol. 39, no. 4, pp. 1331–1337, 2022. https://doi.org/10.18280/ts.390426

[22] Y. X. Zhao, W. Ren, and Z. Li, "Prediction of English scores of college students based on multi-source data fusion and social behavior analysis," *Revue d'Intelligence Artificielle,* vol. 34, no. 4, pp. 465–470, 2020. https://doi.org/10.18280/ria.340411

[23] D. N. Mawardi, C. A. Budiningsih, and Sugiman, "Blended learning effect on mathematical skills: A meta-analysis study," *Ingénierie des Systèmes d'Information,* vol. 28, no. 1, pp. 197–204, 2023. https://doi.org/10.18280/isi.280122

[24] D. Sudrajat, A. I. Purnamasari, A. R. Dikananda, D. A. Kurnia, and D. M. Efendi, "Hybrid learning predictions on learning quality using multiple linear regression," *Ingénierie des Systèmes d'Information,* vol. 28, no. 1, pp. 155–160, 2023. https://doi.org/10.18280/isi.280116

8 AUTHORS

Songhua Liu graduated from Hebei Normal University in 2001 with a Bachelor's degree in decorative design art education. Graduated from Dongseo University in South Korea in 2008 with a Master's degree. Now she is a lecturer in the college of art, Yanching Institute of Technology. Research directions include brand promotion and brand design (E-mail: liusonghua@yit.edu.cn; https://orcid.org0009-0001-1683-2413).

Jing Li graduated from the School of Design and Art at Beijing institute of graphic communication in 2007 with a Bachelor's degree. In 2010, she graduated from the School of Design and Art at Beijing institute of graphic communication with a Master's degree. Now she is a lecturer in the college of art, Yanching Institute of Technology. Her research interests include the theory and innovative practice of Visual communication (E-mail: lijing@yit.edu.cn; https://orcid.org/0000-0003-3027-4355).

Jiannan Zheng Graduated from Industrial Design Department of Hebei University in 2007 with a bachelor's degree. In 2010, she graduated from Hebei University of Technology, with a degree in Literature. Currently, she holds the position of Associate Professor in the college of art, Yanching Institute of Technology. Her research focuses on the theory of product design and innovative practices (E-mail: zhengjiannan@yit.edu.cn; https://orcid.org/0009-0001-3288-4918).