

## PAPER

# Using BERT-Based Textual Analysis to Design a Smarter Classroom Mode for Computer Teaching in Higher Education Institutions

Zhe Xu, Ping Zhu(✉)

Hebei North University,  
Zhangjiakou, China[pingzhu202302@163.com](mailto:pingzhu202302@163.com)**ABSTRACT**

Smarter teaching has been widely popularized in computer teaching in higher education institutions as a key part of modern education. However, this practice faces some problems, such as excessive learning content, a tight teaching schedule, low learning enthusiasm among students, and limited time for practice. These shortcomings can be addressed by incorporating smarter teaching. A computer course in an engineering college was taken as an example in this study to construct a new mode for computer teaching based on deep learning theory, which includes five teaching stages, namely: introduction of new knowledge, pre-testing of knowledge, discussion of knowledge, task-oriented training, and post-testing of knowledge. An intelligent test database was constructed for computer teaching to be carried out under the guidance of the bidirectional encoder representation from transformers (BERT)-based textual analysis approach. Results show that (1) the test database constructed using the BERT-based textual analysis approach is more scientific and effective than other databases. (2) When validated on relevant teaching information and materials, the proposed approach improves students' learning enthusiasm, problem-solving ability, and practicing capability. (3) The smarter teaching mode constructed based on deep learning theory can significantly improve the quality of course teaching and enhance students' professional skills. The conclusions provide necessary technical support for the construction of computer-targeted test databases, which are conducive to pushing the reform and development of smarter teaching in computer science.

**KEYWORDS**

BERT, computer, smarter teaching, informatization

## 1 INTRODUCTION

With the advancement of information technology, schools have imposed strict requirements on teaching methods. The innovative changes in educational

Xu, Z., Zhu, P. (2023). Using BERT-Based Textual Analysis to Design a Smarter Classroom Mode for Computer Teaching in Higher Education Institutions. *International Journal of Emerging Technologies in Learning (IJET)*, 18(19), pp. 114–127. <https://doi.org/10.3991/ijet.v18i19.42483>

Article submitted 2023-05-21. Revision uploaded 2023-07-03. Final acceptance 2023-07-04.

© 2023 by the authors of this article. Published under CC-BY.

technology have shifted the objective of teaching from imparting knowledge to full-range cultivation. As a result, teaching methods have moved toward a combination of preaching and interaction. In this case, constructing a smarter teaching mode plays a significant role in facilitating educational reform. A smarter classroom refers to a teaching environment featuring convenience and efficiency enabled by various communication devices set according to specific teaching needs [1]. Smarter teaching is a brand-new teaching mode where the whole teaching process is embedded with the use of modern “Internet +” technology to change traditional classroom teaching methods through the overall design of teaching activities before, during, and after class [2]. Unlike traditional teaching, smarter teaching is a necessary path for intelligent education that caters to the demands of the times and promotes the integration of teaching.

Computer science has profound theoretical and practical implications as a compulsory subject for college students majoring in different fields. Computer teaching in higher education institutions is dominated by a teaching mode involving active teaching by teachers and passive learning by students. In addition, due to limited class hours, students often face problems during their learning period, such as an inability to grasp learning priorities and poor learning outcomes [3]. An increasing number of teaching practitioners have launched active teaching reforms to improve the effectiveness of computer teaching and arouse the students’ subjective initiative to learn the course. The focus of the current reform lies in the integration of information technology into computer teaching.

With the development of the Internet, educational information has brought significant changes to the field of education. Seeking answers to questions by using search engines and online answering platforms has gradually become a way for students and teachers to learn. Traditionally, teachers need to manually determine the type of exercise, which is both time-consuming and energy-consuming. This study was conducted in an attempt to design and construct a test database using textual analysis technology. Text classification can be applied in an answering system to classify exercises. In other words, the machine can replace human beings in exercise classification to improve teachers’ work efficiency. This study also innovatively applied the smarter classroom teaching mode to computer teaching. Specifically, the bidirectional encoder representation from transformers (BERT)-based textual analysis approach was used to select and analyze the test database for computer information teaching so as to provide a scientific basis for its effective reform.

## 2 STATE OF THE ART

The entry of smarter teaching into academia stems from IBM’s concept of “Smart Planet” and the subsequent proposal of five major landmarks of smarter education [4]. This concept has laid the foundation for the generation of a smarter classroom. Studies on a smarter classroom mainly focus on three aspects: classroom design, classroom application, and national plans and policies. In terms of smarter classroom design, previous studies mainly targeted higher education institutions. Saini and Goel suggested that the use of mobile terminals in smarter classrooms can significantly facilitate cooperation and resource sharing [5]. Active Learning Classrooms (ALCs), designed by the University of Minnesota in the United States, are a typical smarter learning environment design that reflects the concept of cooperative learning to a large extent [6]. Many scholars also explored how to effectively

utilize smarter teaching environments to innovate teaching methods. For instance, a learning-transformation-immersion-interaction mode was put forward for smarter classrooms. A learning mode based on the combination of formal and informal learning was also examined to fully leverage the role of smarter classrooms in cultivating students' knowledge and abilities. As for the practical application of smarter classrooms, Perry and Steck argued that students' engagement in classroom learning can be improved using wireless smart devices [7]. Meanwhile, Kanat argued that the interactive features of presentations on mobile terminals are conducive to children's acquisition of social skills and overall development [8]. Makransky and Mayer proposed a model for immersive situational simulation teaching in smarter classrooms [9]. Kosch et al. believed that the development of human-computer interaction technology allows students to interact with mobile terminals and become very active and happy in their learning by incorporating their somatosensory perceptions into classroom teaching [10]. From the perspective of national plans and policies, many countries have launched smarter classroom practices and accumulated rich and valuable experiences. Leem and Sung released a "Smarter Education Strategy" aiming to enhance teachers' capabilities, reform the education system, and improve the corresponding infrastructure, and called for reforming traditional education with electronic textbooks, cloud classrooms, online evaluation, and educational resource ecosystem construction [11]. Machmud et al. gave priority to "building learner-centered personalized learning spaces" in their "iN2015 Planning" [12]. Ohio raised the smarter education solution of "establishing online data systems, sharing teaching resource databases, and building teacher-oriented social networks."

Studies on smarter classrooms in China primarily focused on theories and teaching mode designs, particularly the integration of smarter classrooms into the teaching of courses such as English and Physics in primary and secondary schools. In terms of content, many of these studies investigated the smarter classroom teaching mode, but only a few examined the current situation of smarter classrooms and the related countermeasures. Although the construction of smarter teaching in higher education institutions is a hot topic among educators, most of the construction work remains concentrated on the smarter management of classroom devices. Device stacking has become a popular method for construction, but a unified resource platform is still lacking, thereby creating a series of problems, including unclear teaching focus, lack of overall planning, inability to achieve large-scale construction, and failure to provide precise teaching evaluations and personalized learning recommendations.

The textual analysis approach [13] is an important branch of computer textual analysis in the field of natural language processing (NLP). This approach uses computer technology to analyze textual data, or corpora, and extract diverse information, including keywords and word vectors. Relevant technologies in this field have also been included in the pre-training technology for NLP. Currently, deep learning methods have been applied in textual analysis, resulting in the emergence of certain technologies, such as wbrd2Vcc and BERT, and further improving the application scenarios for textual analysis. Khan proposed the convolutional recurrent neural network (CRNN) model [14], which was further extended to cover two classical frameworks, namely, 1) the use of CNN to extract sequential features, where the contextual labels of sequential features are extracted using Bi-LSTM, and the recognition result is transcribed via connective temporary classification text recognition based on encoding and decoding, the encoder extracts image features through CNN to obtain a textual sequence, and the decoder decodes the sequence using attention

and outputs the final recognition result. Many studies combined attention with other algorithms to accurately recognize complex scene texts. Some researchers [15] introduced the residual network and attention mechanism into CRNN to solve the problem of gradient explosion caused by training, reduce the time consumed in label alignment processing, allocate textboxes in proportion, and improve the convergence rate and text recognition rate of training. The word2vec model was also applied to learn the representation of word vectors in texts, and the pre-trained model BERT was used to obtain the semantic representation of texts and complete the text classification. Since its introduction by Google, BERT has shown excellent achievements in multiple NLP tasks. The use of the pre-trained BERT model can solve the problem of polysemy and has a good effect on capturing the semantic meanings of Chinese texts. However, the structure of BERT may vary slightly for different downstream tasks.

The BERT-based textual analysis approach has achieved promising results in developed countries. Nevertheless, in China, where the focus is on engineering, the BERT-based textual analysis approach is rarely applied in computer teaching, which to some extent restricts the development of this field. In response to these limitations, the present study proposes a new, smarter teaching mode guided by deep learning theory. It applied this approach to the teaching of “Fundamentals of Computer Application,” a practice-oriented course. The basic framework of BERT-based textual analysis and the key indicators of practice-oriented computer teaching were also analyzed to create a new test database that can provide the necessary guarantee for smarter practice-oriented computer teaching. The use of BERT-based textual analysis in the construction of this database was also given a well-described and relatively complete process that can enrich the results of previous studies. The ideas and results of this study are innovative to some extent.

### **3 CONSTRUCTION OF THE COMPUTER TEACHING MODE BASED ON SMARTER TEACHING THEORY**

The course teaching mode for a smarter classroom shown in Figure 1 was designed according to the characteristics of a smarter classroom. The entire teaching workflow is divided into the pre-class, in-class, and post-class stages. In the pre-class stage of preparation, the students’ overall prior knowledge reserves should be understood, and the teaching design needs to be optimized. During the in-class stage of interaction, collaborative exploration and other learning methods are applied to cultivate students’ cognitive abilities. In the post-class stage of consolidation, homework that matches the students’ abilities is assigned according to specific situations, with the aim of expanding and improving these students’ abilities.

#### **3.1 Pre-class stage**

(1) Preliminary teaching design: The teacher formulates a preliminary teaching scheme for the lesson in accordance with the course standards, teaching content, teaching schedule, and students’ characteristics. (2) Preview resource release: The teacher releases the teaching scheme through an information platform in order for the students to know the teaching objectives of the lesson, access rich learning resources, and preview new lesson content. Pre-class testing is conducted to

examine the students' mastery of previous knowledge. The students fill out the preview record form and summarize their own problems. (3) Teaching design optimization: The teacher adjusts the key and difficult points, the teaching strategy, and the order of teaching activities according to the students' predicted results and preview records, optimizes the teaching design, and achieves precise teaching based on data. Personalized training is provided to students facing significant problems during the preview process to ensure that all students can keep up with the teaching pace. The specific details are shown in Figure 1.



**Fig. 1.** Pre-class stage of the computer teaching mode based on smarter teaching theory

### 3.2 In-class stage

(1) Lesson introduction: The teacher introduces the new lesson content by setting task scenarios or solving the common problems encountered in the preview stage. Relevant knowledge points are explained with reference to the optimized teaching design. After the explanation, an in-class test is conducted to keep track of the students' mastery in a timely manner. (2) Elaboration: The teacher analyzes the results of the in-class test, identifies existing problems, and promptly solves them. The teacher then summarizes and comments on the key and difficult points of the lesson and provides supplementary explanations for the weak links in order for the students to consolidate and master the knowledge learned. (3) Task assignment: The teacher assigns group tasks, and each group determines the division of labor among its members according to the task. Each group must complete the task and present their work within the specified time. (4) Evaluation and Extension: The evaluation step consists of peer evaluation and self-evaluation. Firstly, the work of a group is evaluated by the teacher and the remaining participating groups. Secondly, the members of this group conduct a self-evaluation and summary based on the peer evaluation results. Lastly, the teacher gives a teaching summary for this lesson, assesses the completion of teaching tasks, identifies classroom teaching effectiveness, and points out areas for improvement.

### 3.3 Post-class stage

(1) Assignment release and personalized learning resource recommendation: The teacher releases assignments and tasks according to the students' mastery of knowledge and recommends reference materials needed for the further learning of the corresponding knowledge points in order for the students to break through the teaching objectives of the lesson and achieve their goal of consolidating and

improving their learned knowledge. (2) Summarization and improvement: The teacher reflects on the teaching of the lesson, summarizes the successful experiences, and seeks solutions to existing problems to continuously improve his or her own informational teaching ability and to benefit both the teacher and the students. The specific details are shown in Figure 2.

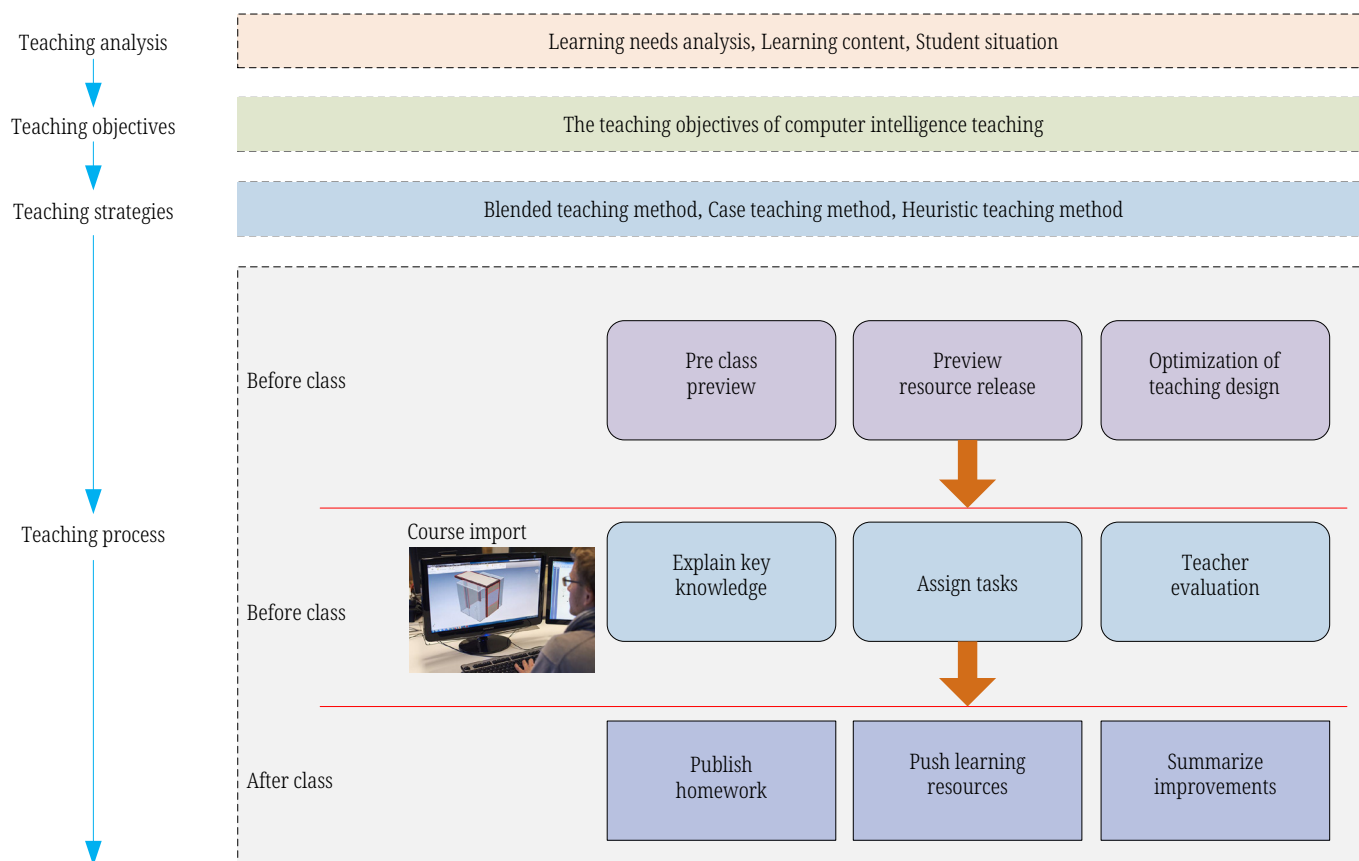


Fig. 2. Construction of the teaching mode based on smarter teaching theory

## 4 APPLICATION OF BERT-BASED TEXTUAL ANALYSIS APPROACH IN SMARTER COMPUTER TEACHING

### 4.1 Technical basis

#### 1. BERT

In 2018, the Google AI Research Institute proposed BERT, a pre-trained model. This model obtained astonishing results in the top-level machine reading and comprehension test SQuAD1.1 and even outperformed humans in both measurement indicators. BERT has also achieved a state-of-the-art (SOTA) performance in 11 NLP tests, including pushing the GLUE benchmark up to 80.4% (an absolute improvement of 7.6%) and achieving an accuracy of 86.7% (an absolute improvement of 5.6%), thereby becoming a prominent model in the history of NLP development.

BERT is a deeply pre-trained model composed of a bidirectional multi-head self-attention encoder based on the transformer model. "Bidirectional" means that the model can obtain the contextual semantic function of a sentence through

certain data. The schematic diagram of BERT is shown in Figure 3, which clearly reveals that the model uses a transformer encoder block for connection but abandons the decoder block. Therefore, this model shows bidirectional encoding ability and impressive feature extraction ability.

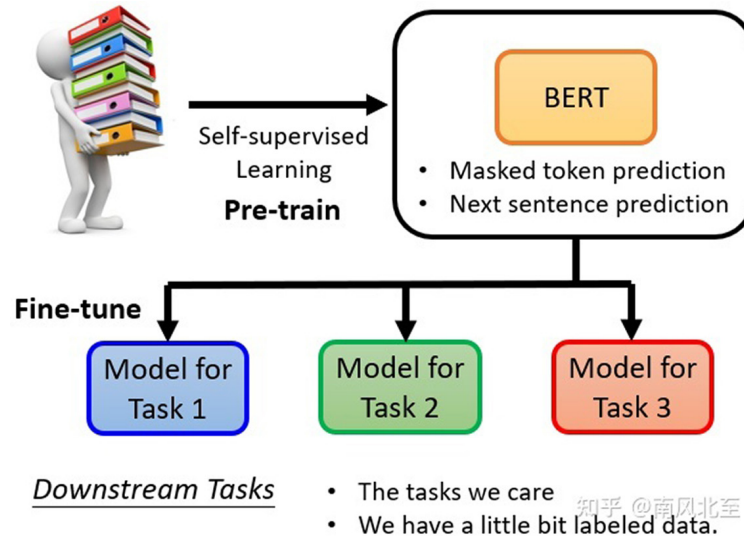


Fig. 3. Schematic diagram of BERT

## 2. Text detection and recognition indicators

$$precision(p) = \frac{TP}{(TP + FP)} \tag{1}$$

This section calculates the recall rate, which indicates whether all textual materials are prepared, and the coverage rate during the text inspection process. A higher recall rate indicates less leakage in text detection.

$$recall(R) = \frac{TP}{TP + FN} \tag{2}$$

The true positives are explored to verify the effectiveness of the treatment in the investigated text segments and to obtain a weighted average value related to the recall rate.

$$F - score(F) = \frac{2 \times (precision \times Recall)}{(precision + Recall)} \tag{3}$$

This above formula is used to investigate true positives, and further research is conducted to confirm whether the text segments have true or false textual information.

$$CRR = \frac{NCE}{NAE} \times 100\% \tag{4}$$

The above formula returns the false reporting rate of text segments, that is, the ratio of false data to actual texts.

$$FRR = \frac{FENTR}{TNR} \times 100\% \tag{5}$$

The missing rate of text segments mainly refers to the probability of errors occurring during the process of text error detection. This indicator is calculated based on the ratio of the number of text segments to the number of image segments.

$$MR = \frac{NTND}{TNT} \times 100\% \quad (6)$$

The above formula focuses on false detection records and calculates the ratio of the number of text segments obtained through detection to the total number of texts that have been searched previously.

$$FDR = \frac{NTFD}{TNT} \times 100\% \quad (7)$$

The error detection rate mainly reflects the presence of certain errors in the quantity of texts in error detection. This indicator is obtained in the process of excluding and calculating those texts with errors.

$$ed_{x,y}(i, j) = \begin{cases} \max(i, j) & \min(i, j) = 0 \\ ed_{x,y}(i-1, j-1) & x_i = y_j \\ \min \begin{cases} ed_{x,y}(i-1, j) + 1 \\ ed_{x,y}(i, j-1) + 1 \\ ed_{x,y}(i-1, j-1) + 1 \end{cases} & otherwise \end{cases} \quad (8)$$

During text federation, the accuracy of each text should be measured, which in itself is rigorous work that requires careful and strict text detection and recognition.

$$Accuracy = \frac{M}{N} \quad (9)$$

In the above formula,  $M$  represents the number of text images, while  $N$  represents the total number of texts. This formula can be used to accurately calculate the number of valid texts.

$$L_{total} = L_{score} - \lambda L_{geo}$$

$$L_{total} = balanced - xent(\hat{y}, y^a)$$

After detecting texts according to the actual situation, the loss function should be formulated. The specific calculation process is shown in the two formulas above, which can clarify the uneven distribution of functions.

$$L_{total} = -\beta Y^a \log Y^{\wedge} - (1 - \beta)(1 - Y^a) \log(1 - Y^{\wedge})$$

The above formula represents the intersection between the predicted framework and the actual framework and is used to determine the actual text situation.

## 4.2 Algorithm derivation process

In the formula above,  $K$  and  $V$  are the constructed values corresponding to the vectors in this study,  $q$  is the relevant dimension of the input word vector, and  $Z$



represents the normalized factor. This formula illustrates the process of calculating multi-text data. Unlike the text calculation method, this formula verifies the effectiveness of textual information in textual data research by calculating the constructed values corresponding to the vectors. At the same time, this formula clarifies the influencing factors that not only affect the efficiency of textual research but also facilitate the in-depth examination of the application of textual information in textual research and contribute to the allocation of texts according to the values of different factors.

$$\begin{aligned}
 x &= [x_1, x_2, \dots, x_n] \\
 E &= [E_1, E_2, \dots, E_n] \\
 T &= [T_1, T_2, \dots, T_n] \\
 C &= [C_1, C_2, \dots, C_n]
 \end{aligned}$$

Following a further examination of the textual data,  $x$ ,  $e$ ,  $t$ , and  $c$  were selected in this study to target education test texts, the items in the texts, feature vectors, and convolutional feature values, respectively, to serve the formulas above. An in-depth analysis of these factors was then conducted to determine their impacts on textual data. These influencing factors were also scrutinized to identify those factors that have a positive promoting effect on research, those that are not important in the research process, or those that have a negative impact on research. In this way, positive textual information can be fully utilized, while negative textual information can be avoided in the research process to maximize the effect of textual information.

### 4.3 Design of a computer teaching test database based on BERT

**Table 1.** Setting of execution parameters

Type	Setting
Number of iterations	100000
Batch Size	14
Learning rate	0.0001
Weight decay coefficient	0.997

The analysis of the above data shows that although the statistical information obtained from the experiment is related to the research content, not all information can be used in the study. Therefore, all statistical information should be shrunk and cut according to the research content to ensure the validity and representativeness of the textual data. The statistical results in Table 1 show that the data provided above can be within  $[-10^\circ-10^\circ]$ . It indicates that the information obtained earlier can not only be applied to this study but can also ensure the application of textual information in various aspects.

**Table 2.** Detection performance of different models in the ICDAR2018 dataset

Method	Precision (%)	Recall (%)	F-Score (%)
CTPN (2016)	93	83	87.7
TextBoxes (2017)	88.2	83.2	85.6
PixtLink (2018)	88.6	87.5	88.1
Liu et al. (2020)	92.7	84.1	88.2
Model	91.1	86.5	88.7

To ensure the effectiveness, applicability, and representativeness of the study, a secondary validation was conducted on the textual information in the process of textual research. The validation results are shown in Tables 2 and 3. Table 2 mainly concerns the level of horizontal text detection before 2018 and presents the evaluation and research results of the models in terms of precision, recall, and F-score. Results show that the textual data obtained in this study is more effective and feasible than the proportional results obtained in traditional text detection research. However, according to the results in Table 2, the TextBoxes algorithm accounts for 3% of horizontal text detection. Therefore, the improved results are highly scientific and effective.

**Table 3.** Detection performance of different models in the ICDAR2022 dataset

Method	Precision (%)	Recall (%)	F-Score (%)
SegLink	73.7	76.5	76.6
TextBoxes++ (2018)	87	76.8	81.7
STEN-OCR (2020)	65.2	78.5	71.8
Model	85.3	79.4	82.2

Table 3 shows that, on the one hand, this study was conducted to examine and validate textual information before 2018 and from 2018 to 2022. On the other hand, multi-directional textual information was detected and validated to provide the necessary assurance for the verification research on textual information. With the continuous development of teaching technology, data collection and analysis face an increasingly complex background. For instance, statistical image information often faces distortion, which increases the difficulty of collecting textual information. The improved model and multifaceted text detection can effectively solve these problems. Furthermore, modern information technology is fully integrated to improve the inspection and collection of textual information, facilitate the establishment of a test database for computer teaching, and ensure the collection of highly scientific and comprehensive exercises for smarter classrooms.

## 5 TEACHING CASE AND TEACHING EFFECT

### 5.1 Teaching scheme design

The proposed smarter teaching approach was applied in the teaching of “Fundamentals of Computer Application,” a practice-oriented and operation-intensive course at a university. When designing the teaching content, the teacher should fully recognize the students’ role as major players and the teacher’s role as an instructor. In other words, the teacher should not simply provide explanations without giving the students the opportunity to practice. As shown in Figure 4, the proposed smarter teaching mode is mainly divided into five teaching stages, namely, introduction of new knowledge, pre-testing of knowledge, discussion on knowledge, task-oriented training, and post-testing of knowledge.

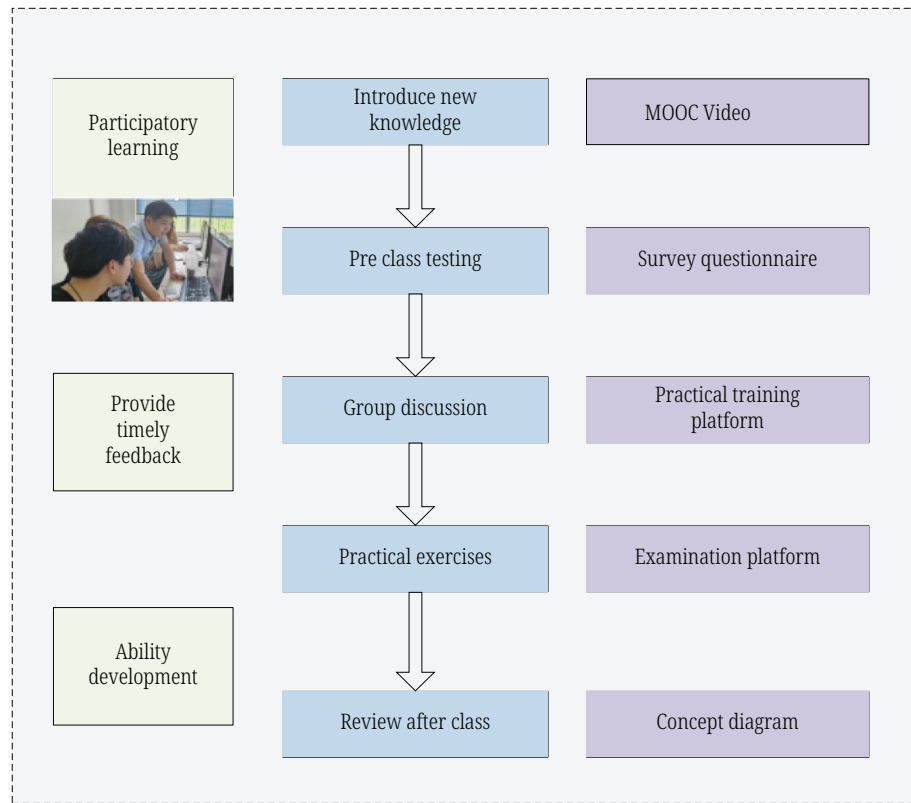


Fig. 4. Smarter classroom mode for computer teaching based on deep learning

1. Introduction of new knowledge: The teacher should closely connect not only with real-life scenarios but also with the students' previous experience and knowledge. After these students show their desire to actively explore, they will fully immerse themselves in their learning. The explanation of the design of database models emphasizes the design of management system databases that are closely related to engineering students.
2. Pre-testing of knowledge: The available methods include test questions, review questions, and group discussion reports. The setting of questions should be closely linked to the teaching objectives of the lesson. The pre-testing of knowledge can also be completed before class by distributing survey questionnaires or assigning exercises on the exam platform. Students may also be pre-tested by showing them clips from MOOC videos or reviewing their materials. Learning tasks should be incorporated into the content for pre-testing. Through pre-testing, the teacher can promptly perceive the students' existing knowledge and adjust his or her classroom teaching in a timely manner.
3. Discussion on knowledge: The discussion on knowledge can be conducted by the teacher by explaining directly or else by making the students solve the questions raised before class through group reports and other forms. This stage aims to address the key and difficult points of the lesson and highlights the importance of students' participation. The teacher should grasp the key and difficult points and seek ways to solve them efficiently. Knowledge should be presented layer by layer through progressive questions. Relevant methods and strategies can be formulated and implemented. For example, before teaching new computer technologies, the teacher can ask students to collect information about big data and AI.

4. Task-oriented training: With the help of the smarter classroom training platform, the teacher can choose or establish suitable training tasks according to the teaching objectives or assign training tasks of varying difficulty according to the students' learning abilities. The "Fundamentals of Computer Application" course covers seven themes, including the fundamentals of Python programming, the fundamentals of object-oriented Python programming, typical application problem solving, information coding and data representation, and about 80 randomly selected training tasks.
5. Post-testing of knowledge: post-testing can take the form of test questions, group discussion reports, survey questionnaires, or exams. This stage should closely correspond to the teaching objectives and highlight the key and difficult points in order for teachers to trace the students' mastery and improve their follow-up teaching. Meanwhile, students can further understand their own mastery and make up for their deficiencies. For example, database model design related to engineering can be used in post-testing for the teaching of database design.

## 5.2 Teaching effect verification

From September 2022 to December 2022, 97 students majoring in engineering at a university were randomly selected as experiment participants in the implementation of a smarter teaching mode based on a textual analysis approach. These students were divided into a control group with 48 members and an experiment group with 49 members. The teaching objectives, online education courses, and teachers for both groups were the same. These two groups were deemed comparable given that they show no statistically significant differences in terms of age or gender.

Conventional teaching methods were adopted for the control group, whereas the experimental group was given smarter resources, such as MOOC videos for "Fundamentals of Computer Application" and online exam platforms. After the course, a survey was conducted. All students in the experimental group were attracted by the novel teaching method, demonstrated a high degree of participation, and achieved good learning results. Moreover, 91% of these students clearly understood the focus and difficulties of the course. The experimental group also received significantly higher grades than the control group.

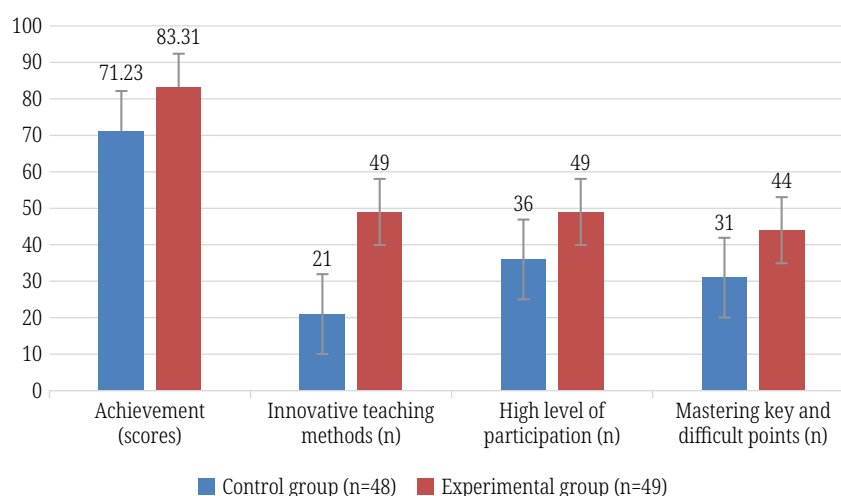


Fig. 5. Teaching effect diagram

On the one hand, from the perspective of students, the test database established based on the textual analysis approach can help them adjust their learning progress, review, and preview in a timely manner, and participate actively in teaching interactions. A smarter classroom greatly facilitates these students' acquisition of relevant knowledge, enhances their enthusiasm for learning, greatly reduces their fatigue in class, and helps them efficiently grasp and thoroughly understand relevant concepts and calculation methods. On the other hand, from the perspective of teachers, feedback information allows them to trace their students' mastery of knowledge and provide targeted reinforcement training. Students using smarter classrooms are increasing in number, thereby proving that the benefits of this teaching mode are recognized by students.

## 6 CONCLUSIONS

1. When teaching “Fundamentals of Computer Application” in universities, which involves numerous systematic knowledge points with close connections, teachers should always follow the procedure from the introduction of new knowledge to the pre-testing of knowledge, discussion on knowledge, task-oriented training, and post-testing of knowledge to enhance the students' engagement in deep learning.
2. As proven by practical testing, the smarter teaching mode supported by intelligence technology significantly improves the quality of course teaching and the students' professional skills. Attention should be paid to the students' participation and timely feedback on mastery to improve their learning effect, problem-solving ability, and academic performance.
3. The BERT-based textual analysis approach was used in this study as technical guidance to construct a test database for smarter computer teaching. On the one hand, validation research was conducted on teaching information before 2018 and from 2018 to 2022. On the other hand, textual information regarding multiple knowledge points was detected and validated to provide necessary technical support for the construction of a computer test database for a smarter classroom.

## 7 ACKNOWLEDGEMENT

Ping Zhu is the Correspondence Author. The work was supported by the Educational Science Research Planning Project of Hebei Province (No.2203213).

## 8 REFERENCES

- [1] D. Purbohadi, S. Afriani, and N. Rachmanio, *et al.*, “Developing medical virtual teaching assistant based on speech recognition technology,” *International Journal of Online and Biomedical Engineering*, vol. 17, no. 4, pp. 107–120, 2021. <https://doi.org/10.3991/ijoe.v17i04.21343>
- [2] A. M. Taj, E. Fabregas, and A. Abouhilal, “Comparative study of traditional, simulated and real online remote laboratory: Student's perceptions in technical training of electronics,” *International Journal of Online and Biomedical Engineering*, vol. 17, no. 5, pp. 33–48, 2021. <https://doi.org/10.3991/ijoe.v17i05.21949>

- [3] X. Y. Hu, Y. He, and G. Z. Sun, "A cognitive diagnostic framework for computer science education based on probability graph model," *Journal of University of Science and Technology of China*, vol. 51, no. 1, pp. 12–21, 2021.
- [4] O. M. Butt, M. Zulqarnain, and T. M. Butt, "Recent advancement in smart grid technology: Future prospects in the electrical power network," *Ain Shams Engineering Journal*, vol. 12, no. 1, pp. 687–695, 2021. <https://doi.org/10.1016/j.asej.2020.05.004>
- [5] M. K. Saini and N. Goel, "How smart are smart classrooms? A review of smart classroom technologies," *ACM Computing Surveys (CSUR)*, vol. 52, no. 6, pp. 1–28, 2019. <https://doi.org/10.1145/3365757>
- [6] R. A. Flores, C. Paolucci, and K. T. Winther, *et al.*, "Active learning accelerated discovery of stable iridium oxide polymorphs for the oxygen evolution reaction," *Chemistry of Materials*, vol. 32, no. 13, pp. 5854–5863, 2020. <https://doi.org/10.1021/acs.chemmater.0c01894>
- [7] D. R. Perry and A. K. Steck, "Increasing student engagement, self-efficacy, and meta-cognitive self-regulation in the high school geometry classroom: Do iPads help?" *Computers in the Schools*, vol. 32, no. 2, pp. 122–143, 2015. <https://doi.org/10.1080/07380569.2015.1036650>
- [8] S. Kanat, "The relationship between digital game addiction, communication skills and loneliness perception levels of university students," *International Education Studies*, vol. 12, no. 11, pp. 80–93, 2019. <https://doi.org/10.5539/ies.v12n11p80>
- [9] G. Makransky and R. E. Mayer, "Benefits of taking a virtual field trip in immersive virtual reality: Evidence for the immersion principle in multimedia learning," *Educational Psychology Review*, vol. 34, no. 3, pp. 1771–1798, 2022. <https://doi.org/10.1007/s10648-022-09675-4>
- [10] T. Kosch, R. Welsch, and L. Chuang, *et al.*, "The placebo effect of artificial intelligence in human–computer interaction," *ACM Transactions on Computer-Human Interaction*, vol. 29, no. 6, pp. 1–32, 2023. <https://doi.org/10.1145/3529225>
- [11] J. Leem and E. Sung, "Teachers' beliefs and technology acceptance concerning smart mobile devices for SMART education in South Korea," *British Journal of Educational Technology*, vol. 50, no. 2, pp. 601–613, 2019. <https://doi.org/10.1111/bjet.12612>
- [12] M. T. Machmud, A. P. Widiyan, and N. R. Ramadhani, "The development and policies of ICT supporting educational technology in Singapore, Thailand, Indonesia, and Myanmar," *International Journal of Evaluation and Research in Education*, vol. 10, no. 1, pp. 78–85, 2021. <https://doi.org/10.11591/ijere.v10i1.20786>
- [13] T. B. Song, Y. J. Chen, and Z. J. Zhu, "Comparison and comment on the application of quantitative text analysis in the field of domestic and foreign business administration," *Chinese Journal of Management*, vol. 18, no. 4, pp. 624–632, 2021.
- [14] M. A. Khan, "HCRNNIDS: Hybrid convolutional recurrent neural network-based network intrusion detection system," *Processes*, vol. 9, no. 5, p. 834, 2021. <https://doi.org/10.3390/pr9050834>
- [15] R. J. Xu and J. L. Gao, "Relation extraction based on BERT and attention-guided graph convolution networks," *Intelligent Computer and Applications*, vol. 13, no. 2, pp. 204–209, 2023.

## 9 AUTHORS

**Zhe Xu** is a Lecturer in Hebei North University, Zhangjiakou, China. Her research interests include computer networks and computer information management (E-mail: [pingzhu202302@163.com](mailto:pingzhu202302@163.com)).

**Ping Zhu** is an Associate Professor in the Hebei North University, Zhangjiakou, China. Her research interests include computer networks and computer information management (E-mail: [pingzhu202302@163.com](mailto:pingzhu202302@163.com)).