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Transforming Pedagogical Assessment: AI and Computer Vision-Enhanced Classroom Observations for Experiment-Centric Learning Environments

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Abstract:

This paper presents an innovative approach to revolutionizing STEM education by seamlessly integrating artificial intelligence (AI) into the assessment of experiment-centric pedagogy. Our research spans diverse disciplines, including biology, chemistry, physics, civil engineering, transportation engineering, mathematics, and computer science. We've transitioned from traditional teaching methods to an immersive approach, embedding experiments into core curriculum modules to convey essential concepts effectively.

Initially, this study employed the Laboratory Observation Protocol for Undergraduate STEM (LOPUS) and later transitioned to the Classroom Observation Protocol for Undergraduate STEM (COPUS), relying on manual observations. Dedicated spaces on sheets were marked at two-minute intervals to record student and instructor activities.

This study proposes a transformative leap forward, introducing an AI-based model to automate the observation process. Our primary goal is to develop a sophisticated deep learning model capable of autonomously tracking and documenting a wide range of activities performed by students and instructors in the classroom. This model will recognize, and document 26 distinct activity constructs evenly distributed between students and instructors, encompassing student questioning frequency, instructor lecturing intervals, and student-led discussions.

Leveraging state-of-the-art AI technologies, we aim to enhance the efficiency, precision, and scalability of pedagogical assessment, providing educators with invaluable insights into the dynamics of the learning environment. Our research extends beyond assessment to measure student engagement within experiment-centric classes, including the frequency of student questions, their predictive abilities concerning experimental outcomes, and participation in discussions.

In conclusion, our research drives a transformative shift in STEM education, offering a novel framework for precise assessment, personalization, and instructional enhancement. This advancement empowers educators to refine teaching strategies, enhancing student engagement, and creating a dynamic and immersive learning environment. Furthermore, the AI-based model complements existing observation protocols, like COPUS, potentially serving as a valuable control measure for assessing classroom activities.

Keywords: STEM education, experiment-centric pedagogy, artificial intelligence, deep learning, education assessment, student engagement, learning dynamics, classroom observation.

Introduction

Science, technology, engineering, and mathematics (STEM) education is shifting from traditional lecture-based methods to more immersive and experiment-centric pedagogy. This pedagogical approach aims to foster self-efficacy, critical thinking, and problem-solving skills among students and enhance their interest and motivation in STEM fields [1], [2]. However, assessing the effectiveness and impact of this pedagogy poses significant challenges, especially in measuring student engagement during the implementation of the pedagogy. This paper proposes a novel solution to address these challenges by leveraging the power of artificial intelligence (AI) and computer vision (CV) to automate and enhance the classroom observation process.

Classroom observation is a widely used method for evaluating and improving teaching and learning practices in STEM education, as it provides rich and detailed information on the behaviors, interactions, and activities of students and instructors in the classroom. However, current observation protocols, such as the Laboratory Observation Protocol for Undergraduate STEM (LOPUS) [3] and the Classroom Observation Protocol for Undergraduate STEM (COPUS), rely on human observers who manually record and code the data using paper-based or digital tools [4]. This process is time-consuming, labor-intensive, subjective, and prone to errors and biases. Moreover, it limits the scalability and generalizability of the observation results, as it depends on the observers' availability, training, and reliability [5].

To overcome these limitations, , this study developed an AI-based model that can autonomously observe, track, and document a wide range of student and instructor activities in the classroom using state-of-the-art CV techniques [6], [7]. Our model will be capable of recognizing and documenting at least 26 distinct activity constructs, evenly distributed between students and instructors, encompassing student questioning frequency, instructor lecturing intervals, and student-led discussions. These constructs are derived from the existing observation protocols, such as COPUS, but are extended and refined to capture the nuances and dynamics of the experiment-centric pedagogy.

This model uses multiple cameras and microphones to capture the audio-visual data from the classroom, and then applies various CV algorithms, such as face detection, face recognition, facial expression analysis, gesture recognition, speech recognition, and natural language processing, to analyze and interpret the data. The model then generates a comprehensive and objective classroom observation report, highlighting the key patterns, trends, and insights on the teaching and learning process. This study spans diverse disciplines, including biology, chemistry, physics, civil engineering, transportation engineering, mathematics, and computer science.

The data gathering phase has begun, and we will be implementing and testing the AI-based model in several experiment-centric courses across seven STEM disciplines and comparing the results with the manual observation protocols. So far, surveys have been conducted, and interviews with the students and instructors who participated in the experiment-centric courses have been conducted to gather their feedback and perceptions on the pedagogy and the previous observation process (COPUS). This study presents research methodology, Preliminary result, and implications on the integration of AI and CV in revolutionizing STEM education classroom assessment. The benefits and challenges of using this AI-based model are discussed, as well as the ethical and social issues that arise from its implementation. Suggestions and recommendations for future research and practice in this emerging and interdisciplinary field are requested as this study will contribute to advancing knowledge and innovation in STEM education and inspire more researchers and educators to explore the potential of AI and CV in enhancing teaching and learning.

Literature Review

As Lombardi et al [8] described, active learning is a broad term among educators. They asserted that the existing comprehension from the literature on active learning is excessively broad and lacks precise particulars, impeding the ability to conduct effective research and enhance teaching methods. The authors suggest a revised interpretation of active learning as "a classroom setting where the teacher/instructor and educational activities deliberately empower students to take charge of their learning." This definition highlights the significance of student involvement and responsibility in the learning process [8].

In the last decade, one of the emerging active learning strategies called experiment-centric pedagogy is an approach that emphasizes hands-on activities and experiments to convey essential concepts in STEM education. As with other active learning strategies, it also aims to foster student engagement, deepen conceptual understanding, and promote critical thinking skills [9]. Several studies have demonstrated the positive effects of active learning on student outcomes, such as academic performance, motivation, interest, and self-efficacy [10] [11], [12]. However, there is a dearth of accurate evidence on the kind of engagement the pedagogy provides and the extent to which these pedagogies allow the student to take ownership during the learning process.

To investigate the kind and extent of student engagement during the implementation of active learning pedagogies, it is crucial to have reliable and valid methods of assessing the learning process and its outcomes. Several observatory frameworks have been developed to guide assessment within these environments, among which are the Laboratory Observation Protocol for Undergraduate STEM (LOPUS) [3] and the Classroom Observation Protocol for Undergraduate STEM (COPUS) [4]. These protocols are based on systematic observations of student and instructor activities in the classroom or laboratory, using predefined codes and categories. The observations are typically recorded on paper or electronic forms at regular intervals, such as every two minutes. The data collected can provide valuable insights into instructor-student interactions, student engagement, and instructional quality [4], [13].

However, these protocols have some limitations, especially concerning their efficiency, applicability, and scalability. Also, they rely on manual observations, which are labor-intensive, time-consuming, and prone to human errors. Second, they require trained observers, which can be costly and difficult to obtain, especially for large-scale studies. Third, they have the potential not to capture the full complexity and diversity of student and instructor behaviors or activities, especially in dynamic and interactive experiment-centric learning environments. Fourth, they may not provide timely and actionable feedback to instructors, as the data analysis and interpretation may take a long time after the observation [14].

The emergence of AI and computer vision technologies presents a compelling opportunity to overcome the limitations of traditional observation protocols and revolutionize pedagogical assessment. AI and computer vision are two technologies that enable machines to perform tasks that require human intelligence and vision, such as recognizing objects, faces, emotions, actions, and events in images and videos [15], [16]. Recent advancements in deep learning algorithms and image recognition have yielded powerful tools for automatically analyzing complex behavior and can provide objective data on classroom activities [17]–[19].

Several studies have shown promising results in applying these technologies to assess teacher-student interactions and student engagement in various educational settings. For example, Kuromiya et al. [20] explored the feasibility of using a pre-trained action recognition model, SlowFast, to automatically label teacher's behaviors in a junior-high school mathematics class in Japan. The model achieved high accuracy in identifying the teacher's posture but low accuracy in detecting the teacher's interaction with objects and students. The study suggests that the model could be improved by considering the specific features of the classroom environment, such as the whiteboard and the masks. The study also highlights the ethical implications and the potential benefits of using AI for teachers in action reflection.

D'Mello et al., [21] developed a computer vision system to measure student engagement levels based on facial expressions, head poses, and eye gaze from webcam images. The system achieved a correlation of 0.74 with self-reported engagement scores and a classification accuracy of 75.6% for three engagement levels (high, medium, and low).

However, integrating AI and computer vision technologies into the specific context of experiment-centric learning environments remains largely unexplored. There is a need for more research on how to develop and evaluate AI-based models that can autonomously track and document a wide range of activities performed by students and instructors in these environments, such as conducting experiments, making predictions, discussing results, and solving problems. Such models could potentially enhance the efficiency, precision, and scalability of student engagement assessment, providing educators with invaluable insights into the dynamics of the learning environment. Moreover, such models could complement existing observation protocols, such as COPUS, potentially serving as a valuable control measure for assessing classroom activities.

Theoretical Framework

A combination of well-founded theories and innovative technologies is built upon to develop and implement the AI-based model used in our study for assessing experiment-centric pedagogy in STEM education. The theoretical foundation integrates various perspectives and concepts from pedagogy and artificial intelligence, creating a coherent and comprehensive framework for our research. This theoretical foundation guides our development and implementation of the AI model, ensuring it aligns with the dynamic realities of these vibrant learning environments.

Figure 1 shows an overview of the study's theoretical framework, which consists of five main components: constructivism and active learning, social constructivism, and collaborative learning, learning analytics and hidden patterns, explainable AI and trustworthy collaboration, and human-in-the-loop for continuous improvement. Each component represents a key aspect of our research problem, objectives, methods, and contributions. Each component is discussed in detail in the following subsections.

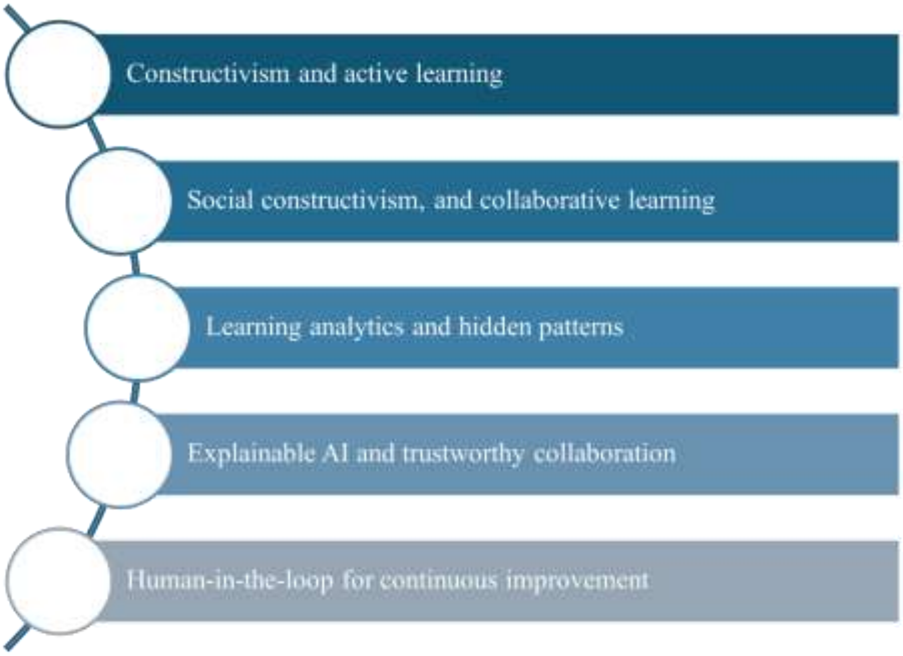

Figure 1: Overview of the Theoretical Framework

1. Constructivism and Active Learning: At the heart of the present study's framework lies the constructivist theory of learning, which postulates that knowledge is actively constructed through individual experiences and interactions within the environment [22], [23].Experiment-centric classrooms provide the perfect stage for this active construction, where students engage in a cyclical process of questioning, hypothesizing, experimenting, and analyzing, building upon their existing knowledge to solidify and refine their understanding [24]. The Present study's AI model aims to capture the intricate dance of these phases, not just recording actions but also inferring cognitive engagement and knowledge construction based on subtle behaviors and interactions.

Figure 2 shows a simplified diagram of the experiment-centric learning cycle, which illustrates the main activities and outcomes involved in this pedagogical approach. This study's AI model will recognize and document these activities and outcomes using a set of predefined codes and categories, similar to the existing observation protocols such as LOPUS and COPUS [4]. However, unlike manual observations, this study's AI model will use computer vision and deep learning techniques to automatically analyze the classroom videos and provide objective and timely data on the learning process.

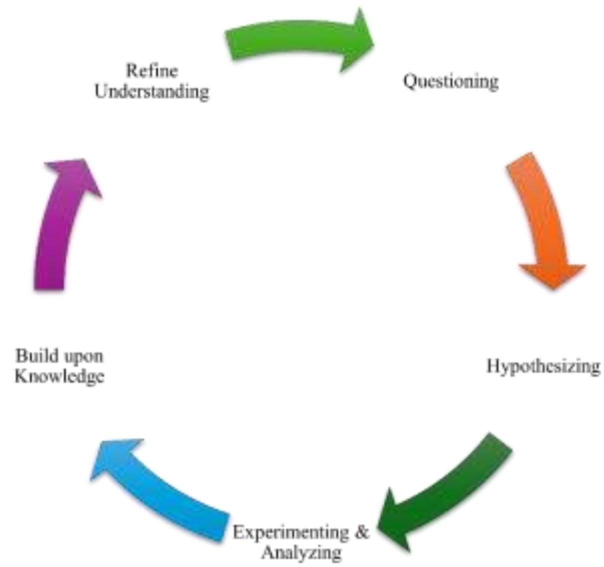

Figure 2: Experimental-centric Learning cycle.

2. Social Constructivism and Collaborative Learning: Idaresit's work [25] emphasizes the essential role of social interaction in constructing knowledge . Building on this, the study adopts the theory of social constructivism, acknowledging the significant role of collaboration and peer learning within experiment-centric classrooms [26]. Therefore, this study's AI model will therefore go beyond individual analyses, utilizing graph convolutional networks to map and analyze the intricate networks of collaboration and knowledge exchange that drive collective understanding and skill development [27].
3. Learning Analytics and Hidden Patterns: The field of learning analytics provides a powerful lens for understanding and optimizing educational practices [28]. The present study's research leverages this framework, integrating the AI model with learning analytics methodologies to uncover hidden patterns and correlations within the rich data generated by classroom observations [10]. By drawing insights from student engagement, question frequency, discussion dynamics, and interaction patterns, the aim is to inform educators about the effectiveness of their instructional strategies and provide data-driven recommendations for individualized learning support. The present study's AI model will support and automate these steps and outcomes using a set of predefined algorithms and techniques, such as data collection, preprocessing, analysis, visualization, interpretation, and intervention [29]. The AI model will use computer vision and deep learning techniques to automatically extract and transform the relevant features and variables from the classroom videos, and to apply various statistical and machine learning methods to discover and display the meaningful patterns and trends in the data [30].
4. Explainable AI and Trustworthy Collaboration: Considering this would be adopted by educators, the study understands the critical importance of transparency and trust when integrating AI tools into the learning process [31]. Therefore, the principles of explainable AI (XAI) is embraced, ensuring that the model's reasoning and insights are

interpretable and accessible to educators [32]. These fosters open communication and collaborative analysis, empowering educators to make informed decisions based on the model's recommendations while retaining ownership over their instructional strategies.

Figure 3 shows a simplified diagram of the explainable AI framework designed by Khosravi et al., which illustrates the main components and processes involved in this explanatory approach. Our AI model will adhere to this framework using predefined methods and techniques, such as feature selection, attention mechanisms, saliency maps, and natural language generation. Our AI model will use computer vision and deep learning techniques to automatically identify and highlight the most relevant and influential factors and evidence for the model's predictions and suggestions, as well as to generate natural and concise explanations and feedback for educators.

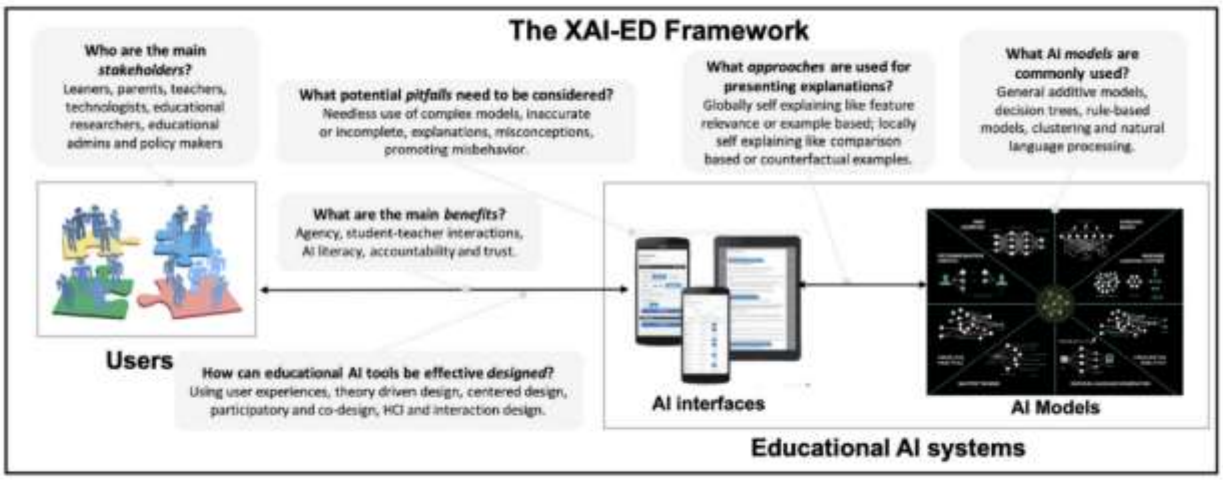

Figure 3: Explainable AI framework by Khrovasi et al [32]

5. Human-in-the-Loop for Continuous Improvement: Our research envisions a dynamic partnership between AI and educators, not a one-way street. The study also seeks to adopt a "human-in-the-loop" approach, where educators provide continuous feedback on the model's performance, guiding its learning and refinement [33]. This feedback loop ensures the model's ongoing adaptation to the specific nuances of each classroom and teaching style, fostering a collaborative environment where human expertise and AI capabilities combine to optimize the learning experience for every student.

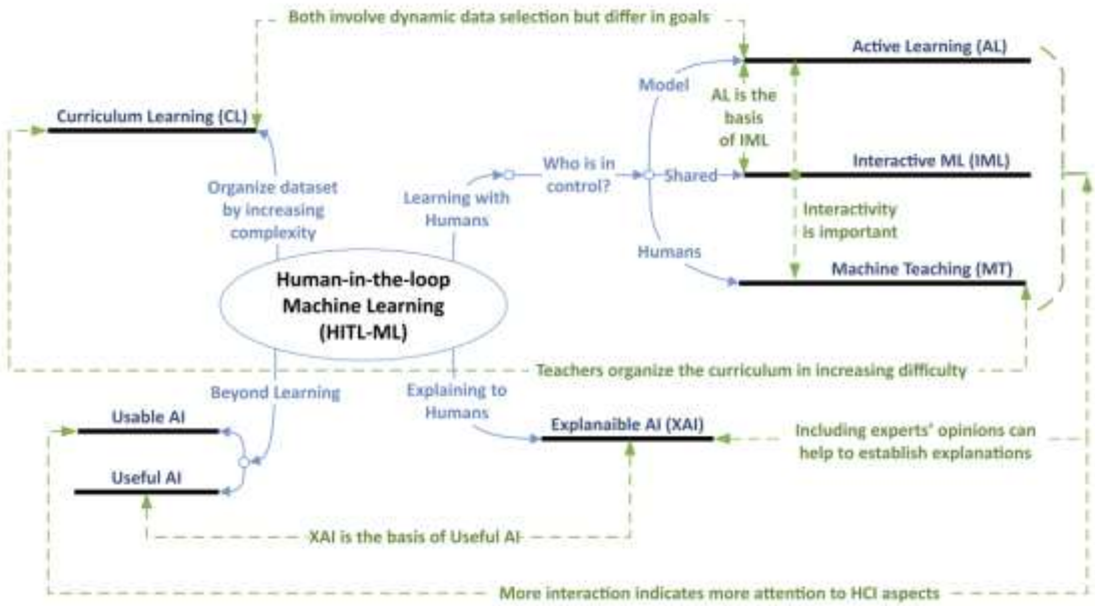

Figure 4: Simplified diagram of the human-in-the-loop system adopted by Eduardo et al [33]

Research Questions:

1. How can AI and computer vision technologies be integrated into pedagogical assessment to enhance the efficiency, precision, and scalability of classroom observations in experiment-centric learning environments?
2. What is the impact of the AI-enhanced observation model on the measurement of student engagement within experiment-centric classes?
3. In what ways can educators leverage AI-based assessments to refine teaching strategies and enhance student engagement in experiment-centric learning environments?

Methodology

The methodology used in our study consists of three main phases: model development and validation, implementation and assessment, and analysis and dissemination. A mixed-methods approach is employed in each phase, combining quantitative data analysis with qualitative inquiries. Figure 5 shows the overview of our methodology and its phases.

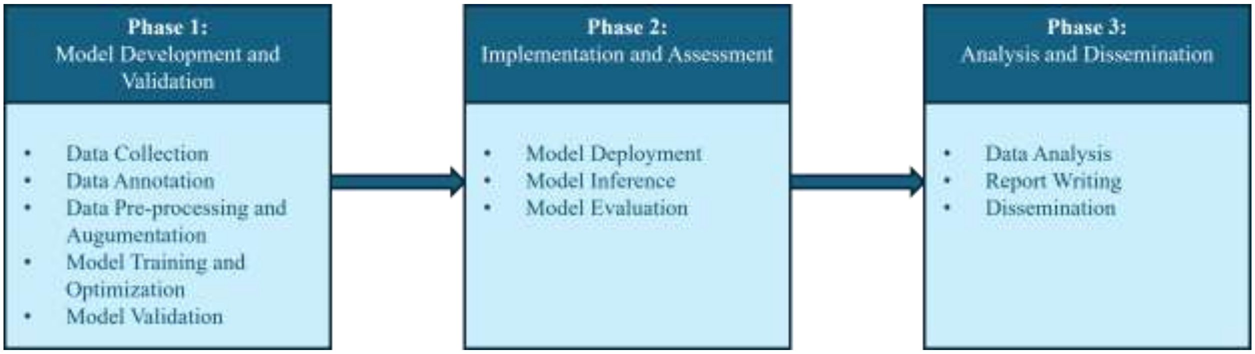

Figure 5: Overview of our methodology and its phases.

The following subsections describe each phase in more detail.

Phase 1: Model Development and Validation:

This phase is aimed at developing and validating a deep learning model capable of automatically identifying and documenting at least 26 distinct activity constructs in experiment-centric STEM classrooms. These constructs are derived from existing observation protocols, such as COPUS, but are extended and refined to capture the nuances and dynamics of the experiment-centric pedagogy. The model will leverage state-of-the-art AI technologies, such as convolutional neural networks (CNNs), object detection models, generative adversarial networks (GANs), and transformer models, to analyze the audio-visual data from the classroom and generate detailed reports on classroom activity and student engagement. The model will also incorporate the principles of explainable AI (XAI) and human-in-the-loop (HITL) to ensure transparency, trust, and continuous improvement.

The steps involved in this phase are as follows:

1. Data Collection: Datasets of high-resolution video recordings will be collected from various STEM disciplines within experiment-centric learning environments. The video recordings will capture the full duration of the classes, the interactions between students and instructors and the experiments conducted by the students. The video recordings will be obtained with the consent of the participants and in compliance with the ethical standards and regulations.
2. Data Annotation: Human coders will be recruited and trained to annotate the video recordings, meticulously labeling each instance of the 26 pre-defined activity constructs. The coders will use a web-based annotation tool that allows them to mark each activity's start and end time, as well as the identity and location of the participants involved. The coders will also briefly describe the activity and its context. The annotation process will follow a rigorous quality control procedure involving multiple rounds of verification and reconciliation.
3. Data Pre-processing and Augmentation: The raw video data will undergo pre-processing to extract relevant frames and activities. The pre-processing will include face detection, face recognition, gesture recognition, speech recognition, and natural language processing. The pre-processed data will then be augmented using GANs, which will

generate synthetic yet realistic representations of classroom activities, enhancing the robustness and diversity of the dataset.

4. Model Training and Optimization: The pre-processed and augmented data will be used to train and optimize a deep learning model to automatically identify and document activities from future video recordings. The model will consist of several components, such as CNNs for feature extraction, LSTMs for temporal dependencies, object detection models for specific activities, and transformer models for contextual understanding. To ensure interpretability and adaptability, the model will also incorporate XAI and HITL techniques, such as attention mechanisms, saliency maps, and feedback loops. The model will be trained iteratively to evaluate and improve its performance using various metrics and methods, such as accuracy, precision, recall, F1-score, cross-validation, and transfer learning.
5. Model Validation: The trained and optimized model will be validated using a separate set of video recordings not used for training. The model's predictions will be compared with the human annotations and the manual observations using COPUS. The model's accuracy and reliability will be rigorously evaluated using statistical tests and measures, such as Cohen's kappa, inter-rater agreement, and confusion matrix. The model's explainability and usability will also be assessed using qualitative methods, such as interviews and surveys with potential users and stakeholders.

Phase 2: Implementation and Assessment:

In this phase, implementing and assessing the AI-based model in real-world experiment-centric STEM classrooms is the focus as the model will be integrated into pilot courses across seven diverse STEM disciplines and use it to monitor and document classroom activities and student engagement. Data-driven insights and recommendations will be provided to the educators participating in the experiment and solicit their feedback and perceptions on the AI-based assessment system then, a comparative analysis will be conducted between the AI-based model and the traditional assessment methods, such as COPUS, to validate the model's effectiveness and impact.

The steps involved in this phase are as follows:

1. Model Deployment: The validated AI model will be deployed on edge computing devices within the pilot classrooms. These edge computing devices will consist of cameras, microphones, and processors that can run the model locally and in real time. The devices will be installed with the consent of the participants and in compliance with ethical standards and regulations.
2. Model Inference: The deployed model will continuously monitor and document classroom activities and student engagement, using the audio-visual data captured by the edge devices. The model will generate detailed reports on the frequency, duration, and distribution of the 26 activity constructs, and the patterns, trends, and insights on the teaching and learning process. The model will also provide real-time feedback and suggestions to the educators and students, such as highlighting areas of improvement, encouraging participation, and facilitating discussions.

3. Model Evaluation: The model's performance and impact will be evaluated using both quantitative and qualitative methods. Qualitative methods will include conducting interviews and surveys with the students and educators to gather their feedback and perceptions on the AI-based assessment system, as well as its benefits, challenges, and implications.

Phase 3: Analysis and Dissemination:

This phase aims to analyze and disseminate the research findings and implications of the AI-based model for pedagogical assessment in experiment-centric STEM education. The data and insights from the previous phases would be synthesized, conclusions and recommendations would be deduced for future research and practice. The study's outcomes and contributions will be communicated and shared with the academic and educational communities, showcasing the potential of AI to revolutionize pedagogical assessment and enhance learning experiences.

The steps involved in this phase are as follows:

1. Data Analysis: A comprehensive data analysis will be performed using various statistical and thematic techniques, the quantitative data from the model's assessments and traditional methods, will be analyzed to assess their alignment and identify any discrepancies. The qualitative data from the interviews and surveys will be analyzed to understand the perceived impact of the AI system on teaching and learning practices, as well as the ethical and social issues that arise from its implementation.
2. Report Writing: Data analyzed in the previous step will be synthesized into a comprehensive report outlining the research objectives, methodology, results, discussion, and conclusion. The report will highlight the efficacy of the AI-based model in enhancing pedagogical assessment and student engagement within experiment-centric STEM education, as well as the challenges and limitations of the approach. The report will also provide recommendations and suggestions for future research and practice in this emerging and interdisciplinary field.
3. Dissemination: as a final step, the findings and contributions of this study will be disseminated through various channels and platforms, such as peer-reviewed publications, conference presentations, and workshops. This will target both academic and educational audiences, aiming to raise awareness and interest in the potential of AI to revolutionize pedagogical assessment and enhance learning experiences. Feedback and collaboration from other researchers and practitioners in the field would be collected to foster a community of inquiry and innovation.

By carefully and intently putting together these various elements, the methodology of the study endeavors to create a robust, adaptive, and ethically sound AI-based model for classroom observations, assured to redefine the prospect of pedagogical assessment in STEM education.

Discussion

By leveraging the power of AI and computer vision, it is anticipated that this study will help move beyond the limitations of traditional methods and provide educators with rich, objective data on classroom dynamics. The AI-based model's ability to capture the intricate interactions accurately and reliably between students, instructors, and the learning environment offers several key advantages, as highlighted below:

Enhanced Efficiency and Scalability: Manual observations of classroom activities are time-consuming and cumbersome, limiting their applicability to large classes or frequent assessments. The AI model, on the other hand, can process vast amounts of data rapidly, allowing educators to conduct ongoing, real-time assessments without compromising valuable teaching time.

Precision and Objectivity: Human observations are inherently subjective and prone to bias. The AI model, trained on meticulously labeled data, delivers objective and consistent assessments, minimizing the influence of personal interpretations and ensuring fairness in evaluating classroom dynamics. Previous studies have also demonstrated that AI and computer vision can achieve high accuracy and reliability in recognizing and documenting classroom activities, comparable or superior to human observers [34], [35].

Deeper Insights into Learning Dynamics: The AI model's ability to track and analyze various activities simultaneously provides educators with a holistic understanding of classroom interactions. This data can reveal hidden patterns and correlations that traditional methods often lack, enabling educators to identify areas for improvement and tailor their instruction to address individual student needs. For example, the model can provide insights into the frequency and quality of student questions, the level and type of student engagement, the effectiveness of instructor feedback, and the impact of experiments on student learning.

Personalized Learning and Improved Engagement: The data-driven insights generated by the model can be used to personalize learning experiences for each student. Educators can provide targeted interventions, scaffolding, and differentiated instruction to maximize student engagement and knowledge acquisition by identifying individual strengths and weaknesses. Previous studies have also shown that personalized learning can enhance student motivation, interest, and self-efficacy in STEM fields [36], [37].

This study acknowledges the limitations and challenges of the approach to be used, and the ethical and social implications of using AI for classroom observations. Some of the potential issues that will be addressed in our research are:

Data Privacy and Security: The collection and processing of video data from the classroom raises concerns about the privacy and security of the participants, especially the students. Strict protocols to anonymize and protect the data will be observed, as well as to obtain the consent of the participants and comply with ethical standards and regulations. The model will also be deployed on edge computing devices, minimizing the need for data transmission and storage on external servers.

Bias and Fairness: The training and validation of the AI model may introduce biases in the data and the predictions, affecting the accuracy and fairness of the assessments. Continuous efforts will be made to mitigate biases in the data collection, annotation, and augmentation processes, as well as in the model training, optimization, and evaluation processes and various metrics and methods will be used to measure and monitor the model's performance and ensure its alignment with human observations.

Trust and Transparency: Integrating the AI model into the teaching and learning process may affect the trust and transparency between the educators and the students, as well as between the educators and the model. The principles of explainable AI will be actively embraced, ensuring that the model's reasoning and insights are interpretable and accessible to educators. Hence, a collaborative and communicative environment will be fostered, where the educators can provide feedback and guidance to the model, and the model can provide suggestions and recommendations to the educators.

This study will contribute to advancing knowledge and innovation in the field of pedagogical assessment in experiment-centric STEM education, benefitting educators and students by providing them with valuable data and insights to enhance their teaching and learning experiences. Feedback and suggestions from other researchers and practitioners in the field, as well as from the audience, on the study's objectives, methodology, and expected outcomes, are sought after.

Conclusion

In conclusion, this study focuses on a transformative shift in STEM education by seamlessly integrating AI into the assessment of experiment-centric pedagogy. The AI-based model provides a framework for accurate, personalized, and data-driven assessment, enabling educators to tailor their instruction to individual student needs and preferences. This advancement enhances student engagement, motivation, and learning outcomes, creating a dynamic and immersive learning environment. Moreover, the model supplements existing observation protocols, such as COPUS, offering a reliable and objective measure for evaluating classroom activities. By constantly improving and validating the AI model, this study envisions a future where assessment is an integral part of the learning process, providing educators with timely and actionable feedback and students with the personalized support they need to achieve their full potential.

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