The Relationship between Classroom Learning Engagement of Secondary Vocational School Students and Psychological Factors based on Video Analysis Technology

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Abstract: - In the quest for quality improvement in higher education, student engagement in the classroom as a core element in evaluating the effectiveness of education has become increasingly important. In particular, the precise measurement and analysis of students' engagement in learning behaviors in the classroom have become a key area for combining learning engagement research with teaching practice in higher education institutions. This study focuses on the use of computer video parsing technology to detect the learning engagement of students in secondary vocational schools in Jiangsu Province (secondary students) and its application. The study analyses the video data generated by secondary students in the learning process, and extracts key information with the help of advanced computer video parsing algorithms, to accurately quantify students' learning engagement. The results of the study show that this technology can effectively monitor the learning engagement of secondary vocational school students, and provide an effective aid for teaching improvement and personalized learning guidance.

Key-Words: - Secondary vocational school students in Jiangsu, Video parsing technology, Learning engagement, Classroom behavior, Machine learning; Psychological factor.

Received: April 25, 2024. Revised: November 19, 2024. Accepted: December 21, 2024. Published: January 27, 2025.

1 Introduction

In today's educational environment, the insufficient classroom learning engagement of vocational school students has become an urgent problem to be solved. Many secondary vocational school students exhibit phenomena such as a lack of motivation and lack of concentration during the learning process, which not only affects their academic performance but also poses hidden dangers to their future career development, [1]. At present, common methods for measuring classroom learning behavior engagement include student self-report and teacher classroom observation. Student self-report is widely adopted due to its ease of operation, ease of management, and ability to obtain a large amount of sample data at a lower cost, [2]. However, this method is susceptible to subjective factors from students and may not accurately reflect the situation in some cases, and there is a certain lag in data collection and processing, [3]. Traditional research methods may have certain limitations in analyzing these complex relationships. The emergence of video parsing technology provides us with a new perspective to gain a deeper understanding of the classroom learning engagement of secondary vocational school students. By analyzing classroom videos, students' behavior and emotional changes can be observed more objectively and accurately, providing strong support for exploring the relationship between learning engagement and psychological factors, [4].

This study aims to explore the relationship between classroom learning engagement and psychological factors among secondary vocational school students and to use video analysis technology to enhance teaching effectiveness. By analyzing the current situation of classroom learning engagement among secondary vocational school students, identify the psychological factors that affect learning engagement. At the same time, video analysis technology is used to monitor and analyze the classroom teaching process in real-time, understand students' learning behavior, emotional changes, etc., provide targeted teaching suggestions for teachers, and improve the learning engagement and effectiveness of secondary vocational school students.

2 Classroom Learning Behaviour Coding and Construction of the Dataset

2.1 Research Objects

In this study, we measured and analyzed the learning behavior of 38 students who participated in a class in the course 'Theory and Practice of Educational Technology' in a secondary school in Jiangsu Province. Before collecting the video data, the researcher informed the students of the purpose of the study and promised to keep the data confidential; after completing the collection of students' behaviors in the classroom, the teacher could view the results of the classroom data analysis and processing through the system.

2.2 Observation Indicators of Students' Learning Behavior

Based on the relevant indicators of students' classroom learning behaviors, this study invited a total of 10 experts, including scholars in the field of educational technology and teachers on the front line of teaching in colleges and universities, to jointly carry out a questionnaire survey and in-depth interviews on the selection of observation indicators of students' classroom behaviors. Through the comprehensive analysis of the questionnaire data and interview information, this study selected five behaviors as the key indicators of engagement: 'looking at the blackboard, reading books, looking at computers, raising hands to answer questions, and discussing with each other', and defined 'using mobile phone' as a signature indicator of students' distraction, the details of which are shown in Table 1 (Appendix).

2.3 Dataset Production Process

This study constructed a student classroom behavior video dataset following the Atomic Visual Actions (AVA) dataset format, [5]. As shown in Figure 1, the model training process of this study first needs to clarify the research purpose and data scope, reasonably arrange high-definition cameras and audio acquisition equipment in the classroom, and deploy sensors as needed. Then carry out data collection, continuously record video and audio in the classroom, synchronously collect sensor data, and record metadata. After the acquisition, the data set suitable for deep learning model training is formed by preprocessing, editing video, processing audio noise reduction transcription, and then labeling students' behavior and characteristics. Then define the behavior label system, such as students' attentive listening, teachers' explanation, and other labels, and organize personnel to manually mark and audit the data based on this to ensure quality. After that, integrate the marked data and metadata, establish an association, and select appropriate storage methods to store multimedia data and marked metadata respectively. Finally, set the integrity, accuracy, and other verification indicators, sample and evaluate the quality of the data set, and correct the problem to ensure its availability.

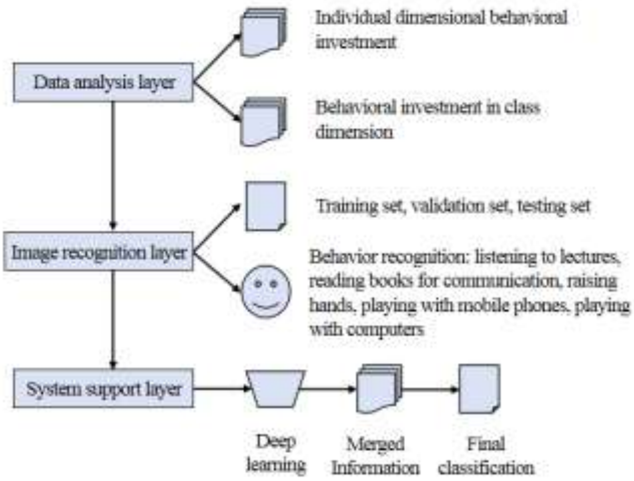

Fig. 1: Flow of the classroom learning behavior engagement measurement and analysis system

2.4 Information Capture

In this study, a high-definition webcam configured inside the classroom was used to systematically capture video of classroom teaching activities. Subsequently, 10% of the image samples were randomly selected from the acquired video streams and deeply analyzed using deep learning and computer vision techniques, which in turn led to the construction of a classroom learning behavior dataset and the training of a classroom learning behavior model, laying the foundation for subsequent research on classroom learning behavior recognition, [6]. The image acquisition process is detailed in Figure 2.

Fig. 2: Image Acquisition

2.5 Information Recognition

In constructing a quantitative analysis framework for student classroom engagement, the image recognition module constitutes the core functional unit, which is further divided into two sub-modules. The first is the learner identification part, which collects real-time visual data in the classroom through video recording equipment, and after image segmentation processing, uses advanced convolutional neural networks (CNN) and facial recognition techniques to capture students' facial images and submit them to a dedicated face recognition interface for further analysis. The second part is the behavior recognition part. This study adopts a gradually accumulating technical method to accurately judge classroom learning behavior [7]: in the initial stage, individual actions are recognized through body posture analysis, and then target detection and position confirmation technologies are integrated to achieve accurate recognition of classroom behaviors such as “reading”, “playing mobile phones”, and “looking at computers” (Figure 3).

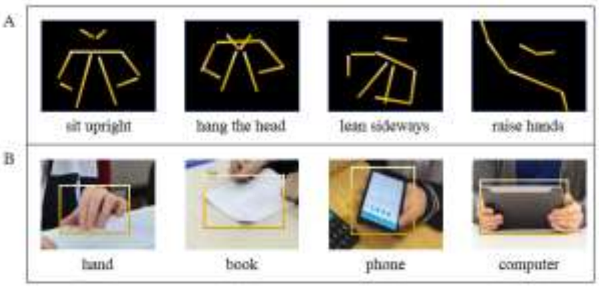

Fig. 3: Image Recognition A: Skeleton Diagram B: Target Recognition Diagram

2.6 Information processing

In the data analysis stage of this study, the indicator function, as well as the affiliation function in the field of fuzzy mathematics, were used to standardize the indicators related to classroom learning behavioral inputs, and the process followed the following formula (1). Further, in this study, the weights of the indicators of classroom learning behavioral inputs were comprehensively rated using hierarchical analysis combined with the entropy assignment method, [8]. First, five experts in the field of educational technology were invited to fill in the importance assessment matrix of learning engagement and disengagement indicators, according to which the subjective weight sequence W_i of each indicator was determined; second, the standardized indicator data were input into the Matlab software, and the objective weight sequence Vi was computed; ultimately, the comprehensive weights were derived by integrating the subjective and objective weights, which was calculated as shown in Equation (2).

$$F(x_i)=\begin{cases} 3.e^{\frac{x_1-x_0}{x_{\max}-x_0}.l_n\frac{5}{3}} & x_i \geq x_{\min} \\ 0 & x_i < x_{\min} \end{cases} \tag{1}$$

$$F(i)=W_i.V_i \,/\sum_{j=1}^{m}\left(W_j.V_j\right) \tag{2}$$

Based on the provided method of determining the weights of indicators, this paper constructed the weight matrix of learning engagement and learning withdrawal, as shown in Table 2 (Appendix). On this basis, this study further implements the quantitative assessment of classroom behavioral engagement, and carefully analyses and evaluates the overall classroom behavioral engagement, individual students' learning behavioral engagement, and their trends over time, [9].

3 Classroom Learning Behaviour Recognition System Application

3.1 Degree of Learning Behavioral Engagement

In this quantitative analysis of classroom teaching behaviors, it is possible to observe the overall degree of students' behavioral engagement in classroom activities. Based on the data collected by the system, the frequency of students' behavioral engagement in learning activities is relatively high at 93.8%, indicating that students generally maintain a high level of engagement in classroom learning. The overall assessment of the weights shown in Table 2 (Appendix) resulted in a behavioral engagement in learning score of 2.89 for this lesson, a score that reflects a moderate level of student engagement in learning. An in-depth analysis shows that such results are partly due to the lack of interactive activities in the classroom, whose actual percentage is only 4.72%.

In terms of the analysis of individual behavioral engagement, 12 out of the 38 students counted did not meet the class average standard for classroom learning behavioral engagement. In particular, some students had significantly lower engagement and higher disengagement, which suggests that teachers need to implement targeted counseling and prompting for these students to ensure the optimization of the teaching effect.

3.2 Trends in Learning Behavioural Engagement

This study takes time as the main line to provide an in-depth analysis of the dynamic changes in students' learning behavioral engagement in the classroom. As presented in Figure 4(A) in Appendix, students’ behavioral engagement in this lesson was maintained at a relatively stable level as a whole, but showed a slight downward trend towards the end of the lesson; students’ learning straying in the initial stage of the lesson was significantly reduced, however, this phenomenon gradually increased as the end of the lesson approached. Figure 4(B) in Appendix presents the frequency of the six behaviors reflecting learning engagement and disengagement over time. From this observation, ‘looking at the blackboard’ and ‘observing the computer screen’ were the main behavioral patterns in the whole lesson, and it is assumed that the teacher mainly used the lecture method in this lesson. In addition, there were multiple peaks of ‘communicating’ and ‘raising hands to answer’ behaviors in the classroom interactions, which indicates that the teacher facilitated the interactive discussions in the classroom and achieved substantial results.

3.3 Analysis of Teaching Applications

In the process of exploring the validation and improvement of the teaching plan, by analyzing the time-series changes in classroom teaching behaviors and their total comparisons, the teacher is able to grasp the students' responses to the teaching activities, and accordingly make necessary adjustments and optimization to the teaching plan or implementation process. In this case, the teacher adopted a lecture-centered teaching mode and introduced communication and questioning to enhance interaction. It was observed that students generally maintained a high level of concentration during the learning process, however, the level of student engagement decreased significantly when the lesson reached the 20-minute mark. In view of this, this study suggests that teachers should take measures to adjust the pace and difficulty of teaching and enhance the interactivity and attractiveness of the lesson according to the student's level of knowledge, in order to promote the recovery and enhancement of students’ engagement in the classroom.

Further, the lack of data on students' disengagement behaviors provides a strategic aid to the academic monitoring of student populations. Teachers should implement individualized counseling and support in those student groups where academic disengagement is longer and occurs more frequently. In this course, 11 students demonstrated significant disengagement, including two students who were disengaged for more than 30% of the class time. Teachers need to proactively engage with these students to explore the root causes of their disengagement in order to prevent possible future academic alerts.

3.4 Analysis of Psychological Factors Affecting Students' Learning Engagement

Learning motivation: in classroom learning situations, intrinsic motivation, such as curiosity about knowledge and desire for self-improvement, will encourage students to actively choose and deeply participate in learning content, [10]. Extrinsic motivation, such as obtaining certificates, completing academic requirements, or obtaining rewards, can also drive learners to engage in learning but may be a relative lack of autonomy and persistence. When learning in class is closely linked to external goals, students may pay more attention to the results of completing the task rather than an in-depth understanding of the learning content itself, which may be reflected in the higher completion rate of classroom viewing, but the lower depth of knowledge mastery.

Cognitive load: cognitive load in learning is affected by many factors, including the complexity of classroom content, the way information is presented, and students' own knowledge base. If the classroom information is too dense, the explanation speed is too fast, or the use of too professional and obscure terms, it may lead to students' cognitive load being too high, thus affecting their learning behavior engagement. In this case, students may be distracted, pause, or give up listening to the class. On the contrary, the reasonable design of video content, such as the gradual explanation, the provision of rich examples, and visual information display, can reduce the cognitive load, make it easier for students to understand and absorb knowledge, and then improve their participation in learning, which is manifested by longer viewing time and higher content understanding.

Attention allocation: in video learning, students need to allocate their attention to a variety of information sources such as video pictures, sounds, and words. The attractive factors of the video, such as vivid pictures, infectious explanation sounds, and fascinating story plots, can help students better concentrate. However, there are many interference factors in the modern learning environment, such as social media notifications, ambient noise, and so on, which are easy to distract learners. When students can effectively allocate attention and maintain concentration, they are more likely to watch the video completely, actively participate in the interaction with teachers (such as answering questions, discussing with classmates, etc.), and better understand and remember the classroom content.

Social interaction: in the classroom, the interactive communication between students (such as discussing with each other, forming study groups to share learning experiences, etc.) can enhance the sense of belonging and motivation of learning. When students see the views and opinions of others on the classroom content, they may stimulate themselves to think and analyze more deeply, so as to improve their investment in classroom learning.

4 Discussion

Classroom learning behaviors are related to brain functions. For example, the prefrontal cortex can help students focus and suppress interference, and play a key role in listening carefully and participating in classroom discussions. If there is a problem with its function, it may be difficult for students to suppress impulses, talk freely, or interrupt others, [11]. In the face of complex tasks, they may also avoid learning because they are unable to effectively plan and make decisions, appear dazed, and have other wrong behaviors. As a special group of students, secondary vocational students' classroom learning engagement is of key significance for the cultivation of vocational skills and the improvement of comprehensive quality. With the continuous development of educational technology, Video Parsing Technology provides a new means for in-depth study of classroom learning behavior.

Relying on the advanced means of computer vision and machine learning, this technology carries out in-depth processing and analysis of video data, so as to mine educational information and features, and expand new teaching and learning paths for educators and learners. In specific applications, computer video parsing technology can achieve monitoring and analysis of students’ learning behaviors, personalised teaching recommendations, intelligent evaluation, and feedback, as well as enhance teachers’ teaching effectiveness. In this study, computer vision technology is applied to college classrooms to refine key indicators for measuring students' classroom engagement, and on this basis, classroom behavior recognition technology is improved to integrate body language and object usage information to accurately identify six common classroom behaviors of students. It is found that the frequency of students' participation in learning activities is relatively high, reaching 93.8%. However, 31.58% of students' classroom learning behavior engagement does not meet the average standard of the class, and students' learning engagement is at the medium level. The reason is the lack of interactive activities in the classroom, and the actual proportion is only 4.72%.

In summary, video parsing technology can accurately assess students' learning engagement, helping teachers grasp students' classroom performance and objectively evaluate the teaching effectiveness of the classroom is an effective means to support teachers in improving teaching effectiveness.

5 Future Research Directions and Suggestions

This study uses less data, belongs to a small sample, and the dimensions of behavioral engagement are not rich, which may lead to the model generalization ability is not very strong. In addition, the impact of online learning engagement is not limited to learners themselves, but also related to peers, teachers, and teaching managers. In subsequent research, a variety of algorithms can be selected to build a multidimensional model to more truly reflect the changes in learning engagement in the process of online learning, and promote the occurrence of higher learning engagement of learners.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the author used Grammarly for language editing. After using this service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.

APPENDIX

Table 1. Observed indicators of students' behavioral engagement in the classroom

Category	Activity	Behavior	Action status
Learning engagement	Attend class and listen to lectures	Look at the blackboard	Sitting + looking ahead
		Read a book	Head down + hands overlapping books.
		Look at the computer.	Head down + hands overlapping with the computer.
	Interactive communication	Raise a hand	Raise your hand
		Discuss with each other.	Twist the body
Learning Disengagement	Learning extracurricular activities	Play with mobile phone	Head down + overlapping hands with mobile phone

Table 2. Classroom Learning Behaviour Engagement Indicator Weighting Scale

Learning behavior		weight		
Dimension	index	Analytic hierarchy process	Entropy assignment method	Combined weights
Learning engagement	Look at the blackboard	0.159	0.076	0.064
	Read a book	0.142	0.242	0.181
	Look at the computer	0.145	0.355	0.271
	Raise a hand	0.2	0.156	0.165
	Discuss with each other	0.353	0.172	0.319

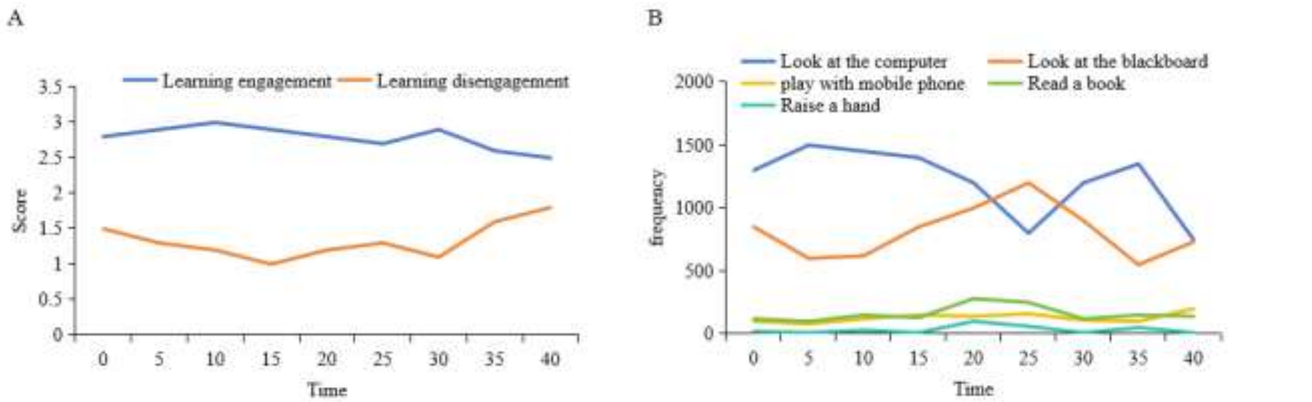

Fig. 4: Trends in learning behavioral engagement A: Learning engagement and disengagement scores over time B: Frequency of individual behaviors over time