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PAPER

The Effect of Intelligent Evaluation Technology on Students' Initiative in Post-lecture Evaluation of Online Teaching

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ABSTRACT

Class evaluation based on intelligent technology is a disruptive innovation and change. Strengthening research, developing key technologies in the education evaluation field, and effectively integrating intelligent technology in higher education evaluation are among the essential measures that can be taken to ensure the high-quality development of higher education. In this study, 352 undergraduates from Anyang Institute of Technology in Henan Province were invited to participate in a questionnaire survey. The influence of four aspects of intelligent evaluation technology (i.e., language analysis, behavioral analysis, emotion analysis, and teaching evaluation techniques) on the initiative of the students in the post-lecture evaluation of online teaching was analyzed. Differences in the initiative of the students in post-lecture evaluation under different frequencies of use of intelligent evaluation technology were measured. Results showed that the overall Cronbach's α is 0.840 and the Kaiser-Meyer-Olkin value is 0.852, indicating that the questionnaire has very good reliability and validity. Language analysis, emotion analysis, and teaching evaluation techniques have a positive promotion effect on the initiative of the students in the post-lecture evaluation of online teaching. The frequency of use of intelligent evaluation technology after class has a significant influence on the initiative of the students in post-lecture evaluation at the 0.01 level ($F = 5.073$, $p = 0.002$). Moreover, the initiative of the students in post-lecture evaluation declines gradually as their frequency of use of intelligent evaluation technology increases. The research conclusions can serve as an important reference for education teaching evaluation mode reform, with artificial intelligence technological support; the interpretability of multidimensional indices (e.g., cognition, emotions, and input) for online teaching quality evaluation; and teaching quality evaluation under man–machine coordination.

KEYWORDS

intelligent evaluation technology, online teaching, evaluation initiative, reliability, validity, online regression, analysis of variance

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1 INTRODUCTION

Owing to the rapid development of the Internet and information, online learning has become an important means for changing people's learning styles. Intelligent evaluation technology is a new intelligent education mode and form that has been extensively employed in education, with the support of the rapid development of artificial intelligence (AI) and big data technology. Accordingly, new modes such as intelligent examinations and intelligent evaluations have also been developed. In the Information Age, intelligent technology can provide opportunities for education evaluation reform. The comprehensive integration of intelligent technology and education evaluation has become an inevitable trend. From the perspective of technology, AI remains in a weak state, and the intelligence level of such technology has yet to meet our expectations. A gap exists between China and foreign countries in the application of intelligent technology in education, and problems remain in the country, such as poor professional skills, few comprehensive service suppliers, the incomplete integration of intelligent technology and innovative education, and so on. Intelligent evaluation technology can significantly promote education informatization reform because education evaluation updating requires advanced technological support, and intelligent technology is an important driving force. The deepening of education evaluation reform by universities and colleges by promoting the integration of intelligent technology and education evaluation can ensure the high-quality development of higher education.

Student post-lecture evaluations refer to learners' initiative to evaluate the design, process, and results of classroom teaching after the completion of a learning task to improve instructors' teaching ability and the classroom teaching quality based on the instructors' teaching and students' learning. Through students' positive involvement in post-lecture evaluations, information on multiple aspects can be collected to explore values, make decisions on teaching improvements, and develop and provide feedback on different functions. Traditional student post-lecture evaluations can be mainly divided into two classical modes, namely, peer evaluation and self-evaluation. Owing to intelligent evaluation technology, students can complete post-lecture teaching evaluations in a positive manner. AI can conduct scientific education data mining, help students perform effective evaluations, and record dynamic emotional information changes based on high-speed calculation and automatic analysis. Thus, AI technology (AIT) can be used to obtain classroom information and track the development of teachers and students. Specifically, intelligent evaluation technology can recognize teachers' and students' emotions and obtain dynamic information on emotional changes by collecting data on their voice, facial expressions, and body posture. Teachers generally show emotions while teaching through their expressions, language, actions, and so on. Passionate teaching can stimulate students' learning enthusiasm. Meanwhile, students' learning performance can be determined and analyzed by using intelligent evaluation technology, which is conducive to self-evaluation and peer evaluation after class. Intelligent evaluation technology can transfer different dimensions of students' classroom performance information (e.g., active emotions and positive emotions) to their post-lecture evaluation judgment, which can help them complete such evaluations positively, scientifically, and seriously. Thus, students' post-lecture evaluation initiatives in online teaching can be unified at an elevated level.

2 THEORETICAL BASIS AND HYPOTHESIS DEVELOPMENT

2.1 Zone of proximal development theory

Doolittle, P. E. [1] summarized zone of proximal development theory comprehensively, which states that students have two development levels, that is, their existing development level and the development level that they may reach in the future. The gap between the two levels is called the zone of proximal development, that is, the gap between the actual level of a student's ability to solve problems independently and the level they may reach by cooperating with their peers or under the guidance of others. In this study, students' participation in the post-lecture evaluation of online teaching conforms to the concept of zone of proximal development theory. Specifically, in the post-lecture evaluation of online teaching, teachers consider the zone of proximal development (or existing level) of students in the content design and build an evaluation index system with appropriate levels of difficulty according to the students' zone of proximal development to stimulate them to complete the post-lecture evaluation and help them advance toward the next zone of proximal development. Hence, various factors, such as a scientific and reasonable online teaching post-lecture evaluation index system, the evaluation mode, and the evaluation time, can help students achieve satisfactory development and exert a positive creative effect on their zone of proximal development. The two developmental levels of students are not constant. Post-lecture evaluations should be designed to develop proper functions and help students master and assimilate the knowledge they learned online.

2.2 Hypothesis development

Intelligent evaluation is a type of advanced technology that can make value judgments under the collaboration of multiple subjects, analyze the teaching process of instructors, give full play to the precise feedback function of intelligent technology, and create teaching value by collecting multidimensional teaching information. Intelligent evaluation technology has attracted the attention of education and AI researchers. Specifically, many scholars examined how the quality of teaching evaluations can be improved using intelligent evaluation technology and how different subjects can conveniently participate in the teaching evaluation process. For instance, Mark, M. A. et al. [2] proposed an intelligent tutoring system (ITS) evaluation method by referring to research results from the field of ITSs, expert systems, and so on. De-kun, J. et al. [3] believed that the teaching tasks of traditional mobile intelligent sports teaching evaluation algorithms are relatively chaotic and thus designed a new algorithm for mobile intelligent sports teaching evaluation. The results showed that the algorithm can achieve higher evaluation precision than traditional mobile intelligent sports evaluation algorithms. Tang, J. et al. [4] created education application evaluation indices and found that the scores of an intelligent evaluation system are highly consistent with the actual scores of users. The research findings proved the feasibility and effectiveness of the proposed intelligent evaluation system. According to Dorça, F. A. et al. [5], AIT can realize the automatic detection and accurate adjustment of students' learning styles and improve their learning outcomes. Chang, F. C. I. [6] developed an automatic tool to help teachers and students conduct online interaction analyses and showed that teachers and students can benefit considerably from a performance evaluation system to redesign course materials and check courses generated automatically. Against the background of

"AI + education," Zhao, J. et al. [7] assisted teachers in using intelligent algorithms to conduct AI evaluations of students' compositions, and the experiment results verified the effectiveness of the built model. Celik, I. [8] reported that teachers can effectively understand the teaching contributions of AI if they have knowledge on the use of AI-based tools, and technological knowledge can help teachers effectively evaluate the decisions made by AIT. Verma, A. et al. [9] proposed a multilayer quality evaluation method based on the Internet of Things (IoT) as a sustainable holistic education remedy. Hooshyar, D. et al. [10] found that ITSs can increase students' learning interest and improve their attitude, technological acceptance, and performance in solving problems. He, Y., et al. [11] demonstrated that computer-assisted evaluations can help teachers give scores effectively. Aleven, V. et al. [12] showed that students' help-searching behavior can be improved through teachers' use of an ITS. Kaklauskas, A. et al. [13] developed an intelligent self-assessment system for the biological recognition of students' progress, which could also analyze students' acquired knowledge through voice and stress analyses and a special algorithm. Meanwhile, Achumba, I. et al. [14] believed that computer-aided learning tools can be used to enhance diversified laboratory learning methods and employed the latest method to simulate the traditional laboratory process with virtual laboratory technology. Ivanova, M. [15] analyzed a major vision summarizing the e-learning informatics field and examined scientific articles related to the theme. Uglev, V. A. et al. [16] suggested the intermediary evaluation of ability development levels with intelligent education systems using expert techniques. The aforementioned studies indicate that Artificial Intelligence (AIT) and computers have the potential to augment human intelligence and physical capabilities significantly, potentially enabling comprehensive longitudinal evaluations of online learning conditions for university students. Additionally, they open the door to a thorough horizontal evaluation of the learning process, leveraging AI, big data, and modern information technology. Teaching evaluations occur mainly after class; thus, students' post-lecture teaching evaluation has value in enriching the evaluation content, changing the evaluation mode, and promoting the efficient development of intelligent evaluation. Hence, this study analyzes how the initiative of students in the post-lecture evaluation of online teaching based on intelligent evaluation technology can be improved through a questionnaire survey. Intelligent evaluation technology can further enrich online teaching evaluation content against the AI background, collect information on the academic performance of teachers and students throughout the online teaching process, and facilitate scientific teaching evaluations. Based on the above discussion, this study proposes the following hypotheses:

H1: Classroom language analysis will have a positive promotion effect on students' initiative in the post-lecture evaluation of online teaching.
H2: Classroom behavioral analysis will have a positive promotion effect on students' initiative in the post-lecture evaluation of online teaching.
H3: Classroom emotion analysis will have a positive promotion effect on students' initiative in the post-lecture evaluation of online teaching.
H4: Classroom teaching evaluation will have a positive promotion effect on students' initiative in the post-lecture evaluation of online teaching.

3 METHODOLOGY

3.1 Questionnaire design

Based on existing studies, a questionnaire was designed in this study to investigate the influence of intelligent evaluation technology on students' initiative in the post-lecture

evaluation of online teaching. The questionnaire consisted of 26 questions covering three aspects. (1) The first aspect was the measure of intelligent evaluation technology in online teaching. According to Zawacki-Richter, O. et al. [17], Han, E. R. et al. [18], and Liu, Y. et al. [19], intelligent evaluation technology in online teaching mainly covers four aspects, namely, language analysis, behavioral analysis, emotion analysis, and teaching evaluation. In this study, the four aspects were investigated using 5, 4, 4, and 5 questions. (2) The second aspect was the measure of students' initiative in post-lecture evaluations. Following Marsh, H. W. et al. [20] and Struyven, K. et al. [21], this study proposed four measurement problems of students' initiative in post-lecture evaluations. (3) The third aspect was the general information of the respondents, including their gender, grade level, school, and frequency of use of intelligent evaluation technology after class. All the items were measured using a five-point Likert scale.

3.2 Respondents

Henan Province is recognized among the education provinces in Central China. Online teaching was launched comprehensively as a response to the COVID-19 pandemic. Students from level-two schools focusing on engineering courses at Anyang Institute of Technology in Henan Province were chosen to participate in the questionnaire survey. The survey was conducted using paper and online questionnaires. For the paper questionnaire survey, the questionnaires were sent to the students of Anyang Institute of Technology to answer during their break time. For the online questionnaire survey, an electronic questionnaire was designed using a Chinese mainstream online questionnaire survey system (www.wjx.cn), and a QR code was generated and sent to the students. The questionnaire survey was conducted for three days during the spring semester of academic year 2022–2023. A total of 486 questionnaires were collected, and 339 valid questionnaires were retained, which showed an effective recovery rate of 69.75%. The general information of the respondents is shown in Table 1.

Table 1. Descriptive statistical results of respondents

Information	Description	Frequency	Percentage (%)
Gender	Female	123	36.28
	Male	216	63.72
Grade level	Freshman	41	12.09
	Sophomore	111	32.74
	Junior	130	38.35
	Senior	57	16.81
School	School of Mechanical Engineering	50	14.75
	School of Electronic Information and Electrical Engineering	63	18.58
	School of Computer Science and Information Engineering	54	15.93
	School of Civil and Architectural Engineering	47	13.86
	School of Chemical and Environmental Engineering	52	15.34
	School of Material Science and Engineering	73	21.53
Frequency of use of intelligent evaluation technology	1–2 times a week	50	14.75
	2–3 times a week	87	25.66
	3–4 times a week	94	27.73
	> 4 times a week	108	31.86

It can be seen from Table 1 that the proportion of female participants in the total number of participants was relatively low (only 36.28%) because this study focused on engineering science schools. Regarding the grade level, most of the respondents were in their junior or sophomore year. In terms of school, the proportion of respondents belonging to one of the six engineering schools was relatively balanced. With respect to the frequency of use of intelligent evaluation technology, most of the students used the technology more than four times a week. The findings revealed that, because of the COVID-19 pandemic, numerous courses adopted the online teaching mode. As a result, intelligent evaluation technology became popular at Anyang Institute of Technology, and the students gradually accepted the practice of online teaching, post-lecture peer evaluation, and self-evaluation.

4 RESULT ANALYSIS

4.1 Reliability and validity tests

A reliability test is the primary step in the analysis of a questionnaire and is generally measured using Cronbach's α. If the Cronbach's α value is higher than 0.8, then the reliability is high. If the Cronbach's α value is between 0.7 and 0.8, then the reliability is relatively good. If the Cronbach's α coefficient is between 0.6 and 0.7, then the reliability is acceptable. If the Cronbach's α value is lower than 0.6, then the reliability is poor.

Table 2. Reliability test results

Type of Variable	Name of Variable	Number of Questions	Cronbach's α	Overall Cronbach's α
Independent variables	Language analysis technique	5	0.885	0.840
	Behavioral analysis technique	4	0.865	
	Emotion analysis technique	4	0.835	
	Teaching evaluation technique	5	0.879	
Dependent variable	Students' initiative in post-lecture evaluation	4	0.858	

It can be seen from Table 2 that the overall Cronbach's α of the questionnaire was 0.840 (> 0.8), which indicated the high reliability of the research data. Moreover, the Cronbach's α of the five variables was higher than 0.8, which proved that the original data from the questionnaire survey had high reliability and could be used for further analysis.

After the reliability test, a validity test is typically conducted. Validity is tested using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. If the KMO value is higher than 0.8, then the data are appropriate for information extraction. If the KMO value is 0.7–0.8, then the data are relatively suitable for information extraction. If the KMO value is 0.6–0.7, then information may be extracted. If the KMO value is lower than 0.6, then information extraction would be difficult. The validity analysis results must pass Bartlett's test of sphericity. In other words, the corresponding P-values must be lower than 0.05.

Table 3. KMO test and Bartlett's test of sphericity results

KMO		0.852
Bartlett's test of sphericity	Approximate chi-square	3590.415
	df	231
	P-value	0.000

It can be seen from Table 3 that the KMO value was 0.852 (> 0.8), and the corresponding P-value was lower than 0.01. The results proved that the original research data collected through the questionnaire survey were suitable for information extraction and demonstrated satisfactory validity.

4.2 Linear regression

Table 4. Linear regression results

Variable	Standardized Coefficient	T-Value	P-Value	Collinearity Diagnosis	
				VIF	Tolerance
Constant	–	3.127	0.002***	–	–
Language analysis technique	0.186	3.689	0.000***	1.025	0.975
Behavioral analysis technique	0.032	0.616	0.538	1.060	0.943
Emotion analysis technique	0.207	4.037	0.000***	1.054	0.949
Teaching evaluation technique	0.238	4.660	0.000***	1.051	0.952
Adjusted R^2	0.867				
F	F (4,334) = 17.055, p = 0.000				
DW value	1.717				

Note: ***Indicates significance at 1% level.

It can be seen from Table 4 that the adjusted R^2 value of the model was 0.867, which meant that the four independent variables can interpret 86.7% of the changes in the dependent variable. The model passed the F-test (F = 17.055, p = 0.000 < 0.05), which indicated that at least one of the four independent variables may influence the dependent variable. In addition, the multicollinearity test showed that the VIF values were all lower than 5, which indicated the absence of collinearity. Furthermore, the DW value was around 2, which proved the absence of autocorrelation in the model and correlation among the sample data. Thus, the model was relatively satisfactory.

1. H1 was supported. The language analysis technique had a positive promotion effect on the students' initiative in the post-lecture evaluation of online teaching because language is the main means of communication in online teaching activities. In addition, language behaviors account for a considerable proportion of all teaching behaviors. The teaching process, which is based on the language behaviors of teachers and students, can reproduce the overall appearance of teaching and its overall structure. Analysis of the teaching language structure from the perspective of interaction can benefit teacher-student interaction and

reflect whether teachers' language can stimulate students' thinking processes and whether students' speeches can trigger responses from teachers. Statistical analysis should be conducted on communication and interaction between teachers and students based on AIT, as well as on teachers' behavioral values in proposing problems and behavioral feedback orientation to adjust online teaching structures and increase the efficiency of teacher-student interaction. Analysis of teachers' language type and structure based on AIT can help teachers recognize problems in their teaching language and thus correct their language behaviors, which may improve online teaching quality and increase learners' enthusiasm to participate in post-lecture assessments.

2. H2 was not proven and thus was unsupported. The behavioral analysis technique had no positive promotion effect on the students' initiative in the post-lecture evaluation of online teaching. Several reasons may explain this finding. For instance, as a type of cognitive activity, online teaching comprises a series of teaching behaviors and involves the behaviors of students and teachers. The behavioral analysis of students based on a behavioral analysis technique can help identify the learning states of students in class (e.g., listening carefully, sitting sideways and speaking, sleeping on their desk) and provide results to teachers in a timely manner, which can enable teachers to provide specific reminders and tutorship suggestions. Moreover, it can combine interpretation, blackboard writing, inspection tours, and instructors' teaching behaviors to summarize general teaching behavior characteristics, which may be conducive to teachers' optimization of online teaching activities. Nevertheless, behavioral analysis may fail to trigger post-lecture evaluation initiatives directly because of students' diversified learning behaviors and instructors' diversified teaching behaviors. Other mediating variables may increase the promotion effect of behavioral analysis on students' initiative in the post-lecture evaluation of online teaching. This finding may motivate university administrators to consider student fatigue caused by the complexity of test procedures using intelligent evaluation technology.
3. H3 was supported. The emotion analysis technique had a positive promotion effect on the students' initiative in the post-lecture evaluation of online teaching, mainly because online teaching is a process for not only knowledge transfer from teachers to students but also emotional interactions between teachers and students. Students will give feedback in the process of learning, perceiving, and mastering knowledge through external facial expressions and body language. For example, when students are concentrating, they will sit properly and listen to the lectures carefully. In addition, they may show relaxed and positive facial expressions. Such behavior may reflect students' lack of cognitive burden when participating in teaching activities. Thus, students may be able to master the knowledge effectively. AIT can collect data on students' facial expressions and body language. Hence, AIT can collect students' emotional features and then provide feedback to teachers to adjust the online teaching content and teaching method in a timely manner. Students' emotional features can be obtained by intelligent evaluation technology from their facial expressions, body language, and voice. Furthermore, learning emotions were analyzed. Thus, this study can provide comprehensive data support to guide teachers and students in comprehensive and accurate post-lecture evaluations and increase students' enthusiasm to participate in post-lecture evaluations.
4. H4 was supported. The teaching evaluation technique had a positive promotion effect on the students' initiative in the post-lecture evaluation of online teaching. By collecting multimodal online teaching activity data and combining various

recognition and analysis techniques, this study attempted to build an online teaching evaluation system. The automatic acquisition, operation, analysis, and evaluation of online teaching data based on AIT are the basic goals of teaching evaluation applications against an AI background. Intelligent evaluation technology can cover the teaching process comprehensively and three-dimensionally, facilitate online teaching evaluation, and analyze teaching events and comments through natural language and big data processing, thus creating a new mode for man-machine-coordinated teaching analysis. Multimode data in classroom teaching can form an organic whole. This study attempted to build a teaching evaluation mechanism using multimodal data and determined the internal correlations among the data to explore the significance and value of education as reflected in the academic performance of learners. Online teaching evaluation reform based on AI should be conducted to realize the development routes and goals of AI-based online teaching evaluation.

4.3 Analysis of variance

Table 5. Difference analysis of students' initiative in post-lecture evaluation based on frequency of use of intelligent evaluation technology

Analysis Term	Frequency of use of Intelligent Evaluation Technology	Mean	SD	F-Value	P-Value
Students' initiative in post-lecture evaluation	1–2 times a week	4.25	0.63	5.073	0.002***
	2–3 times a week	4.10	0.77		
	3–4 times a week	3.98	0.84		
	> 4 times a week	3.76	0.89		
	Total	3.98	0.83		

Note: ***Indicates significance at 1% level.

It can be seen from Table 5 that the frequency of use of intelligent evaluation technology after class had a significant effect on the students' initiative in post-lecture evaluation at the 0.01 level ($F = 5.073$, $p = 0.002$). Moreover, the students' initiative in post-lecture evaluation declined gradually as their frequency of use of intelligent evaluation technology increased. A potential reason for this result may be that teaching evaluation based on AI can enable AIT to not only be the new evaluation subject and replace teachers in the evaluation of students' initiative, engagement, knowledge comprehension, and other learning information in online learning but also provide individualized learning tasks to students. This can give students sufficient basic evaluation information and thus increase the scientificity and rationality of their post-lecture evaluations. With the increasing frequency of use of intelligent evaluation technology for post-lecture evaluations, students may gradually develop high technological dependence instead of completing post-lecture evaluations seriously, which may decrease their enthusiasm to participate in evaluations. Thus, university administrators should pay attention to private data protection for students in their use of intelligent evaluation technology during the learning process. In the post-lecture evaluation of students based on AIT, their facial expressions, language, actions, and other information are recorded throughout the online learning process; thus, learners may encounter learning privacy infringement. Therefore, the evaluation

of teaching data based on AIT should be implemented cautiously. Meanwhile, it can avoid teaching ethical risks and collect students' learning data based on evaluations. The students involved in the data acquisition should be informed, and the data collected by the intelligent evaluation technology should be standardized for reasonable use and safe storage. Privacy should also be protected. Under the premise of information safety, the changes in the comprehensive evaluation of online teaching quality brought about by intelligent evaluation technology should be discussed.

5 CONCLUSIONS

The teaching performance of instructors, including their tone, attitude, and emotions, can be recognized and analyzed by AIT, which is conducive to controlling their emotions in the classroom, creating an active classroom learning atmosphere, and increasing the efficiency of their teaching. A total of 352 undergraduates from Anyang Institute of Technology in Henan Province participated in a questionnaire survey in this study, and the influence of language analysis, behavioral analysis, emotion analysis, and teaching evaluation techniques on the students' initiative in the post-lecture evaluation of online teaching was analyzed. The variations in the students' initiative in post-lecture evaluation based on their frequency of use of intelligent evaluation technology were also measured. Three major conclusions were drawn from the results. (1) The overall Cronbach's α of this study was 0.840, and the KMO value was 0.852. (2) Language analysis, emotion analysis, and teaching evaluation techniques had a positive promotion effect on the students' initiative in the post-lecture evaluation of online teaching. (3) As the frequency of use of intelligent evaluation technology increased, the students' initiative in post-lecture evaluation declined gradually. Attention should be paid to the private data protection of students in their use of intelligent evaluation technology during the learning process. Further research on the creation of new intelligent education evaluation systems, collection of actual, objective, and accurate evaluation data with precise acquisition tools, and the establishment of multidimensional and multilevel online teaching quality evaluation systems is necessary.

6 REFERENCES

[1] P. E. Doolittle, "Vygotsky's zone of proximal development as a theoretical foundation for cooperative learning," *Journal on Excellence in College Teaching*, vol. 8, no. 1, pp. 83–103, 1997.

[2] M. A. Mark and J. E. Greer, "Evaluation methodologies for intelligent tutoring systems," *Journal of Artificial Intelligence in Education*, vol. 4, pp. 129–153, 1993.

[3] J. De-kun and F. H. Memon, "Design of mobile intelligent evaluation algorithm in physical education teaching," *Mobile Networks and Applications*, vol. 27, pp. 527–534, 2022. https://doi.org/10.1007/s11036-021-01818-1

[4] J. Tang and L. Hai, "Construction and exploration of an intelligent evaluation system for educational APP through artificial intelligence technology," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 5, pp. 17–31, 2021. https://doi.org/10.3991/ijet.v16i05.20293

[5] F. A. Dorça, L. V. Lima, M. A. Fernandes, and C. R. Lopes, "Comparing strategies for modeling students learning styles through reinforcement learning in adaptive and intelligent educational systems: An experimental analysis," *Expert Systems with Applications*, vol. 40, no. 6, pp. 2092–2101, 2013. https://doi.org/10.1016/j.eswa.2012.10.014

[6] F. C. I. Chang, "Intelligent assessment of distance learning," *Information Sciences*, vol. 140, no. 1–2, pp. 105–125, 2002. https://doi.org/10.1016/S0020-0255(01)00183-9

[7] J. Zhao, Y. Li, and W. Feng, "Investigating the validity and reliability of a comprehensive essay evaluation model of integrating manual feedback and intelligent assistance," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 18, no. 4, pp. 248–261, 2023. https://doi.org/10.3991/ijet.v18i04.38241

[8] I. Celik, "Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education," *Computers in Human Behavior*, vol. 138, p. 107468, 2023. https://doi.org/10.1016/j.chb.2022.107468

[9] A. Verma, A. Singh, E. Lughofer, X. Cheng, and K. Abualsaud, "Multilayered-quality education ecosystem (MQEE): An intelligent education modal for sustainable quality education," *Journal of Computing in Higher Education*, vol. 33, pp. 551–579, 2021. https://doi.org/10.1007/s12528-021-09291-1

[10] D. Hooshyar, R. B. Ahmad, M. Yousefi, M. Fathi, S.J. Horng, and H. Lim, "Applying an online game-based formative assessment in a flowchart-based intelligent tutoring system for improving problem-solving skills," *Computers & Education*, vol. 94, pp. 18–36, 2016. https://doi.org/10.1016/j.compedu.2015.10.013

[11] Y. He, S. C. Hui, and T. T. Quan, "Automatic summary assessment for intelligent tutoring systems," *Computers & Education*, vol. 53, no. 3, pp. 890–899, 2009. https://doi.org/10.1016/j.compedu.2009.05.008

[12] V. Aleven, I. D. O. Roll, B. M. McLaren, and K. R. Koedinger, "Automated, unobtrusive, action-by-action assessment of self-regulation during learning with an intelligent tutoring system," *Educational Psychologist*, vol. 45, no. 4, pp. 224–233, 2010. https://doi.org/10.1080/00461520.2010.517740

[13] A. Kaklauskas, E. K. Zavadskas, V. Pruskus, V. Vlasenko, M. Seniut, G. Kaklauskas, and V. Gribniak, "Biometric and intelligent self-assessment of student progress system," *Computers & Education*, vol. 55, no. 2, pp. 821–833, 2010. https://doi.org/10.1080/00461520.2010.517740

[14] I. Achumba, D. Azzi, J. Stocker, B. P. Haynes, and I. E. Chika, "Genuine lab experiences for students in resource constrained environments: The RealLab with integrated intelligent assessment," *International Journal of Online Engineering*, vol. 4, no. 3, pp. 18–24, 2008.

[15] M. Ivanova, "eLearning informatics: From automation of educational activities to intelligent solutions building," *Informatics in Education-An International Journal*, vol. 19, no. 2, pp. 257–282, 2020. https://doi.org/10.15388/infedu.2020.13

[16] V. A. Uglev and V. A. Ustinov, "The new competencies development level expertise method within Intelligent Automated Educational Systems," *Trends in Practical Applications of Heterogeneous Multi-Agent Systems*, The PAAMS Collection, pp. 157–164, 2014. https://doi.org/10.1007/978-3-319-07476-4_19

[17] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education–where are the educators?" *International Journal of Educational Technology in Higher Education*, vol. 16, no. 1, pp. 1–27, 2019. https://doi.org/10.1186/s41239-019-0171-0

[18] E. R. Han, S. Yeo, M. J. Kim, Y. H. Lee, K. H. Park, and H. Roh, "Medical education trends for future physicians in the era of advanced technology and artificial intelligence: An integrative review," *BMC Medical Education*, vol. 19, no. 1, pp. 1–15, 2019. https://doi.org/10.1186/s12909-019-1891-5

[19] Y. Liu and L. Ren, "The influence of artificial intelligence technology on teaching under the threshold of 'Internet+': Based on the application example of an English education platform," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–9, 2022. https://doi.org/10.1155/2022/5728569

[20] H. W. Marsh and L. A. Roche, "Making students' evaluations of teaching effectiveness effective: The critical issues of validity, bias, and utility," *American Psychologist*, vol. 52, no. 11, p. 1187, 1997. https://doi.org/10.1037//0003-066X.52.11.1187

[21] K. Struyven, F. Dochy, and S. Janssens, "Students' perceptions about evaluation and assessment in higher education: A review," *Assessment & Evaluation in Higher Education*, vol. 30, no. 4, pp. 325–341, 2005. https://doi.org/10.1080/02602930500099102

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