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Exploring the Learning Process and Effectiveness of STEM Education via Learning Behavior Analysis and the Interactive-Constructive-Active-Passive Framework

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Abstract

Given the inadequacy of assessed outcomes (e.g., final exam) and the importance of evaluating the learning process in STEM education, we use deep learning to develop the STEM learning behavior analysis system (SLBAS) to assess the behavior of learners in STEM education. We map learner behavior to the ICAP (interactive, constructive, active, passive) framework, helping instructors to better understand the learning process of learners. The results show that SLBAS exhibits high accuracy. Moreover, Cohen's kappa coefficient between expert coding and SLBAS is high enough to support replacing expert coding in the observation method with SLBAS to recognize the learning process of learners during STEM activities. Finally, statistical analysis establishes a correlation between the learning process and learning effectiveness. The results of this study are in line with most previous studies, demonstrating that STEM education differs from traditional teacher-centered courses in that it helps learners to improve the process of knowledge construction with practice and hands-on opportunities rather than simply receiving knowledge passively.

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Keywords
science, technology, engineering, and mathematics education, learning behavior analysis, deep learning, interactive-constructive-active-passive framework

Introduction

In the 1990s, the National Science Foundation proposed an education program integrating science, technology, engineering, and mathematics (STEM) to correct the shortage of research and development talent and address the challenges of the future social economy (Bybee, 2013). Since then, STEM research has mushroomed. STEM education cultivates the ability to identify and solve daily-life problems by incorporating knowledge from different fields of science and technology (Martín-Páez et al., 2019; Sanders, 2009). Hsiao et al. (2022) show that STEM education is characterized by a student-centered approach which nurtures learners' problem-solving, collaborative, and creative thinking skills. Compared with the traditional teacher-centered approach, where learners passively receive knowledge from a teacher, in the student-centered STEM method learners combine interdisciplinary knowledge and their personal experience to actively complete the construction of their own knowledge using practice and experiments (Christensen et al., 2015; Wang et al., 2022). These differences make traditional methods, which focus solely on the final learning outcome, increasingly unsuitable for student-centered STEM education. Gao et al. (2020) believe that only evaluating the final outcome (e.g., final exam and final project) in STEM education could reduce important information for learners as they construct knowledge via problem solving, interdisciplinary integration, and collaboration. This reveals the importance of evaluating the learning process in STEM education.

How to effectively understand the learning process of learners in STEM activities has also become a crucial part in the assessment of STEM education. According to a systematic review of STEM assessment tools by Gao et al. (2020), the literature primarily addresses self-reporting and observation methods. Self-reporting tools generally adopt traditional subjective measurement methods to allow learners to express their motivational beliefs, experiences, and feelings in the learning process through questionnaires or interviews (Zimmerman, 2008). Observation methods evaluate the learning processes and effectiveness of learners by encoding and labeling classroom data (Harari et al., 2017; Lathia et al., 2013). These methods exhibit several limitations; for example, self-reporting is susceptible to subjective awareness, the subject's memory limitations, and interference from social expectations (Baumeister et al., 2007; Paulhus & Vazire, 2007), and D'Mello et al. (2017) indicate that the observation method is time-consuming and labor-intensive for coding and labeling and cannot be executed in some learning environments (such as the learner's home). To address these challenges, this study presents a new and original method that combines deep learning and computer vision techniques for the development of the STEM learning behavior analysis system (SLBAS).

However, because STEM education involves interdisciplinary practice, it cannot be classified into a specific discipline (Brown et al., 2011). Therefore, methods adopted to measure the learning process in a specific discipline of education may be unsuitable for STEM education. Chi and Wylie (2014) address this with the ICAP (interactive-constructive-active-passive) framework, which views the learning process as a gradual process and clearly describes the process of knowledge construction. In this study we use the ICAP framework to map the SLBAS output to the learning process, which can put the learners' learning process into perspective during STEM activities in an objective and automatic manner. In this study we seek to answer the following two research questions:

i. Whether SLBAS can effectively assess the learners' learning process in STEM activities?
ii. How does the learning process influence learning effectiveness in STEM activities?

Literature Review

Deep Learning Based Human Behavior Recognition

In the deep learning field, human behavior recognition has received extensive attention in the past few years due to its wide applications in fields as varied as human-computer interaction, sports, and healthcare (Khan et al., 2020b; Majd & Safabakhsh, 2020). Common methods to recognize human behavior can be divided into image-based human behavior recognition (Dai et al., 2020; Jaouedi et al., 2020; Khan et al., 2020a), human behavior recognition based on wearable devices (Demrozi et al., 2020; Nweke et al., 2019), and human behavior recognition based on wireless network devices (Cui et al., 2021; Liu et al., 2020). Of these, as image-based human behavior recognition boasts the highest recognition accuracy and easy deployment, it has received the most research attention in practice (Kamel et al., 2019). Since the release of the Microsoft Kinect in 2011, more and more research has been carried out on the recognition of human behavior through images of 3D human keypoints (Lin et al., 2021) for applications such as step measurement and health monitoring (Al-Naji et al., 2017).

However, the extraction of 3D human body keypoints requires specific sensors and depth cameras, and joint overlap easily leads to inaccuracy (Lin et al., 2021). Cao et al. (2019) propose the OpenPose system, which quickly extracts human body keypoints from 2D RGB images and employs part affinity fields (PAFs) to connect human body keypoints and complete behavior recognition. Compared with the Microsoft Kinect, OpenPose requires only commercially available cameras to complete keypoint extraction, and adopts convolutional neural networks (CNNs) to solve the overlap problem (Cao et al., 2019).

Many studies have been conducted on OpenPose applied to human behavior recognition. For example, Nakai et al. (2018) employ OpenPose to extract body keypoints which are then used as the basis by which to evaluate the shooting action in basketball games and predict the possibility of hitting the basket with such shooting behavior. Yan et al. (2020) combine OpenPose and Kalman filters to track the accuracy of patients' movements during rehabilitation and thus understand their status. Qwu et al. (2021) propose ROpenPose based on OpenPose to detect the motion and operation behavior of astronauts in a weightless environment.

Researchers have also used OpenPose to implement educational systems. For instance, Lin et al. (2021) exploit OpenPose for real-time pose recognition in a badminton teaching app which helps students to enhance their badminton skills and learning effectiveness. In this context, OpenPose is thus often applied in physical education but rarely used in other disciplines. Due to the diversity and dynamics of STEM education (Brown et al., 2011), it is possible to use OpenPose to track student behavior in STEM education. Accordingly, in this study we propose an OpenPose-based system to identify learner behaviors during STEM activities and utilize this information to assess the learning process.

ICAP Framework

The ICAP framework was proposed by Chi and Wylie (2014), who divide the learning process into four different modes, allowing researchers to map learning behavior to different modes and ultimately understand the process by which the learner's knowledge changes. Specifically, in the ICAP framework the in-class learning process is classified as passive, active, constructive, and interactive as follows:

- Passive: Learners passively receive information from instructional materials and do not actively do anything related to their learning. For example, learners listen intently without doing other things such as taking notes or recording.
- Active: Learners actively exhibit visible behavior or physical manipulation. For example, learners may pause, fast-forward, or rewind while viewing learning videos, they may highlight and take notes on learning content, or they may manipulate learning materials through gestures to solve the problems at hand.
- Constructive: This refers to behaviors by which learners generate or produce additional externalized outputs or products beyond what is provided in the learning materials. For example, learners construct programming knowledge by assembling and operating robots, and draw concept maps to understand the process of constructing their own knowledge.
- Interactive: It requires two criteria to operationalize interactive behaviors, including both partners' utterances must be primarily constructive, and a sufficient degree of turn taking must occur(Chi & Wylie, 2014). Chi and Wylie (2014) indicate that both parties must engage in constructive behavior so that these discussions are meaningful. In addition, when there is enough rotation in the interaction, it is easier for both parties to integrate each other's understanding of the domain and adjust their own cognitive states. As long as these criteria are met,

the interactors need not be peers; teachers, parents, or robots, for example, could also be interactors.

Thus the ICAP framework views the learner's learning process as a gradual process (Chi & Wylie, 2014). Using learning materials to attain increasingly higher levels, learners gradually deepen their cognitive status and engagement in the curriculum (Chi & Wylie, 2014; Sailer et al., 2021). Given the ICAP description of learner engagement, many studies employ the framework as an indicator when evaluating the learning process (Hsiao et al., 2022). For example, Zhang et al. (2016) define learners' behavioral indicators during online learning based on the ICAP framework to help researchers to better understand engagement and habits during online learning. To explore the benefits of teacher professional development from the learner's perspective, Atapattu et al. (2019) utilize word embeddings (word2vec) in natural language processing (NLP) to develop an automated system and integrate the ICAP framework as an indicator to assess the learning process. Raković et al. (2020) incorporate the framework for the analysis of learner messages in forums, helping teachers to comprehend the process of knowledge construction and serving as a predictor of learners' exam and debate effectiveness. The practical perspective afforded by the ICAP framework helps researchers to systematically understand the learning process during courses. Therefore, in this study we also develop a system based on the ICAP framework to help researchers and teachers better understand the learning process in STEM education, and to serve as a basis for educational assessment in STEM education.

Assessment in STEM Education

In the systematic review of Gao et al. (2020), self-reporting and observation are the main methods for assessing the learning effectiveness and learning process of learners in STEM education. Self-reporting is a way for learners to express their motivational beliefs, experiences, and feelings in the learning process through questionnaires or interviews by traditional subjective measurement methods (Zimmerman, 2008). For example, Sahin and Yilmaz (2020) use questionnaires about the attitude towards science and augmented reality (AR) to recognize changes in learners' attitudes towards science and AR after using AR technology in STEM activities. Ekatushabe et al. (2021) use self-reporting questionnaires to assess levels of teacher autonomy support, self-efficacy, and boredom when engaging in STEM activities. However, some studies suggest that self-reporting is susceptible to subjective awareness, subject's memory limitations, and interference from social expectations (Baumeister et al., 2007; Paulhus & Vazire, 2007).

To account for these disadvantages of self-reporting, many studies employ observation methods to assess learning effectiveness in the classroom in relatively objective ways (Harari et al., 2017; Lathia et al., 2013). Observation methods measure the learning processes and effectiveness objectively by encoding and labeling data collected by sensors or instruments (Harari et al., 2017; Lathia et al., 2013). For example, (Chen et al., 2020) develop four behavioral indicators suitable for hands-on learning and invite two experts to encode hands-on virtual reality (VR) activity video through the developed indicators, helping researchers to gain a comprehensive understand of the learning process. Sun et al. (2021) invite two experts to encode learner behaviors in videos of unplugged STEM activities and identify differences between learning processes and learning behaviors during traditional classroom courses and unplugged STEM activities. However, D'Mello et al. (2017) reveals that the observation method is time-consuming and labor-intensive for coding and labeling and cannot be performed in learning environments such as the learner's home.

With the rapid development of technology, more and more studies have used deep learning based recognition to reduce the time and labor needed for observation (Cojocea & Rebedea, 2022; He et al., 2020). For example, Zhang et al. (2020) use cameras to record learners' facial expressions as a basis for judging learner engagement in online learning, and Liu et al. (2019) use keypoints on the teacher's hand to identify gestures and explore the impact of using gestures to attract learner attention on learning outcomes. Liang et al. (2019) believe that with the popularization of smart devices, the traditional education mode is increasingly being challenged. Therefore, they analyze the physical condition and interaction situation of learners through sensors in smart watches and use adaptive feedback after diagnosis. Kim et al. (2021) use computer vision technology to analyze the movement of each keypoint and explore whether aromatherapy influences the learner's learning outcome.

In summary, despite the many recent studies that employ deep learning techniques for educational assessment, few studies focus on building systematical models to explore student-centered STEM education. Therefore, to address the limitations of self-reporting and observation methods and fill the gaps in the current STEM education assessment, we combine deep learning and computer vision to recognize actions of hands on learning materials to assist researchers in evaluating learning behavior during STEM activities. We then map this learning behavior to the ICAP framework as the basis for objective assessment of the learning process.

Method

In this study, we propose seven steps to understand the learning processes of learners and identify relationships between learning processes and learning effectiveness in STEM activities (as shown in Figure 1).

Collecting Simulated Data

In Step 1 (Figure 1), because there was no usable large dataset with which to train our model, we adopted *transfer learning* to transform model parameters from the COCO dataset to our dataset. We also applied fine-tuning to train SLBAS using a small amount of STEM activity data to achieve higher performance. To collect STEM activity data for

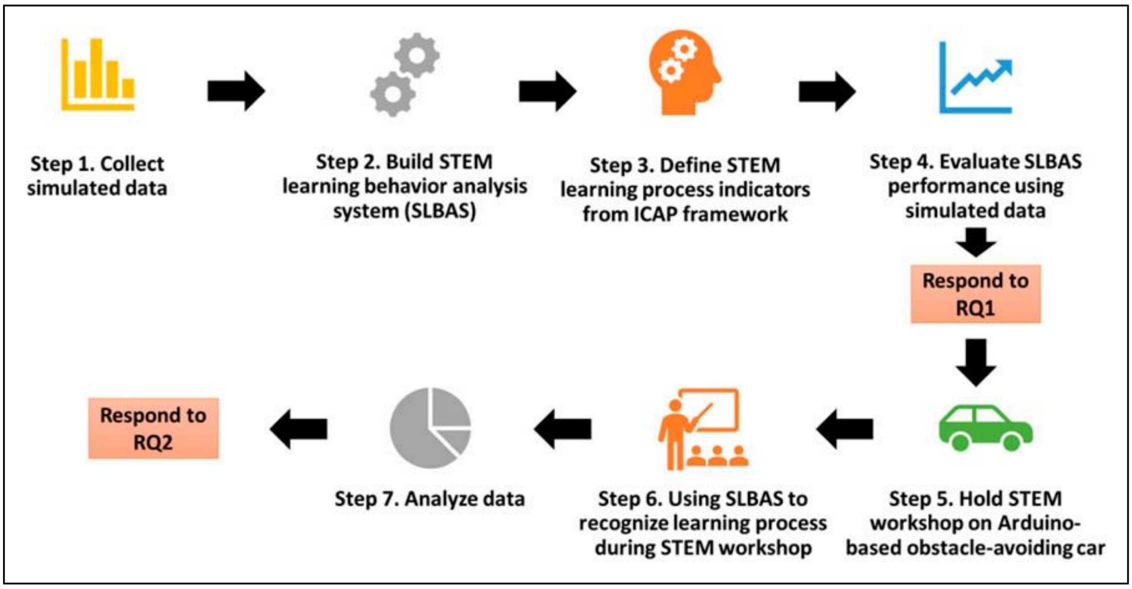

Figure 1. Research design and architecture.

model training and validation, three researchers simulated behavior common to STEM activities and recorded these behaviors with a camera. To clearly record both hands and all learning materials, the shooting angle of the camera was from top to bottom. The camera parameters were set to 20 frames per second (fps) with a resolution of 1920 × 1080. We collected a total of 21 simulated videos, from which we captured one image every 10 seconds, as required for model building.

Building the STEM Learning Behavior Analysis System (SLBAS)

In Step 2, recalling Hofstein and Lunetta's (1982) definition of the learning processes as the learner's learning experience, which includes interaction between the learner and the learning material. In this study, to objectively and automatically understand the learners' learning process during STEM activities, we exploited this concept to develop a system to recognize hand actions with learning materials as a basis by which to judge learners' learning behavior and the learning process. Figure 2 shows the SLBAS flow chart. SLBAS processes videos of STEM activities by frame by frame using OpenPose (Martin Paez et al., 2019) to capture learners' hand keypoints and YOLOv4 (Bochkovskiy et al., 2020) to detect the position of learning materials. Finally, SLBAS recognizes learning behavior in STEM activities by combining hand keypoints and the learning material positions to analyze the learning process.

We used OpenPose (Martin Paez et al., 2019) to extract learners' hand keypoints. The set parameters are shown in Table 1. OpenPose uses PAF technology to learn human muscle connections through CNN, and uses two-dimensional vectors to present various possible keypoint connections, which greatly improves the efficiency of human keypoint detection. The architecture outputs 135 × 3 × N three-dimensional vectors, where 135 is the total number of body keypoints (25 keypoints for the torso and limbs, 70 for the face, and

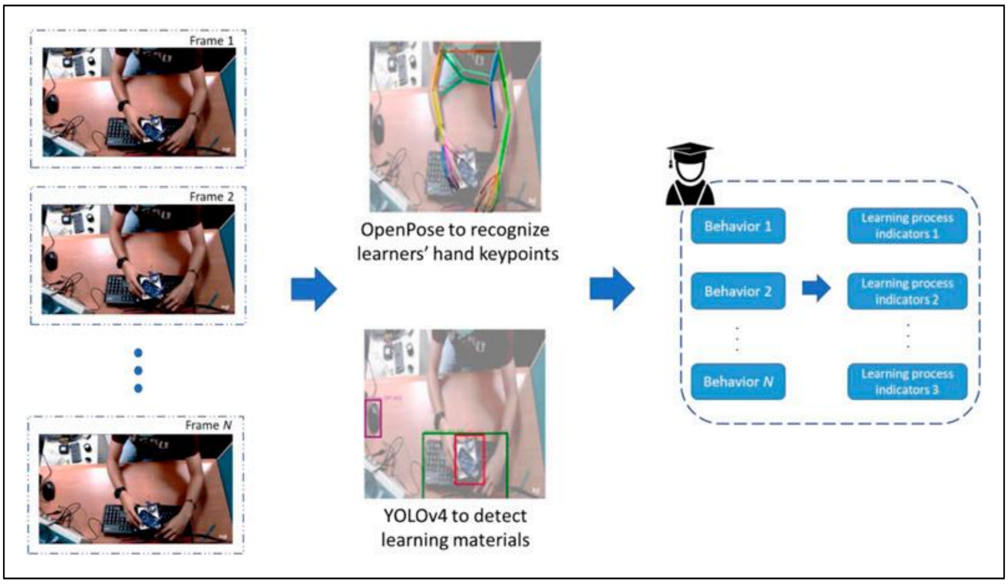

Figure 2. SLBAS architecture.

Table 1. OpenPose Parameters in SLBAS.

Parameter	Camera resolution	Model pose	Net resolution	Face
Value	608 × 608	BODY_135	−1×480	false

Table 2. YOLOv4 Training Parameters in SLBAS.

Parameter	Batch	Subdivision	max_batch	Steps	Height	Width	Class
Value	64	8	12000	9600, 10800	608	608	6

40 for the hands), 3 is the attributes of each keypoint (X and Y coordinates and the keypoint confidence), and N is the number of people in the frame. In this study we used only the 40 hand keypoints (OpenPose keypoints 26–65) as the basis for judging learning behavior.

We also applied YOLOv4 (Bochkovskiy et al., 2020) to detect the positions of objects commonly used in STEM activities. However, most such objects are not in the native YOLOv4 pretrained weights, implying that the objects are not labeled items in the COCO dataset. Therefore, to accurately detect common objects in STEM activities to meet the requirements in this study, we trained YOLOv4 using *transfer learning*. The YOLOv4 training parameters are shown in Table 2. In *transfer learning*, the weights trained on a large dataset are used as the initial weights for training; weights in deeper network layers are frozen, and only weights in shallow layers are retrained. Thus, *transfer learning* inherits pretrained weights from models trained for other fields, saving the time needed for retraining and increasing the model accuracy.

Via this image processing we extracted the hand keypoints of learners and the positions of learning materials from STEM activity videos and integrated these to understand the action of hands on learning materials and characterize learner behavior in STEM activities. The output diagram is shown in Figure 3. In addition, we following the manual coding frequency of Sun et al. (2021), recognizing learner behavior every 5 seconds. SLBAS recorded learning behavior every 5 seconds in the learning process log file of each learner and produced visual reports for teachers and researchers to facilitate a better understanding of the distribution of learning behavior at different times during STEM activities.

Defining STEM Learning Process Indicators From ICAP Framework

In Step 3 (Figure 1), STEM learning behavior indicators are developed from the ICAP framework to help researchers better comprehend the learning process during STEM activities. First, this study was based on hand actions with learning materials to define

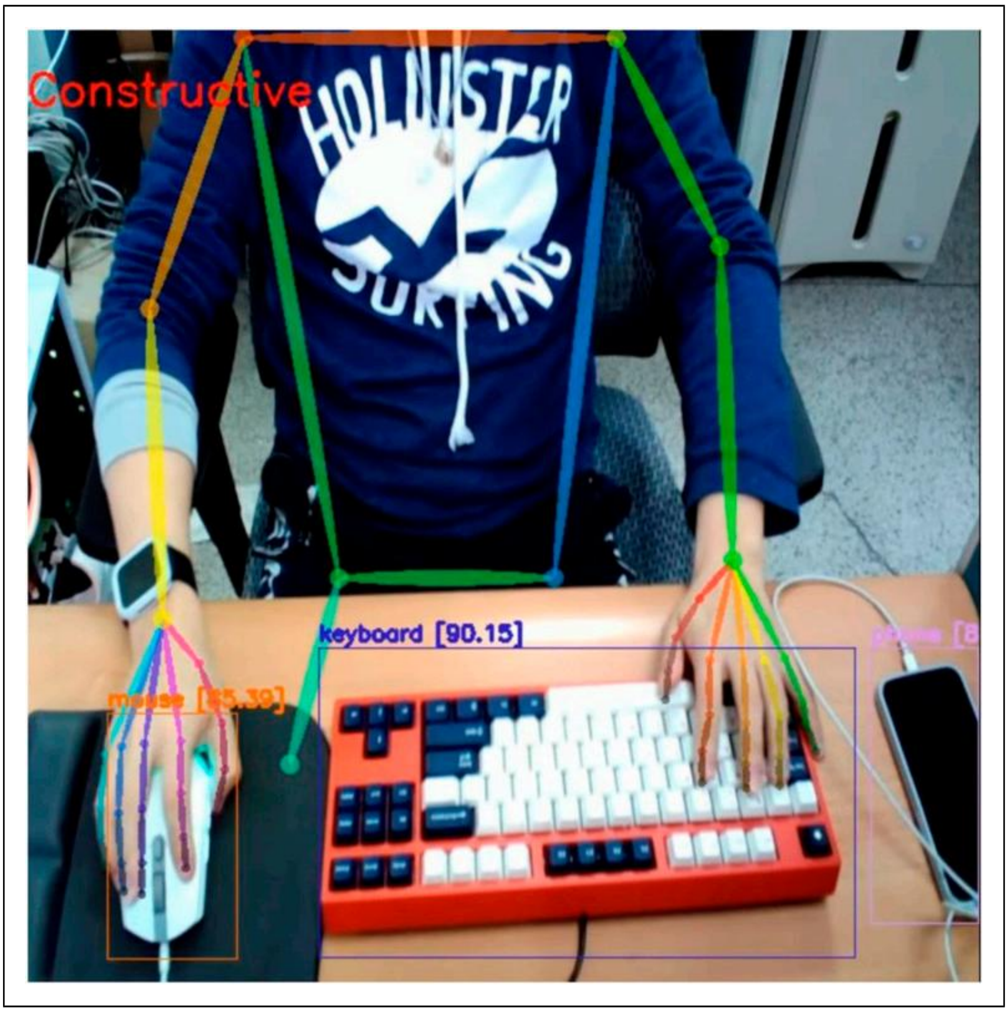

Figure 3. SLBAS output.

learning behaviors: behavior is recognized when the learner touches learning material. In addition, to evaluate the learning process during STEM activity, we exploited the ICAP framework (Chi & Wylie, 2014), which defines the passive, active, constructive, interactive, and other indicators. Given the nature of STEM workshops, we explored only how individual learning behaviors influence learning effectiveness. As learners in the STEM workshop complete each task and project individually, *interactive* in this study focuses solely on interaction between learners and teaching assistants. Table 3 describes the relationship between learning behavior and the learning process indicators.

Evaluating SLBAS Performance Using Simulated Data

After Steps 2 and 3 (Figure 1), SLBAS was developed to comprehend learning behaviors and the learning process during a STEM workshop. To address the first research question, this study verifies the performance of SLBAS by simulating data to ensure

Table 3. STEM Learning Process Indicators.

Indicator	Definition	Learning behavior
Passive	Learners passively receive information from instructional materials and do not actively do anything related to their learning (Chi & Wylie, 2014)	● Learners' hands do not touch any objects related to the STEM workshop
Active	Learners actively employ visible behavior or physical manipulation (Chi & Wylie, 2014)	● Learners use a pencil to take notes to record what they are learning ● Learners actively operate tablets containing learning materials to solve their questions instead of passively receiving knowledge from teachers
Constructive	Learners employ behaviors in which they generate or produce additional externalized outputs or products beyond what are provided in the learning materials (Chi & Wylie, 2014)	● Learners operate the laptop using the keyboard and mouse to finish programming ● Learners take Arduino components and assemble them by hand to solve the task
Interactive	Learners construct their own knowledge by asking questions and responding to others in a conversation (Chi & Wylie, 2014)	● Learners ask teaching assistants questions when they encounter problems when constructing knowledge
Other	Other unrelated behaviors	● SLBAS fails to recognize hand keypoints ● Learners use their smartphone to do something unrelated to the STEM workshop

that the SLBAS output is effective and efficient enough to replace observation methods. For verification, we used accuracy, recall, precision, and a confusion matrix to evaluate the performance of each learning behavior and learning process. Then, to confirm whether expert coding could substitute the SLBAS output, we invited two experts to encode the same video from the simulated data. Inter--rater reliability was used to measure the experts' coding and the SLBAS output. A high kappa value would indicate that SLBAS achieves the same performance as time-consuming and labor-intensive manual coding.

STEM Workshop on Arduino-Based Obstacle-Avoiding Car

In Step 5 (Figure 1), a STEM workshop on an Arduino-based obstacle-avoiding car merged STEM concepts with an obstacle-avoiding car. Learners thus completed knowledge construction from simple to deep by manipulating electronic components. For this workshop the learning sheet was regarded as a form of scaffolding learning by which to guide learners to progressively understand the function and operation of an obstacle-avoiding car. Learners employed the content learned in the workshop to design their own obstacle-avoiding car and win a football competition with their best design. The procedure for this STEM workshop is shown in Figure 4.

Twenty-eight participants (17 boys and 11 girls), all senior high school students in southern Taiwan, took part in the STEM workshop on Arduino-based obstacle-avoiding cars. All possessed similar prior knowledge before participating in the workshop. There were enough teaching assistants in the workshop to provide immediate assistance to learners when they had problems. Participants spent the first 60 minutes understanding the development environment and the Arduino components. They then spent another 60 minutes learning how to control the obstacle-avoiding car. The next 60 minutes were spent teaching them about the avoidance function of the obstacle-avoiding car, including component assembly and programming. Participants then spent 30 minutes combining what they had learned in the workshop to design their own obstacle-avoiding car. Better-adjusted parameters resulted in higher rankings in the football competition. After all workshop activities were complete, a 20-minute learning effectiveness posttest was administered to workshop participants.

Using SLBAS to Recognize the Learning Process During STEM Workshop

In Step 6 (Figure 1), all participants' behaviors and learning processes during the workshop were recorded by commercially available webcams at 1920 × 1080 resolution and 20 fps. The shooting angle of the video cameras is shown in Figure 5. Note that the participants' hands and learning materials should be on-screen as much as possible. After the workshop, the collected videos were inputted to SLBAS to recognize the learning behaviors and learning process for use in the follow-up analysis.

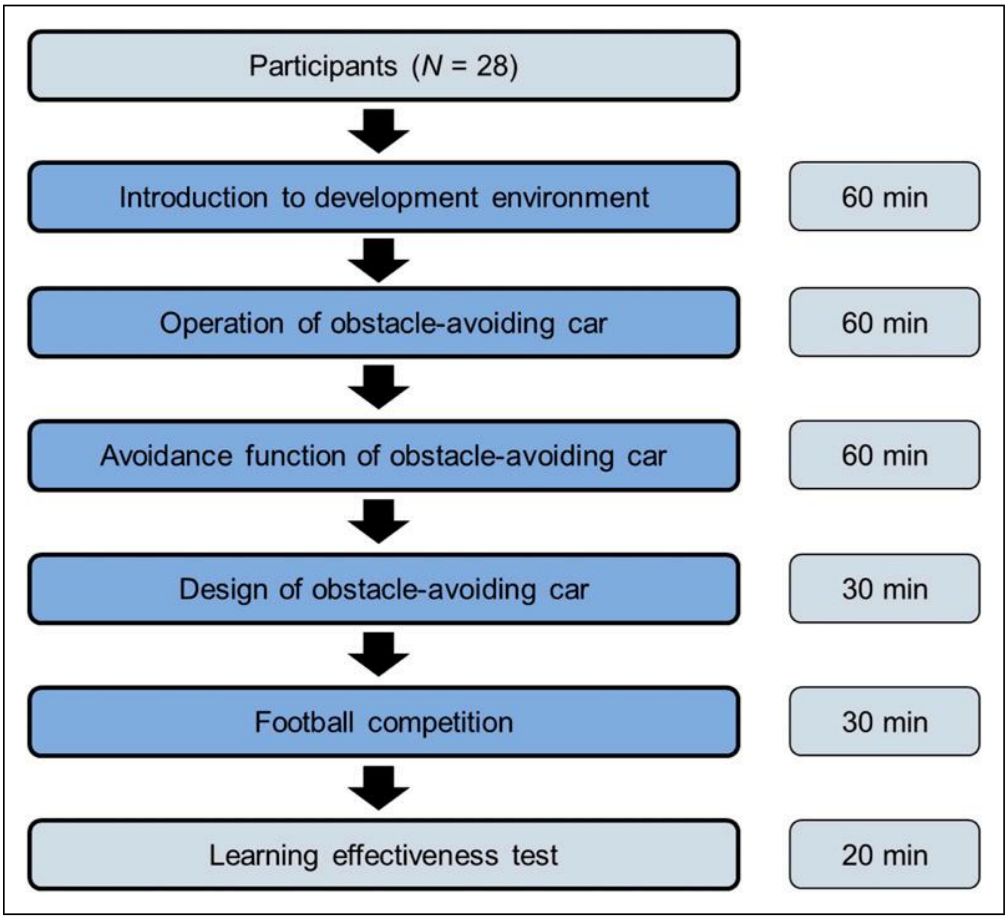

Figure 4. Procedure for STEM workshop on Arduino-based obstacle-avoiding car.

Data Analysis

In Step 7 (Figure 1), we adopted the learning effectiveness test to examine the participants' programming skills and understanding capability as they constructed the obstacle-avoiding car. Twenty single-choice questions were included in the test, each worth five points. Two experts developed the test for this study, both of whom were computer science majors and had taught programming in primary schools for more than 2 years. To verify the appropriateness and validity of the test, we calculated the internal consistency (Cronbach's α value) as .71, which is high enough for reliable results (Nunnally, 1978).

To address the second research question, we used the SLBAS output as the basis by which to judge participants' learning processes, and administered a test to understand participants' learning effectiveness to further identify relationships between the two. We thus adopted three steps to investigate how the learning process impacts learning effectiveness. First, Pearson's correlation coefficient was used to confirm the relationship between the learning process and learning effectiveness. Second, to differentiate the learning processes of highly effective and slower learners, participants were divided into two groups according to their learning effectiveness test scores. The top

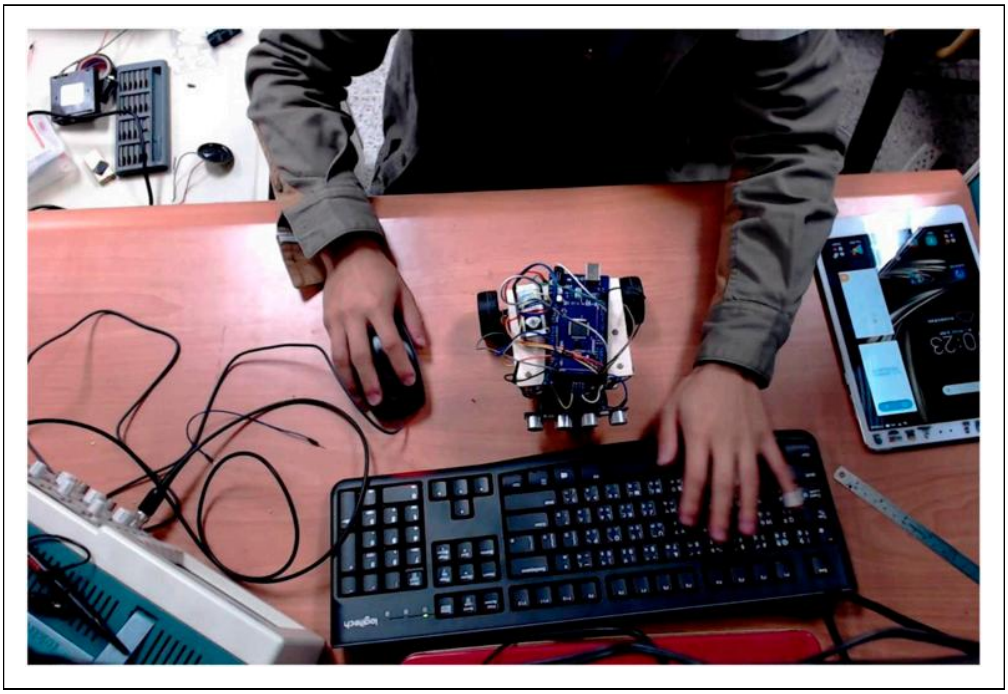

Figure 5. Camera angle.

50% participants were allocated to the high learning effectiveness group, and the remaining participants were allocated to the low learning effectiveness group. Finally, an independent *t*-test was conducted and Pearson's correlation coefficient was calculated to identify differences in each learning process indicator in the high and low learning effectiveness groups.

Results

Does SLBAS Effectively Assist Instructors and Researchers to Assess the Learners' Learning Process in STEM Activities?

To address this research question, we evaluated the performance of SLBAS. First, we used a confusion matrix and the accuracy, precision, and recall measures to quantify the performance of SLBAS. However, as there were no automatic models similar to SLBAS, a comparative investigation was not possible. Thus we not only calculated the accuracy, precision, recall, and confusion matrix to provide a basis for comparisons in follow-up studies, but also calculated Cohen's kappa to verify whether SLBAS could replace experts in coding in the observation method. A high enough kappa coefficient in expert coding and SLBAS output would confirm the feasibility of SLBAS. Given the same accuracy as expert coding, SLBAS encodes automatically, greatly reducing the time and labor costs of coding.

To evaluate the recognition performance of SLBAS in each learning process indicator, a confusion matrix was adopted to measure the advantages and disadvantages of SLBAS in recognition. This confusion matrix is shown in Figure 6: the *constructive* indicator is easily confused with the *passive* (n = 14) indicator. This is because learners often placed their hands near the learning materials used to finish their task even if they were doing nothing. In addition, the *passive* indicator was easily confused with the *active* (n = 12) and *other* (n = 11) indicators. Because the video capture rate was only 20 fps, small learning materials (e.g., pens and smartphones) blurred easily when learners moved, impeding the detection of small objects. As small objects were unrecognizable, indicators defined by small objects were easily confused.

As shown in Table 4, the accuracy, average precision, and the average recall of SLBAS calculated from the confusion matrix are .858, .864, and .837, respectively.

Given the lack of a baseline by which to judge the performance of SLBAS, we calculated Cohen's kappa to compare SLBAS output and expert coding. Two experts and SLBAS encoded the three one-minute videos from simulated data, with a resultant Cohen's kappa between expert A and expert B of .74, expert A and SLBAS of .71, and expert B and SLBAS of .72, which exceeded .70 (Landis & Koch, 1977). This indicates a sufficiently high inter-rater reliability; that is, there were no differences between coding from experts and that from SLBAS. Therefore, SLBAS could be used to replace experts for coding in the observation method. Furthermore, SLBAS not only demonstrated the same accuracy as expert coding in the observation method, but it also encoded automatically, significantly reducing time and labor costs.

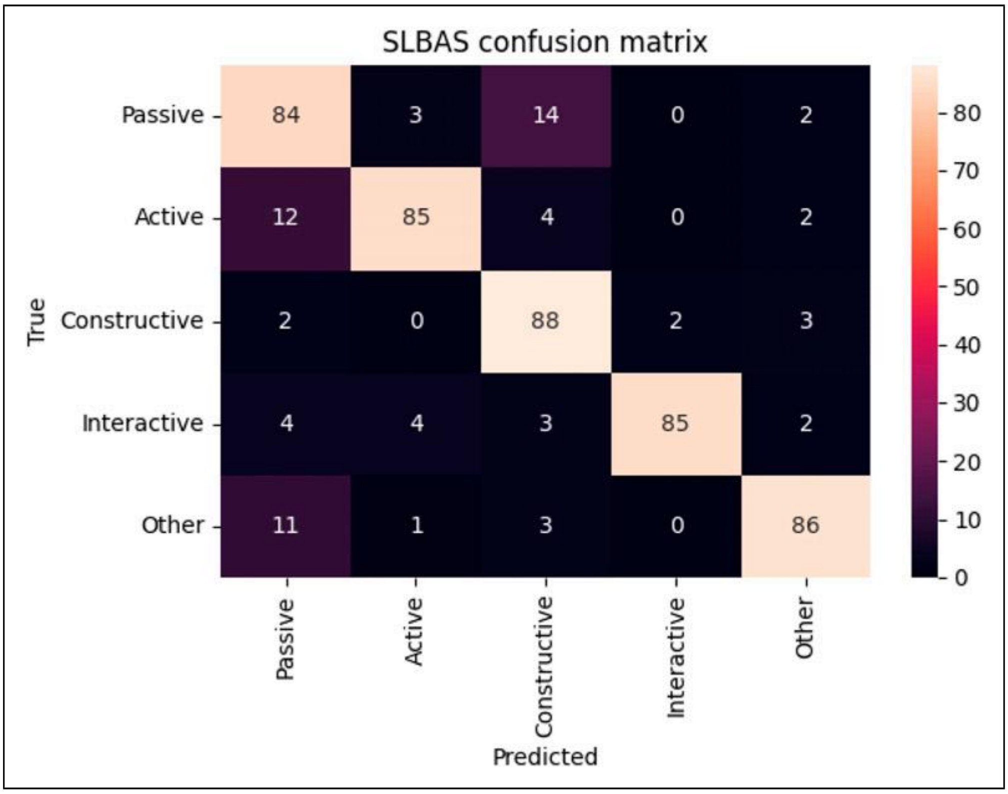

Figure 6. SLBAS confusion matrix.

How Does the Learning Process Influence Learning Effectiveness in STEM Activities?

After verifying the SLBAS performance, we explored how the learning process influences learning effectiveness in STEM activities by using SLBAS to assess the learning process and then using the learning effectiveness a test to evaluate the learning effectiveness. In the first step, Pearson's correlation was calculated to confirm the relationship between the indicators in the learning process and learning effectiveness. Table 5 reveals a significantly positive correlation between interactive and the test score ($p < .001$), where r is .809. We also note a significantly positive correlation between constructive and the test score ($p < .01$), where r is .677. There is also a significantly negative correlation between passive and the test score ($p < .05$), where r is −.630.

In the second step, to explore learning effectiveness, learners were divided into two groups according to the learning effectiveness test score. The highest-scoring 50% of learners were allocated to a high learning effectiveness group and the other learners were assigned to the low learning effectiveness group. Thus, given the mean test score of 62.5, 13 learners were assigned to the high learning effectiveness group and 15 to the low learning effectiveness group.

In the third step, to determine the differences between the high and low learning effectiveness groups, an independent *t*-test was conducted, as shown in Table 6. Significant differences in *pa*ssive ($t = 2.655, p < .05$), *constructive* ($t = -3.635, p < .01$), and *interactive* ($t = 10.768$, $p < .001$) indicate that learners with higher learning

Table 4. SLBAS Precision and Recall.

	Passive	*Active*	Constructive	*Interactive*	*Other*	Average
Precision	.743	.914	.786	.977	.900	.864
Recall	.816	.725	.926	.867	.851	.837

Table 5. Pearson's Correlation Coefficient Between Learning Process and Learning Effectiveness.

	Passive	*Active*	*Constructive*	*Interactive*	*Other*	Test score
Passive	1					
Active	−.391	1				
Constructive	−.794***	.154	1			
Interactive	−.475*	.231	.545**	1		
Other	.056	−.187	−.439	−.150	1	
Test score	−.630**	.146	.677**	.809***	−.302	1

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

effectiveness exhibited higher *constructive* and *interactive* indicators and a lower *passive* indicator than those with lower learning effectiveness.

In additional, Pearson's correlation coefficient was calculated in this step to confirm the relationship between the indicators and the test scores in the high and low learning effectiveness groups. The relationship for the low effectiveness group is shown in Table 7. Compared with Pearson's correlation for all learners, there was a significantly negative correlation between the test score and *passive* ($r = -.589$, $p < .01$). However, the relationship between the test score and *constructive* was insignificant in the low learning effectiveness group ($r = 0.484$, $p > .05$). The relationship between the test score and *other* was significantly negative ($r = -.528$, $p < .05$).

The relationships for the high effectiveness group are shown in Table 8. Compared with Pearson's correlation for all learners, there is no significant correlation between the test score and *passive* ($r = .008$, $p > .05$), between the test score and *constructive* ($r = .296$, $p > .05$), and between the test score and *interactive* ($r = .118$, $p > .05$). The was a significantly positive correlation between the test score and *active* ($r = .571$, $p < .05$).

Table 6. Differences Between High and Low Learning Effectiveness Groups.

	Group	*M*	*SD*	*t*
Passive	High	208.5	80.4	**−2.655***
	Low	342	164.9	
Active	High	124.5	71.9	−0.871
	Low	99.3	80.3	
Constructive	High	425	110.5	**3.635****
	Low	232.3	160.9	
Interactive	High	38.3	7.00	**10.768*****
	Low	13.5	5.14	
Other	High	58.2	43.9	0.948
	Low	82.1	81.1	

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

Table 7. Relationship Between Indicators and Test Scores in Low Learning Effectiveness Group.

	L_passive	*L_active*	*L_constructive*	*L_interactive*	*L_other*	L_test score
L_passive	1					
L_active	−0.461	1				
L_constructive	−0.729**	0.247	1			
L_interactive	−0.263	0.001	0.328	1		
L_other	−0.07	−0.231	−0.398	−0.046	1	
L_test score	−0.589*	0.064	0.484	0.586*	−0.528*	1

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

Table 8. Relationship Between Indicators and Test Scores in High Learning Effectiveness Group.

	H_passive	*H_active*	*H_constructive*	*H_interactive*	*H_other*	H_test score
H_passive	1					
H_active	−0.134	1				
H_constructive	−0.757**	−0.266	1			
H_interactive	−0.012	0.371	−0.267	1		
H_other	0.132	−0.007	−0.483	0.177	1	
H_test score	0.008	0.571*	0.296	0.118	−0.635*	1

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

The relationship between the test score and *other* was a significantly negative correlation (r = −.635, $p < .05$).

Discussion

In this study we propose SLBAS to automatically and objectively comprehend the learner's' learning process during STEM activities. Compared to traditional assessment methods such as self-reporting and observation, SLBAS combines deep learning and computer vision to measure the STEM learning process in a standard, fair way, potentially overcoming mitigating the limitations of self-reporting. Moreover, because SLBAS is an automatically recognition system, it reduces the time and labor of manual coding needed in the observation method. Nevertheless, according to Gao et al. (2020), as yet there is no STEM assessment tool like that presented in the current study. Note that automatic assessment of the STEM learning process is difficult, because STEM education is an integrated approach for teaching and learning, where discipline-specific content was is not separated but is instead addressed and treated as a dynamic, fluid study (Brown et al., 2011; Hsiao et al., 2022).

Therefore, given that most learning behavior in STEM education occurs when learners touch the learning material (Christensen et al., 2015; Thuneberg et al., 2018), we develop SLBAS to recognize the learning process in dynamic and diverse STEM activities. SLBAS achieves an accuracy of 0.858, an average precision of .864, and an average recall of .837, which could serve as the baseline for future studies on automatic STEM learning process evaluation systems to validate their performance. To further understand whether SLBAS efficiently assesses the learning process of learners in STEM activities, we additionally calculate Cohen's kappa to investigate the reliability between coding from experts and SLBAS: all kappa coefficients exceed .7 (Landis & Koch, 1977). Therefore, in response to the first research question, the proposed SLBAS effectively evaluates the learning process during STEM activities.

With this study we further answer the second research question by exploring how the learning process influences the learning effectiveness of STEM activities. Table 5 shows a significantly positive correlation between the interactive indicator and learning effectiveness, and a significantly negative correlation between the passive indicator and learning effectiveness. This suggests that interactive is crucial to improving the learning effectiveness of STEM education, whereas passive is less important, confirming the gradual process in the ICAP framework (Chi & Wylie, 2014); that is, learning proceeds from passive to active, from active to constructive, and from constructive to interactive. Accordingly, learners who exhibit a higher interactive indicator remain at a higher cognitive level, resulting in higher learning effectiveness test score. Conversely, learners with a higher passive indicator are at a lower cognitive level, and obtain a lower learning effectiveness test score. This result fits the interactive>constructive>active>passive trend mentioned for the ICAP framework (Chi & Wylie, 2014; Hsiao et al., 2022). Combined with the definition of cognitive domain in Bloom's taxonomy proposed by Krathwohl (2002), the higher the interactive indicator, the higher the cognitive level of the learner. Note that we define interactive as learners interacting with teaching assistants. Learners construct their knowledge by asking and responding to questions with teaching assistants. This process facilitates higher cognitive levels such as critical thinking and problem solving (Krathwohl, 2002; Meng et al., 2020).

Table 6 shows that passive in the high learning effectiveness group is significantly lower than that in the low learning effectiveness group, and constructive and interactive in the high learning effectiveness group are significantly higher than those in the low learning effectiveness group. When learners passively receive knowledge from instructors as in the traditional teacher-centered paradigm, they exhibit poorer learning effectiveness. This result further confirms that STEM education is no longer suitable for traditional teacher-centered teaching methods, which reflects the literature (Chen et al., 2019; Freeman et al., 2014; Waldrop, 2015). Conversely, better learning effectiveness is achieved when learners construct more knowledge by manipulating the learning materials or interacting with teaching assistants or others as in the student-centered method. This further indicates that hands-on learning is suitable as a STEM education teaching strategy (Bradberry & De Maio, 2019; Chen et al., 2020; Thuneberg et al., 2018). Learners deepen the knowledge construction process by hands-on practice, thereby improving their learning effectiveness in STEM activities, in accordance with the literature (Chen et al., 2020; Glaroudis et al., 2019; Ziaeefard et al., 2017).

Table 7 shows that in addition to passive, other exhibits a significantly negative correlation with the test score in the low learning effectiveness group. This is because learners in this group often leave their seats for reasons unrelated to the STEM activity, and the SLBAS is thus unable to detect their hand keypoints. When learners do things unrelated to the STEM activity, they are not focusing on the STEM activity. Thus, learners with a higher other indicator in the low learning effectiveness group exhibit poorer learning effectiveness. Furthermore, interactive has a significantly positive correlation with the test score in the low learning effectiveness group: this indicates that teaching assistants who help learners in a timely manner have a greater impact on learners with lower learning effectiveness. This result is also consistent with the literature (Bernacki et al., 2020).

Table 8 indicates that only active exhibits a significantly positive correlation with the test score in the high learning effectiveness group. Learners who are more active in the high learning effectiveness group exhibit better learning effectiveness. This supports the application of active learning theory to STEM education (Julià & Antolí, 2019; Tomkin et al., 2019). Learners who often manipulate learning materials actively are able to rapidly solve problems encountered during STEM activities (Chi & Wylie, 2014; Seo et al., 2021). In this way, learners cultivate their cognitive level and further improve their learning effectiveness (Hsiao et al., 2022).

Conclusion

In view of the importance of the learning process in STEM education and the lack of objective STEM assessment tools, we propose SLBAS, which combines deep learning and computer vision to recognize hand actions with learning materials objectively and automatically. Since as yet there is no baseline by which to verify the performance of SLBAS, we measure the performance of SLBAS as a baseline for future comparative research. In addition, Cohen's kappa was calculated for two experts and SLBAS, yielding a high enough Cohen's kappa coefficient to support replacing expert coding in the observation method with SLBAS. Because the type and nature of most STEM activities is hands-on with extensive practice, SLBAS recognizes interaction between learners and the learning materials (Hofstein & Lunetta, 1982): if the learning materials are recognizable, SLBAS can be applied to other courses, even traditional lectures.

SLBAS yields a better understanding of the learning process during STEM activities and identifies relationships between the learning process and learning effectiveness. The results indicate that STEM education differs greatly from traditional teacher-centered courses in that it helps learners to improve the process of knowledge construction with practice and hands-on opportunities rather than simply receiving knowledge passively; this is consistent with findings in the literature (Chen et al., 2019; Glaroudis et al., 2019; Ziaeefard et al., 2017).

We note several research limitations. Because COVID-19 made it difficult to recruit a larger number of participants, we conducted the experiment with a small number of participants (28 learners): this may affect the reliability of the statistical analyses presented here. Furthermore, although it is important for learners to interact with peers in STEM education, given the nature of the STEM workshop in this study, learners completed the task individually. Thus, this study only explored interaction between learners and teaching assistants, and lacked peer-to-peer interaction. Because of this limitation, the study described here omits the collaboration and discussion aspects of the STEM learning process.

Future work could involve the design of a simple user interface to help instructors apply SLBAS to quickly and easily understand the learning process. As this study has explored only how the learning process influences learning effectiveness in STEM education, it focuses on cognitive-level learning. Nevertheless, some studies indicate that emotions have a more substantial impact on learning effectiveness than cognition

(Graesser, 2020; Liu et al., 2022). Therefore, both emotional and cognitive changes could be explored during STEM activities to yield a more comprehensive understanding of the learning process. Secondly, given the importance of peer-to-peer interaction in STEM education, a multimodal learning analytics (MMLA) tool could be developed that combines SLBAS and NLP techniques to further explore the relationship between the quality of discussion and behaviors in the learning process and learning effectiveness.

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Declaration of Conflicting Interests

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Authors' Contributions

Hsin-Yu Lee is the leader of this research, he is in charge of the research design, conducting teaching and learning experiment, data analysis, and writing the manuscript.

Yu-Ping Cheng is responsible for assisting in the conduct of experiments.

Wei-Sheng Wang is responsible for assisting in the conduct of experiments and surveying related literature.

Chia-Ju Lin is responsible for assisting in the conduct of experiments and surveying related literature and proofreading the manuscript.

Yueh-Min Huang is responsible for designing research experiments, providing fundamental education theories and comments to this research, and he is also responsible for revising the manuscript. All authors spent more than 2 months to discuss and analyze the data. The author(s) read and approved the final manuscript.

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References

Al-Naji, A., Gibson, K., Lee, S. H., & Chahl, J. (2017). Real time apnoea monitoring of children using the Microsoft Kinect sensor: A pilot study. *Sensors*, *17*(2), 286. https://www.mdpi.com/1424-8220/17/2/286

Atapattu, T., Thilakaratne, M., Vivian, R., & Falkner, K. (2019). Detecting cognitive engagement using word embeddings within an online teacher professional development community. *Computers & Education*, *140*, 103594. https://doi.org/10.1016/j.compedu.2019.05.020

Baumeister, R. F., Vohs, K. D., & Funder, D. C. (2007). Psychology as the science of self-reports and finger movements: Whatever happened to actual behavior? *Perspectives on Psychological Science*, *2*(4), 396–403. https://doi.org/10.1111/j.1745-6916.2007.00051.x

Bernacki, M. L., Chavez, M. M., & Uesbeck, P. M. (2020). Predicting achievement and providing support before STEM majors begin to fail. *Computers & Education*, *158*, 103999. https://doi.org/10.1016/j.compedu.2020.103999

Bochkovskiy, A., Wang, C.-Y., & Liao, H.-Y. M. (2020). YOLOv4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934. https://doi.org/10.48550/arXiv.2004.10934

Bradberry, L. A., & De Maio, J. (2019). Learning by doing: The long-term impact of experiential learning programs on student success. *Journal of Political Science Education*, *15*(1), 94–111. https://doi.org/10.1080/15512169.2018.1485571

Brown, R., Brown, J., Reardon, K., & Merrill, C. (2011). Understanding STEM: Current perceptions. *Technology and Engineering Teacher*, *70*(6), 5–9.

Bybee, R. W. (2013). *The case for STEM education: Challenges and opportunities*. NSTA Press

Cao, Z., Hidalgo, G., Simon, T., Wei, S.-E., & Sheikh, Y. (2019). OpenPose: Realtime multi-person 2D pose estimation using part affinity fields. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *43*(1), 172–186. https://doi.org/10.48550/arXiv.1812.08008

Chen, J. C., Huang, Y., Lin, K. Y., Chang, Y. S., Lin, H. C., Lin, C. Y., et al. (2020). Developing a hands on activity using virtual reality to help students learn by doing. *Journal of Computer Assisted Learning*, *36*(1), 46–60. https://doi.org/10.1111/jcal.12389

Chen, W., Shah, U. V., & Brechtelsbauer, C. (2019). A framework for hands-on learning in chemical engineering education—training students with the end goal in mind. *Education for Chemical Engineers*, *28*, 25–29. https://doi.org/10.1016/j.ece.2019.03.002

Chi, M. T., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, *49*(4), 219–243. https://doi.org/10.1080/00461520.2014.965823

Christensen, R., Knezek, G., & Tyler-Wood, T. (2015). Alignment of hands-on STEM engagement activities with positive STEM dispositions in secondary school students. *Journal of Science Education and Technology*, *24*(6), 898–909. https://doi.org/10.1007/s10956-015-9572-6

Cojocea, E., & Rebedea, T. (2022). Exploring a large dataset of educational videos using object detection analysis. In Ó. Mealha, M. Dascalu, & T. Di Mascio (Eds.), *Ludic, Co-design and tools supporting smart learning ecosystems and smart education* (pp. 213–225). Springer

Cui, W., Li, B., Zhang, L., & Chen, Z. (2021). Device-free single-user activity recognition using diversified deep ensemble learning. *Applied Soft Computing*, *102*, 107066. https://doi.org/10.1016/j.asoc.2020.107066

Dai, C., Liu, X., & Lai, J. (2020). Human action recognition using two-stream attention based LSTM networks. *Applied Soft Computing*, *86*, 105820. https://doi.org/10.1016/j.asoc.2019.105820

Demrozi, F., Pravadelli, G., Bihorac, A., & Rashidi, P. (2020). Human activity recognition using inertial, physiological and environmental sensors: A comprehensive survey. *IEEE Access*, *8*, 210816–210836. https://doi.org/10.1109/ACCESS.2020.3037715

D'Mello, S., Dieterle, E., & Duckworth, A. (2017). Advanced, analytic, automated (AAA) measurement of engagement during learning. *Educational Psychologist*, *52*(2), 104–123. https://doi.org/10.1080/00461520.2017.1281747

Ekatushabe, M., Kwarikunda, D., Muwonge, C. M., Ssenyonga, J., & Schiefele, U. (2021). Relations between perceived teacher's autonomy support, cognitive appraisals and boredom in physics learning among lower secondary school students. *International Journal of STEM Education*, *8*(1), 8. https://doi.org/10.1186/s40594-021-00272-5

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, *111*(23), 8410–8415. https://doi.org/10.1073/pnas.1319030111

Gao, X., Li, P., Shen, J., & Sun, H. (2020). Reviewing assessment of student learning in interdisciplinary STEM education. *International Journal of STEM Education*, *7*(1), 1–14. https://doi.org/10.1186/s40594-020-00225-4

Glaroudis, D., Iossifides, A., Spyropoulou, N., Zaharakis, I. D., & Kameas, A. D. (2019). STEM learning and career orientation via IoT hands-on activities in secondary education. In 2019 IEEE international conference on pervasive computing and communications workshops (PerCom workshops), 11–15 March 2019, Kyoto, Japan. https://doi.org/10.1109/PERCOMW.2019.8730759

Graesser, A. C. (2020). Emotions are the experiential glue of learning environments in the 21st century. *Learning and Instruction*, *70*, 101212. https://doi.org/10.1016/j.learninstruc.2019.05.009

Harari, G. M., Müller, S. R., Aung, M. S., & Rentfrow, P. J. (2017). Smartphone sensing methods for studying behavior in everyday life. *Current Opinion in Behavioral Sciences*, *18*, 83–90. https://doi.org/10.1016/j.cobeha.2017.07.018

He, Y., Hu, X., Wang, H., & Li, J. (2020). Development and realization of home online teaching system based on video data analysis. In 2020 5th international conference on mechanical, control and computer engineering (ICMCCE), 25–27 December 2020, Harbin, China. https://doi.org/10.1109/ICMCCE51767.2020.00456

Hofstein, A., & Lunetta, V. N. (1982). The role of the laboratory in science teaching: Neglected aspects of research. *Review of Educational Research*, *52*(2), 201–217. https://doi.org/10.2307/1170311

Hsiao, J.-C., Chen, S.-K., Chen, W., & Lin, S. S. (2022). Developing a plugged-in class observation protocol in high-school blended STEM classes: Student engagement, teacher behaviors and student-teacher interaction patterns. *Computers & Education*, *178*, 104403. https://doi.org/10.1016/j.compedu.2021.104403

Jaouedi, N., Boujnah, N., & Bouhlel, M. S. (2020). A new hybrid deep learning model for human action recognition. *Journal of King Saud University - Computer and Information Sciences*, *32*(4), 447–453. https://doi.org/10.1016/j.jksuci.2019.09.004

Julià, C., & Antolí, J. Ò. (2019). Impact of implementing a long-term STEM-based active learning course on students' motivation. *International Journal of Technology and Design Education*, *29*(2), 303–327. https://doi.org/10.1007/s10798-018-9441-8

Kamel, A., Sheng, B., Yang, P., Li, P., Shen, R., & Feng, D. D. (2019). Deep convolutional neural networks for human action recognition using depth maps and postures. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *49*(9), 1806–1819. https://doi.org/10.1109/TSMC.2018.2850149

Khan, M. A., Sharif, M., Akram, T., Raza, M., Saba, T., & Rehman, A. (2020a). Hand-crafted and deep convolutional neural network features fusion and selection strategy: An application to intelligent human action recognition. *Applied Soft Computing*, *87*, 105986. https://doi.org/10.1016/j.asoc.2019.105986

Khan, M. A., Zhang, Y. D., Khan, S. A., Attique, M., Rehman, A., & Seo, S. (2020b). A resource conscious human action recognition framework using 26-layered deep convolutional neural network. *Multimedia Tools and Applications*, *80*(28–29), 35827–35849. https://doi.org/10.1007/s11042-020-09408-1

Kim, H., O'Sullivan, D., Kolykhalova, K., Camurri, A., & Park, Y. (2021). Evaluation of a computer vision-based system to analyse behavioral changes in high school classrooms. *International Journal of Information and Communication Technology Education (IJICTE)*, *17*(4), 1–12. https://doi.org/10.4018/IJICTE.20211001.oa12

Krathwohl, D. R. (2002). A revision of bloom's taxonomy: An overview. *Theory Into Practice*, *41*(4), 212–218. https://doi.org/10.1207/s15430421tip4104_2

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174. https://doi.org/10.2307/2529310

Lathia, N., Rachuri, K. K., Mascolo, C., & Rentfrow, P. J. (2013). Contextual dissonance: Design bias in sensor-based experience sampling methods. In *Proceedings of the 2013 ACM international joint conference on pervasive and ubiquitous computing*. (pp. 183–192) ACM. https://doi.org/10.1145/2493432.2493452

Liang, J. M., Su, W. C., Chen, Y. L., Wu, S. L., & Chen, J. J. (2019). Smart interactive education system based on wearable devices. *Sensors*, *19*(15), 3260. https://doi.org/10.3390/s19153260

Lin, K. C., Ko, C. W., Hung, H. C., & Chen, N. S. (2021). The effect of real-time pose recognition on badminton learning performance. *Interactive Learning Environments*, 1–15. https://doi.org/10.1080/10494820.2021.1981396

Liu, J., Teng, G., & Hong, F. (2020). Human activity sensing with wireless signals: A survey. *Sensors*, *20*(4), 1210. https://doi.org/10.3390/s20041210

Liu, S., Liu, S., Liu, Z., Peng, X., & Yang, Z. (2022). Automated detection of emotional and cognitive engagement in MOOC discussions to predict learning achievement. *Computers & Education*, *181*, 104461. https://doi.org/10.1016/j.compedu.2022.104461

Liu, T., Chen, Z., & Wang, X. (2019). Automatic instructional pointing gesture recognition by machine learning in the intelligent learning environment. In *Proceedings of the 2019 4th international conference on distance education and learning*. (pp. 153–157). ACM. https://doi.org/10.1145/3338147.3338163

Majd, M., & Safabakhsh, R. (2020). Correlational convolutional LSTM for human action recognition. *Neurocomputing*, *396*, 224–229. https://doi.org/10.1016/j.neucom.2018.10.095

Martín Páez, T., Aguilera, D., Perales Palacios, F. J., & Vílchez González, J. M. (2019). What are we talking about when we talk about STEM education? A review of literature. *Science Education*, *103*(4), 799–822. https://doi.org/10.1002/sce.21522

Meng, Q., Jia, J., & Zhang, Z. (2020). A framework of smart pedagogy based on the facilitating of high order thinking skills. *Interactive Technology and Smart Education*, *17*(3), 251–266. https://doi.org/10.1108/ITSE-11-2019-0076

Nakai, M., Tsunoda, Y., Hayashi, H., & Murakoshi, H. (2018). Prediction of basketball free throw shooting by openpose. In JSAI international symposium on artificial intelligence, 12–14 November 2018, Tokyo, Japan. https://doi.org/10.1007/978-3-030-31605-1_31

Nunnally, J. C. (1978). An overview of psychological measurement. *Clinical Diagnosis of Mental Disorders*, 97–146. https://doi.org/10.1007/978-1-4684-2490-4_4

Nweke, H. F., Teh, Y. W., Mujtaba, G., & Al-Garadi, M. A. (2019). Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions. *Information Fusion*, *46*, 147–170. https://doi.org/10.1016/j.inffus.2018.06.002

Paulhus, D. L., & Vazire, S. (2007). The self-report method. In R. W. Robins, R. C. Fraley, & R. F. Krueger (Eds.), *Handbook of research methods in personality psychology* (pp. 224–239). The Guilford Press

Qwu, E., Tang, Z., Xiong, P., Wei, C. F., Song, A., & Zhu, L. (2021). ROpenPose: A rapider OpenPose model for astronaut operation attitude detection. *IEEE Transactions on Industrial Electronics*, *69*(1), 1043–1052. https://doi.org/10.1109/TIE.2020.3048285

Raković, M., Marzouk, Z., Liaqat, A., Winne, P. H., & Nesbit, J. C. (2020). Fine grained analysis of students' online discussion posts. *Computers & Education*, *157*, 103982. https://doi.org/10.1016/j.compedu.2020.103982

Sahin, D., & Yilmaz, R. M. (2020). The effect of augmented reality technology on middle school students' achievements and attitudes towards science education. *Computers & Education*, *144*, 103710. https://doi.org/10.1016/j.compedu.2019.103710

Sailer, M., Schultz-Pernice, F., & Fischer, F. (2021). Contextual facilitators for learning activities involving technology in higher education: The C♭-model. *Computers in Human Behavior*, *121*, 106794. https://doi.org/10.1016/j.chb.2021.106794

Sanders, M. (2009). Integrative STEM education: Primer. *The Technology Teacher*, *68*(4), 20–26

Seo, K., Dodson, S., Harandi, N. M., Roberson, N., Fels, S., & Roll, I. (2021). Active learning with online video: The impact of learning context on engagement. *Computers & Education*, *165*, 104132. https://doi.org/10.1016/j.compedu.2021.104132

Sun, D., Ouyang, F., Li, Y., & Zhu, C. (2021). Comparing learners' knowledge, behaviors, and attitudes between two instructional modes of computer programming in secondary education. *International Journal of STEM Education*, *8*(1), 1–15. https://doi.org/10.1186/s40594-021-00311-1

Thuneberg, H., Salmi, H., & Bogner, F. X. (2018). How creativity, autonomy and visual reasoning contribute to cognitive learning in a STEAM hands-on inquiry-based math module. *Thinking Skills and Creativity*, *29*, 153–160. https://doi.org/10.1016/j.tsc.2018.07.003

Tomkin, J. H., Beilstein, S. O., Morphew, J. W., & Herman, G. L. (2019). Evidence that communities of practice are associated with active learning in large STEM lectures. *International Journal of STEM Education*, *6*(1), 1–15. https://doi.org/10.1186/s40594-018-0154-z

Waldrop, M. M. (2015). Why we are teaching science wrong, and how to make it right. *Nature*, *523*(7560), 272–274. https://doi.org/10.1038/523272a

Wang, Q., Peng, Y., & Wang, H. (2022). A curation activity-based self-regulated learning promotion approach as scaffolding to improving learners' performance in STEM courses. *Journal of Educational Computing Research*, *60*(4), 843–876. https://doi.org/10.1177/07356331211056532

Yan, H., Hu, B., Chen, G., & Zhengyuan, E. (2020). Real-time continuous human rehabilitation action recognition using OpenPose and FCN. In 2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), 24–26 April 2020, Shenzhen, China. (pp. 239–242). https://doi.org/10.1109/AEMCSE50948.2020.00058

Zhang, H., Lin, L., Zhan, Y., & Ren, Y. (2016). The impact of teaching presence on online engagement behaviors. *Journal of Educational Computing Research*, *54*(7), 887–900. https://doi.org/10.1177/0735633116648l7

Zhang, Z., Li, Z., Liu, H., Cao, T., & Liu, S. (2020). Data-driven online learning engagement detection via facial expression and mouse behavior recognition technology. *Journal of Educational Computing Research*, *58*(1), 63–86. https://doi.org/10.1177/0735633119825575

Ziaeefard, S., Miller, M. H., Rastgaar, M., & Mahmoudian, N. (2017). Co-Robotics hands-on activities: A gateway to engineering design and STEM learning. *Robotics and Autonomous Systems*, *97*, 40–50. https://doi.org/10.1016/j.robot.2017.07.013

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166–183. https://doi.org/10.3102/0002831207312909

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