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# Education Quality Evaluation of Colleges and Universities Based on Advanced Technologies and Multimodal Artificial Intelligence Sensors in Colleges and Universities

Wanzhi Ma, <sup>1</sup> Tiantian Zhuang, <sup>1</sup> Yuanli Xu, <sup>1</sup> and Na Chu<sup>2\*</sup>

<sup>1</sup>School of Educational Science, Ningxia Normal University, Guyuan, Ningxia 756099, China <sup>2</sup>School of Foreign Languages, Ningxia Normal University, Guyuan, Ningxia 756099, China

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As advanced technologies involving multimodal AI sensors have been increasingly adopted to improve teaching quality, student engagement, and learning outcomes, it is crucial to evaluate their effectiveness in education. In this study, we surveyed 103 participants to evaluate the technologies in terms of effectiveness and user perception by analyzing the obtained statistics. The perception and use of multimodal AI sensors were significantly correlated with student engagement while they were less correlated with learning outcomes, as various factors might influence academic achievement represented by learning outcomes. The results of the survey also showed that educational institutions need to prioritize ethical considerations regarding privacy protection and data usage, especially data containing personal information, and persuade stakeholders in education to use innovative devices such as multimodal AI in the classroom. Then, various AI technologies can be more effectively and efficiently used in education.

## 1. Introduction

Multimodal AI sensors are used to capture and process multiple types of data including texts, images, audio, videos, and environmental parameters in the classroom. Multimodal AI sensors have come to be widely used, transforming the learning environment efficiently and effectively. They are also used for the timely assessment of the outcomes of education, especially the degree of student engagement in learning, which is an important indicator of education quality as a whole.<sup>(1)</sup> Traditionally, such an assessment has been conducted through student self-evaluation and peer assessment. While the results are rather subjective, objective assessment is enabled by using multimodal AI sensors and corresponding technologies. Multimodal AI sensors are used to capture multimodal interactions between teachers and students in the classroom. For instance, voices, facial expressions, and physiological parameters can be monitored and analyzed to enhance education and boost student interest in learning activities. These innovative technologies are adopted in smart classrooms, which are more extensively installed in higher educational

\*Corresponding author: e-mail: <u>82007063@nxnu.edu.cn</u> https://doi.org/10.18494/SAM5584 institutions than in primary and secondary ones (Fig. 1).<sup>(2)</sup> These technologies help teachers realize the best way to teach students and improve their learning outcomes as teachers can obtain feedback in real time and adjust their teaching methods and strategies on the basis of the monitored real-time data.

Educational systems with multimodal AI sensors are constructed with data collection, processing, and learning. (3) The system continuously collects various forms of data, including texts, voices, and videos, and integrates the data into a well-defined dataset for further analysis. The data are processed to provide information or recommendations for teachers and students and, ultimately, to evaluate educational outcomes. Machine learning algorithms are often used for the efficient use of the gathered data. Deep learning algorithms are used to elucidate correlations and patterns in large datasets to accurately predict and enhance student performance and activity. For example, the level of participation in learning of a student or a group is monitored using videos and audio and is compared with those of other students or groups. (4) To encourage active participation and increase student interest, teachers can change their teaching methods or learning materials in a timely manner. Using the collected data, augmented reality (AR) or virtual reality (VR) can be also used by students and teachers to easily interact with the educational content. The sensory data acquired from AR/VR devices and multimodal AI sensors can be used to formulate technological and educational strategies to enrich student learning and support students in learning, and valuable information can be provided to enhance the quality of teaching.

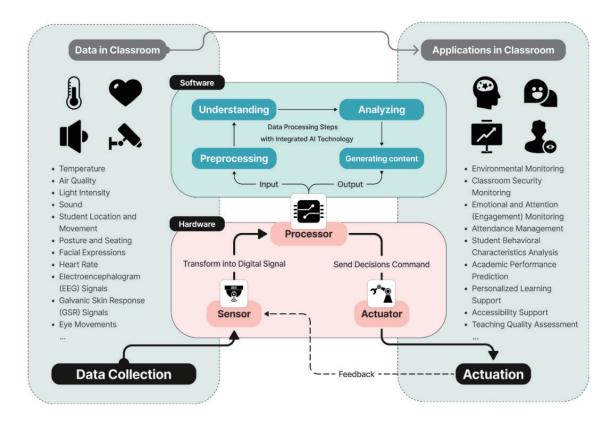


Fig. 1. (Color online) Smart classroom with multimodal sensors. (2)

Consequently, effective advanced technologies with multimodal AI sensors are crucial for improving student learning outcomes and satisfying their needs. However, it is still essential to understand the key indicators of the effectiveness of using advanced technologies, examine their impact on education, and evaluate the perception and effectiveness of using them in the classroom.

Therefore, this study was carried out to evaluate the effectiveness of using advanced technologies in higher education. On the basis of the results, recommendations for implementing technologies in various teaching models were developed with the balance between the perceptions of teachers and students.

## 2. Advanced Technology and Multimodal AI Sensors In Education

Advanced technology in this study refers to the integration of AI with sensor technology to enhance data acquisition and processing for personalized learning and automated assessment and feedback in smart classrooms and campuses. Multimodal sensors combined with advanced technology enable the collection of visual, auditory, tactile, and thermal data simultaneously to provide accurate and reliable intervention. AI integrated with multimodal sensors enhances the system's ability of real-time analysis and adaptability, which are useful for autonomous vehicles, healthcare monitoring, and human—computer interaction.<sup>(5)</sup>

In education, AI and sensor technologies are used to monitor environmental conditions and student behaviors by collecting and processing environmental parameters such as temperature, lighting, and noise levels. A student's engagement level is assessed by monitoring facial expressions, eye movements, and physiological responses. AI algorithms analyze such data to provide information on student attention levels and emotional states, allowing teachers to adjust teaching strategies accordingly. AI systems with multimodal sensors also are used to tailor educational content to individual student needs. For instance, when confusion or disengagement of a student is detected, the system adjusts the difficulty or presentation style of the material to better suit the learner's preferences and comprehension level. AI and sensor technologies also contribute to efficient campus management by monitoring and controlling lighting, heating, and security systems, as well as student attendance using biometric sensors.<sup>(6,7)</sup>

While various benefits are enabled, the implementations of AI and sensor technologies present challenges including data privacy and security. Therefore, educational institutions must ensure compliance with regulations and data protection measures.<sup>(6)</sup> Advanced technology in higher education creates engaging, personalized, and efficient learning environments, and multimodal AI sensors are being increasingly integrated into higher education to enhance learning experiences, monitor student engagement, and personalize educational content based on multimodal data—visual, auditory, and physiological data.<sup>(7,8)</sup>

## 3. Methods

A questionnaire survey was conducted with 103 participants to assess the efficiency of multimodal AI and related technologies in higher educational institutions. The results were used to determine the patterns and relationships between factors affecting the user perception and

effectiveness of advanced technologies with multimodal AI sensors. The participants in the survey were students and professors of colleges and universities worldwide who had used multimodal AI sensors and related technologies in educational activities. The geographical distribution and specialization of the colleges and universities were considered to ensure their representativeness and to account for endogenous factors in assessing perception and effectiveness. The participants' readiness to adopt innovative technologies and their desire to use related devices were also surveyed since we used voice and video recording devices, which are widely used in advanced technologies for education, in the interviews. A structured questionnaire was created on a five-point Likert scale. The results were analyzed using several statistical tools to obtain descriptive statistics of the participants, determine the level of engagement and effectiveness in using the technologies, and conduct correlation, variance, and regression analyses.<sup>(9)</sup>

Informed consent was obtained from the participants, and permission for the research was granted by the Institutional Review Boards (IRBs) of the institutions with which the participants were affiliated. The participants were informed of their rights and privacy protection for their audio-visual records.

#### 4. Results

A total of 103 participants offered valid responses. The mean score for the use of multimodal AI sensors was 3.43 [standard deviation (SD) = 0.67], indicating a moderate level of user acceptance and their evaluation of the effectiveness of technologies. Student engagement showed a mean score of 3.40 (SD = 0.59), suggesting that the participants were moderately engaged in learning using the technology. Teaching quality scored lower than previous items with a mean score of 3.35 (SD = 0.50), reflecting a general perception of the effectiveness of the technology. Learning outcomes scored the highest with a mean score of 3.74 (SD = 0.51), indicating that the participants positively perceived the use of advanced technologies and multimodal AI sensors to enhance learning outcomes (Table 1).

Table 2 presents the correlation coefficients among the variables. A significant positive correlation was observed between the use of advanced technologies and multimodal AI sensors and student engagement (r = 0.747, p < 0.001), suggesting an association of such technologies with improved student engagement. There was a moderate positive correlation between teaching quality and learning outcomes (r = 0.268, p = 0.006), indicating that improvements in teaching

Descriptive statistics.

Variable	Number of valid responses	Minimum score	Maximum score	Mean score	SD
Use of advanced technologies and multimodal AI sensors	103	1.40	4.80	3.4272	0.66748
Student engagement	103	1.80	4.80	3.4000	0.58812
Teaching quality	103	2.40	4.80	3.3456	0.49956
Learning outcomes	103	2.60	5.00	3.7379	0.51031

Table 2 Correlation analysis result.

105410	Use of advanced technologies	Student	Teaching	Learning	
Statistics	and multimodal AI sensors	engagement	quality	outcomes	
Pearson correlation	1	1 0.747**		0.027	
coefficient	1	0.747	0.200	0.027	
Two-tailed		0.000	0.043	0.788	
significance		0.000	0.043	0.788	
Number of	103	102	102	103	
observances	103	103	103	103	
Pearson correlation	0.747**	1	0.013	0.000	
	0.000		0.894	1.000	
1 (441110 41 01	103	103	103	103	
observances	103		103		
Pearson correlation	0.200*	0.013	1	0.268**	
		0.013		0.200	
	0.043	0.894		0.006	
significance	0.015	0.071			
Number of	103	103	103	103	
observances	103	103	103		
Pearson correlation	0.027	0.000	0.268**	1	
coefficient	0.027	0.000	0.200		
Two-tailed	0.788	1.000	0.006		
significance	0.788	1.000	0.000		
Number of	103	103	103	103	
observances	103	103	103	103	
	Pearson correlation coefficient Two-tailed significance Number of observances Pearson correlation coefficient Two-tailed significance Number of	Pearson correlation coefficient Two-tailed significance Number of observances Pearson correlation coefficient Two-tailed significance Pearson correlation coefficient Two-tailed significance Number of 0.027	Pearson correlation coefficient Two-tailed significance Pearson correlation coefficient Two-tailed significance Number of observances Pearson correlation coefficient Two-tailed significance Number of observances Pearson correlation coefficient Two-tailed significance Number of observances Pearson correlation coefficient Two-tailed significance Pearson correlation coefficient Two-tailed significance Number of observances Pearson correlation coefficient Two-tailed significance Number of observances Pearson correlation coefficient Two-tailed significance Pearson correlation coefficient Two-tailed significance Number of 0.027 Pearson correlation coefficient Two-tailed significance Number of 0.788 1.000	Statistics         and multimodal AI sensors         engagement         quality           Pearson correlation coefficient         1         0.747**         0.200*           Two-tailed significance         0.000         0.043           Number of observances         103         103         103           Pearson correlation coefficient         0.747**         1         0.013           Two-tailed significance         0.000         0.894           Number of observances         103         103         103           Pearson correlation coefficient         0.200*         0.013         1           Two-tailed significance         0.043         0.894         103           Number of observances         103         103         103           Pearson correlation coefficient         0.027         0.000         0.268**           Two-tailed significance         0.788         1.000         0.006           Number of         0.788         1.000         0.006	

<sup>\*</sup>Correlation is significant at p < 0.05 (2-tailed).

quality are linked to better learning outcomes for students. However, the correlation between the use of advanced technologies and multimodal AI sensors and learning outcomes was not significant (r = 0.027, p = 0.788), suggesting that even though the technologies enhanced student engagement and teaching quality, their direct impacts on learning outcomes were limited, which requires further investigation.

Table 3 presents the regression model created to predict learning outcomes for independent variables of teaching quality, student engagement, and the use of advanced technologies and multimodal AI sensors. The *R*-squared value was 0.073, suggesting that approximately 7.3% of the variance in learning outcomes was explained by these variables. The adjusted *R*-squared value of 0.045 indicated a modest explanatory power of the variables. While relationships between the variables and learning outcomes were determined, the variables did not significantly influence learning outcomes.

The results of the analysis of variance (ANOVA) are shown in Table 4. The F-statistic was 2.611, and the p-value was 0.056. Although the independent variables accounted for variation in learning outcomes, such association was significant at p = 0.05. A moderate association between teaching quality, student engagement, and the use of the technologies with the learning outcomes was verified but further research is mandated to elaborate the associations of the variables.

<sup>\*\*</sup>Correlation is significant at p < 0.01 (2-tailed).

Table 3 Statistics of regression model.

$\overline{R}$	R-square	Adjusted R-square	Standard error of estimate
0.271 <sup>a</sup>	0.073	0.045	0.49863

Table 4 ANOVA result.

Model parameter	Sum of squares	Degree of freedom	Mean square	F	Significance
Regression	1.948	3	0.649	2.611	$0.056^{b}$
Residual	24.615	99	0.249		
Total	26.562	102			

## 5. Discussion

## 5.1 Impact of multimodal AI sensors and technologies on teaching quality

The use of multimodal AI sensors and related technologies in teaching significantly enhanced the teaching quality. As diverse data ranging from audio and video to physiological data are gathered, teaching quality and student learning outcomes can be enhanced using the data appropriately. One of the most important effects is timely feedback to teachers and students. For example, the recognition of student attention levels identified using facial expressions and voice enables teachers to adapt teaching methods. Such timely feedback and responses promote effective addressing of students' needs to improve teaching and learning. Since educational institutions are implementing these technologies, a large amount of data and information on classes are accumulated and used to assess teaching effectiveness. This, in turn, enables educational institutions to design and offer development programs to enhance teaching capabilities and address the identified gaps between teaching quality and student needs. For instance, referring to the gathered data, teachers can design a curriculum that increases student attentiveness and teaching quality.

Multimodal AI sensors and technologies enhance cooperation among teachers in assessing teaching and learning practices and activities. (1) Teachers can share what they have learned from the data to enhance their teaching methods and develop professional ways of providing knowledge. Such an approach furthers personalized teaching and cooperative teaching in an institution, which enhances the quality of education. The technologies also benefit students as learning activities can be personalized to address each student's needs. For example, when a student can be found to have difficulty understanding certain concepts or to be disengaged in a class, alternative instructional support can be given to the student individually. In this way, learning outcomes can be fostered, and student autonomy in learning can be increased. Moreover, by using the technologies in assessing teaching quality and learning outcomes, new learning paradigms in education can be established for learner-centered and learner-adaptive educational methods. (11) With the growing importance of data-driven knowledge, the vast amount of data collected through these technologies provides various ways to meet students' needs and desires. This approach aligns with modern education philosophies, thereby enhancing the usefulness of educational practices (Fig. 2).

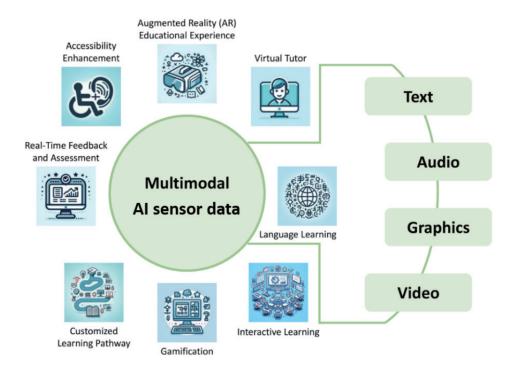


Fig. 2. (Color online) Use of multimodal AI sensor data in education.

#### 5.2 Student engagement and learning outcomes

The effects of student engagement and learning environment on student learning have been researched extensively, and a significant positive relationship between them has been indicated. Emotional engagement is known to positively correlates with learning outcomes. Students with an emotional attachment to teachers and the learning environment performed better in learning. Such cognitive interaction significantly contributes to learning effectiveness, including retention and understanding. (12) Such a finding underscores the importance of affective and cognitive learning in enhancing learning outcomes. Behavioral engagement also affects learning outcomes in the learning-teaching process. (12) Behavioral engagement is defined as the degree of student involvement in learning, and has inconclusive effects on learning outcomes. Behavioral engagement showed a negative relationship with learning outcomes, which implies that different types of engagement produce different results when teachers encourage students to engage in behavioral activities. Therefore, teachers must design various engagement activities to support students in achieving the intended learning goals and exclude activities that negatively impact student performance. Students' active engagement in learning affects their outcomes as well as their satisfaction levels and retention rates. The level of student engagement is positively correlated with their satisfaction in learning. Active learning and purposeful teaching significantly increase the students' satisfaction in their learning environment. This relationship shows that satisfied students showed a higher rate of staying in school and completing their courses. Hence, the quality of the learning environment and the degree of student engagement affect learning outcomes in general. (13)

The results of this study indicated that student engagement is critical in designing classrooms meant to foster the relationships between students and teachers and student's academic skills. Group tasks, feedback in real time, and the use of multimodal AI sensors and related technologies in the learning environment considerably enhance student engagement during learning. Therefore, multimodal AI sensors and related technologies enable the collection of important data to monitor students' emotional reactions and engagement levels, allowing for appropriate adjustments in teaching strategies. Such a data-driven strategy enables the improvement of the teaching quality to meet the student's needs.

#### 5.3 Technology in teaching quality assessment

Technology is critical in assessing teaching quality and outcomes. Applying advanced technologies related to AI, big data analytics, and sensor technology enhances the objectivity, thoroughness, and assessment of teaching quality. Traditional evaluation methods have limitations in providing a holistic view to accommodate the highly dynamic modern teaching and learning processes. Therefore, big data analytics are applied to establish a complex assessment index system for teaching quality and learning outcomes using various methods such as the analytic hierarchy process (AHP) and functional capacity evaluation (FCE). To improve the objectivity and effectiveness of teaching quality evaluation, an automated teaching evaluation (AET) system is used (Fig. 3). The system employs voice and text analyses to assess teacher–student interactions in the UTeach observation protocol (UTOP). Data collected through sensors helps evaluators remove bias since the data is objective. Through efficient data collection and analysis, teachers receive feedback that can be used for improving their teaching quality; this is required in modern learning.

Advanced technologies are also used in the professional development of teachers. The degree of user acceptance of the technologies in education depends on the teachers' readiness and mastery of skills. When teachers integrate new technologies into their teaching, training in technology use and career development is mandatory. In the training, technical skills in using AI tools and collecting data must be taught. Educational institutions need to promote lifelong learning so that teachers can effectively utilize the technologies to improve their teaching quality. The resources and environments of institutions influence the acceptance and incorporation of technologies in teaching. Well-coordinated leadership is necessary for the acceptance of advanced technologies for teaching quality enhancement. For technological interventions in teaching, institutions must establish the purposes of using the technology.

While advanced technologies have the potential to solve traditional problems in evaluating teaching quality, their acceptance and application are hindered by concerns over data privacy and security. (21) Additionally, many teachers remain skeptical of computerized processes and question their credibility. To address these issues, stakeholders must embrace the positive aspects of technology-based assessments while considering the ethical implications of integrating advanced technologies.

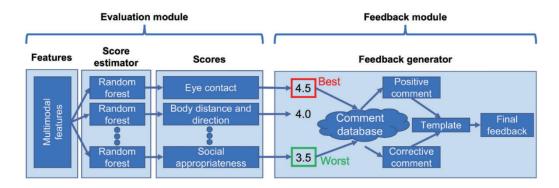


Fig. 3. (Color online) AET for teaching quality.

## 5.4 Implication of survey results

In this study, the participants recognized the positive impact of advanced technologies in education, particularly in providing timely feedback and adjusting teaching strategies with a mean score of 3.43. This aligns with the results of a previous study that depicted technology as a medium for adaptive learning. For example, multimodal AI sensors were used effectively to change teaching methods for different students. (16) However, no direct relationship was observed between learning outcomes and the use of advanced technologies and multimodal AI sensors, suggesting that the mere adoption of these technologies may be insufficient. Teachers need to be extensively trained to effectively utilize advanced technologies. (22)

A strong positive relationship was observed between the use of advanced technologies and multimodal AI sensors and students' engagement in this study. This indicates that advanced interactive technologies are vital to increasing student engagement. The participants presented moderate engagement levels with a mean score of 3.40 when using such technologies. Student engagement during the learning activity is generally correlated with their academic performance. As multimodal AI sensors are used to feed back and update students' engagement levels immediately, teachers must design a teaching process based on the collected data to increase student engagement and improve their learning outcomes.<sup>(23)</sup>

The participants also had a moderate perception of teaching quality assessment using advanced technologies (a mean score of 3.35). The positive relationship between teaching quality and learning outcomes (r = 0.268) indicated that enhanced teaching quality improves students' learning outcomes. However, a lower mean score of teaching quality indicated that improving the effectiveness of using advanced technologies is required for an appropriate pedagogy. Teachers need to be trained to improve their teaching quality by efficiently using advanced technology. Additionally, data from multiple AI sensors can help identify areas where teaching quality needs improvement, thereby enhancing students' learning outcomes more effectively. (24)

The participants positively perceived the use of advanced technologies and multimodal AI sensors to enhance learning outcomes. However, the correlation between learning outcomes and the use of advanced technologies and multimodal AI sensors was low in this study (r = 0.027). There are diverse factors affecting learning outcomes, including motivation, background knowledge, and group interactions. Technology can increase engagement through immediate

feedback and is considered as a major factor in an educational model.<sup>(14)</sup> Therefore, in using advanced technologies, teachers must understand the relationships among various factors in the curriculum, pedagogy, and culture. Subsequent studies are necessary to determine the effects of the other factors in using advanced technologies in education.

#### 5.5 Current challenges and barriers

Several challenges exist in adopting advanced technologies and multimodal AI sensors in education: the compatibility of diverse types of data, efficient algorithms, and hardware to analyze the data; integration with other systems;<sup>(25)</sup> a lack of technical support and infrastructure; and insufficient preparation and training. Because of such challenges, teachers might lack the confidence and ability to use advanced technology, which would lead to the underutilization or incorrect application of advanced technologies as well as reducing student engagement. Therefore, professional training programs must be provided, and a culture of lifelong learning must be promoted along with the continuous development and upgrading of data analytics and hardware. Ethical issues and privacy protection must be addressed for students and teachers. Education institutions must develop corresponding policies to avoid the misuse or exploitation of the collected data. The reluctance of teachers to use advanced technologies needs to be addressed by explaining the benefits and positive outcomes, which may not be fully appreciated.

#### 6. Conclusions

This study was aimed at examining how advanced technologies and multimodal AI sensors can be used in education to enhance student engagement, learning outcomes, and teaching quality. The findings revealed a moderate awareness of the effectiveness of advanced technologies with a highly positive correlation between advanced technologies and student engagement. Teaching quality positively influenced learning outcomes but the correlation was not strong because of the effects of other factors. The result also indicated that advanced technologies impact diverse aspects of education and must be embedded into teaching to enhance the learning environment. There are challenges that must be addressed in adopting advanced technologies including the compatibility of collected data, algorithms, and hardware in data analysis, and integration with other systems. It is crucial to develop specialized training programs for teachers to successfully integrate advanced technologies into teaching with the meaningful interpretation and use of the data. Privacy protection and ethical issues need to be solved with appropriate policies and support. Increasing user acceptance is critical to reduce teachers' reluctance to use advanced technologies. By advertising the benefits and positive outcomes from previous uses, educational institutions need to encourage teachers to use technology actively to enhance teaching quality and learning outcomes. Teachers must be aware of innovative evaluation methods and cooperate in implementing advanced technologies and sharing the results. It is also necessary for authorities to develop and provide useful and easy-touse data analytics and hardware.

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#### **About the Authors**



Wanzhi Ma earned his M.S. degree in software engineering from the Beijing University of Posts and Telecommunications, China in 2009, and his Ph.D. degree in Education from Woosuk University, Korea, in 2021. From 2015 to 2019, he served as a lecturer at Shizuishan Vocational College of Industry and Trade in Ningxia, China. Since 2021, he has held the position of associate professor at Ningxia Normal University. His research interests encompass educational informatization, educational evaluation, teacher education, and artificial intelligence. (mawanzhi79@nxnu.edu.cn)



**Tiantian Zhuang** is a postgraduate student at Ningxia Normal University. Her research interests span educational informatization, educational evaluation, teacher education, and artificial intelligence. (19992023@163.com)



**Yuanli Xu** is a postgraduate student majoring in modern educational technology at Ningxia Normal University. Her interests lie in the application of new technologies in education, with a particular focus on the integration of artificial intelligence and education, as well as the development of digital educational resources. (15389516063@163.com)



Na Chu received her B.A. degree from Ningxia University, China in 2004 and her M.A. degree from Minzu University, China in 2012. She completed her Ph.D. degree in education at Woosuk University in Korea in 2025. Since 2004, she has been serving as a full-time associate professor at Ningxia Normal University in China. Her research interests include the informatization of English education, educational evaluation, and English teacher education. (82007063@nxnu.edu.cn)