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# Development and Application of Interactive Teaching Systems for Online Design Courses

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## ABSTRACT

Digital education has recently become a mainstream education model. Despite digital education's increasing popularity, there remain issues when it comes to teacher-student interactions in digital space, which have made it impossible for this model to achieve the same teaching quality as traditional in-person education. Compared with other academic subjects, online courses in design practice have even more severe problems with teacher-student interaction. This study proposes a new teaching interaction assistance model in online design practice courses. The model uses the TAPs method to establish evaluation codes based on students' design thinking as well as through feedback-thinking related codes. This teaching interaction assistance model is established by combining these thinking codes and the LSTM model. This study takes an online design practice course as a case study, and the results have shown that this model can help teachers and students communicate more effectively and improve the teaching quality of online design practice courses.

## KEYWORDS

Digital Education, Interaction Mode, LSTM Model, Teaching Practice, Think-Aloud Protocols

## INTRODUCTION

Rapid development of digital education in the post-pandemic era has initiated a digital transformation at all levels of education—the education system has undergone a subversive change. In the wake of the COVID-19 pandemic, many studies have shown that a sustainable demand for digital education has appeared within the education system—online education has changed from a supplementary to a primary teaching method (Alraimi et al., 2015; Sandrone et al., 2021; Saw et al., 2020). The market size

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of online education grew 35.5% year-over-year in 2020 compared with 2019 (Haroon et al., 2020). Online education has also grown rapidly, with more than $16 billion in venture capital having been invested recently in the education technology domain (Rajab et al., 2020). While the market capacity of online education is expanding, the technology, design, and user interfaces which accompany it have not seen a corresponding transformation. This tremendous shift in purpose and usage poses obvious difficulties and challenges for online tutoring platforms (OTPs). Educational research shows that the relationship between teaching and learning is a dynamic process of knowledge exchange and relationship building, rather than a one-way transfer of knowledge(Craig & Savage,2014). Related studies have found that student-teacher and student-student interactions are hindered by online education, with 60% of students believing that online instructors lack clear communication and offline face-to-face interactions are more effective (Biggs & Tang, 2011; Zhao et al, 2020). A survey conducted by Missouri University of Science and Technology revealed, compared with traditional in-person education, online education often lacks both teacher-student and student-student interactions (Hokayem & Gotwals, 2016). In addition, most teaching orientations are teacher-centered in formulating teaching strategies, making it difficult to respond to the needs of students and receive their feedback. Some studies have shown interaction has a positive impact on students' academic performance and satisfaction (Beauchamp & Kennewell, 2010; So et al., 2010), and teacher-student and student-student interactions can help students gain a better understanding of the curriculum, improving the quality of both teaching and learning (Sousa et al., 2022). Despite awareness of the benefits of interaction, studies have also found the current norms of digital teaching cannot achieve the same quality as traditional classrooms due to differences in online and in-person teaching strategies, concepts, and methods (Dost et al., 2020; Williamson, 2021). There is often a discernible gap in the quality of online teaching in many disciplines compared with in-person teaching, which is especially significant among design courses owing to their usage of a one-module multistage teaching method. In design courses, it is necessary to establish evaluation points for each design stage and its corresponding product to offer a comprehensive evaluation of the project as a whole. It is also necessary to allow students to demonstrate their mastery of the material through real-time evaluation of their design ideas throughout each design stage. This method helps teachers to adjust their instruction strategies, students to develop their abilities effectively (e.g., collaboration ability, knowledge-to-skill transformation ability), and the teacher and student to clarify each other's thinking; therefore, online design courses require more frequent, more efficient, and higher quality platforms for teacher-student interaction compared with other disciplines (He, 2019; Sun et al., 2014). To reach this goal, however, there are two primary issues that need to be resolved in the current online design course framework.

## ONLINE DESIGN COURSES SUFFER FROM SEVERE INTERACTION DIFFICULTIES

Online education interaction provides a variety of functions and is an important cornerstone of online learning (Shanshan, 2014; Yan & Zhong-Wen, 2020). Online design courses are unique in that the format is not based on a strict logical system following a few prerequisites; but a more subjective, empirical, emotional, and personalized reasoning. Therefore, interaction plays a significant role in the teaching process. The teacher usually discusses all aspects of the design and then reaches a unified consensus with students. Nonverbal cues such as facial expressions and postures, which serve as expressions of personal thinking, help teachers and students understand one another's thought processes. Online courses still only create a facsimile of the interactions found in traditional teaching methods through the technical design, which is not conducive to the construction of an inquiry-based learning environment or for facilitating teacher-student interactions—ultimately reducing the efficiency of knowledge-to-skill transfer (Craig & Savage, 2014, Da-Guang & Wen, 2020). In order to confirm the importance of nonverbal cues, Craig (2014) conducted a study on the influence of teachers' attire on students. The results showed that compared with teachers wearing casual attire, students' grades and attendance improved when teachers wore formal attire (Craig & Savage, 2014). Cheng and Jiang (2015) show that online courses have varying levels of impact on students' cognitive abilities and are lower than face-to-face discourse in in-person teaching. The research also shows that nonverbal cues are helpful to students' understanding of knowledge in teacher-student communication; however, facial expressions, postures, and other nonverbal cues are not as effective through existing technologies in the online teaching environment. This study attempts to externalize the students' subjective thinking, compensate for the lack of nonverbal cues in online courses, help teachers and students better understand each other's thoughts, and enhance the interaction between teachers and students.

Where body language cannot be expressed effectively through online education modes, language has the vital role of conveying personal thinking. The TAPs method helps people express individual thought processes, and is commonly used by teachers to help them understand the interactive relationship between teaching and learning—teachers can observe students' cognitive thinking and psychological activities and educate students on how to improve their learning plans (Kosminsky et al., 2008). This study uses TAP method for online education, collects and processes personal thinking data, and presents it to teachers as an intuitive visual diagram to help teachers obtain students' thinking activities, thus enhancing the interaction between teacher and student.

## ONLINE DESIGN COURSE INTERACTION MODES ARE IMPERFECT

The modes of interactions in an online course consist of three primary components: 1) participation, 2) communication, and 3) feedback. Feedback is established via participation and effective communication. It is the driving force that constitutes the ability for students and teachers to self-regulate, which in turn facilitates the development of deep learning. Effective feedback between teachers and learners is the key to successful learning. Current design online courses suffer from a lack of feedback in their interaction models. Related research has confirmed that personalized feedback is difficult to achieve in online education (Nicol, 2010). Because design courses are inherently creative, there is a necessity of constant on-going evaluation and self-evaluation. Design achievements are synthesized from the components of each stage of development, such as concept generation and preliminary planning. Obtaining student feedback during the design process is an important part of design guidance; it helps teachers to fully consider the students' mastery of design techniques. At the same time, it helps students establish good self-regulation and evaluation skills; therefore, online design practice courses need sufficient student feedback to improve their interaction models, to ensure that when teaching at each design stage, teachers have a clear idea of the skills and knowledge that each student has acquired previously. Increased feedback can also help teachers interact with students deeper throughout the design process. The actual teacher-student interaction models currently found in online courses, however, are characterized by one-way feedback given by teachers to students, and two-way feedback between teachers and students is lacking. Without feedback, the teacher has no way of knowing whether the student has made the appropriate modification after receiving guidance. Design courses need to fully account for student feedback in order to improve teacher-student interactions and ensure that teachers have a clear understanding of each student's knowledge and ability throughout each step of the design process.

## PRESENT EVALUATION MODEL

Gong et al. (2020) collected the behavioral data of teachers and students engaged in traditional classroom teaching, made cross-judgments on multi-source data, and then introduced a completely random number algorithm and a transformation regression model to regularize the classroom data and build a prediction model. Zhang (2014) analyzed the new teacher-student relationship in the network environment, and after analyzing the current situation of this relationship, proposed the establishment of an equal and interactive teacher-student relationship in the network environment. He then discussed how teachers and students can use these findings to adapt and develop their relationship in online learning settings. Chen et al. (2021) based on using virtual office hours (VOH) to enhance teacher-student interaction and used principal component analysis (PCA) to separate and conduct early interventions or provide prior guidance for students in weaker behavioral groups. The analysis of learning behavior and preferences in the above research focuses on students' external behavior trajectories including their active learning time period, learning resources, average learning level, number of completed learning resources, completion level of homework, number of course topic discussion posts, and course topic discussion number of replies. The study of external behavior cannot fully reflect the cognitive thinking of students, especially for design courses, which show strong preferences for subjective thinking and evaluations. Nevertheless, changes in the development of students' cognitive thinking have an important impact on final learning outcomes.

At present, scholars' research on online education platforms focuses on the use of the graph convolutional neural network (GCNN), artificial neural networks, and other methods to build models to analyze learning behavior and preferences, learning trajectory, and time spent online, among other factors. He constructed a teacher-student interaction preference feature model based on the GCNN and a teacher-student interaction relationship model based on multi-task learning. Cao (2022) believed that existing similarity correlation discovery methods used, clustering results in their algorithms, would lead to large amounts of noise in the teacher-student interaction data. Cao (2022) used a normal distribution method to classify the relationship between teachers and students, described the calculation process of the fitness of teacher-student interaction, and used an artificial neural network (ANN) and genetic algorithm (GA) to identify how to create synergy between online and in-person teaching. The research on the external behavior trajectory, however, cannot fully reflect the student's cognitive thinking situation. Especially for the design of courses with strong subjective favor, the development and change of students' cognitive thinking have an important impact on the final learning outcomes.

## REVIEW OF RELATED WORKS

To solve the issues related to low-quality online interactions between teachers and students in design courses, this study proposes to build an intelligent teaching interactive assistance system by combining the LSTM and TAPs methods. The following is an introduction to both the LSTM method and the TAPs method.

### Research Method

#### *Long Short-Term Memory (LSTM)*

LSTM was originally designed to resolve the problem of text sentiment analysis in natural language processing (NLP). The three mainstream methods for text sentiment analysis using machines are: 1) sentiment analysis based on a sentiment dictionary, 2) sentiment analysis based on traditional machine learning, and 3) sentiment analysis based on deep learning. The sentiment classification method based on deep learning can make full use of the contextual information of a text—it can actively learn features of the text and retain the order information of the words in the text, so as to extract semantic information of related words to identify the sentiment classification of the text. The deep learning network provides key information which reveals further characteristics of the data thereby improving learning performance. Compared with the traditional method, the language model pre-training method makes full use of a large-scale monolingual corpus, which can help to model the polysemy of words, effectively alleviating the problem of dependence on model structure. Sentiment analysis methods based on deep learning are conducted using neural networks. Typical neural network learning methods are the convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) network, among others.

The main issue with RNN is that of gradient disappearance or gradient explosion, and the accuracy of GRU calculation is inferior to that of LSTM. LSTM was first proposed by Hochreiter & Schmidhuber (1997) to solve the problem of gradient disappearance or gradient explosion in RNN.

For the gradient disappearance problem, LSTM introduces a gate mechanism. For the problem of short-term memory covering long-term memory, LSTM uses a cell state to save data in the long-term memory and then selectively filters and transmits information through the gate mechanism, so as to invoke information from long-term memory when reasonable. Based on the advantages listed above, this study preferentially selects the LSTM neural network with the highest accuracy as the implementation method for this study's automated text sentiment analysis.

This study is based on a LSTM Python algorithm for model building, which refers to a structure that cycles over a time series, as shown in Figure 1 where $h_{t-1}$ is the output of the previous layer, $C_{t-1}$ is the information of the previous LSTM structure, $h_t$ is the output, and $C_t$ is the information of the LSTM structure.

### *Think-Aloud Protocols*

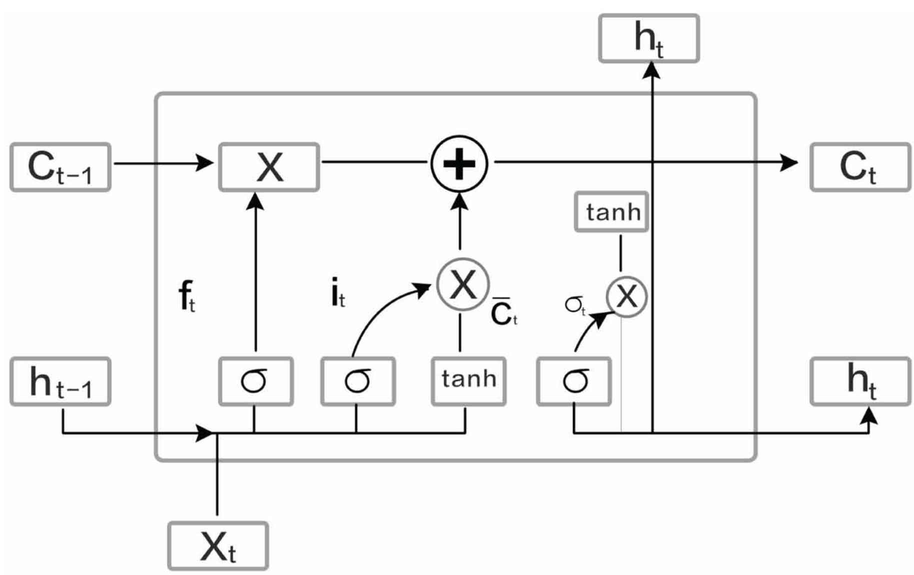
Think-aloud protocols (TAPs) are metacognitive instructional strategies, which can improve students' problem-solving processes. When students share their thought processes while solving problems it helps them focus on the problem at hand and enables teachers to understand students' thinking. This is beneficial to teachers' for providing feedback and also for the students' learning outcomes (Wilson & Smetana, 2009; Pate, M. & Miller. 2011). TAPs are used in this study to help students speak their minds. The advantage of the TAPs method is that it can be used to communicate the characteristics of people's immediate psychological strategies and knowledge representation through external speech. By externalizing the thought processes of students, teachers can gain insight to students' internal mental processes that cannot be directly observed. TAPs are ideal for promoting the deep interaction between teachers and students, and for promoting the improvement of the interactive components of design online courses.

This study proposes to use the cognitive psychology method TAPs combined with the LSTM algorithm to develop a teaching interactive assistance model written in Python, with the objective of building an online intelligent teaching assistance system.

## METHODOLOGY

Coding is an operational process that deconstructs collected or translated textual data, identifies phenomena, conceptualizes phenomena, and then re-abstracts, promotes, and integrates concepts into categories and core

**Figure 1. LSTM Structure (Note: Structure cycle over time)**



categories in an appropriate way. In this study, coding is divided into design thinking coding and feedback coding. Design thinking coding analyzes students' design thinking process, and feedback coding analyzes students' thinking about the application of teacher guidance information after receiving such guidance.

## Design Thinking Coding

Design thinking is divided into the cooperative and mutually beneficial categories of analytical and creative thinking (Baer, 2003; Goldschmidt, 2016). There are three specific stages within the design process: 1) analysis, 2) synthesis, and 3) evaluation (Kim & Ryu, 2014). The synthesis stage is influenced by creative thinking, while the analysis and evaluation stages are impacted by analytical thinking. When initiating a new design process, designers analyze the scope of the design through user research (i.e., problem framing), then use their creative ideas to generate and synthesize solutions (i.e., problem solving), and finally evaluate the results (i.e., evaluation) (Alexander, 1964). These three stages repeat in a cycle until a final solution is reached (Wong & Siu, 2012).

Coding for design thinking is also based on these three stages. The analysis stage is the design preparation process, which focuses on collecting relevant information on design topics not limited to market research, competitive product analysis, related technologies, product shapes, colors, and materials. Next, design problems are broken down into several classes or subproblems—these subproblems are the constraints (Kolodner & Wills, 1993; Jones, 1992). Speech with such representation can be included in the analysis phase of coding. The synthesis phase is a compounding activity to brainstorm ideas in order to create new design solutions, which can include verbal agreements to express new ideas, developments in dictation, adding or changing features in the design, linking to other examples, and inspiration for idea development. The evaluation stage involves designers evaluating their own design proposals and clarifying the language to express preference for a function, shape, material, and structure (Dahiya, & Kumar, 2021).

This research is based primarily on the design thinking code proposed by Dahiya, & Kumar (2021), although contributions from similar codes have been added to form the current design thinking code as shown in Table 1. The following lists the oral cases and corresponding codes for the three stages of analysis, synthesis, and evaluation:

- **Analysis phase example:** "My idea is to design a household vacuum cleaner for the elderly, because the elderly may have arthritis and other physical inconveniences, so household cleaning may be difficult for them." This sentence describes that it is difficult for elderly people to clean their homes due to their physical problems. This is a design pain point, so it is classified as a collection design requirement (CDR) in the analysis phase.
- **Synthesis phase example:** "The vacuum cleaners on the market today are single-sided." This describes the design problem that needs to be solved and is classified as a referring existing design (RED) solution. "The existing product is one-piece, I think the section below the vacuuming part can be improved, the area can be increased, and the handle made more manageable." This sentence provides innovative solutions, so it is classified as creating a new solution (CNS) in the synthesis stage.
- **Evaluation phase example:** "The guard plate could be replaced with a guardrail, but the guardrail has a low safety factor." This sentence compares design proposals and therefore belongs to comparing solutions or design features (CSF) under evaluation.

## Feedback Coding

There is a strong correlation between online learning, feedback, and self-regulation (Fernández-Michels, & Fornons, 2021). High-quality feedback, both direct and indirect, can help learners strengthen their self-regulation ability, resulting in a positive impact on learning. Direct feedback, a

**Table 1. Design Thinking Coding**

| Coding | Abbr. | Coding Definition | Example |
|---|---|---|---|
| Analysis | CDR | Collection design requirements | Describe design pain points. |
| | RDR | Referring design requirements | Problems that should be solved in response to design pain points. |
| | RED | Referring existing design solutions | The current design has not solved the problem that still exists. |
| Synthesis | CNS | Creating a new solution | Propose a solution. |
| | ANF | Adding a new feature to design | What specific structures and functions are used to solve design problems? |
| | AEC | Altering an earlier created solution | Change of previous program. |
| | EI | Explaining the idea | Extension ideas (e.g., "this is also possible.") |
| Evaluation | CSF | Comparing solutions or design features | Compare each design feature. |
| | JPS | Justifying a Proposed Solution | Compare solutions. |
| | AES | Altering an earlier created solution | This solution better than that one. |

more intuitive methodology, notes the correct answer alongside the error (Bitchener & Knoch, 2010; Nassaji, 2015). Indirect feedback notes a wrong answer next to a correct one, thus cultivating reflective, in-depth, and autonomous learning. Most design courses do not have a standard fixed answer or goal to guide student design in an appropriate direction. This research model uses an indirect feedback strategy to evaluate student work. Fernández-Michels & Fornons (2021) divide feedback coding into eight categories: 1) orientation, 2) information seeking, 3) identification, 4) correction, 5) reflection, 6) intention, 7) self-judgment, and 8) feedback evaluation. The detailed definitions are shown in Table 2.

Scholarly categorization of self-regulation coding strategies, depicted in Table 3, is divided into three categories: 1) intention, 2) reflection, and 3) self-judgment. Various scholars have created definitions for the three categories (Pedro, 2021). The present study selects the definitions of Pintrich (1991), shown in Table 3, as the basis for feedback coding because it is like design behavior (i.e., problem definition, problem-solving, evaluation). Two routines for identification, feedback, and evaluation are added to make the feedback coding more complete. The final coding diagram is shown in Table 4.

**Table 2. Feedback Coding Detail Definitions**

| Coding | Definition |
|---|---|
| Orientation | The learner collates information such as counting the number and type of errors. |
| Information Seeking | The learner collects further information about the flagged errors such as finding the correct form and extending the information. |
| Identification | The learner is shown to identify correct or incorrect feedback. |
| Correction | The learner changes or does not change the wrong place; the change succeeds or does not succeed. |
| Reflection | The learner's utterances indicate reflective behavior such as thinking about the cause of the error, commenting on the rules related to the error, and making assumptions about the nature of the error. |
| Intention | The learner expresses the intention to correct mistakes by repeating a specific language point, looking for information related to mistakes, and trying not to repeat mistakes. |
| Self-judgment | The learner makes judgments about self-performance, the number and nature of errors, and knowledge. |
| Feedback evaluation | The learner judges the quality or usefulness of the feedback received. |

**Table 3. Basic Coding Definitions**

| Coding | Duncan et al. (1991) |
|---|---|
| Intention | Help seeking |
| Reflection | Critical thinking;<br>Elaboration |
| Self-judgment | Self-appraisal |

**Table 4. Feedback Coding**

| Coding | Abbr. | Coding Definition | Example |
|---|---|---|---|
| Identification | IE | Identifying errors | Finding the shortcomings of the previous sketch. |
| Intention | HS | Help seeking | Finding the technical, material, or structural basis for the modification. |
| Reflection | CT | Critical thinking | Thinking about the solution. |
| | EL | Elaboration | Refine the solution. |
| Self-judgments | SA | Self-appraisal | Self-assessment of the performance of a solution or a functional component. |
| Feedback evaluation | FE | Feedback evaluation | The learner's evaluation of the feedback. |

# CONSTRUCTION OF AN ONLINE INTELLIGENT TEACHING ASSISTANCE SYSTEM

## Construction of the Teaching Interaction Assistance Model

The teaching interaction assistance model is an important part of the online intelligent teaching assistance system, which evaluates and analyzes student reflection activities. It is constructed using the TAP method and the LSTM algorithm, using Python programming language.

The LSTM text sentiment classification model is shown in Figure 2. The words in the text are split into word vectors and mapped one by one. Each word vector is fed into a single LSTM class neuron for processing. Output result is used as the reference input for the next word vector neuron, which is analyzed word by word, transmitted layer by layer, and then filtered by the classifier. Finally, the judgment of the entire sentence is formed.

The main construction process of the teaching interaction assistance model can be divided into three steps: 1) learning sample construction, 2) model building, and 3) automated output.

For modeling accurate student feedback, each feedback sample receives a score and then a maximum value and a minimum value are removed and the average value of the remaining sample is taken. The category is determined according to the score interval. There are 1500 samples (each coding is a sample) in the training set, which are divided into six categories, and 01 coding is carried out for each category, as shown in Table 5.

The learning rate of the training design is 0.01, the forgetting rate is 0.1, the number of neurons in the hidden layer is 150. The maximum number of iterations is 1000, the minimum batch is 50, and the gradient threshold is 0.1. The effect after training is shown in Table 6. Selecting the training output summation of six training samples, the actual 01 code corresponds well to the LSTM output training probability and 01 code, less errors. After the output converter, the category can be accurately identified as shown in Table 6.

LSTM training convergence shows the training fitting is accurate as shown in Table 7. The mean square error, the mean absolute error, and the mean deviation is 0.028, 0.06, and 0.008, respectively.

Figure 2. LSTM Text Sentiment Classification Model

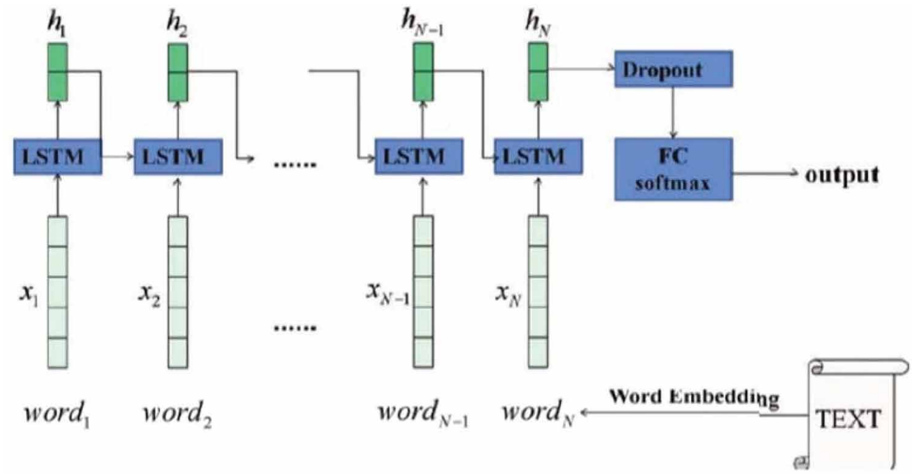



Table 5. Coding Chart

| Coding | Abbr. | Basis of Coding | 01 Coding |
|---|---|---|---|
| Identification | IE | Identifying errors | 1 0 0 0 0 0 |
| Intention | HS | Help seeking | 0 1 0 0 0 0 |
| Reflection | CT | Critical thinking | 0 0 1 0 0 0 |
| | EL | Elaboration | 0 0 0 1 0 0 |
| Self-judgments | SA | Self-appraisal | 0 0 0 0 1 0 |
| Feedback evaluation | FE | Feedback evaluation | 0 0 0 0 0 1 |

Table 6. LSTM Training Output

| Sample No. | Category | 01 Coding | LSTM Training Output | Main Output Category |
|---|---|---|---|---|
| Sample 1 | IE | 1 0 0 0 0 0 | 0.982 0.025 0.031 0.017 0.062 0.013 | 1 |
| Sample 2 | HS | 0 1 0 0 0 0 | 0.012 0.091 0.005 0.036 0.090 0.021 | 2 |
| Sample 3 | CT | 0 0 1 0 0 0 | 0.162 0.002 0.996 0.035 0.016 0.011 | 3 |
| Sample 4 | EL | 0 0 0 1 0 0 | 0.008 0.018 0.013 0.981 0.025 0.037 | 4 |
| Sample 5 | SA | 0 0 0 0 1 0 | 0.059 0.046 0.028 0.027 0.098 0.069 | 5 |
| Sample 6 | FE | 0 0 0 0 0 1 | 0.001 0.001 0.023 0.002 0.087 0.953 | 6 |

The quality of fit is 0.0983. The LSTM model is successful in modeling students' feedback emotion and indicates the LSTM training model's accuracy.

Figure 3 is a comparison diagram between the actual categories in the LSTM training set data and the LSTM training output. The black asterisk represents the actual categories, red circles represent the actual output of LSTM. Figure 3 show that categories IE, CT, EL, SA and FE have the highest classification accuracy, while HS has the worst classification accuracy. The reason may be that the technical, material, and structural basis for the modification of the scheme is similar during the identification scheme process; therefore, some HS was wrongly classified as CT, and the overall recognition accuracy was 98.4%.

**Table 7. LSTM Training Evaluation Parameters**

| Name of Parameter | Formula of Parameter | Parameter Value |
|---|---|---|
| Mean square error | $\sum\left(predict-actual\right)^2 / n$ | 0.028 |
| Mean absolute error | $\sum\left\|predict-actual\right\| / n$ | 0.016 |
| Mean variation | $\sum predict-actual / n$ | 0.008 |
| R-squared | $1-\left(predict-actual\right)^2 / \sum\left(actual-\right)^2$ | 0.983 |

Figure 4 is the training classification error diagram, which can accurately show the distribution of errors. Errors are concentrated in the CT part, and the errors are mainly equal to plus or minus 1, indicating that adjacent categories are easily misidentified.

Figure 5 is the training confusion matrix. It shows the IE has 250 samples with 100% classification accuracy. HS has 254 samples, among them, 233 samples are accurately classified. Twenty-one samples are misclassified in total, of which 17 samples are misclassified as CT, 3 samples are misclassified as EL, and 1 sample is misclassified as SA. The classification accuracy rate of HS is 91.5%. CT, EL and FE are classified with 100% accuracy. The sample numbers are 244, 264, and 233, respectively. SA has 256 samples in total. Among them, 251 samples accurately classified, 1 sample is misclassified as IE, 1 sample is misclassified as HS, and 3 samples are misclassified as EL. The accuracy rate of SA is 98%. The overall classification accuracy is high with an accuracy rate of about 98%. The HS classification accuracy is lower than other parts, which indicates the definition of HS needs modification.

**Figure 3. LSTM Training Effect Picture**

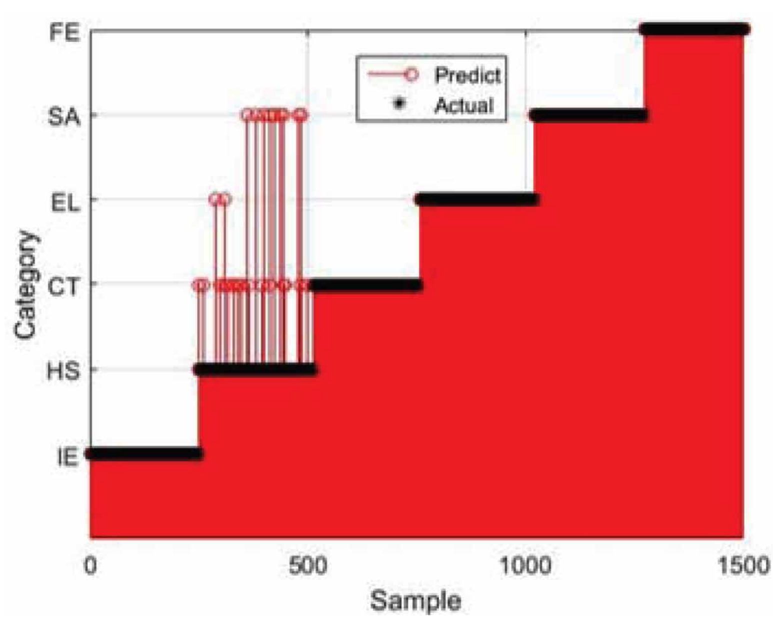


**Figure 4. Training Classification Error Diagram**

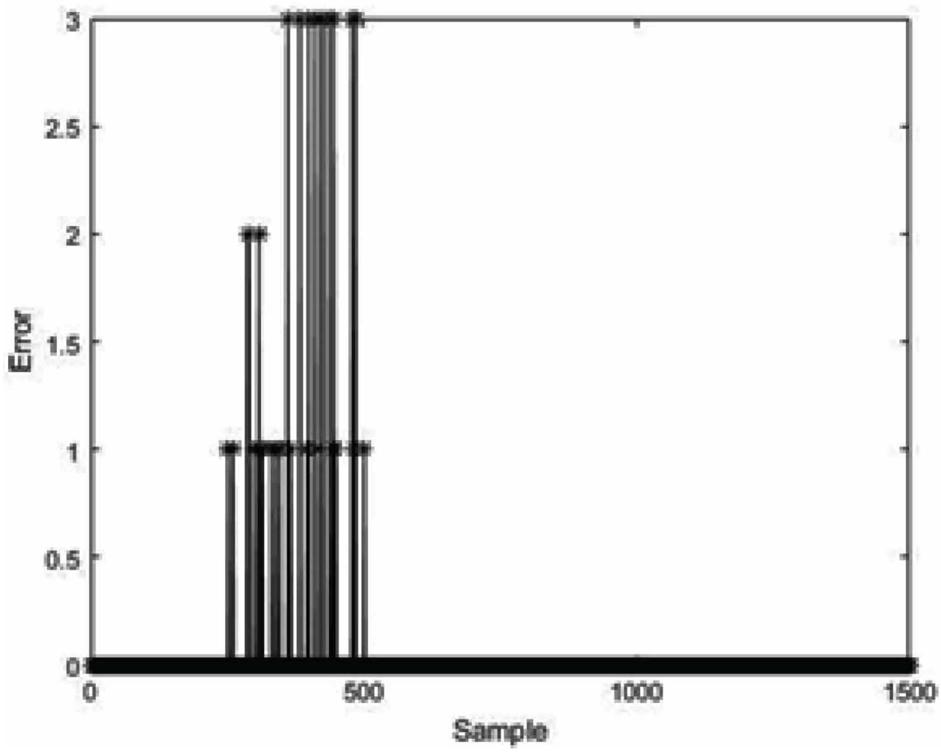
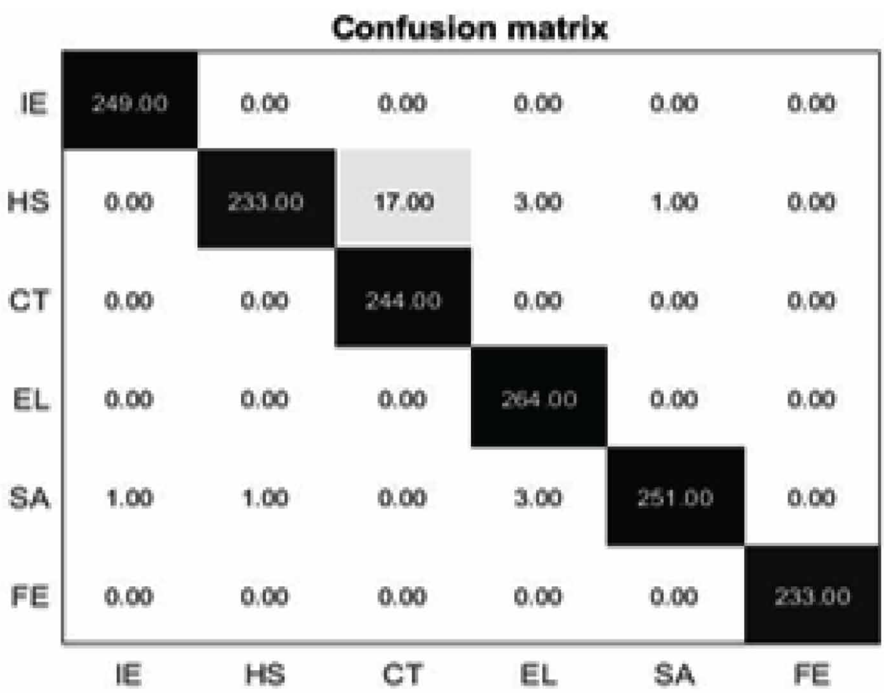



**Figure 5. Training Classification Error Diagram**



The confusion matrix of validation set is shown in Figure 6. It can be seen from Figure 6 that IE, CT, EL, SA and FE samples are 43, 5, 41, 46, and 57, respectively, and their accuracy is 100%. HS had 254 samples. There are 59 samples accurately classified, 3 samples are misclassified as CT, 1 sample is misclassified as IE, and 1 sample is misclassified as SA. A total of 5 samples are misclassified with an overall accuracy rate of 91%. The accuracy rate of HS is lower than other parts. The HS category needs to be improved. Through the above training, the teaching interaction assistance model was formed, as shown in Figure 7.

### Constructing Supporting Functions of the Teaching Assistance System

The research uses the Python programming language to develop a set of online intelligent assistance teaching systems based on the teaching interactive assistance model. The system is used to obtain the results of students' thinking activities, to assist teachers in formulating corresponding guidance strategies, and to help students and teachers conduct online activities. The system is divided into a teacher login terminal and a student login terminal. The teacher login terminal includes three parts: 1) learning statistics, 2) course space, and 3) notifications. The course space includes past courses (i.e., course history) and course lists. The subfunctions of the course list are divided into four parts: 1) course construction, 2) course notification, 3) student management, and 4) course sharing. Course construction consists of unit study, student study, course resources, and course activities. Homework management, acquisition of student cognitive activities, and question-answer portions are all included in this part of student learning. After logging into the student side, two modules of study records and homework from My Study can be accessed. The study record contains all relevant information pertaining to current and past courses. Teacher feedback can be viewed in the homework section,

Figure 6. The Confusion Matrix of Validation Set

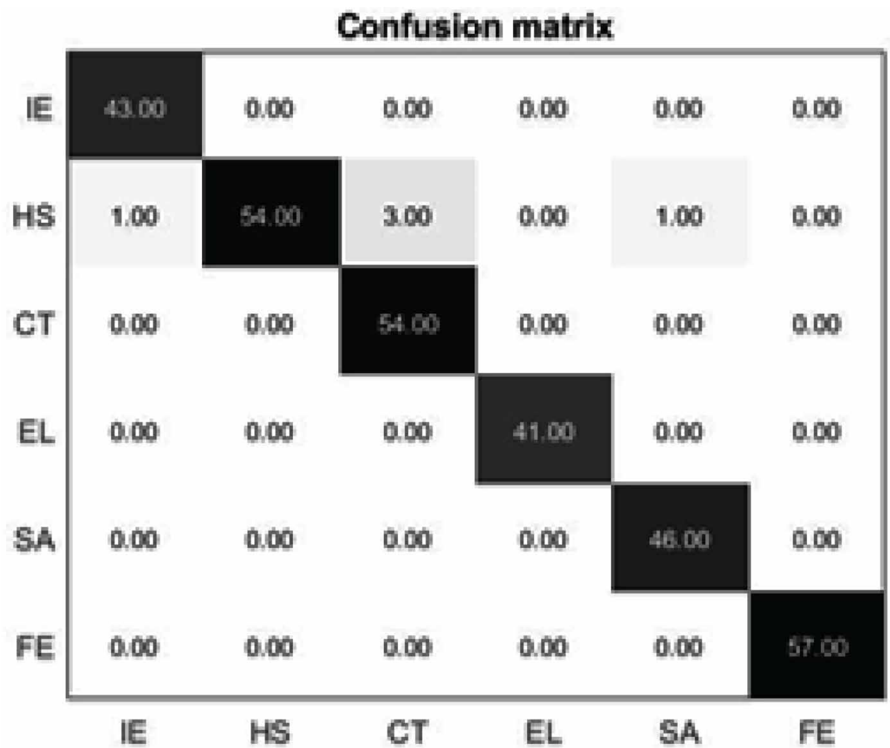
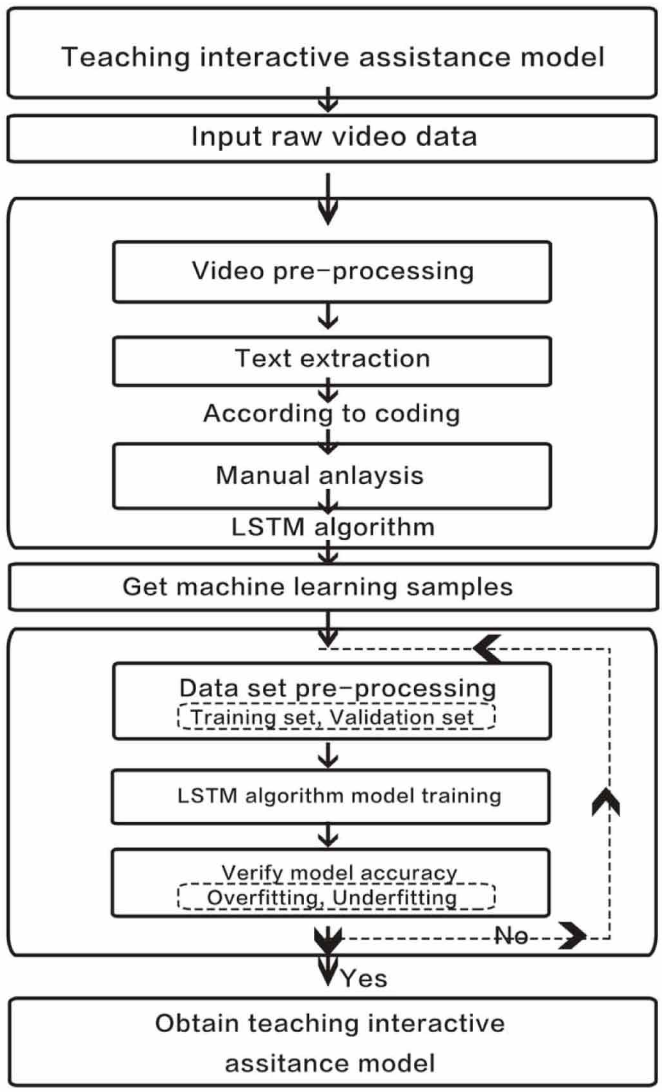


Figure 7. Teaching Interactive Assistance Model




which includes revision and discussion components. The specific process is shown in Figure 8. Figures 9 and 10 show the teacher operation interface and the student operation interface, respectively.

## EXPERIMENTATION

The generation of cognitive thinking in design is closely related to design thinking. Design thinking can be described as the process of the externalization of abstract thought, which also represents the process of design scheme development. Keeping these foundational assumptions in mind, the research takes the concept divergence (design sketching) chapter of a 2022 online design course as the experimental object. The subjects were 30 third-year university students majoring in product design. The research team conducted a single-group pre- and post-experiment with a threefold purpose: 1) to understand whether teachers could use the system to evaluate student cognitive thinking both before

**Figure 8. Flow Chart of Intelligent Assistance Teaching System**

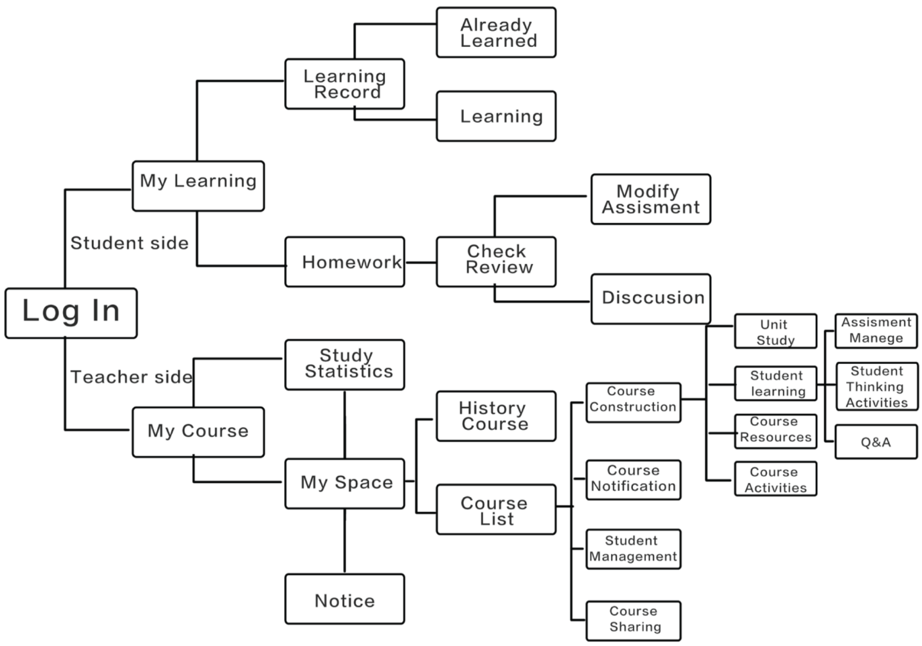



**Figure 9. Teacher Terminal Interface**

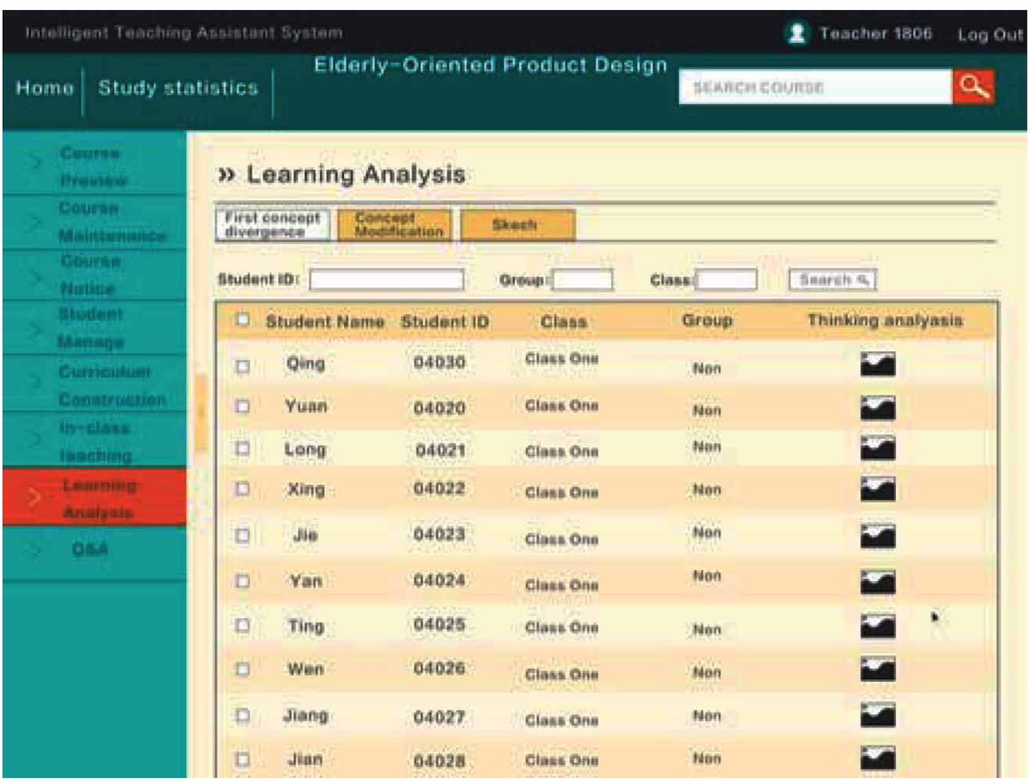
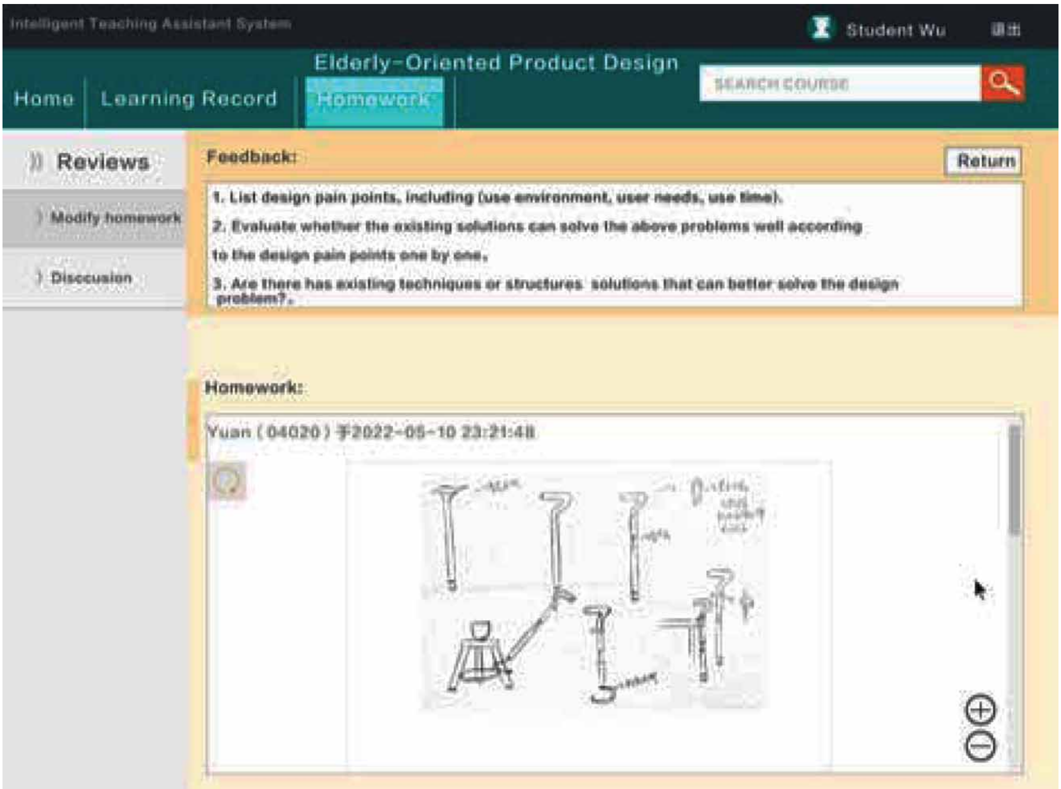


Figure 10. Student Terminal Interface




and after using the teaching interactive assistance system, 2) to improve teacher-student interaction, and 3) to enhance learning outcomes.

## The Experimental Process of Teaching Evaluation

To solve the problems of deep interaction between teachers and students and the imperfect interaction mode of online courses, this study proposes a set of one-module multi-stage teaching evaluation experimental processes for designing online courses, as shown in Figure 11.

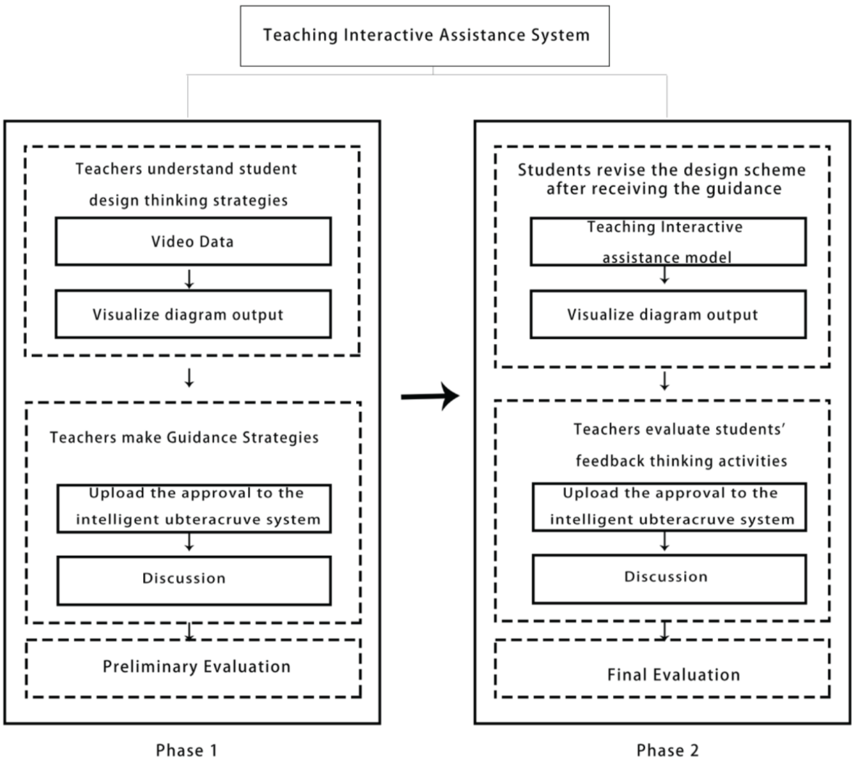
The first stage is the pre-test experiment. The pre-test experimental tool uses the original platform of the school network for teachers to teach the course content and students to communicate with students. The experiment is first administered by teachers for two class hours (one class hour is 45 minutes), and then students test and draw. In the preliminary design scheme, teachers will conduct an assessment according to the students' design scheme.

The purpose of the second stage is to gain understanding of students' feedback thinking as a post-test experiment. The post-test is administered using the original platform of the school network and the online intelligent assistance system.

## The Experiment Divided Into Two Steps

**Step 1:** The teacher leads two classes (45 minutes each). The students then describe the design ideas while drawing the design plan and recording the design thinking video. They then upload the video to the interactive assistance system, use the system to convert it into the corresponding design thinking code, and present it to the teacher in the form of a code map through a visualization

Figure 11. Teaching Evaluation Experiment Flow Chart




program. Finally, teachers formulate guidance strategies and upload them to the teaching assistance system, simultaneously providing verbal guidance to students.

**Step 2:** Students revise the plan after receiving the teacher's guidance. They describe the revision ideas, record a video, and upload it to the interactive system. The interactive assistance system obtains student feedback thinking on the teaching plan and transfers the feedback thinking to the teacher through visualization. The teacher then grades the student design results. The visual coding map of student feedback thinking can help teachers understand student ideas and improve their own programs.

## Design Scheme Scoring Criteria

To understand whether the intelligent teaching assistance system is effective in facilitating teacher-student interaction, this study invited five design faculty members with more than five years of teaching experience to form a panel of experts. This panel used the nonquantitative scoring criteria for design outcomes proposed by Li.et al. (2020) and set the weight of the scoring criteria. The panel used the combined comprehensive scoring method to separately assess the learning outcomes of 30 product design students participating in this online design course at two stages, the initial and final assessments. The comprehensive scoring method first scores each evaluation index according to different evaluation standards and then uses a weighted sum to obtain the total score. It is divided into four steps: 1) determining the evaluation items, 2) determining the evaluation criteria and grades (see Tables 8 and 9), 3) developing the rating scale to include all evaluation indicators and grade distinctions, 4) and calculating the score values based on the indicators and grades.

**Table 8. Design Outcomes Evaluation Standard**

| | Content and Weight of Evaluation Criteria | | | | |
|---|---|---|---|---|---|
| Design outcomes evaluation standard | Ability for basic knowledge of the course (0.1). | Does not have basic knowledge. | Poor application of basic knowledge. | Basic application. | Skilled application. |
| | Ability to execute the skills and use design tools required for design (0.2). | Does not have basic ability. | Poor application of basic design tools. | Basic application. | Skilled application. |
| | Ability to integrate design knowledge and technology (0.4). | Does not have ability to integrate. | Poor application of integrate ability. | Can sort out the design knowledge basically. | Proficient in integration and application. |
| | Ability to identify, analyze, and respond to complex design problems (0.3). | Does not have the ability to explore design issues. | Poor application of explore ability. | Able to find design problems independently. | Identify, analyze, and classify design problems well. |

**Table 9. Evaluation Standard Corresponding to the Quantitative Score**

| Evaluation Standard | Quantitative Score |
|---|---|
| Does not have ability | 0.25 |
| Poorly applied | 0.5 |
| Basic application | 0.75 |
| Proficient or good application | 1 |

## RESULTS AND ANALYSIS

### Pre-Test Scores

The study was based on the evaluation criteria of the comprehensive scoring method and the quantitative score scale. The expert group evaluated the student first-stage design schemes in terms of mastery of basic course knowledge; ability to execute the required skills and use design tools; ability to integrate design knowledge and techniques; and ability to discover, analyze, and respond to complex design problems according to the quantitative scores (see Table 13 in Appendix A). The overall assessment of student first-stage design outcomes was obtained by combining the quantitative scores of the five teachers in the expert group and then taking the weighting average, as depicted in Table 7.

### Post-Test Scores

Using the intelligent teaching assistance system, educators can evaluate the design thinking divergence stage on the teachers' side. At the same time, the visual chart of student design thinking coding can be used to interpret the correlation between student design thinking and design results. According to the cognitive activities of each student in the first stage and the overall evaluation of the total design results of the class, a teaching program is generated. Additionally, guidance strategies for design suggestions are proposed one by one according to any respective lack in student cognitive activities. This research is based both on the revised schemes that students obtain from teacher guidance and on suggestions from the intelligent teaching assistance system. At this stage, the expert group first quantifies the design schemes, then integrates the quantified scores of the five teachers in the expert group to obtain the final grade of the students following the weighted average (see Table 14 in Appendix B).

## Experiment Results

### *Case Study of Student Design Thinking Activities*

In the post-test experiment, 30 preliminary plans were collected from students. At the same time, students uploaded videos to the designated page through the intelligent teaching interactive assistance system. Teachers had access to the design thinking coding visualization chart of students in the divergent stage of design thinking on the teacher side of the intelligent teaching interactive assistance system, as shown in Figure 13.

Teachers could also obtain visual charts of student design thinking coding on the teacher side of the smart teaching interactive assistance system, as illustrated in Figure 14. The visual diagram of the student design thinking activity and the preliminary design sketch (see Figure 12) show that the design thinking of Case Student 1 is reflected in the design pain point description (CDR) to the proposed concrete solution (ANF) section. This student completed the process from design problem formulation to design solution sketch. However, the conclusion of the student's design thinking activity revealed that their thought patterns modified the AEC schemes, and that the evaluation (AES) component was missing. This finding indicates that the student did not proceed with program modification, comparison, and evaluation between design schemes. This result shows a lack of advanced activity in terms of this student's design thinking. The basic elements of design thinking include generation, exploration, comparison, and selection. Generation and exploration expand the problem space, whereas comparison and selection narrow the solution space. When expanding a problem, solutions are generated and examined for the relationship between solutions, schemes, and targets. Then, during the iterative process, new solutions can be modified or developed to attain the best results. If students omit this section of the activity, the final design outcome is affected. So, the teacher provides the design guidance to the student base and uploads the guidance to the teacher side of the intelligent teaching assistance system (see Figure 14), adhering to the following process: 1) list out the design pain points, 2) evaluate whether the existing solutions are effective at resolving the above problems according to the design pain points one by one, and 3) determine whether the existing solutions have other technologies or structures that can better solve the pain point problems.

### *Case Study of Student Feedback Thinking Activities*

This study was conducted to understand whether the students adopted the teacher's strategies well in the process of revising their design scheme and to evaluate whether the design thinking activities based on the feedback activity codes during student revision of design solutions could be obtained from the intelligent teaching assistance system, as shown in Figure 13. Students are clearly informed of teacher instructions and modifications to the design scheme through the design process. The teacher can also select the type of coding to view student activity in a particular range. The figure shows the feedback thinking activity for Case Student 1, where the student completed a thinking activity that included identifying the inadequacy of existing schemes (IE) and ended with evaluating multiple existing schemes (SA). Students were encouraged to first reflect on the design problem. Then, they proposed design schemes based on the design problem one by one. After completing a scheme, they evaluated it for reflection. The students repeatedly performed the above feedback thinking activities and eventually obtained the best solution to the design problem in the solution evaluation process (see Figure 14). Case Student 1's activity confirms that good feedback can help learners strengthen self-regulatory skills.

## Experiment Results Analysis

The Statistical Product and Service Solutions (SPSS) was used to conduct paired sample t-test on the pre-test and post-test scores to analyze the differences between the two groups of samples. Table 10 shows the paired sample statistics. The mean scores of the pre-test and post-test are 77.47 and 83.57, respectively. Compared with the pre-test, the average score of the post-test is improved. Table 11 shows the correlation detection of paired samples, in which the correlation between the pre-test

**Figure 12. Obtain Design Thinking from Case Student 1**

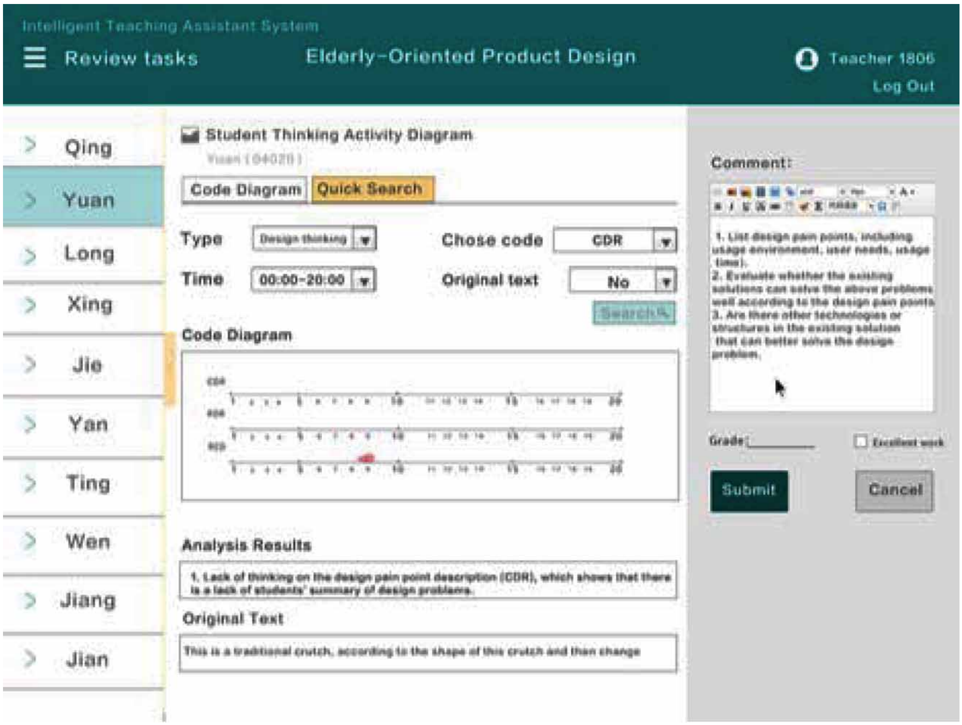



**Figure 13. Obtain Feedback Thinking from Case Student 1**

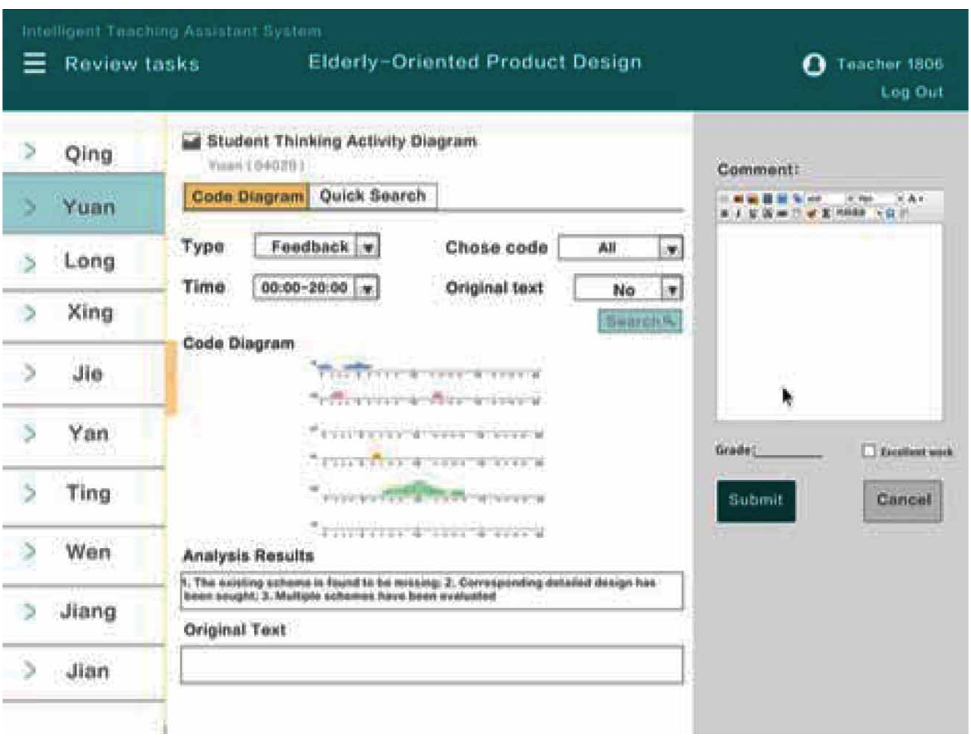
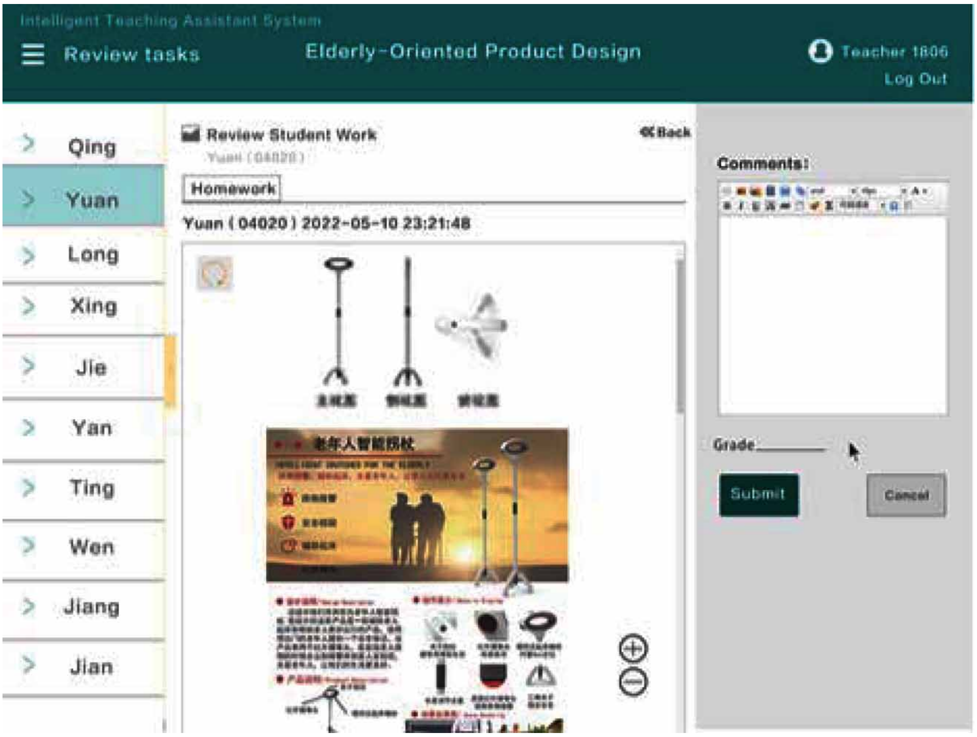


Figure 14. Final Design Outcome of Case Student 1




score and the post-test score is 0.838, The p-value corresponding to the t-test statistic of correlation coefficient test is 0.000 < 0.05, This indicates that there is a significant positive correlation between them at the significance level of 0.05. Table 12 shows the test of paired samples. According to the t-test of paired samples, the mean range between the pre-test score and the post-test score is -6.100, The p-value corresponding to the t-test statistic is 0.000 < 0.05, This indicates a significance level of 0.05. The mean range between pre-test scores and post-test scores is significant. The post-test score was 6.100 points higher than the pre-test score.

The results of SPSS analysis show that the average score of students significantly improved after using the teaching interactive assistance system. The experiment's results show that the system can help teachers and students interact with each other.

Table 10. Paired Samples Statistics

| | | Average Value | Number of Cases | Standard Deviation | Standard Error Mean |
|---|---|---|---|---|---|
| Paired 1 | Pre-test | 77.47 | 30 | 7.583 | 1.384 |
| | Post-test | 83.57 | 30 | 6..521 | 1.191 |

Table 11. Correlation of Paired Samples

| | | Number of Cases | Correction | Significance |
|---|---|---|---|---|
| Paired 1 | Pre-test & Post-test | 30 | .838 | .000 |

**Table 12. Paired Samples Test**

| | | Paired Difference | | | | | t | DOF | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|---|---|
| | | Average Value | Standard Deviation | Standard Error Mean | 95% CI | | | | |
| | | | | | Lower Limit | Upper Limit | | | |
| Paired 1 | Pre-test & Post-test | -6.100 | 4.139 | .756 | -7.645 | -4.555 | -8.073 | 29 | .000 |

The evaluation criteria are used to analyze overall student improvement. Pre-test score results from Appendix A showed that students who earned excellent, good, medium, and pass scores accounted for 3%, 47%, 40%, and 10% of the total, respectively. Students with excellent scores were lacking in "Identification, Analysis, and Response to Complex Problems" (hereafter referred to as the ability to analyze and design problems), while the rest scored excellently in all items, representing their outstanding overall ability. Students with good scores had a best score of 0.89 in the four items of "Integration of Knowledge and Technology" (hereafter referred to as the ability to integrate design), suggesting that students were proficient in applying knowledge related to integrated application design, though slightly lacking in ability to analyze and design problems. The worst performance category was "Knowledge of the Course" (0.66) (hereafter referred to as ability for basic knowledge reserve), indicating students' insufficient knowledge reserve. The students in the medium score range performed contrary to the students in the good and excellent score ranges, with the best performance of 0.79 in the ability to analyze and design problems. Yet the ability to integrate design was less pronounced, showing that the main gap between students in the intermediate score range and those in the good and excellent score ranges is the ability to apply knowledge skillfully and integrally in all aspects of design. The students in the pass score band were diametrically opposed to the students in the medium score band. Their ability to analyze design problems scored the lowest (0.43), showing that they lacked design analysis thought, and the ability to sort and summarize information effectively. Analysis represents a crucial way to solve poor design problems effectively, which is an key factor causing the significant gap in student performance in this score band. The ability for basic knowledge was rated poorly in all score sections, with the ability to apply design skills being the next most significant finding. The results of the first-stage assessment showed that the ability to analyze design problems was the most critical factor in influencing the excellence of design outcomes. The second was the ability to integrate design; therefore, teachers' strategies should first focus on helping students analyze design problems and integrate design knowledge. The second step is to enhance the depth of teaching professional knowledge and design skills knowledge.

The post-test score (Appendix B) shows that the percentages of students in the excellent, good, and medium score bands were 16.7%, 70%, and 13.3%, respectively, indicating that the number of students in the high score brackets all increased significantly. The number of students in the medium section decreased sharply. Among them, students in the excellent score bracket improved their ability to retain basic knowledge and ability to analyze problems and design effective solutions. Students in the good and medium score categories improved their knowledge base and ability to integrate designs. Most students showed a slight increase in their ability to analyze design problems, while some students showed no change because they had some deficiency in ordering subdivisional design problems. Overall, it shows that the students are good at establishing self-regulation.

The results show that students were less likely to collect relevant information comprehensively before designing. Teachers can focus on guiding student enthusiasm for autonomous learning in response to this problem. In addition, the visual function of student thinking established by the interactive assistance system can help both teachers and students by providing effective feedback modification. This important design process can help students receive systematic feedback from teachers, assist students in design reflection, and improve their academic performance.

## CONCLUSION

This study analyzes the level of online teacher-student interaction with or without the interactive assistance system. In this paper, a teaching interaction assistance model based on the LSTM algorithm and TAPs method is established to analyze student thinking situations. Then, combined with the experiment, the student design results are scored from different angles, and a paired sample t-test analysis is carried out. The results show that the system can effectively help teachers clarify student thinking content, understand student design ideas through a reasonable thought analysis process, and develop appropriate guidance strategies. The final evaluation results show that the system helps teachers and students to establish communication and improves the teaching quality of online design courses. The development of this system is still in the early stage; there are many functions that need to be improved through continued research. In addition, the system also needs more data to improve the accuracy of the algorithm.

## AUTHOR NOTE

The authors of this publication declare there is no conflict of interest.

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## APPENDIX A

**Table 13. Pre-test scores**

| | Evaluation Standards | | | | | |
|---|---|---|---|---|---|---|
| | Knowledge of the Course (0.1) | Execution of Skills and Tools (0.2) | Integration of Knowledge and Technology (0.4) | Identification, Analysis, and Response to Complex Problems (0.3) | Quantitative Score | Total Score |
| Student 1 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 75.00 |
| Student 2 | 1 | 0.75 | 0.75 | 1 | 0.85 | 85.00 |
| Student 3 | 0.5 | 1 | 0.75 | 1 | 0.85 | 85.00 |
| Student 4 | 0.5 | 0.75 | 0.75 | 0.75 | 0.725 | 72.00 |
| Student 5 | 0.75 | 1 | 0.75 | 0.75 | 0.8 | 80.00 |
| Student 6 | 0.5 | 0.75 | 0.75 | 1 | 0.8 | 80.00 |
| Student 7 | 0.5 | 0.75 | 0.75 | 0.75 | 0.72 | 72.00 |
| Student 8 | 0.5 | 0.75 | 0.75 | 0.75 | 0.72 | 72.00 |
| Student 9 | 0.75 | 0.5 | 0.75 | 0.5 | 0.625 | 63.00 |
| Student 10 | 1 | 0.25 | 0.75 | 1 | 0.75 | 75.00 |
| Student 11 | 1 | 0.75 | 0.75 | 0.75 | 0.77 | 77.00 |
| Student 12 | 0.5 | 0.75 | 1 | 0.75 | 0.82 | 82.00 |
| Student 13 | 0.75 | 0.5 | 1 | 0.75 | 0.8 | 80.00 |
| Student 14 | 0.75 | 1 | 0.5 | 0.75 | 0.7 | 70.00 |
| Student 15 | 0.5 | 0.5 | 1 | 0.75 | 0.775 | 78.00 |
| Student 16 | 0.25 | 0.75 | 0.75 | 1 | 0.775 | 78.00 |
| Student 17 | 0.75 | 0.5 | 1 | 0.75 | 0.8 | 80.00 |
| Student 18 | 1 | 0.5 | 1 | 0.75 | 0.82 | 82.00 |
| Student 19 | 1 | 1 | 1 | 0.75 | 0.92 | 92.00 |
| Student 20 | 0.75 | 0.5 | 1 | 0.75 | 0.8 | 80.00 |
| Student 21 | 0.5 | 0.75 | 0.75 | 0.5 | 0.65 | 65.00 |
| Student 22 | 1 | 0.75 | 0.75 | 0.75 | 0.775 | 78.00 |
| Student 23 | 0.5 | 1 | 1 | 0.75 | 0.87 | 87.00 |
| Student 24 | 0.75 | 0.75 | 0.75 | 1 | 0.82 | 82.00 |
| Student 25 | 0.5 | 1 | 1 | 0.75 | 0.87 | 87.00 |
| Student 26 | 0.75 | 0.75 | 0.75 | 1 | 0.82 | 82.00 |
| Student 27 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 75.00 |
| Student 28 | 0.25 | 1 | 1 | 0.75 | 0.85 | 85.00 |
| Student 29 | 0.5 | 0.75 | 0.75 | 0.5 | 0.65 | 65.00 |
| Student 30 | 0.75 | 0.75 | 0.75 | 0.25 | 0.6 | 60.00 |
| Average | 0.656452 | 0.724194 | 0.81129 | 0.751613 | 0.77 | 77 |

## APPENDIX B

**Table 14. Post-test scores**

| | Evaluation Standards | | | | | |
|---|---|---|---|---|---|---|
| | Knowledge of the Course (0.1) | Execution of Skills and Tools (0.2) | Integration of Knowledge and Technology (0.4) | Identification, Analysis, and Response to Complex Problems (0.3) | Quantitative Score | Total Score |
| Student 1 | 1 | 0.75 | 1 | 0.5 | 0.8 | 80 |
| Student 2 | 1 | 1 | 0.75 | 1 | 0.9 | 90 |
| Student 3 | 0.75 | 1 | 1 | 0.75 | 0.9 | 90 |
| Student 4 | 0.75 | 1 | 0.75 | 0.75 | 0.8 | 80 |
| Student 5 | 1 | 0.75 | 0.75 | 1 | 0.85 | 85 |
| Student 6 | 1 | 0.5 | 1 | 0.75 | 0.82 | 82 |
| Student 7 | 0.5 | 0.75 | 0.75 | 1 | 0.8 | 80 |
| Student 8 | 0.5 | 0.75 | 0.75 | 1 | 0.8 | 80 |
| Student 9 | 0.5 | 0.75 | 0.75 | 1 | 0.8 | 80 |
| Student 10 | 0.75 | 0.75 | 0.75 | 1 | 0.82 | 82 |
| Student 11 | 0.5 | 1 | 1 | 1 | 0.95 | 95 |
| Student 12 | 0.5 | 1 | 1 | 0.75 | 0.87 | 87 |
| Student 13 | 0.75 | 0.5 | 1 | 0.75 | 0.9 | 90 |
| Student 14 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 75 |
| Student 15 | 1 | 0.5 | 1 | 0.75 | 0.82 | 82 |
| Student 16 | 0.75 | 0.75 | 0.75 | 1 | 0.82 | 82 |
| Student 17 | 1 | 0.5 | 1 | 0.75 | 0.82 | 82 |
| Student 18 | 0.75 | 1 | 1 | 0.75 | 0.9 | 90 |
| Student 19 | 0.75 | 1 | 1 | 1 | 0.94 | 94 |
| Student 20 | 0.75 | 0.75 | 1 | 1 | 0.86 | 86 |
| Student 21 | 0.75 | 1 | 0.75 | 0.75 | 0.8 | 80 |
| Student 22 | 0.5 | 1 | 1 | 0.75 | 0.83 | 83 |
| Student 23 | 0.75 | 1 | 1 | 0.75 | 0.9 | 90 |
| Student 24 | 1 | 0.75 | 0.75 | 1 | 0.85 | 85 |
| Student 25 | 1 | 1 | 0.75 | 1 | 0.9 | 90 |
| Student26 | 0.75 | 0.75 | 1 | 0.75 | 0.84 | 84 |
| Student27 | 0.75 | 0.5 | 0.75 | 0.75 | 0.8 | 80 |
| Student28 | 1 | 1 | 0.75 | 1 | 0.875 | 88 |
| Student29 | 1 | 0.75 | 0.75 | 0.5 | 0.7 | 70 |
| Student30 | 1 | 0.5 | 0.75 | 0.25 | 0.65 | 65 |
| Average | 0.791667 | 0.8 | 0.866667 | 0.825 | 0.8355 | 83.57 |

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