Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 14 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i14.57009

PAPER

Data-Driven Evaluation of MOOC-Based Blended College English Teaching via Enhanced Neural Networks

Ciren Deji, Huajie Chen (✉)

School of Foreign Languages & Cultures, Xizang University, Lhasa, China

hjchen@utibet.edu.cn

ABSTRACT

The rapid proliferation of massive open online courses (MOOCs) presents both opportunities and challenges for traditional higher education. As MOOCs offer scalable, high-quality educational resources, they have the potential to significantly enhance instructional outcomes in university settings. In this context, the online-offline hybrid teaching model has emerged as a promising pedagogical approach, particularly in the domain of college English instruction. However, the effective integration of MOOCs into blended learning frameworks remains a complex and evolving challenge. This study presents a data-driven analysis of MOOC-based hybrid teaching for college English. It first identifies key limitations in current implementations, including issues related to interactivity, learner engagement, and instructional design. To address these challenges, a strategic framework is proposed to optimize the blended teaching process. Furthermore, this work introduces an enhanced back propagation (BP) neural network model to evaluate the effectiveness of hybrid English instruction. The improved model incorporates an additional momentum term (AMT), adaptive learning rate (ALR), and a conjugate gradient (CG) optimization algorithm to overcome the limitations of traditional BP networks. Experimental results demonstrate that the proposed model achieves superior performance in terms of accuracy and F1 score compared to conventional methods such as support vector machines (SVM) and deep belief networks (DBN). These findings validate the effectiveness of the proposed framework and highlight the potential of intelligent evaluation models in advancing MOOC-based blended learning environments.

KEYWORDS

hybrid teaching, college English, massive open online course (MOOC), back propagation (BP)

1 INTRODUCTION

The rapid expansion of the global open education movement has necessitated the integration of educational and information technologies to facilitate the sharing of high-quality learning resources. This integration is not only a strategic response to technological advancement but also an essential prerequisite for the globalization

Deji, C., Chen, H. (2025). Data-Driven Evaluation of MOOC-Based Blended College English Teaching via Enhanced Neural Networks. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(14), pp. 137–150. https://doi.org/10.3991/ijim.v19i14.57009

Article submitted 2025-03-03. Revision uploaded 2025-05-05. Final acceptance 2025-06-03.

of education. As a transformative medium, the Internet plays a crucial role in disseminating public opinion and fostering ideological and cultural exchange. Its profound societal influence is undeniable, and it is increasingly intertwined with the development of modern education. Consequently, educational development strategies must align with broader societal trends and emphasize the deep integration of educational practices with internet technologies [1, 2].

Massive open online courses (MOOCs) originated from the open educational resources (OER) movement and gained widespread recognition with their emergence in the United States around 2012. Compared to traditional courses, MOOCs offer several distinct advantages. First, they provide access to a vast repository of high-quality learning resources. Major MOOC platforms such as Coursera, edX, and Udacity host a diverse array of courses across multiple disciplines, enabling learners to find content that aligns with their individual needs. Notably, many of these courses are developed by leading academic institutions, ensuring a high standard of instructional quality.

Second, MOOC content is typically short and concise, often structured into 6–10 minute segments that are ideal for self-paced, flexible learning. Students have the autonomy to determine when and where they engage with the material, provided they have internet access. Although MOOCs often impose deadlines, the overall learning schedule is relatively adaptable, allowing learners to plan their study time based on personal circumstances.

Despite these benefits, MOOCs also exhibit certain limitations. One major issue is the low course completion rate, largely due to a lack of effective supervision. Learners with limited self-motivation may struggle to remain engaged and are prone to dropping out. Additionally, the learning experience can be incomplete, as meaningful interaction between students and instructors is often limited. This may prevent timely identification and resolution of learning difficulties, ultimately hindering student progress.

To address these shortcomings, college English instruction should adopt a multifaceted approach that leverages the strengths of MOOCs while compensating for their weaknesses through blended teaching models. By integrating online and offline components, educators can enhance student engagement, improve learning outcomes, and create a more comprehensive and effective instructional environment [3–5].

The term hybrid refers to a kind of college English instruction that incorporates both online and traditional methods of instruction in the classroom. It has a few advantages over standard college English classroom instruction or Internet-based online instruction. In college English teaching, classroom contact is the primary mode of instruction, and teachers accomplish their objectives through interacting directly with students. Students can work on their assignments whenever they want, which leads to higher levels of efficiency. Traditional classroom teaching, on the other hand, is constrained by time and location and lacks a degree of adaptability. Traditional classroom instruction has its drawbacks, but students can use mobile devices to learn whenever and wherever they want. Students' learning concepts have been widened by the abundance of online learning resources, which encourages the development of students' innovative ability. Learning material, learning environment, learning medium, and other aspects are naturally combined in this teaching method, which maximizes the benefits of both online and traditional classroom education. In addition, this teaching mode serves as a primary source of inspiration, guidance, and monitoring for teachers. Teaching efficiency is improved as a result of the students' enthusiasm and creativity, which in turn increases their enthusiasm and creativity [6, 7].

The appropriate teaching design of hybrid online and offline English courses for college students properly integrates time. Pre- and post-class activities go much beyond the usual preview and review. Students are encouraged to use the internet to gather important knowledge by assigning activities before the class. This encourages students to fully stimulate their interest in the subject matter. Students' language application skills are bolstered by rigorous classroom lectures that focus on the most significant concepts and information. Students' learning deficiencies can be identified and filled more quickly with post-class task feedback. As a result, a combination of online and face-to-face hybrid teaching approaches aims to break through the obstacles of the course and collaborate to carry out project-based education. All levels of teaching are mirrored in this teaching method's incorporation. Cooperative learning and the completion of assignments assigned by teachers can both be accomplished by students via the Internet. This allows students to use their individual skills to gather information and participate in online and offline debates, overcoming the limits of time and space [8, 9].

This work studies the online and offline hybrid teaching for college English via MOOC from a data perspective. First, this work analyzes issues existing in current MOOC-based college English blended teaching. On this basis, this work proposes a strategy for building an online-offline blended teaching model. Second, this work proposes an improved back propagation (BP) network to evaluate the effect of mixed teaching of English. It uses an additional momentum term (AMT), adaptive learning rate (ALR), and conjugate gradient (CG) BP algorithm to improve the traditional BP network. Third, this work has carried out various experiments; data analysis validates the effectiveness of the proposed model.

2 RELATED WORK

Massive open online courses have been widely recognized for promoting educational equity due to their open, large-scale, and high-quality curriculum resources. Viswanathan [10] notes that MOOCs enable broad access to quality education through online platforms. Chenjie [11] emphasizes that MOOCs facilitate learner interaction and experience sharing but also highlights the importance of improving course completion rates and establishing standardized systems for credit recognition.

Massive open online courses have driven innovation in the education sector through diverse, flexible, and scalable delivery methods. Al-Atabi and DeBoer [12] argue that MOOCs can reduce the burden of classroom management and commuting for instructors, allowing them to focus more on student needs and feedback. Bing [13] points out that MOOCs reshape the dynamics of teaching evaluation and the teacher-student relationship. Guo [14] suggests that MOOCs, particularly in combination with small private online courses (SPOCs), could become a dominant form of mobile learning in the future.

The core strength of MOOCs lies in leveraging modern internet technologies to disseminate knowledge widely. They promote a blend of self-directed and collaborative learning, addressing the increasing demand for lifelong and flexible education. However, to ensure their long-term success, MOOCs must be adapted to cultural and institutional contexts. Evans and Myrick [15] stress the importance of localized implementation, warning against blindly adopting foreign pedagogical models without considering local educational characteristics.

Blended teaching, which integrates face-to-face instruction with online learning, has also received considerable attention. Pape [16] sees blended learning as a cost-effective method that maximizes teaching resources. Gerbic [17] describes it as a learner-centered approach that fosters active participation, confidence, and a sense of achievement. Tynan, Ryan, and Lamont-Mills [18] highlight the role of internet infrastructure in enabling flexible, efficient learning environments, extending classroom interactions beyond physical constraints.

Van Doorn [19] views blended learning as a strategic innovation that enhances educational technology and cultivates effective learning habits. Ocak [20] notes that this model fosters real-time interaction and reciprocal feedback, moving beyond the simple combination of traditional and distance learning. Shand and Farrelly [21] further argue that blended learning environments encourage learners to independently seek resources tailored to their personal knowledge construction.

Gagnon et al. [22] emphasize that the effectiveness of blended learning depends more on clearly defined learning goals than on specific platforms or technologies. Ocak [23] attributes the rapid adoption of blended models to the emphasis placed on learner experience and engagement. Joosten et al. [24] demonstrate that integrating MOOCs within blended teaching frameworks yields positive instructional outcomes, offering a viable path for future educational reform.

3 METHOD

First, this work analyzes issues existing in current MOOC-based college English blended teaching. On this basis, this work proposes a strategy for building an online-offline blended teaching model. Second, this work proposes an improved BP network to evaluate the effect of mixed teaching of English. It uses AMT, ALR, and CG BP algorithm to improve the traditional BP network. Third, this work has carried out various experiments, and the results data verify the feasibility of this work.

3.1 Existing problems and construction of teaching mode

There are still a number of issues with MOOC-based blended teaching of college English. First, MOOC lacks effective management and supervision. The online blended teaching via MOOC requires learners to have a high degree of learning consciousness. On MOOC, there is no manager or supervisor who urges learners to complete the learning plan. The course itself has a course end time set by the teacher, and learners need to plan their own online college English course study time. Many learners lack self-management and self-supervision capabilities and do not plan their online learning time properly.

Second, the MOOC platform has a single mode of interaction between teachers as well as students. Although MOOC has established a bridge for online communication. However, it is mostly limited to unilateral interaction, interaction mode on the platform is relatively simple, and there is a lack of effective two-way interaction. Teachers are often unable to check and answer students' questions in a timely manner, and it is difficult to follow up on students' learning dynamics in a timely manner. This affects the learning effect. Many students speak in the discussion area to obtain module scores, thus raising invalid questions, which is not conducive to the two-way effective interaction.

Third, there is a dearth of blended teaching system training for teachers. Using MOOCs for online and offline hybrid teaching requires teachers to be more information literate. Teachers should not only learn how to build MOOC video resources, but they need also be familiar with the platform's basic maintenance and management functions. Teachers' knowledge of information literacy and their ability to integrate educational resources are essential to the creation of these activities. However, there are only a few college and university English professors who are adept in using MOOCs in their classrooms. Teachers are ill-prepared for online teaching activities because they lack training in the blended teaching system. It is difficult to improve the quality of college English courses because of this.

Fourth, the subject of course assessment and evaluation is still dominated by teachers. Nowadays, many colleges and universities have adopted diversified evaluation methods for course assessment. The evaluation method is no longer a single summative evaluation, and more emphasis is placed on the online and offline process evaluation and formative evaluation. However, the main body of the assessment and evaluation of college English courses is still mainly teachers. Although the evaluation methods are more diverse, the main body of evaluation is still mainly teachers.

This work proposes several strategies for the construction of a blended teaching model. The first is to improve the online teaching stage. Teachers should make MOOC teaching videos before teaching. When designing college English teaching videos, it is significant to analyze the situation. Redesign the pre-class study task list of college English to help students have an overall perception of the unit in the online self-learning stage. The duration of MOOC teaching videos is different from that of traditional offline teaching. The duration of MOOC teaching videos should be controlled between 2 and 4 hours per week. The weekly teaching video is divided into several small units, and the duration of each short unit is preferably 6–10 minutes. When setting up the MOOC online teaching module, teachers can embed a simple in-class test in the MOOC video. The purpose of the in-class test is to test the students' mastery and remind students to keep their attention. Teachers should set up learning discussion areas where students can ask questions. Teachers also need to assign unit assignments and assessments. After the staged unit is taught online, unit assignments or unit assessments are set up based on the video courses of this unit.

The second is the improvement of the offline teaching stage of college English. Students' dynamic and individualized learning needs are an important factor affecting classroom teaching. Teachers should diagnose and analyze learners' online self-directed learning before classroom teaching so as to conduct targeted teaching activities. Teachers and students have in-depth exchanges on the online self-learning of MOOC before class, and teachers use group lectures to answer students' questions on the MOOC platform. Then, according to the pre-class activity groups, various forms of teaching activities will be carried out. This gives play to initiative, and cultivates students' innovative English thinking and awareness of collaboration and cooperation. Teachers give guidance and evaluation according to the students' activities and do a good job of summarizing the knowledge of this lesson. Teachers also assign after-class knowledge points to review and consolidate homework and issue a pre-class preview task list for the next unit.

The third is improvement of the evaluation stage of English teaching. The evaluation quality system of hybrid teaching mode is jointly determined by the online teaching platform, teachers, learners, and their teaching evaluation. Therefore, the establishment of a complete, diversified evaluation system is conducive to the high-quality and effective implementation of the blended teaching model. Formative evaluation, procedural evaluation, and summative evaluation run through the whole process of college English blended teaching. Summative assessment no longer occupies a major part of course assessment. Among them, the evaluation of the classroom activity display part adopts a tripartite evaluation mechanism.

3.2 Improved BP for mixed teaching quality evaluation

Error back-propagation is used to train the BP network, a multi-layer feedforward neural network model. Gradient descent and back-propagation of the error are used to update the weights and thresholds in the model so that the training error is minimized as much as possible. Figure 1 is a three-layer BP network's topology.

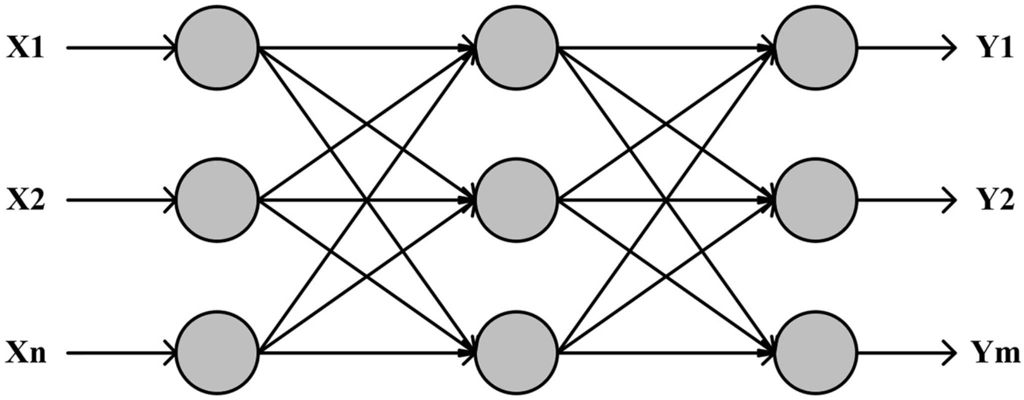

Fig. 1. Back propagation network

It is necessary to initially send the signal to one of the network's hidden layers in order for a multilayer feedforward network to work. The output layer should then use the calculated value to output the conversion function for each unit. A neural network's learning process can be broken down into two phases: forward pass and backward pass. This layer's neuron information can only be communicated to the neuron network in the subsequent layer during the forward transmission process, as this has a beneficial effect. A reverse transfer is necessary to correct an error if the disparity between the theoretical and real results is too great. Layer by layer, the system's neural network is rebalanced, and the reverse transmission returns along the original link route to rebalance all of the neurons' weights. Return to the initial step and keep passing the contrast. Re-run the previous procedure if the difference between the actual and predicted results is still high enough. When the neural network reaches the necessary level of learning, the process is over.

The output and error are calculated as:

$$o_i = f\left(\sum_{i}^{N} w_i x_i + b_i\right) \tag{1}$$

$$loss = \sum_{i=1}^{N} (o_i - t_i)^2 \tag{2}$$

Where w is weight, b is bias, t is true label.

The BP pipeline is demonstrated in Figure 2. The BP network first performs network initialization and then selects training samples for forward propagation. Then calculate the forward error, and end the training if the termination condition is met. Otherwise, back-propagation is performed based on the error to update the network parameters until the training termination condition is met.

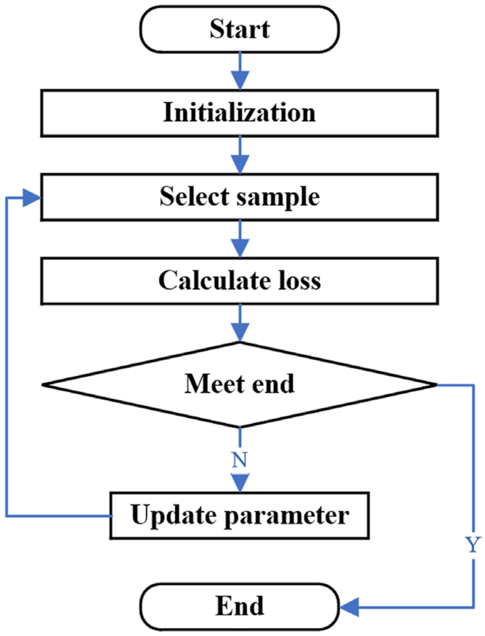

Fig. 2. Back propagation pipeline

The benefits of the BP network have been widely utilized in the field of information technology. There are, however, several BP network system limitations that are rapidly becoming more apparent as application scope and depth increase. This method is slow to learn, and it takes a long time for it to reach a stable state. Because of the network's fixed learning rate and inertia constant, a higher learning rate increases the weight correction coefficient, allowing the system to pick up new information more quickly. Learning rates should not be too high or low, however. The system may vibrate if it's too huge. If it's too small, the system's weight will be volatile, making it harder to achieve equilibrium. The goal function of the BP network method must be continuously improved by training it on a large number of samples. This will suck up a lot of processing power and slow down the BP network's convergence. As a second point, network training tends to slip into local minima. The sample training problem of easily falling into the local minimum is the most typical problem during the operation of the BP network technique. Because the search algorithm limits the BP network's ability to search, this occurrence is referred to as a search restriction. If the search step size is small enough and the solution space function has a local minimum, all the solutions discovered point to the method of the minimum value. Third, the type of network structure that will be used is unknown. Neural networks come in a variety of shapes and sizes, and in the course of a project, numerous challenges will be encountered. It's impossible to tackle every problem using the same structure. Based on the experience of debugging personnel, the structure of the network can be determined. It is required to make appropriate changes to the fundamental BP algorithm in order to speed up the learning process and achieve optimization in order to tackle these challenges.

The essence of the AMT strategy is to improve the performance of network system by changing learning efficiency. The iterative relationship of the network connection weight is:

$$\Delta w(n+1) = \alpha \frac{\partial E}{\partial w} + \beta w(n) \tag{3}$$

Where α is learning rate, β is momentum factor.

The momentum term of the system represents the meaning of memory and stores the direction of change in the last system connection weight. Then, the learning rate of the system is appropriately adjusted according to the value of the variation. Increasing the learning rate can increase the learning rate of the system, enabling the system to complete training faster. Excessive adjustment of the learning rate may cause the system to oscillate. The AMT mainly suppresses the oscillating effect that occurs in the training of network samples through its inertia effect and plays a role in a smooth transition.

The ALR strategy is considered to be the simplest and most commonly used method to improve BP networks. In the BP network algorithm, the adjustment of network connection weights depends on the learning rate and the gradient of the system. But in the most basic BP algorithm, the learning rate will remain stable. By setting the learning speed of the network by itself, the convergence speed of the system can be greatly improved. Heuristic regulation is performed using the information of the changing value of the error. If error decreases, learning rate increases. If error increases, learning rate decreases.

$$\alpha(n+1) = \begin{cases} 1.05\alpha(n), & E(n+1) < E(n) \\ 0.7\alpha(tn), & E(n+1) > 1.05E(n) \\ \alpha(n), & other \end{cases} \tag{4}$$

Where E is loss, n is iteration.

Positive gradient is the most common algorithm used in BP networks. It's a characteristic of the negative gradient method to alter the system's connection weighting and thresholds in a downward gradient. However, in this negative gradient algorithm, the iterative search directions between neighbors continue to change orthogonally. Sawtooth-such as oscillations may occur as the search direction approaches local extrema. Different from the traditional gradient descent method, the CG method not only uses the information of the first derivative of the objective function but also needs to obtain the information of the second derivative of the system. The CG method first searches according to the current search direction. The search is then performed according to the conjugate directions of the existing directions so that the system can reach the optimum value quickly. Compared with most gradient methods, the CG method requires only a small amount of computation and can achieve faster convergence. For a network with relatively many weights and a complex network, the CG method has a better effect.

4 EXPERIMENT

4.1 Data detail

This work collects the data of the MOOC-based online and offline hybrid teaching mode of college English in the corresponding data field to construct the data required for the training and testing of the BP network. Table 1 shows the quality evaluation indicators used in this work. The BP network evaluation indicators used in this work are the accuracy and F1 score.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \tag{5}$$

$$F1 = 2 * Precision * Recall / (Precision + Recall) \tag{6}$$

Table 1. Quality evaluation indicators

Symbol	Indicator
x_1	Student attendance
x_2	Teacher-student interaction
x_3	Class rule
x_4	Classroom performance
x_5	Teaching attitude
x_6	Q & A after class
x_7	Student attitude
x_8	Student test

4.2 Back propagation training experiment

This work evaluates whether the training of the improved BP network meets expectations. The evaluated metrics are the accuracy rate and F1 score during training, as demonstrated in Figure 3.

As iterations increase, the accuracy and F1 score of network increase significantly. However, when the training reaches a certain number of iterations, these two metrics tend to stabilize. This indicates that the network has converged at this time.

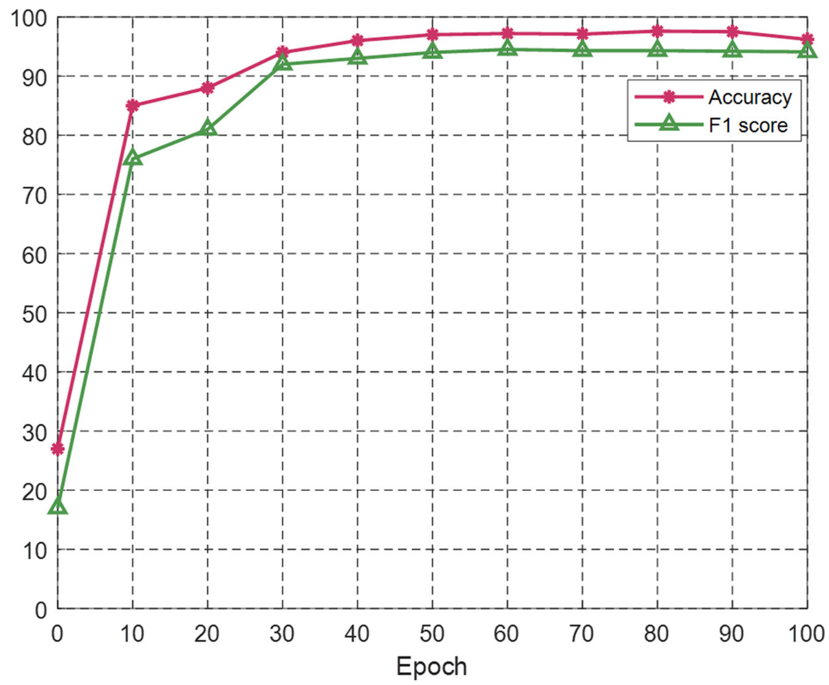

Fig. 3. Back propagation training loss

4.3 Comparison with different method

To verify feasibility of improved BP network, it is compared with other methods, as demonstrated in Table 2.

Table 2. Performance of different method

Method	Accuracy	F1 Score
SVM	90.7%	88.6%
DBN	92.2%	90.3%
Ours	95.1%	92.7%

Compared with other methods, the improved BP network proposed in this work can achieve the best accuracy and F1 score.

4.4 Analysis on additional momentum term

This work uses the AMT strategy to improve the BP network. To verify the superiority of this strategy, this work compares the performance without AMT and with AMT, respectively, as demonstrated in Figure 4.

Compared with the BP network performance without AMT, after using the AMT strategy, the accuracy rate and F1 score are improved by 1.8% and 1.5%. This proves the superiority of the AMT strategy.

4.5 Analysis on adaptive learning rate

This work uses the ALR strategy to improve the BP network. To verify the superiority of this strategy, this work compares the performance without ALR and with ALR, respectively, as demonstrated in Figure 5.

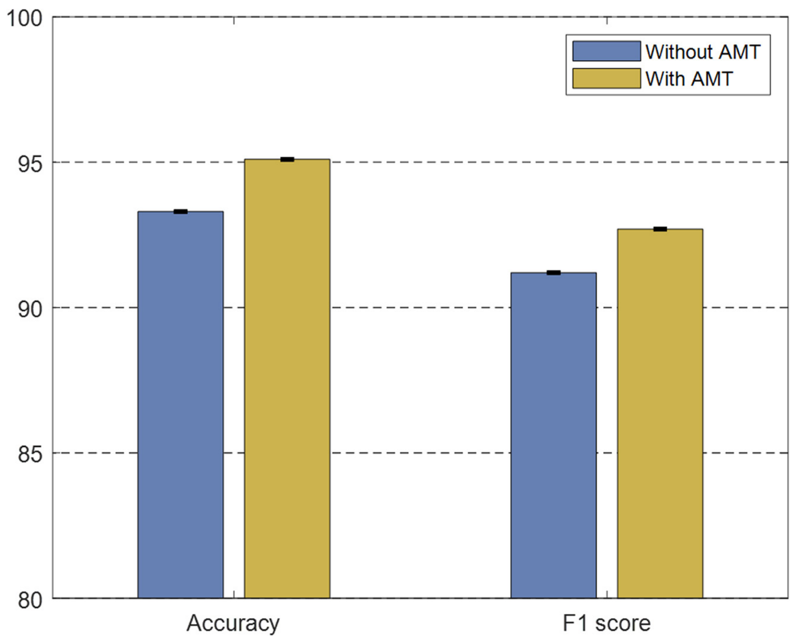

Fig. 4. Analysis on additional momentum term

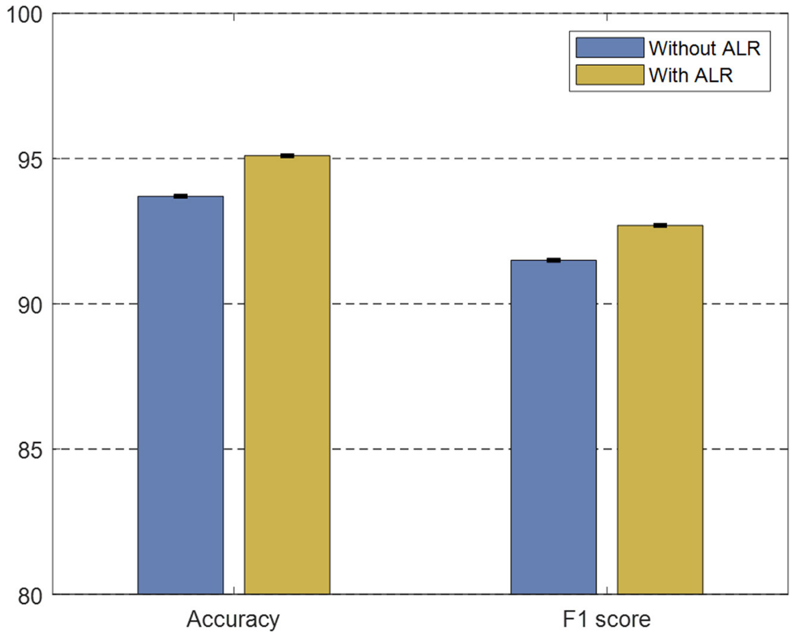

Fig. 5. Analysis on adaptive learning rate

Compared with the BP network performance without ALR, after using the ALR strategy, the accuracy rate and F1 score are improved by 1.4% and 1.2%. This proves the superiority of the ALR strategy.

4.6 Analysis on conjugate gradient

This work uses the CG strategy to improve the BP network. To verify the superiority of this strategy, this work compares the performance without CG and with CG, respectively, as demonstrated in Figure 6.

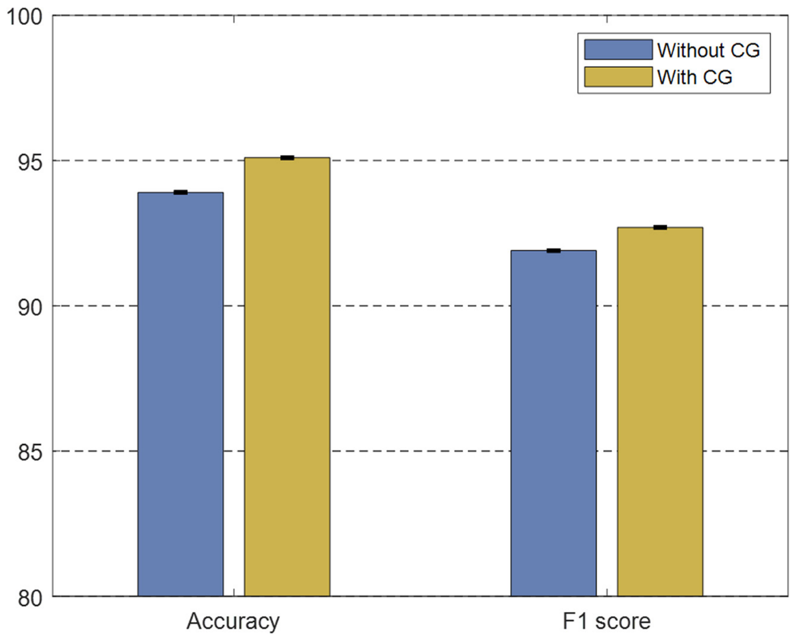

Fig. 6. Analysis on conjugate gradient

Compared with the BP network performance without CG, after using the CG strategy, the accuracy rate and F1 score are improved by 1.2% and 0.8%. This proves the superiority of the CG strategy.

4.7 Analysis on teaching mode strategy

This work proposes a series of strategies for the online and offline hybrid teaching mode of college English based on MOOC in the data perspective. To verify the correctness of these strategies, this work compares the English teaching quality before and after using these strategies. The specific comparison indicators are demonstrated in Table 1, and the percentile score is used to measure the teaching quality. The comparison data is demonstrated in Table 3.

Table 3. Analysis on teaching mode strategy

Index	Before	After
x_1	84.5	87.8
x_2	73.2	79.2
x_3	61.9	70.3
x_4	85.5	89.1
x_5	79.3	83.8
x_6	68.1	74.1
x_7	65.7	69.3
x_8	67.9	74.2

Obviously, after using the teaching mode construction strategy proposed in this work, the teaching quality has been significantly improved. Specifically, each teaching quality evaluation index can be improved to a certain extent. This corroborates the superiority of the proposed strategy.

5 CONCLUSION

Students' ways of learning are evolving as the Internet and mobile devices become more widely available. A fresh road for the reform of college English classroom education was opened up by MOOCs, online/offline hybrid teaching modes, etc. College English curriculum and teaching methods have been impacted by MOOCs. Not only should college English instruction adapt to the growing trend of online learning, but it should also weigh the benefits and drawbacks of incorporating MOOC resources into the curriculum. For the advancement of MOOC resources, academic institutions should focus on their strengths while avoiding their flaws in order to enhance the quality of English instruction in higher education institutions across the country and around the world. As a result, the combined method of online and offline college English instruction based on MOOCs is an essential topic to research. This work studies the online and offline hybrid teaching for college English via MOOC from a data perspective. First, this work analyzes issues existing in current MOOC-based college English blended teaching. On this basis, this work proposes a strategy for building an online-offline blended teaching model. Second, this work proposes an improved BP network to evaluate the effect of mixed teaching of English. It uses AMT, ALR and CG BP algorithm to improve the traditional BP network. Third, this work has carried out various experiments, and the results data verify the feasibility of this work.

6 REFERENCES

[1] H. Sun, X. Wang, and X. Wang, "Application of blockchain technology in online education," *Int. J. Emerg. Technol. Learn.*, vol. 13, no. 10, pp. 252–259, 2018. https://doi.org/10.3991/ijet.v13i10.9455

[2] A. M. Tessema and L. Nicola-Gavrilă, "Assessment of the experiences of higher education institution on online learning: The case of some selected institutions," *Journal of Research, Innovation and Technologies*, vol. II, no. 1(3), pp. 49–56, 2023. https://doi.org/10.57017/jorit.v2.1(3).04

[3] A. F. Tatang and A. M. Algarni, "MOOCMaven: Bridging M-learning and open data for enhanced unified MOOC exploration," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 20, pp. 4–20, 2023. https://doi.org/10.3991/ijim.v17i20.42445

[4] Y. Jiang, Y. Chen, J. Lu, and Y. Wang, "The effect of the online and offline blended teaching mode on English as a foreign language learners' listening performance in a Chinese context," *Front. Psychol.*, vol. 12, p. 742742, 2021. https://doi.org/10.3389/fpsyg.2021.742742

[5] A. M. Nidhom, A. B. N. R. Putra, A. A. Smaragdina, G. D. K. Ningrum, and J. M. Yunos, "The integration of augmented reality into MOOC's in vocational education to support education 3.0," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 3, pp. 20–31, 2022. https://doi.org/10.3991/ijim.v16i03.28961

[6] Y. He, "Implementation strategy of college English online blended teaching model," in *2020 5th Int. Conf. Humanit. Sci. Soc. Dev. (ICHSSD 2020)*, 2020, pp. 279–282. https://doi.org/10.2991/assehr.k.200727.112

[7] Y. Miao, "Online and offline mixed intelligent teaching assistant mode of English based on mobile information system," *Mobile Inf. Syst.*, vol. 2021, no. 1, p. 7074629, 2021. https://doi.org/10.1155/2021/7074629

[8] A. Guan, "Research on blended teaching model in college English based on mobile learning app," *J. Contemp. Educ. Res.*, vol. 5, no. 1, pp. 78–81, 2021. https://doi.org/10.26689/jcer.v5i1.1808

[9] Q. Xie and S. B. Tsai, "An empirical study on innovation of college blended teaching under big data analysis," *Math. Probl. Eng.*, vol. 2021, no. 1, p. 3752037, 2021. https://doi.org/10.1155/2021/3752037

[10] R. Viswanathan, "Teaching and learning through MOOC," *Front. Lang. Teach.*, vol. 3, no. 1, pp. 32–40, 2012.

[11] C. Yu, "Challenges and changes of MOOC to traditional classroom teaching mode," *Can. Soc. Sci.*, vol. 11, no. 1, pp. 135–139, 2015. https://doi.org/10.3968/6023

[12] M. Al-Atabi and J. DeBoer, "Teaching entrepreneurship using massive open online course (MOOC)," *Technovation*, vol. 34, no. 4, pp. 261–264, 2014. https://doi.org/10.1016/j.technovation.2014.01.006

[13] W. Bing, "The college English teaching reform based on MOOC," *Eng. Lang. Teach.*, vol. 10, no. 2, pp. 19–22, 2017. https://doi.org/10.5539/elt.v10n2p19

[14] P. Guo, "MOOC and SPOC, which one is better?" *EURASIA J. Math. Sci. Technol. Educ.*, vol. 13, no. 8, pp. 5961–5967, 2017. https://doi.org/10.12973/eurasia.2017.01044a

[15] S. Evans and J. G. Myrick, "How MOOC instructors view the pedagogy and purposes of massive open online courses," *Distance Educ.*, vol. 36, no. 3, pp. 295–311, 2015. https://doi.org/10.1080/01587919.2015.1081736
[16] L. Pape, "Blended teaching and learning," *Educ. Dig.*, vol. 76, no. 2, pp. 22–27, 2010. https://facultycenter.ischool.syr.edu/wp-content/uploads/2012/02/blended-learning-and-teaching.pdf
[17] P. Gerbic, "Teaching using a blended approach – what does the literature tell us?" *Educ. Media Int.*, vol. 48, no. 3, pp. 221–234, 2011. https://doi.org/10.1080/09523987.2011.615159
[18] B. Tynan, Y. Ryan, and A. Lamont-Mills, "Examining workload models in online and blended teaching," *Br. J. Educ. Technol.*, vol. 46, no. 1, pp. 5–15, 2015. https://doi.org/10.1111/bjet.12111
[19] J. R. Van Doorn and J. D. Van Doorn, "The quest for knowledge transfer efficacy: Blended teaching, online and in-class, with consideration of learning typologies for non-traditional and traditional students," *Front. Psychol.*, vol. 5, p. 00324, 2014. https://doi.org/10.3389/fpsyg.2014.00324
[20] M. A. Ocak, "Blend or not to blend: A study investigating faculty members perceptions of blended teaching," *World J. Educ. Technol.*, vol. 2, no. 3, pp. 196–205, 2011.
[21] K. Shand and S. G. Farrelly, "Using blended teaching to teach blended learning: Lessons learned from pre-service teachers in an instructional methods course," *J. Online Learn. Res.*, vol. 3, no. 1, pp. 5–30, 2017. https://files.eric.ed.gov/fulltext/EJ1148421.pdf
[22] M. P. Gagnon, J. Gagnon, M. Desmartis, and M. Njoya, "The impact of blended teaching on knowledge, satisfaction, and self-directed learning in nursing undergraduates: A randomized, controlled trial," *Nurs. Educ. Perspect.*, vol. 34, no. 6, pp. 377–382, 2013. https://doi.org/10.5480/10-459
[23] M. A. Ocak, "Why are faculty members not teaching blended courses? Insights from faculty members," *Comput. Educ.*, vol. 56, no. 3, pp. 689–699, 2011. https://doi.org/10.1016/j.compedu.2010.10.011
[24] T. M. Joosten, D. Barth, L. Harness, and N. L. Weber, "The impact of instructional development and training for blended teaching on course effectiveness," in *Blended Learning*, New York, NY: Routledge, 2013, pp. 173–189. https://doi.org/10.4324/9781315880310

7 AUTHORS

Ciren Deji is a Lecturer and Master's Supervisor in the School of Foreign Languages and Cultures at Xizang University. Her research focuses on TESOL and Cross-cultural Studies (E-mail: tseringdigi@utibet.edu.cn)

Huajie Chen is a Professor and Master's Supervisor in the School of Foreign Languages and Cultures at Xizang University. His research focuses on TESOL and Intercultural Studies (E-mail: hjchen@utibet.edu.cn).