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PAPER

Enhancing Students' Metacognition via AI-Driven Educational Support Systems

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ABSTRACT

As the penetration of digital technology deepens and the demands for educational modernization grow, attention is increasingly being drawn towards the application of artificial intelligence (AI) in the field of education. Especially in educational practice, the optimization of students' learning experiences and the enhancement of their metacognitive abilities through AI technology have captivated the interest of numerous educators and scholars. Metacognition, which represents a core skill in student self-regulation and self-management, has a significant impact on student learning outcomes and quality. However, current educational support systems primarily rely upon traditional methods of data collection and analysis, which have limitations in terms of real-time responsiveness, granularity, and comprehensiveness. The present research aims to investigate the integration of AI technology with a specific focus on the learning process through educational support systems and the development of a cooperative teaching interaction model. This will ultimately enhance the development of students' metacognitive abilities more effectively.

KEYWORDS

artificial intelligence (AI), educational support systems, metacognitive abilities, learning process monitoring, cooperative teaching

1 INTRODUCTION

In the 21st century Information Age, the educational field has been presented with an unprecedented opportunity for transformation through the increasingly integrated use of digital technology and education [1–8]. Artificial intelligence (AI), identified as one of the most powerful technologies currently available, has been extensively utilized in various domains, with the field of education being particularly notable. Traditional educational methods frequently struggle to meet the requirements of modernized, personalized, and intelligent education, whereas the incorporation of AI technology is perceived to offer a more expansive developmental sphere for education [9–14]. Metacognition, a pivotal educational concept, represents the

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capability of students for self-regulation, self-reflection, and self-management, playing an indispensably critical role in their learning process [15, 16]. Thus, the integration of AI technology and metacognition, which explores how to enhance students' metacognitive processes through AI educational support systems, undoubtedly constitutes a valuable research topic.

The significance of metacognitive abilities in the learning process has been acknowledged by a broad spectrum of educators and scholars [17–20]. It not only serves as a driving force for student learning but also serves as a key for their self-monitoring and self-adjustment of the learning process. With the educational environment becoming increasingly complex and diverse, traditional teaching methods often fall short of satisfying the personalized needs of students. AI-based educational support systems, on the other hand, can offer a more personalized and intelligent learning experience, thereby promoting the development of their metacognitive abilities. Furthermore, teachers can access more detailed and real-time student learning data through these systems, which provides a more scientific basis for making teaching decisions.

This research will explore the application of AI technology in optimizing students' metacognitive processes. Firstly, we thoroughly investigate technologies for monitoring the learning process based on AI educational support systems. This includes facial detection and recognition algorithms, micro-expression recognition algorithms, and head posture estimation algorithms. These algorithms can capture and analyze the learning states and emotional changes of students in real-time, providing valuable feedback for educators. Subsequently, a cooperative teaching interaction model has been designed to enhance student metacognitive processes. The aim of this model is to provide students with more precise and personalized feedback, thereby fostering the development of their metacognitive abilities. This research provides a new perspective and approach for educational practice while also establishing a strong foundation for future research on the integration of AI and education.

2 LEARNING PROCESS MONITORING THROUGH AN AI-ASSISTED EDUCATIONAL SUPPORT SYSTEM

2.1 Facial detection and recognition

One core value of the AI-assisted educational support system lies in providing educators with timely and accurate information regarding the learning statuses of students, thereby enabling more personalized and efficient teaching strategies. In this context, the monitoring functionality of the learning process becomes imperative. It is capable of capturing the students' learning states in real time and providing essential feedback to educators. The facial detection and recognition algorithm introduced in this discourse plays an essential role in performing these functions.

Employing the Haar feature-based facial detection and recognition algorithm, a classic and efficient method, provides precise student facial information for the system, enabling further in-depth analysis. Initial feature extraction involves capturing linear features that capture image brightness variations, edge features that aid in facial contour detection, central features that capture brightness variations in regions such as the eyes and nose, and object line features that assist in detecting facial linear structure. In the educational support system, capturing and identifying these features ensures accurate student facial detection under varied environmental and lighting conditions.

Furthermore, the algorithm quickly and efficiently calculates the sum of all pixels above and to the left of each pixel position. This ensures smooth system performance and fast response times for real-time facial detection. Assuming the cumulative sum of the image in the row direction is represented by $a(z, t)$, and the integral image is represented by $uu(z, t)$, the construction process of the integral image is exhibited as:

$$uu(z,t) = \sum_{z' \leq z, t' \leq t} t(z', t') \tag{1}$$

$$a(z,t) = a(z,t-1) + u(z,t) \tag{2}$$

$$uu(z,t) = uu(z-1,t) + u(z,t) \tag{3}$$

Initialization is first undertaken, establishing $a(z, -1) = 0$ and $uu(-1, u) = 0$. Row scanning then ensues, with recursive calculations of the pixel (z, t) row direction cumulative sum $a(z, t)$ based on formulas (2) and (3), and obtaining the sub-image $uu(z, t)$ value based on equation (1). Proceeding according to the aforementioned steps, the integrated image uu can be constructed.

Figure 1 illustrates the diagram for pixel computation in the image area. The following formula provides the computational method for calculating the sum of pixels in F:

$$F_{SU} = uu(4) + uu(1) - (uu(2) + uu(3)) \tag{4}$$

Further enhancement of aggressive classifiers is based on the AdaBoost algorithm. The AdaBoost algorithm, an iterative method, is utilized to select and combine multiple weak classifiers in order to construct a robust classifier. In facial detection, the system can effectively distinguish between facial and non-facial regions through the use of AdaBoost, while simultaneously minimizing false detection rates. Assuming the weak classifier is composed of a sub-window image z, a feature d, an inequality direction indicator o, and a threshold φ it is represented by $g(z, d, o, \varphi)$. To accurately determine whether the monitoring image during the learning process is positively or negatively correlated, an optimal threshold needs to be established. This threshold characterizes the best classification effect when its value is minimized. Based on the following formula, an error value can be obtained. Presuming that the classification error value of each element is represented by "e," where the total weight of all face samples is "$y1$" and the total weight of all non-face samples is "$y0$," we can calculate the sum of the weights of the face samples before this element as "$a1$," and the sum of the weights of the non-face samples before this element as "$a0$." Based on these values, the following can be obtained:

$$g(z,d,o,\varphi) = \begin{cases} 1, od(z) < o\varphi \\ 0, OT \end{cases} \tag{5}$$

$$e = MIN((a1 + (y0 - a0)), (a0 + (y1 - a1))) \tag{6}$$

In order to further enhance computational efficiency, weak classifiers are organized into a cascading structure. This implies that in the early stages of detection, most non-facial regions will be swiftly eliminated, and only those regions that are more likely to be facial will be transmitted to subsequent stages of the cascade. Assuming the detection rate of the cascade classifier is represented by F, the misrecognition rate of the cascade classifier is F, the number of layers of a cascaded detector is J, the detection rate of the strong classifier is f, and the misrecognition rate of the strong classifier is d, a more accurate expression for the cascaded detection classifier is:

$$f^J = F, d^J = D \tag{7}$$

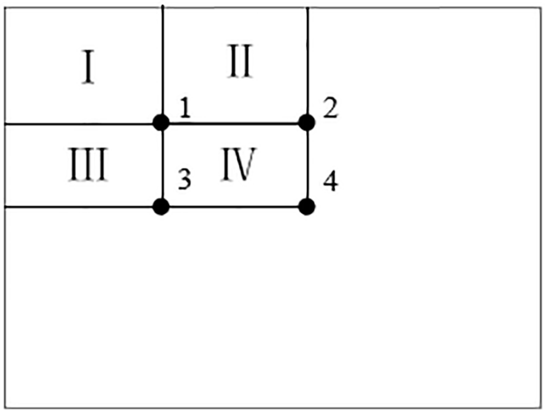


Fig. 1. Pixel computation diagram of image area

2.2 Design of micro-expression recognition

Due to the inherently brief and localized nature of micro-expressions, capturing and identifying these subtle facial changes poses a significant challenge for algorithms, especially in an educational environment where micro-expressions serve as crucial indicators of students' emotional, cognitive, and learning attitudes. To address this, a neural network equipped with a self-attention weighting module is employed in this study.

The self-attention mechanism allocates diverse weights to each segment of the input data. In the context of micro-expression recognition, this implies that the network can autonomously identify facial regions that are critical for micro-expressions, thereby recognizing them and assigning higher weights to them. This allows the model to focus on significant changes in microexpressions, enhancing recognition precision. The dynamic variations in microexpressions involve temporal sequence data, which can be processed by the self-attention mechanism. This mechanism is capable of identifying and correlating key features at different time points, allowing it to effectively capture instantaneous changes in micro-expressions. The self-attention importance weighting module assumes that the facial features of B images are represented by $DD = [z_1, z_2, \ldots, z_B] \in E^{F \times B}$. It takes DD as input and outputs the importance-weighted results of each feature. Supposing the importance value weight of the uth sample is represented by $\propto_u$, the parameters for the fully connected (FC) layer used for attention are given by Q_s^Y, and the sigmoid function is denoted by δ, the module can be represented as follows:

$$\propto_u = \delta(Q_s^Y z_u) \tag{8}$$

To accurately calculate attention weights, the module utilizes a multi-class cross-entropy loss. The kth classifier is represented by Q_k, as shown in the following formula:

$$M_{SS} = -\frac{1}{B}\sum_{u=1}^{B} \log \frac{r^{\propto_u q_{c_u}^{Y} z_u}}{\sum_{k=1}^{V} r^{\propto_u q_{c_u}^{Y} z_u}} \tag{9}$$

Grade regularization, a crucial model constraint strategy, incorporates extra information or assumptions during neural network training to ensure that the model conforms to specific expected properties or structures. In the context of micro-expression recognition and the potential limitations of sample sizes in educational scenarios, grade regularization is implemented to restrict model complexity. This helps prevent overfitting to noise within the training data and enhances the generalizability of the model. Concurrently, grade regularization allows researchers to incorporate domain-expert knowledge or prior information into the model. The grade regularization module of the model utilizes grade regularization loss. The margin, denoted by σ_1, can be a fixed hyperparameter or a learnable parameter. The average values of the high weight importance group and low weight importance group of $\alpha{*}B = L$ samples are represented by $\propto_G$ and $\propto_M$, respectively. The total loss function, denoted as $M_{AL} = \varepsilon M_{EE} + (1-\varepsilon)M_{SS}$, is given as:

$$M_{NE} = MAX\{0, \sigma_1 - (\beta_G - \beta_M)\} \tag{10}$$

$$\propto_G = \frac{1}{L}\sum_{u=0}^{L} \propto_u, \propto_M = \frac{1}{B-L}\sum_{u=0}^{L} \propto_u \tag{11}$$

Reannotation, a strategy that is gaining increasing attention in machine learning and AI research, is particularly useful in scenarios where data is scarce or annotation costs are high. In the context of micro-expression recognition, a reannotation module has been implemented to provide significant assistance in improving model performance and efficiency. This is due to the transient and subtle nature of micro-expressions, which makes manual annotation extremely challenging and can result in numerous inconsistencies or errors. The reannotation module can provide feedback based on model prediction results, helping to correct or optimize the original data annotation and thus improving the overall quality of the dataset. Moreover, by combining the model's prediction results with the original annotations, the reannotation module can provide more accurate and representative training samples for the model. This means that within the same training cycles, the model can achieve faster convergence and improved performance.

The reannotation module will compare the maximum prediction probability with the given label probability. If the label threshold for a given sample is lower than the maximum prediction probability, the sample will be reannotated with a pseudo-label. Assuming the new label is represented by t', the threshold is denoted by σ_2, the maximum prediction probability is given by O_{MAX}, and the prediction probability of the given label is represented by O_{GT}. The original given label and the maximum prediction's index values are respectively given by m_{OR} and m_{MAX}. The definition of the reannotation module is given by the following formula:

$$t' = \begin{cases} m_{MAX}, IF \quad O_{MAX} - O_{GT} > \sigma_2 \\ m_{OR}, OW \end{cases} \tag{12}$$

2.3 Head pose estimation

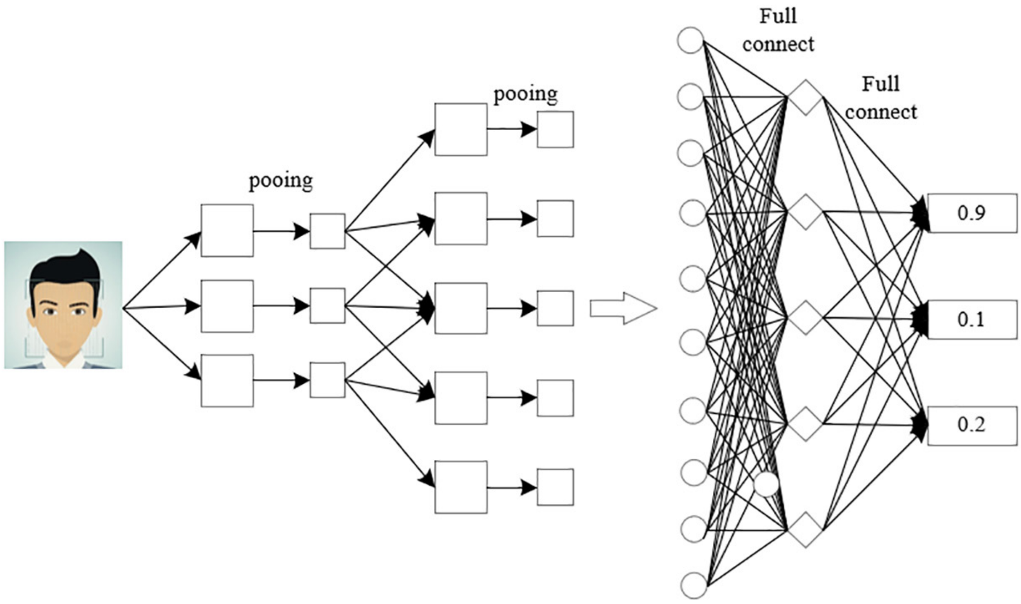


Fig. 2. Structure of convolutional neural network

A convolutional neural network (CNN) algorithm is used for the task of head pose estimation, as shown in Figure 2. The application of CNNs in head pose estimation primarily aims to capture the subtle head movements of students during the learning process. This enables a more accurate analysis of their attention, interest, and emotional state. The input layer receives facial images of students from cameras or other image sources. The convolutional layer, consisting of multiple kernels, scans the input image to extract features relevant to head pose. Through convolutional operations, the network is capable of identifying features in the image, such as edges, textures, and shapes. The pooling layer serves to reduce the dimensionality and computational load of the data while retaining essential feature information. Upon the foundation of features extracted by convolutional and pooling layers, the fully connected layer performs the final classification or regression task, accurately identifying the specific pose of the head. The output layer generates the parameters of the head pose, including yaw, pitch, and roll angles.

Once the facial images of students are captured by the camera, they are initially input into the network's input layer. Within the convolutional layer, the image undergoes scanning by multiple convolutional kernels, each responsible for detecting a specific feature within the image. Through progressive convolution across layers, the network is capable of incrementally extracting head-form features from basic edges and texture features. After passing through the pooling layer and entering the fully connected layer, the network utilizes all the extracted feature information. Through a series of weights and bias parameters, it then generates predictions of head pose. Ultimately, the output layer presents specific parameter values of the head pose, which are utilized for analyzing student attention and emotional state.

3 ENHANCING STUDENTS' METACOGNITIVE PROCESSES THROUGH A COLLABORATIVE TEACHING INTERACTION MODEL

A collaborative teaching interaction model is formulated, which enables educators and AI systems to participate in joint instructional activities that are customized to meet the individual needs and progress of each student. Real-time analysis of student responses and progress is enabled by the AI system, which then provides feedback to educators, thus facilitating a more nuanced and personalized teaching approach. Metacognition, which refers to the process of thinking about one's own thinking, specifically a student's comprehension, evaluation, and adaptation of their own learning strategies, is significantly enhanced through the collaborative efforts of educators and AI. An attempt is made herein to construct a model in which both educators and AI teaching assistance systems collaborate in student instruction. Through and through this interaction, an enhancement of students' metacognitive abilities is promoted.

Let the collaborative teaching knowledge stock of teacher R_1 and AI teaching assistance system R_2 be denoted by J_1 and J_2, respectively. The proportions of complementary collaborative teaching knowledge in their teaching knowledge stock are represented by s_1 and s_2. Regarding the enhancement of students' metacognitive abilities, the complementary collaborative teaching knowledge provided by Teacher R_1 and the AI teaching assistance system R_2 is represented by s_1J_1 and s_2J_2, respectively. This forms a crucial foundation for establishing a collaborative teaching interaction relationship between educators and AI teaching assistance systems. Let the degree of misalignment of collaborative teaching knowledge between teacher R_1 and the AI teaching assistance system R_2 be symbolized by O_1 and O_2 respectively. Consequently, the compatibility of collaborative teaching knowledge compatibility of teacher R_1, who acts as the leading party in collaborative teaching knowledge, is represented by $1–O_1$. The compatibility of the AI teaching assistance system R_2 is represented by $1–O_2$. Let $\varphi1$ and $\varphi2$ denote the energy efficiency coefficients of the collaborative teaching knowledge output of teacher R_1 and AI teaching assistance system R_2, respectively. Hence, the collaborative teaching knowledge output efficiencies of Teacher R_1 and the AI teaching assistance system R_2 are $s_2J_2(1–o_1)\ \varphi_1$ and $s_2J_2(1–o_2)\ \varphi_2$ respectively. Let the matching coefficients of the collaborative teaching knowledge of Teacher R_1 and AI teaching assistance system R_2 be represented by n_{11} and n_{22}, respectively. Therefore, the matching inputs of the collaborative teaching knowledge of teacher R_1 and AI teaching assistance system R_2 are $s_2J_2(1–o_2)n_{21}$, respectively. primarily reflects the implicit relationship between the output capability of collaborative teaching knowledge output capability and collaborative teaching knowledge. Let the matching capability coefficients of teacher R_1's collaborative teaching knowledge and AI teaching assistance system R_2 be symbolized by T_1 and T_2, respectively.

Teacher R_1 and AI teaching assistant system R_2 deploy collaborative interactive teaching, exhibiting complementarity in their knowledge of collaborative teaching. They are represented respectively by $s_1J_1(1–o_1)$ and $s_2J_2(1–o_2)$. The elasticity coefficient of the knowledge stock in collaborative teaching impacts the synergy effect between them because the level of their relationship affects the collaborative effect of synergistic teaching knowledge. Let $i1$ and $i2$ respectively represent the elastic coefficients of the complementary synergistic teaching knowledge stock of Teacher R_1 and AI teaching assistant system R_2, where $i1 > 0$, $i2 > 0$, and $i1 + i2 = 1$. Let β_{12} represent the coefficient of the lead-assist level for Teacher R_1 and

AI teaching assistant system R_2. Consequently, the collaborative teaching knowledge they possess results in a synergistic energy efficiency expressed as $\beta_{12}[s_1J_1(1–o_1)]^{i1}[s_2J_2(1–o_2)]^{i2}$. The respective synergistic energy efficiencies of collaborative teaching knowledge are represented by $\alpha_1\beta_{12}[s_1J_1(1–o_1)]^{i1}[s_2J_2(1–o_2)]^{i2}$ and $\alpha_2\beta_{12}[s_1J_1(1–o_1)]^{i1}[s_2J_2(1–o_2)]^{i2}$.

The premise for the interactive behavior in collaborative teaching between Teacher R_1 and AI teaching assistant system R_2 is that their collaborative teaching knowledge efficiency should be higher than the knowledge efficiency before the behavior occurs. Therefore, the following two inequalities are always assumed to be true:

$$\begin{aligned}\beta_1\alpha_{12}[a_1K_1(1-p_1)]^{u1}[a_2K_2(1-p_2)]^{u2} > a_1K_1(1-p_1)b_{13}\\ \beta_2\alpha_{12}[a_1K_1(1-p_1)]^{u1}[a_2K_2(1-p_2)]^{u2} > a_2K_2(1-p_2)b_{23}\end{aligned} \tag{13}$$

$$\begin{aligned}\alpha_1\beta_{12}[\beta_1J_1(1-o_1)]^{i1}[s_2J_2(1-o_2)]^{i2} > s_1J_1(1-o_1)n_{13}\\ \alpha_2\beta_{12}[s_1J_1(1-o_1)]^{i1}[s_2J_2(1-o_2)]^{i2} > s_2J_2(1-o_2)n_{23}\end{aligned} \tag{14}$$

This study defines the combinations of the collaborative teaching interaction strategies adopted by Teacher R_1 and AI teaching assistant system R_2 as follows: (active interaction strategy, active interaction strategy), (active interaction strategy, passive interaction strategy), (passive interaction strategy, active interaction strategy), and (passive interaction strategy, passive interaction strategy). Assuming that the total efficiencies of Teacher R1 and AI teaching assistant system R_2 under the respective strategy choices are represented by C_{11}, C_{21}, C_{12}, C_{22}, C_{13}, and C_{23}, the following calculation formulas are applied:

$$\begin{aligned}C_{11} = {} & \alpha_1\beta_{12}[s_1J_1(1-o_1)]^{i1}[s_2J_2(1-o_2)]^{i2} + s_1J_1(1-o_1)\varphi_1\\ & + s_2J_2(1-o_2)\varepsilon_1 - s_1J_1(1-o_1)n_{11} - s_2J_2(1-o_2)n_{12} - s_1J_1(1-o_1)n_{13}\end{aligned} \tag{15}$$

$$\begin{aligned}C_{21} = {} & \alpha_2\beta_{12}[s_1J_1(1-o_1)]^{i1}[s_2J_2(1-o_2)]^{i2} + s_1J_1(1-o_1)\varphi_2\\ & + s_2J_2(1-o_2)\varepsilon_2 - s_1J_1(1-o_1)n_{21} - s_2J_2(1-o_2)n_{22} - s_1J_1(1-o_1)n_{23}\end{aligned} \tag{16}$$

$$C_{12} = s_1J_1(1-o_1)\varphi_1 - s_1J_1(1-o_1)n_{11} \tag{17}$$

$$C_{22} = s_1J_1(1-o_1)\varepsilon_2 - s_1J_1(1-o_1)n_{22} \tag{18}$$

$$C_{13} = s_2J_2(1-o_2)\varepsilon_1 - s_2J_2(1-o_1)n_{12} \tag{19}$$

$$C_{23} = s_2J_2(1-o_2)\varphi_2 - s_2J_2(1-o_2)n_{21} \tag{20}$$

The analytical insights into the following expressions reveal:

1. When both Teacher R_1 and the AI teaching assistant system R_2 choose an active interaction strategy, their total efficiencies are represented as C_{11} and C_{21}. Herein, the collaborative teaching knowledge output by Teacher R_1 is $s_1J_1(1–o_1)$, whereas the AI teaching assistant system R_2 outputs a collaborative teaching knowledge of $s_2J_2(1–o_2)$. The collaborative teaching knowledge output from one party can be matched with the collaborative teaching knowledge of the other party. The efficiency gained by Teacher R_1 through collaborative teaching knowledge interaction can be calculated using the formula $s_1J_1(1–o_1)\varphi_1 + s_2J_2(1–o_1)\varepsilon_1 – s_1J_1(1–o_1)n_{11}–s_2J_2(1–o_1)n_{12}$. Complementary collaborative teaching

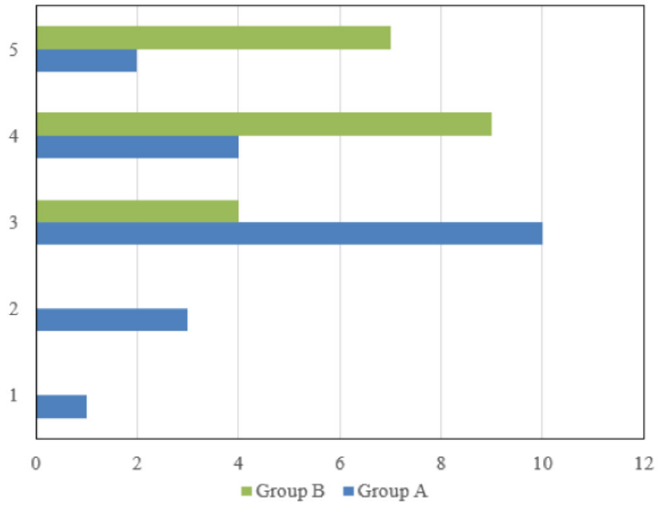
knowledge is shared by both parties, thereby facilitating smooth interactions in collaborative teaching.

2. When Teacher R_1 selects an active interaction strategy and AI teaching assistant system R_2 chooses a passive interaction strategy, the corresponding total efficiencies are denoted as C_{12} and C_{22}. In this scenario, the collaborative teaching knowledge output by Teacher R_1 is $s_1J_1(1–o_1)$, while the AI teaching assistant system R_2 provides a collaborative teaching knowledge that is lower than $s_2J_2(1–o_2)$. Consequently, Teacher R_1 obtains a smaller amount of matchable collaborative teaching knowledge, and the value efficiency of collaborative teaching interactions is not maximized without the participation of complementary collaborative teaching knowledge.
3. Upon selecting a passive interaction strategy, Teacher R_1 and an active interaction strategy, AI teaching assistant system R_2, their respective efficiencies are denoted as C_{13} and C_{23}. In this instance, the collaborative teaching knowledge output by Teacher R_1 is less than $s_1J_1(1–o_1)$, while the AI teaching assistant system R_2 outputs a collaborative teaching knowledge of $s_2J_2(1–o_2)$. AI teaching assistant system R_2 thus acquires a smaller amount of matchable collaborative teaching knowledge. Without the participation of complementary collaborative teaching knowledge, the parties do not obtain the maximum collaborative value efficiency.
4. When both Teacher R_1 and AI teaching assistant system R_2 select a passive interaction strategy, the efficiency of both will be even lower.

Further exploration of the inherent mechanisms and promotion mechanisms in the collaborative teaching interaction process between teachers and AI teaching assistant systems can be based on the above analysis. Firstly, both teachers and AI systems possess their own respective information advantages. Teachers, with their extensive experience and profound understanding of students, can deliver personalized and empathetic instruction. Meanwhile AI systems utilize data analysis and pattern recognition technologies to offer teachers timely and, accurate student learning data and analysis results. When information from both sources is integrated, teaching optimization can be achieved providing students with more targeted and personalized support.

4 RESULTS AND ANALYSIS

A comparative experiment was designed to measure the satisfaction with collaborative teaching efficacy among groups A, B, and C of students, both with teachers and AI systems. As observed in Figure 3, there is a significant difference in medium satisfaction between groups A and B, while high satisfaction levels seem to be relatively close. A significant number of students in group A maintain a more neutral stance towards the effects of collaborative teaching, although some express dissatisfaction. A significant disparity in satisfaction, particularly in the categories of fairly satisfied, is evident between groups B and C. Specifically, group B has a significantly higher number of students at the very satisfied level compared to group C. On the other hand, group C has a higher number of students in the dissatisfied and somewhat dissatisfied satisfaction levels. By integrating data from all three groups, it becomes apparent that when teachers and AI systems collaborate in a reasonable manner, a majority of students have a satisfactory view of teaching outcomes. This implies that collaborative teaching by teachers and AI systems can optimize students' learning processes and enhance their satisfaction with learning. Nonetheless, attention must be given to a segment of students who express dissatisfaction, suggesting a potential need for further research and optimization of collaborative teaching strategies to meet the learning needs of a broader student population.



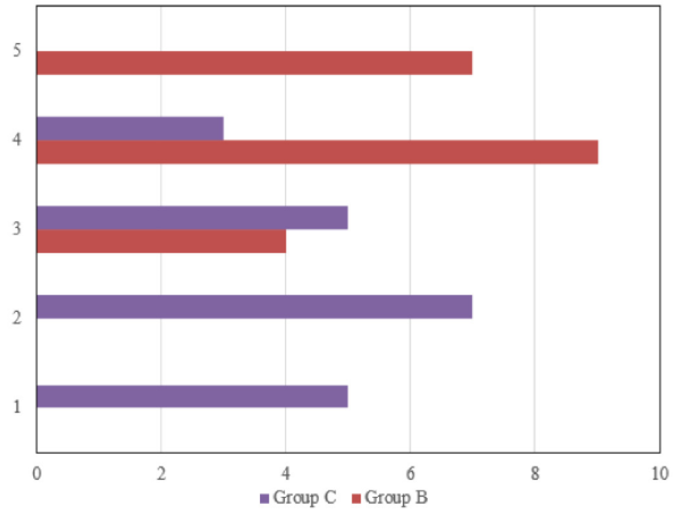


Fig. 3. Comparative graph of collaborative teaching efficacy satisfaction between roups A, B, and groups B, C

Table 1. Detailed analysis of collaborative teaching efficacy between teachers and AI systems

Project	Mean	Median	Standard Deviation	Option Frequency (%)				
				Totally Agree	Somewhat Agree	Unclear	Somewhat Disagree	Totally Disagree
1	3.21	3.10	1.125	10.2	21.5	12.5	35.2	17.9
2	3.45	3.10	1.026	3.6	21.6	15.3	42.6	18.9
3	3.12	3.10	1.035	5.6	27.3	32.6	21.3	10.3
4	3.29	3.10	1.214	4.5	22.0	27.3	26.9	18.3
5	3.58	3.10	1.203	4.5	15.9	15.2	36.8	24.3
6	3.57	3.10	1.125	3.6	15.3	16.9	44.3	18.3

Six testing projects were designed to evaluate the efficacy of collaborative teaching between teachers and AI systems. These projects specifically focused on: curriculum content adaptability, real-time feedback mechanisms, interactive teaching, richness of learning resources, personalization of learning progression, and comprehensive evaluation and diagnostic capabilities. These six testing projects, which cover multiple key aspects of collaborative teaching between teachers and AI systems, allow for a comprehensive assessment of the effects of collaborative teaching. It can be discerned from Table 1 that the collaborative teaching of teachers and AI systems demonstrates positive outcomes in certain aspects, particularly in terms of personalized adaptation of learning progression and comprehensive evaluation and diagnostic capabilities.

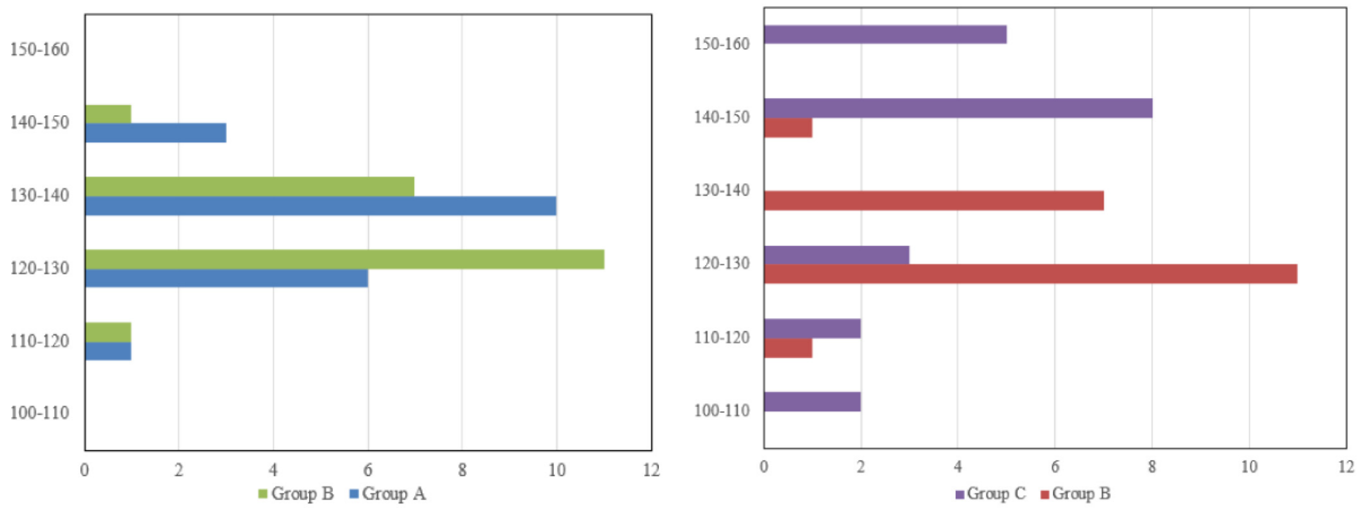


Fig. 4. Comparative graph of online learning duration between groups A, B, and groups B, C

Figure 4 presents the distribution of online learning durations among groups A, B, and C. It is evident that both groups A and B show a concentration in the 110–130 duration range. Specifically, group A students tend to have a higher concentration between 120–130, whereas group B students are more inclined towards a duration of 110–120. In contrast, groups B and C exhibit distinct patterns. Group B predominantly falls within the 110–130 duration range, whereas group C shows a broader distribution, notably with a substantial increase in the 140–160 duration range. Notable disparities exist in the duration of online learning among the various student groups. Students from groups A and B demonstrate a tendency to haves shorter learning durations, particularly within the 110–130 timeframe, while group C tend to have longer durations, especially within the 140–160 range. It can be inferred that collaborative teaching involving teachers and AI systems may offer students more personalized and targeted learning resources and methods. This could be one of the factors contributing to the difference in duration. This further accentuates the potential of collaborative teaching between teachers and AI systems for optimizing students' learning processes. Through a deep understanding and analysis of students' learning habits, needs, and feedback, teaching methods can be adjusted and optimized, thereby improving student learning efficiency and satisfaction.

Figure 5 illustrates the distribution of module knowledge test scores among groups A, B, and C. It is evident that the scores of students in Group A are more varied, ranging from 50 to 90. In contrast, the majority of group B's scores are concentrated between 70 and 100, with a particular emphasis on the range of 80 to 100. This indicates that students in group B generally performed at a higher level. In comparison between groups B and C, Group B has a higher number of students in the high-score bracket (specifically 80–100), while group C's scores range from 50–100. According to the aforementioned data analysis, students in group B generally score higher on knowledge tests, especially within the high-score bracket of 80–100. This suggests that collaborative teaching, which involves both teachers and AI systems, can offer group B students more effective and focused learning resources and strategies. As a result, it helps them achieve higher test scores. Conversely, the more dispersed scores of groups A and C might suggest that they encountered difficulties during the learning process or did not fully leverage the advantages of collaborative teaching. This further underscores the significance of collaborative teaching between teachers and AI systems in optimizing students' learning processes. Through collaboration with AI systems, teachers can more effectively identify student needs, adapt teaching strategies, and offer more personalized assistance, thereby improving student learning outcomes and satisfaction.

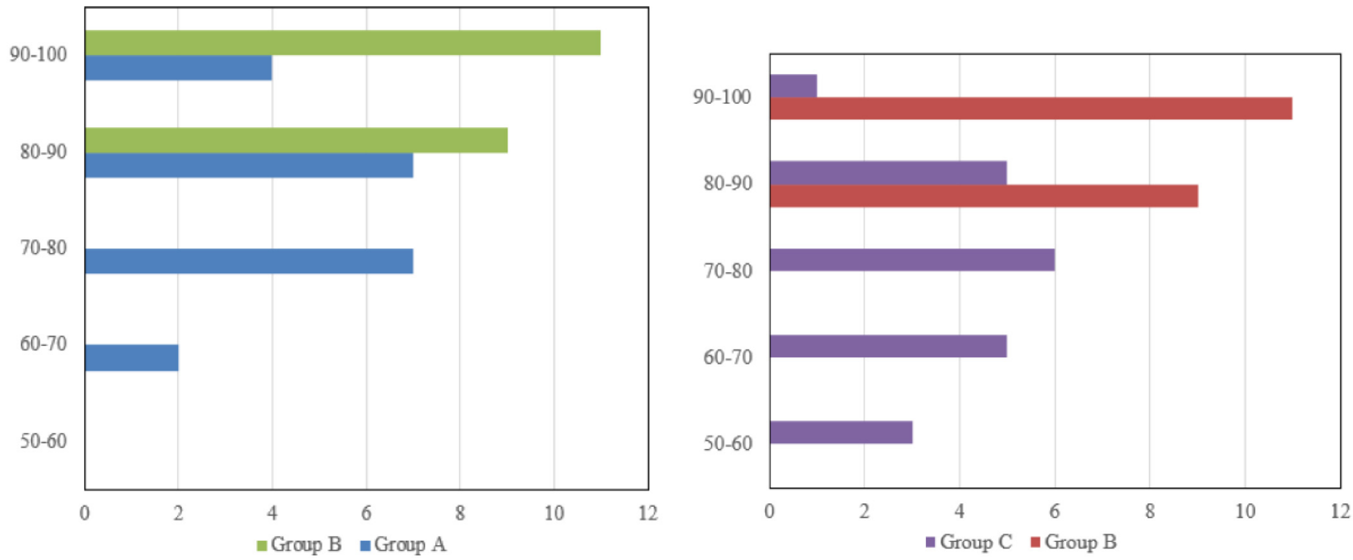


Fig. 5. Comparative analysis of module knowledge test scores among groups A, B, and C

Table 2. Detailed analysis of the learning process status

Project	Mean	Median	Standard Deviation	Option Frequency (%)				
				Totally Agree	Somewhat Agree	Unclear	Somewhat Disagree	Totally Disagree
1	3.45	3.10	0.965	15.9	33.6	32.5	13.9	1.2
2	3.78	3.10	1.125	3.6	9.1	15.6	36.5	32.8
3	3.89	3.10	1.236	2.8	9.8	13.7	32.4	42.3
4	3.69	3.10	1.124	5.6	12.9	14.9	24.8	3.6

Four items were designed in this study to assess the state of student learning processes, specifically attention concentration, understanding and mastery, interactive engagement, and autonomous learning capability. The intention behind these items was to assess the student's condition during the learning process, including their level of attention, comprehension skills, engagement, and willingness to learn independently. Through these tools, a deeper understanding of students' actual performance in the teaching process can be achieved, thereby offering targeted guidance and suggestions for teaching. Based on the data in Table 2, an analysis can be conducted regarding the state of the learning process. It is evident from the table that students demonstrate relatively strong performance in terms of attention concentration and autonomous learning capability, particularly in regards to attention. The majority of students are able to maintain good focus. However, a significant number of students do not perform optimally in terms of understanding, mastery, and interactive engagement. This might suggest that teaching methods or content need further adjustment and optimization. In relation to the previous discussion on collaborative teaching with AI systems, it is hypothesized that the use of AI systems for real-time feedback and personalized recommendations could enhance students' performance in comprehension, mastery, and interactive engagement. This, in turn, would optimize the learning process for students.

Lastly, six test items were designed in this study to assess the enhancement of students' metacognitive abilities. These include self-assessment and reflection, learning strategy selection, learning plan and goal setting, learning process monitoring, situational cognitive adaptation, and recognition and response to learning barriers. The test items mentioned above were designed to target key areas of students' metacognitive abilities. The aim was to evaluate students' capabilities in these areas in a concise manner. Observing the data from Table 3, it is noted that the enhancement of metacognitive abilities is well displayed in certain areas, such as items 1 and 7. However, the satisfaction in many other items is relatively low, particularly in items 3 through 6, and Items 8, 9, and 10. This suggests that when implementing metacognitive ability training, it is important to give special attention to these items and identify possible reasons in order to optimize teaching strategies.

Table 3. Detailed analysis of the enhancement of metacognitive ability

Project	Mean	Median	Standard Deviation	Option Frequency (%)				
				Totally Agree	Somewhat Agree	Unclear	Somewhat Disagree	Totally Disagree
1	3.15	3.10	0.923	18.3	51.2	16.9	11.2	1.6
2	3.26	3.10	1.152	6.3	32.5	16.5	32.5	12.4
3	3.78	3.10	1.235	4.5	13.2	12.4	31.4	37.6
4	3.75	3.10	1.148	3.2	13.5	12.3	35.2	33.4
5	3.74	3.10	1.125	2.8	13.4	13.5	36.9	33.6
6	3.71	3.10	1.235	4.3	12.6	13.4	32.1	36.7
7	3.63	3.10	1.211	16.9	42.5	15.9	15.8	6.5
8	3.78	3.10	1.123	5.2	13.2	15.6	23.4	42.3
9	3.61	3.10	1.231	3.6	17.8	12.4	32.8	31.8
10	4.12	3.10	1.268	3.2	8.9	12.6	25.6	47.6
11	2.78	3.10	0.963	7.2	42.6	27.3	18.9	1.9

5 CONCLUSION

The research aimed to explore the integration of AI technology, specifically focusing on monitoring the learning process through teaching assistance systems. The goal was to develop a collaborative interactive teaching model that would enhance students' metacognitive abilities. An in-depth investigation was conducted on learning process monitoring technologies based on AI teaching assistance systems. The investigation focused on algorithms for face detection and recognition, micro-expression recognition, and head posture estimation. Furthermore, a collaborative interactive teaching model was developed to enhance students' metacognitive processes. The goal of this model is to provide students with more accurate and personalized feedback, thereby fostering the development of their metacognitive abilities.

Experimental data revealed that student feedback regarding collaborative teaching with AI systems is complex. Some students felt the method either fully or partially met their learning needs. Compared to group B, students in group A demonstrated a greater variation in dispersed learning durations. When comparing group B to group C, the former demonstrated better performance in longer-duration learning, while the latter showed superiority in short-duration learning. High-scoring performance was better in group B than in group A. Additionally, group B maintained high-scoring superiority compared to group C. However, it is worth noting that group C had a higher number of students in the mid-to-low scoring range. Data indicates that students have varied perceptions regarding their learning process status, with a high level of satisfaction across most items. Concerning the enhancement of metacognitive abilities, the data provided mixed feedback, with most aspects receiving positive evaluations.

Therefore, collaborative teaching involving teachers and AI systems introduces new possibilities for student learning but also presents certain challenges. Data pertaining to the duration of online learning and module knowledge test scores revealed differences among various learning groups, offering insights for optimizing teaching strategies. In general terms, collaborative teaching with AI systems holds potential. However, to maximize its efficacy, it is imperative to have a profound understanding of specific student needs and feedback and make strategic adjustments accordingly. Moreover, in the pursuit of continually enhancing teaching outcomes, regular evaluation and adjustments based on feedback should be performed.

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