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Enhancing Engagement in Virtual Classroom in Higher Education Using Artificial Intelligence

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We explored the impact of AI in virtual medical classes to enhance medical students' engagement and learning outcomes. Virtual reality, natural language processing, and adaptive learning were employed to simulate experiments involving animals. The AI technology used in this study demonstrated its capability as an educational tool, fostering personalized learning experiences, promoting collaborative efforts, and addressing ethical concerns related to animal-based procedures. An analytical framework for the evaluation of the AI technology in education was defined using the sensor-dependent engagement and proficiency adaptation indices. The survey results of the students indicated the necessity of AI technology in education to ensure efficiency and fill the technological gap between educational institutions. Student engagement and learning outcomes related to animal-based procedures were enhanced using the AI technology. Optimizing AI for virtual education is necessary to develop the necessary sensors and related technologies, driving faster and more impactful educational transformation than before.

1. Introduction

The integration of AI technology has significantly transformed virtual learning environments, particularly within higher education. Over the last decade, advancements in virtual classes have focused on enhancing student collaboration and interaction. This progress is driven by AI-based educational tools such as generative AI, intelligent tutoring models, and adaptive learning platforms, which simulate real-life situations, offer personalized assistance, and facilitate dynamic group interactions.(1) Generative AI tools, including virtual whiteboards and AI chatbots, enable dynamic, real-time engagement between instructors and students, promoting active learning and hands-on practice (Fig. 1).(2) Through these mechanisms, teaching strategies are adjusted to individual student needs and capabilities, thereby enhancing learning outcomes and engagement.

Effective AI implementation in the classroom is linked to sensor technology. Wearable, environmental, and smart sensors are essential for monitoring student behavior, engagement,

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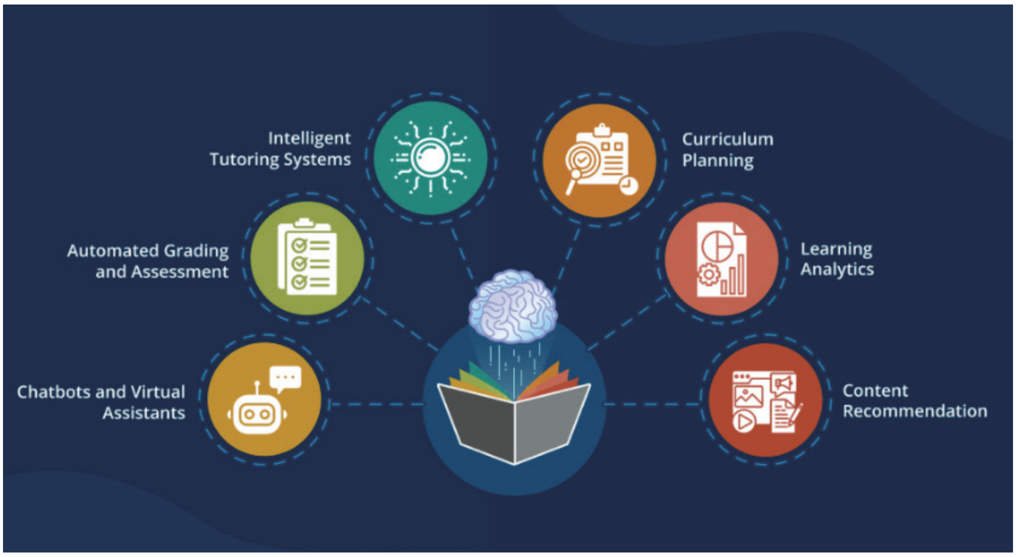

Fig. 1. (Color online) Diverse applications of generative AI in education.

and classroom conditions to support adaptive learning and environment optimization. The sensor data enables the immediate feedback and modification of learning materials based on students' emotional and cognitive responses. In a virtual environment, data from biometric and optical sensors are essential for achieving true interactivity and personalization. For instance, facial recognition and voice analysis are applied to assess student interest, allowing instructors to provide real-time feedback.(3) These applications enhance learning effectiveness by enabling instructors to focus their efforts on personalized student assistance.

While the effectiveness of virtual reality (VR) environments in education is generally accepted, a research gap persists in providing a quantifiable, sensor-driven analytical framework to validate the adaptive mechanisms of AI. By introducing metrics for assessing personalized learning, we examined the role of multimodal sensor data, such as electroencephalography (EEG) or eye-tracking, in computing the engagement index (EI) and the proficiency adaptation index (PAI). By establishing the mathematical relationship between these sensor-derived indices and student proficiency, we provide the technical rationale for the robust implementation of next-generation specialized sensors and AI tools.

In virtual medical education, AI technology enables new pedagogical strategies and enhances student–teacher relationships. Given that the effectiveness of medical education depends on personalized, adaptive, and ethically sound simulated learning experiences, it is important to understand how to optimally incorporate AI. Accordingly, we examined the usage of AI technology and its impact on collaborative learning and teaching in virtual medical education. Specifically, we determined the effectiveness of using AI technology in virtual animal experiments at a medical college and investigated the role and associated issues in AI-driven collaborative learning. The results serve as a basis for understanding the impact of AI technology on students' learning processes and collaborative activities.

2. Materials and Methods

2.1 Data collection

The data analyzed in this study were collected from previous publications that presented the results of the assessment of the effectiveness of virtual animal experiments in veterinary and biomedical colleges.[4–9] The animal experiments in the references included different experiment modules to learn animal anatomy and anatomical procedures, and the data included student attendance, engagement, time-on-task, and assessment scores as performance indicators. The simulated animal experiments offered an interactive experience to students without ethical problems. Permission was granted by the authors of the relevant articles to use their data, and the anonymity of the participants in the studies was maintained throughout this study. The qualitative assessment results of student engagement and interaction in group activities were obtained from professors online. The obtained qualitative data were used for their assessment of the effects of virtual experiments on student engagement and performance. The professors provided their opinions anonymously to maintain confidentiality.

We integrated the quantitative and qualitative data to assess student performance and satisfaction with VR animal experiments and the overall effectiveness of VR experiments on learning outcomes. We analyzed the reported results of the original articles to extract patterns in student engagement, task completion, and performance measures. The results presented how effectively virtual experiments helped students learn and practice in classes.

2.2 Adaptive learning

Algorithms for adaptive learning customize learning content according to each student's knowledge, cognitive style, and engagement in medical education.[10] Their functions are similar to those of Duolingo, a free language-learning app, which adjusts exercise difficulty in real time using a reinforcement learning algorithm that analyzes user performance. This adaptability was measured with *PAI* [Eq. (1)].

$$PAI = \alpha \frac{\sum_{i=1}^{n}\left(C_i - E_i\right)}{n} + \beta \log\left(T_e\right) \tag{1}$$

Here, C_i is the correctness of the i-th response, E_i is the expected error rate, T_e is the time spent on each attempt, and α and β are the accuracy and engagement, respectively.[11,12]

Students benefit from AI-driven personalized instruction. AI-augmented instruction enabled 23–37% enhancement in medical-related vocabulary retention for Chinese students in the English as a Foreign Language (EFL) course.[13] NLP was also used to automatically detect syntactic and semantic omissions, and provide detailed feedback regarding sentence structures and vocabulary. Such applications categorize subjects, verbs, and tenses, and analyze them for agreement and misuse analysis to determine and correct prevalent errors based on interactions with students.[12]

2.3 Real-time feedback and engagement

AI-powered speech recognition models and chatbots provide instantaneous feedback to help students identify and correct wrong language patterns. For example, Duolingo's AI evaluates pronunciation using a phonemic accuracy score (*PAS*) [Eq. (2)].

$$PAS = \frac{\sum_{k=1}^{m} Match\left(P_k, T_k\right)}{m} \times 100\% \tag{2}$$

Here, P_k is the student's phoneme, T_k is the target phoneme, and m is the total number of phonemes analyzed.(12)

The AI-mediated instruction group showed significantly higher post-test scores in English learning than the control group and reduced phonological errors by 18–29%. The use of the AI model also increased the students' motivation to learn English. The AI model was highly effective and efficient, enhancing students' performance, their motivation to learn, and their ability to manage their learning process.(12)

The AI model is also used to assess student engagement based on multimodal sensor data, such as attention tracking or facial recognition (gaze duration or blinking) data. *EI* is widely used to assess student engagement [Eq. (3)].

$$EI = r\left(\frac{F_a}{F_{max}}\right) + \sigma\left(\frac{D_v}{D_{total}}\right) \tag{3}$$

Here, F_a is the audio engagement frequency, D_v is the video engagement duration, and r and σ are modality-specific weights. High *EI* scores (≥0.75) were correlated with faster vocabulary acquisition (by 31%) in university-level EFL.(12)

2.4 Data-driven learning paths

AI tools aggregated longitudinal data to model language acquisition. For example, the regression analysis result of 60 EFL students revealed that AI instruction accounted for 42% of the variance ($R^2 = 0.42$) in post-test scores in the regression model [Eq. (4)].(12)

$$\Delta Proficiency = 0.58.PAI + 0.32.EI + \varepsilon \tag{4}$$

Here, Δ*Proficiency* presents the change in standardized assessment achievement.(12) Subgroups were clustered, and "high-engagement students" outperformed "low-engagement students" and scored 2.1 times higher on average. However, plateau phases were identified in the learning curve during spaced repetition exercises or gamified challenge interventions. Students with stagnant reading comprehension were provided with customized instructions and gradually introduced more challenging texts each week. This approach increased the retention of understanding by 19% in ten weeks.(13)

2.5 NLP and error typology

NLP contributes to the advancement of AI learning tools by enabling the precise detection, classification, and hierarchy prioritization of errors in learning. Transformer-based architectures such as bidirectional encoder representations from transformers (BERT) and generative pre-trained transformer 4 (GPT-4) were used to synthesize texts and speeches based on input texts or speeches of students. The architectures categorize mistakes into lexical (wrong word), morphological (conjugated verb forms), syntactic (subject and verb agreement), and pragmatic (inappropriate phrase use in context) types. Adding transformer layers to neural networks allows for calculating attention weights about particular error patterns, while bidirectional long short-term memory (LSTM) layers schematize surrounding discourse structures in which errors occur.

AI tools create an error severity metric (*ESM*) algorithm to rank the importance of errors and correct them. *ESM* is calculated using as

$$ESM = \frac{w_1 \cdot F_e + w_2 \cdot C_h}{\sqrt{t}}. \tag{5}$$

Here, F_e indicates the frequency of a certain error type over a student's rubric error correlation submission, C_h quantifies historical correlation with persistent weaknesses (persistent errors such as recurrent errors of tense due to mental models), $\sqrt{t}$ stands for time since the last occurrence (to give priority to the most recent mistakes), and w_1 and w_2 are domain-specific weights calibrated through supervised learning. For beginner students in EFL, morphological errors were $w_1 = 0.7$ and $w_2 = 0.3$, and pragmatic errors were $w_1 = 0.4$ and $w_2 = 0.2$. Foundational errors, such as article misuse, were corrected before correcting advanced problems such as stylistic redundancy.

ESM is effectively used in static correction methods as it helps reduce the recurrence of errors by 44%. For example, students who frequently made tense errors were given advanced grammar drills to practice more complex structures, whereas those with high C_h scores for lexical errors received targeted training in contextual vocabulary usage. Feedback was refined using sentiment analysis results when students presenting frustration (as indicated by sudden increases in keystroke rate or pitch of their voice) were provided with simpler explanations, while confident students were provided with subtle meta-linguistic cues.[14]

3. Impact of AI technology in Medical Education

AI-driven virtual experiments delivered effective medical education through language-based operations. Natural language processing (NLP) was used to create interfaces to facilitate communication among students and teachers in the virtual environment. Precise and unambiguous communication was required as students used simulated animal bodies. Interactive diagnostic assessment systems and team-based simulated clinical environments were created in the virtual environment. Implementing NLP models enabled students to understand medical terms and study medical cases simultaneously using chatbots or virtual instructors.

In AI-driven medical education, sensors were used to monitor and analyze students' emotional and physiological statuses (Table 1).[15–17] States captured by such sensors were used to understand their responses and learning processes, and provide necessary feedback.

AI tools such as machine learning classifiers, deep learning models, and reinforcement learning agents are used to adjust verbal interventions and tailor activities by modifying their difficulty levels or experiment pace, utilizing sensor data to optimize student learning outcomes.[18–20] In virtual medical education, programmable logic controllers were used to help students learn complex content effectively through automated linguistic assessment and medical term understanding. AI tools analyzed medical terminology that professors used to provide students with appropriate content for learning. Speech recognition tools were also used for the on-site assessment of students' diagnostic presentations and procedure explanations. The tools help students master medical terminology and develop effective communication skills essential for professional communication in medical practices.

4. Student Collaboration

Advanced algorithms optimize communication, cooperation, and information sharing amongst students to enhance student collaboration on AI platforms. NLP algorithms analyze team conversations and recommend the best ways to collaborate with each student's contributions.[21] NLP algorithms also analyze text data, as shown in Fig. 2, which is important in design teams, as more ideas and points of view are required to solve problems creatively. For example, AI algorithms discern students who are behind the learning schedule to provide particular interventions. The algorithms analyze student data to ensure their active participation and encourage collaboration by promoting a positive atmosphere.

AI algorithms also enhance collaborative learning by offering immediate personalized feedback and evaluation. Teachers are provided with analytics regarding student engagement and achievement to refine and optimize their teaching methods to provide improved instruction. For instance, AI algorithms enhance teamwork and sophisticated role assignments, enabling personalized learning by providing customized learning content. AI-incorporated collaborative learning enhances the information retention, collaboration, communication, and flexibility of

Table 1
Sensors used in studying emotional and physiological states.[15–17]

Sensor/method	Physiological/emotional status	Analysis
Electroencephalography (EEG)	Cognitive load, engagement, attention, and electrical activity in the brain	Brainwave patterns
Electrodermal activity (EDA) / galvanic skin response (GSR)	Arousal, stress, and emotional intensity changes in the electrical conductance of the skin	Skin conductance
Electrocardiography (ECG) / photoplethysmography (PPG)	Stress, relaxation, cognitive effort, heart rate, and heart rate variability (HRV)	HRV
Eye-tracking sensor (cameras)	Attention, focus, cognitive processing, gaze direction, fixation duration, and pupil diameter	Fixation duration and saccade speed
Facial expression analysis (cameras)	Emotional valence (eg, confusion, frustration, joy) and subtle movements of facial muscles (action units)	Combinations of facial movements

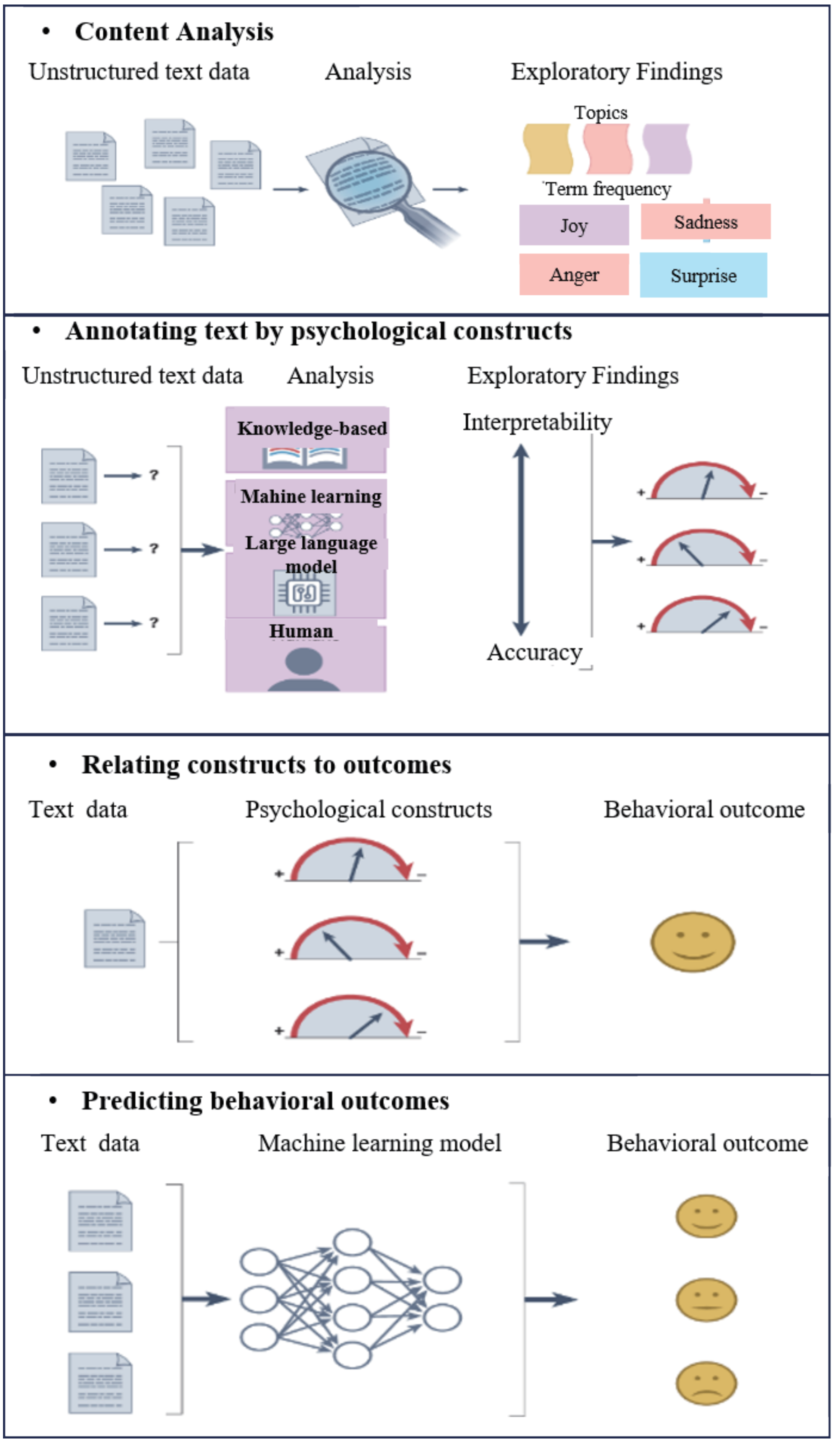

Fig. 2. (Color online) NLP text analysis process.

students (Fig. 3).[22] AI algorithms also enable collaborative learning by analyzing student performance, learning, and adaptive capacity, and grouping the students to enhance individual abilities through group activities.

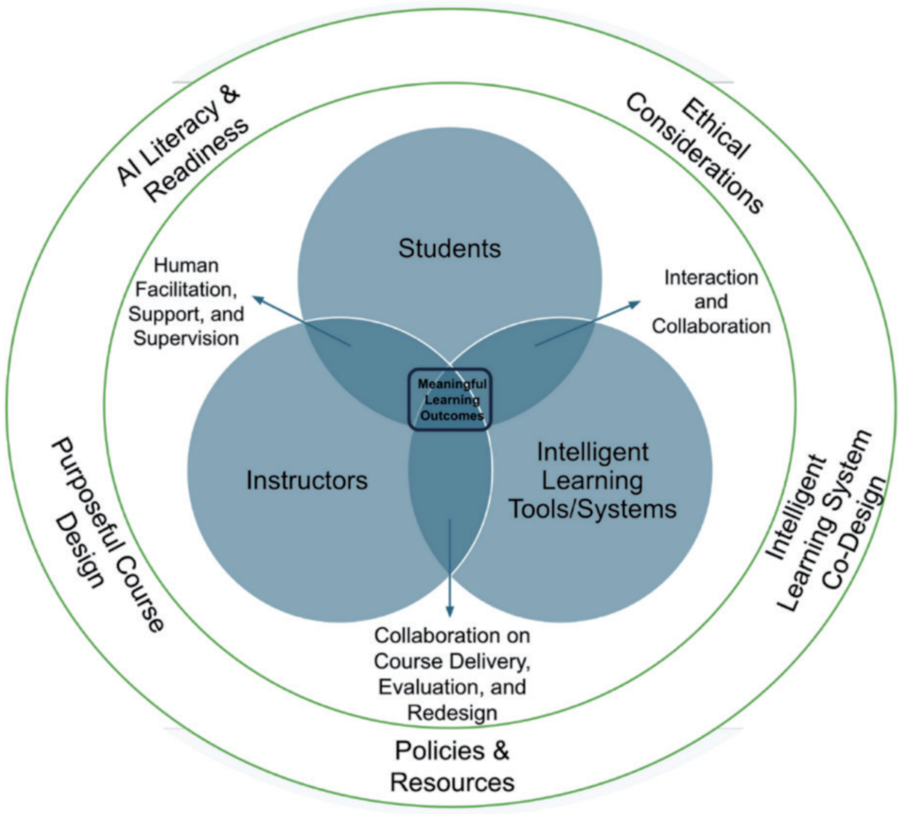

Fig. 3. (Color online) Collaborative learning model.

AI in collaborative learning contributes to the development of sophisticated communication tools that enable students from different cultures to collaborate effectively. Using advanced AI technology, students interact actively. AI tools provide tailored assignments and activities, enabling students to identify and rectify errors while enhancing their understanding of the learning material. They can also create a learning cycle essential for collaboration. By using the engagement index (*EI*), the degree of collaboration among students is estimated as

$$EI = r\left(\frac{F_a}{F_{max}}\right) + \sigma\left(\frac{D_v}{D_{total}}\right). \tag{6}$$

Here, F_a is the audio engagement frequency, D_v is the video engagement time, and r and σ are weighting coefficients for frequency and time, respectively. *EI* scores represent the degree of collaboration and learning performance in advanced integration.

Collaborative learning with AI tools integrates gamification elements to enhance learning engagement. Game features are used in educational activities to increase students' motivation and perceptions of groups by fostering cooperation to share and achieve goals. AI tools provide students with immediate feedback for group progress and adjust and improve their outcomes.[23]

AI analytics assist teachers in monitoring student engagement and performance to customize their teaching methods effectively and meet students' needs. Students' engagement and performance are assessed and reflected in optimizing teaching strategies to ensure active engagement through collaborative tasks.

In adopting AI in collaborative learning, ethical considerations, data privacy, and AI dependence must be considered. It is necessary to prepare students to use innovative technologies through collaborative learning. AI tools significantly bolster creativity and student collaboration to develop inventive solutions and have satisfactory learning outcomes. The sensor technology presented in Table 1 is widely used to monitor student engagement and emotional state in group interactions. AI tools modify collaboration processes based on the monitoring data of students' attention, expression, and stress to have students more actively engage in activities at all levels to achieve optimal collaboration and obtain improved learning outcomes.

AI tools personalize learning paths, provide instantaneous feedback, and improve communication skills. AI tools in collaborative learning cultivate a partnership with students and enhance inclusivity and effectiveness in learning.[(24)] The advanced AI technology used in education provides a new way for students to engage and interact in learning. It also allows teachers to assist students in maximizing their potential in learning by increasing their interest and enhancing achievement through the collaboration and communication of students.

AI technology contributes to the development of cooperative learning as it helps form learning groups and provides automated guidance and smart supervision. AI technology is used to evaluate students' abilities, values, and learning techniques, and help them practice learning skills in various activities. AI technology provides individual assistance and customized learning processes by offering instant responses and explanations, and aiding students in comprehending learned knowledge. Such supports help students acquire knowledge and critical thinking, problem-solving, and analysis skills.[(25)]

The improvements through collaborative learning are facilitated by AI technology. AI–human communication and cooperation through NLP are mandatory to optimally personalize learning and enhance learning outcomes. The advancements in learning enable teachers to design advanced pedagogical frameworks to educate students to embrace future technological advancements.

AI technology in collaborative learning provides automated and personalized feedback to maximize learning efficiency and creates the synergy of human creativity and machine intelligence, resulting in paradigm shifts in education. AI technology also enables student collaboration in learning so that teachers can design inclusive and adaptive learning environments to meet the requirements of students.[(26)] The interplay of humans and machines is changing education by improving collaborative learning environments.

5. Innovations in Teaching and Learning

Teaching methods have been developed according to educational paradigm changes through technology integrations in gamified learning, immersive learning with augmented reality (AR) and virtual reality (VR), and blended learning. In gamified learning, interest and motivation in class are focused. Classcraft and Kahoot are examples with which students engage in interactive learning by playing educational games and learn lessons enjoyably and effectively. AR and VR allow students to actively participate in learning history or science through virtual experiences similar to real ones. Blended learning enables flexibility in learning to meet individual needs through online and offline instruction. Such innovative learning methods enhance students' engagement and their learning outcomes. The three methods are compared in Table 2.

Gamification and immersive technologies spark interest, brainstorming, and interaction, whereas blended learning enhances flexibility. Such methods increase accessibility to learning tools and change the ways of teaching and learning to meet the needs of students.(27) Other than such innovative methods, social and emotional learning is important for students to learn essential social skills such as empathy and awareness of self. Although not widely accepted, social and emotional learning enables students to develop teamwork and problem-solving skills effectively. It also enhances academic achievement as it helps students adapt and respond to changes responsively and actively.

With AI technology, learning can be personalized to meet various learning needs based on data analysis. Sensor technology plays a vital role in enhancing student engagement and emotions, and providing essential information to adjust teaching methods to various learning needs.(28) Advanced AI and sensor technologies contribute to developing innovative, relevant, engaging, and effective teaching methods.

6. Results and Discussion

6.1 Introduction of AI Tools

Tang *et al.* assessed students' engagement in virtual learning environments based on sensor data.(4) The sensor data contribute to the improvement of the functionality of AI tools used in education. In animal experiments, the attention and emotional data from sensors are used to refine algorithms to maximize student attention and performance. The virtual animal experiments increased student engagement and learning effectiveness. Tang *et al.* used an immersive VR method to educate students on complex animal handling techniques.(4) Students actively interacted in the simulated environment and showed superior performance to students without virtual hands-on practice, proving the advantages of the VR learning environment.

The virtual learning environment presented simulated training sessions without harming living animals. Students showed intense immersion levels with scores above 5.5 (out of 10) for

Table 2
Comparison of innovative teaching/learning methods.

Innovation	Description	Benefit	Challenge
Gamification	Incorporates game elements into learning	Increases motivation and engagement	Risk of over-reliance on rewards
Immersive technology (AR/VR)	Provides immersive, interactive experiences	Enhances retention and understanding	High cost of equipment, limited accessibility
Blended learning	Combines online and offline instruction	Offers flexibility and personalized learning	Robust infrastructure and teacher training

active involvement (a mean score of 5.92) and focusing on tasks (a mean score of 5.96).[4] This demonstrated the effectiveness of interactive and immersive learning of complex concepts in the VR learning environment (Table 3). The result indicated that AI tools in virtual classes enhanced student engagement and learning outcomes in hands-on laboratory practices.

6.2 Ethical consideration in virtual animal experiments

In animal experiments, the 4R principles, which stand for replacement, reduction, refinement, and responsibility, are emphasized to ensure ethical research practices using animals. In virtual experiments, students interact with digital animals using the ViSi simulator following the ethical guidelines described by Tang *et al.*[4] Students provided positive feedback and demonstrated high engagement in virtual experiments, achieving an average score of 5.9. They favored multi-angle views, which significantly enhanced their understanding of animal anatomy with a score of 5.63.[29] The VR environment supported the reduction and replacement principles, and offered an affordable training method that minimized the use of living laboratory animals.[24]

Immersive simulated learning environments provided students with realistic practices while eliminating ethical concerns associated with the use of living animals. The VR simulation helped students learn animal anatomy under ethical guidelines more effectively than in experiments with living animals.

6.3 Student engagement and learning effectiveness

VR learning environments significantly enhanced student engagement and learning effectiveness in animal experiments. Students in the VR simulation performed animal anatomy

Table 3
Perception of virtual biomedical experiments of students.[4]

Items	Mean score	*t* value	*p* value
How natural did your interactions with the environment seem?	4.83	2.63	0.014
To what extent did the visual aspects of the environment involve you?	5.67	7.78	0.000**
How natural was the mechanism that controlled movement through the environment?	5.13	4.37	0.000**
How compelling was your sense of objects moving through space?	5.13	4.94	0.000**
How completely were you able to actively survey or search the environment using vision?	5.92	12.11	0.000**
How compelling was your sense of moving around inside the virtual environment?	5.42	6.55	0.000**
How closely were you able to examine objects?	5.21	4.73	0.000**
How well could you examine objects from multiple viewpoints?	5.63	4.92	0.000**
How involved were you in the virtual environment experience?	5.74	9.56	0.000**
How proficient in moving and interacting with the virtual environment did you feel at the end of the experience?	5.75	9.49	0.000**
How well could you concentrate on the assigned tasks or required activities rather than on the mechanisms used to perform those tasks or activities?	5.96	9.6	0.000**
Overall, were you able to anticipate what would happen next in response to the actions that you performed?	5.46	7.31	0.000**
Overall, were you able to gain hands-on experience from the VR game?	5.42	6.31	0.000**

experiments better than the students who only observed, as those who engaged in VR experiments understood and remembered what they learned better.[29] The VR experiment helped them to master the necessary skills in practicing animal autopsy. Student feedback also indicated the advantages of VR-based learning and immersive experiences (a mean score of 5.75) and concentration on learning (a mean score of 5.96). Table 4 presents the comparison of AI-driven and traditional learning in terms of personalized learning, learning engagement, collaborative learning, instructor support, feedback, and technological requirements. Students showed improved cognitive engagement in VR simulations to better understand and remember the procedure of animal experiments. Virtual learning environments provided customized content according to student performance, which enhanced their learning effectiveness. Integrating immersive learning in the VR environment enabled improved educational experiences, leading to efficient knowledge acquisition. Virtual technologies enabled active student engagement and provided prompt feedback to enhance learning outcomes.

6.4 Current challenges and recommendations

Despite the advantages of AI-integrated and collaborative learning, the effective use of this technology presents challenges. First, the digital divide caused by inequalities in accessibility to technology and learning opportunities due to different geographical or socio-economic locations must be mitigated. Students lacking smart devices and satisfactory internet access find it difficult to utilize AI tools, resulting in a deficiency in learning experiences. Second, AI tools require basic training to be used effectively in education. Third, biases that might be created by AI algorithms must be considered in using AI tools.

To overcome such challenges, every student is allowed to use AI tools without restrictions. AI tools need to be used on accessible platforms for all students to use them without barriers. Teachers need to be trained in appropriate programs to learn how to use AI tools. Future research is necessary to explore how to mitigate the biases in AI tools' outcomes through collaboration between engineers, teachers, students, and policymakers.

Table 4
Comparison of AI-driven and traditional learning.

Aspect	AI-driven learning	Traditional learning
Personalized learning	AI customizes learning paths based on individual progress and needs.	Personalization is limited in one-size-fits-all lesson plans.
Learning engagement	Real-time feedback and interactive activities keep students engaged.	Student engagement depends on instructor's teaching style and classroom dynamics.
Collaborative learning	Online collaboration is facilitated through virtual whiteboards, chatbots, and group activities.	Collaboration may be limited to in-person group work and discussions.
Instructor support	AI tools assist instructors by automating grading, providing analytics, and offering personalized recommendations for each student.	Instructors rely heavily on their own time and skills to provide personalized support to each student.
Feedback	Provides immediate real-time feedback on the performance of language skills, such a grammar, pronunciation, and vocabulary usage.	Feedback is typically delayed, given manually by the instructor, and is often less frequent.
Technological requirement	Internet access and devices are required for AI tools and virtual learning platforms.	Minimal technology is required, typically reliant on textbooks and classroom-based resources.

7. Conclusions

Integrating AI tools with advanced sensor technology in virtual education enhances the learning experiences of students. Sensors are used to monitor and detect student emotions and cognitive levels, enabling real-time feedback to customize teaching methods and materials to meet the students' needs. We established a novel, sensor-dependent validation method, using *EI* calculated from biometric and optical sensor data, and *PAI* statistically linked to student proficiency changes ($\Delta Proficiency$). This establishes the quantifiable goal for sensor development in educational technology. Advancements in technologies make teaching and learning engaging and interactive, and satisfy each student with individual learning goals. Differences in the availability of technology, a lack of training, and biases made by AI tools need to be addressed to make advanced technologies available to all students. As AI technology develops, teachers, researchers, and policymakers must collaborate to address potential issues and increase efficiency in education, prioritizing the development of highly accurate, non-intrusive sensor systems to fully implement and validate the proposed *EI* and *PAI* models.

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