

The impact of smart classrooms on the core literacy of college English learners and the relationship between core literacy and learning outcomes: Evidence from China

Xuefei Fan

Binhai School of Foreign Affairs of Tianjin Foreign Studies University, 60 Xuefu Rd., Dagang Str., Binhai New District, Tianjin, China

Abstract. College English major students are taken as the subjects of evaluation, applying learning analysis technology based on learning behaviour data sets and traditional evaluation and comprehensively using the analytic hierarchy process for index weighting and evaluation practice to construct a comprehensive evaluation index system for the core literacy of college English major students. Secondly, this study deeply examines the impact of smart classrooms on the core literacy of college English learners. By applying different regression models, including Ordinary Least Squares (OLS), fixed effects model, and dynamic lagged fixed effects regression, the research results consistently show that the smart English teaching model significantly improves the core literacy of college students. The regression coefficients of all models are between 0.2150 and 0.2818, and they are robust and reliable at a significance level of 1%. In addition, the study explores the role of academic resources as a mediating variable and finds that smart English classrooms improve students' English core literacy by increasing academic resources. Academic resources are confirmed to mediate the positive impact of smart English classrooms on students' English core literacy, producing a mediating effect of 30.78%. Using deep neural networks, this study further explores the complex relationship between core literacy and learning outcomes. Therefore, as an innovative teaching model, the application potential of smart English classrooms in improving students' English core literacy is significant.

Keywords: learning analytics, core literacy, comprehensive evaluation, index system, smart classroom

1. Introduction

With the rapid development of information technology, we are witnessing a revolutionary change in educational models. In this transformation, smart teaching, utilizing advanced tools such as big data analysis, cloud computing, and artificial intelligence, has not only reshaped traditional classrooms but also greatly promoted interaction between teachers and students [4, 15]. The integration of these technologies is widely recognized for its significant potential to enhance students' deep learning and core literacy [12, 24]. In the higher education stage, university education plays a dual role: it is not only the cradle for cultivating high-level talents but also a key stage in the formation of students' core literacy [32, 36].

Smart English classrooms, by integrating information technology, provide rich teaching

✉ fx988w@163.com (X. Fan)

🆔 0009-0000-2770-9499 (X. Fan)



© Copyright for this paper by its authors, published by Academy of Cognitive and Natural Sciences (ACNS). This is an Open Access article distributed under the terms of the Creative Commons License Attribution 4.0 International (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

resources and personalized learning support, creating an efficient, dynamic, and interactive learning environment, which is considered an important means to enhance core literacy [17]. However, despite the high regard for smart English classrooms, there is a significant gap in the existing literature in empirically verifying their teaching models and benefits [31]. Current research mostly focuses on theoretical argumentation or case analysis, lacking extensive empirical data support [10]. In addition, there is also a deficiency in existing research in using statistical analysis methods to explore the benefits and influencing factors of smart English classrooms [1].

Core literacy, which encompasses multiple dimensions such as critical thinking, creativity, communication skills, and collaborative abilities, has a profound impact on student's academic achievements and personal development [11, 21]. In the smart classroom environment, students have access to a broader range of learning resources and diverse learning methods, which provide strong support for enhancing core literacy. However, quantifying the specific relationship between core literacy and learning outcomes and how to promote this impact through smart teaching strategies effectively remains a problem that current research needs to address [6, 7].

To fill these gaps, this study aims to evaluate the effectiveness of smart teaching strategies in promoting the enhancement of core literacy through empirical analysis and to explore the relationship between core literacy and student learning outcomes in the smart classroom environment. This will not only help deepen the understanding of the effects of smart teaching but also provide valuable guidance for educational practice, helping to design more effective teaching strategies to promote the comprehensive development of students.

Specifically, the research will focus on the following areas:

- (1) Utilizing extensively collected data to conduct empirical analysis of the impact of smart English classroom teaching models on the core literacy of college students in order to provide a scientific basis for quantitative assessment.
- (2) Applying advanced statistical methods to examine the specific impact of smart English classrooms on the enhancement of different areas of core literacy and to explore influencing factors and internal connections.
- (3) Systematically exploring how the richness of academic resources in smart English classrooms acts as an intermediary variable, playing a role between teaching models and the enhancement of students' core literacy.
- (4) Implementing robustness tests to quantitatively assess the effectiveness and general applicability of smart English classroom teaching models in different teaching environments and student populations.
- (5) Integrating teacher evaluation and peer assessment methods, combining multimodal data for learning outcome evaluation, and using the evaluated data as labelled data to construct a multimodal supervised learning dataset.
- (6) Based on an optimized deep neural network, combining multimodal supervised training datasets, building and training a teaching evaluation neural network model, and assessing the model's generalization ability in conjunction with actual teaching situations.

2. Literature review and research hypotheses

With the rapid development of information technology, traditional educational models are undergoing an unprecedented transformation. Particularly in the field of higher education, the application of information technology has not only driven innovation in educational methods but also provided new avenues for enhancing students' core literacy [3, 8]. English, as the lingua franca of the globalized era, has a decisive impact on students' international competitiveness [26]. Against this backdrop, smart English classrooms have emerged, integrating information technologies such as big data, cloud computing, and artificial intelligence to provide students with personalized learning support and a more efficient and interactive learning environment [14, 16]. The promotion and practice of this teaching model are considered to effectively enhance college students' critical thinking, communication skills, and innovative consciousness [34].

Previous studies have mainly focused on theoretical derivation and case analysis, exploring the conceptual framework, teaching design, and expected effects of smart English classrooms [23]. Some scholars have recognized the importance of personalized learning resources and teaching strategies and have conducted related experiments and explorations [22]. Nevertheless, these studies often rely on qualitative research methods, such as interviews and observations, and there is little knowledge about how to quantify the teaching effects of smart English classrooms [5]. The core concepts and variables used to explain the effects of smart English classrooms include the richness of teaching resources, students' participation, and the integration level of information technology.

Despite the valuable theoretical foundations and preliminary practical experience provided by previous research, there are deficiencies in the breadth and depth of empirical data in existing literature [27]. Firstly, few studies have conducted scientific quantitative assessments, and evidence supports the effectiveness of smart English classrooms. Secondly, current research often does not use advanced statistical methods to deeply explore the specific impact of smart English classrooms on different areas of core literacy [30]. In addition, the mechanism by which academic resources in smart English classrooms contribute to the enhancement of students' literacy is not clear, and there is insufficient stability testing of causal relationships and pathways of action, which limits the universality and adaptability of research conclusions [2, 19].

In the field of smart education, the smart English classroom model, based on technology-enhanced learning theory, has become a focus of academic attention [28]. This theoretical system emphasizes how technology can optimize the teaching process and learning experience, as well as how to enhance students' initiative and participation through technological means [20]. However, the theoretical status of the smart English classroom model in the cultivation of core literacy has not been fully established, and more empirical research is needed to verify its effectiveness and clarify its role in educational reform [29].

Based on the above background, this study proposes two key hypotheses to assess the potential impact of smart English classrooms on enhancing college students' core literacy.

The verification of Hypothesis H1 is crucial because it will provide an empirical basis for assessing whether the smart English classroom teaching model can achieve the expected educational goals. This provides strong support for educational decision-makers when formulating relevant policies and also provides a reference for teaching methods for front-line teachers. Only through rigorous research to confirm that smart English classrooms can indeed enhance

students' core literacy can this teaching model be more widely applied and promoted. The analysis of Hypothesis H2 helps to deeply understand how smart English classrooms promote the enhancement of students' core literacy through the effective use of academic resources. This not only helps to improve the existing teaching resource allocation and utilization strategies but also guides the development and integration of future educational resources, improving the quality of education and ultimately achieving sustainable development of education. Through the study of these two hypotheses, a deeper and more comprehensive understanding of the teaching model of smart English classrooms and their internal mechanisms affecting students' core literacy can be achieved.

While discussing the impact of smart English classrooms on students' core literacy, it is essential to recognize the intrinsic connection between core literacy and learning outcomes. Core literacies, such as critical thinking, problem-solving abilities, creativity, and communication skills, have been widely recognized as key factors in improving students' academic achievements and personal development [11, 21]. Recent studies have shown that these literacies can positively affect students' learning motivation, participation, and ultimately, their academic performance [6, 7].

In addition, with the development of educational technology, more and more research has begun to focus on how information technology can promote the cultivation of core literacies and ultimately improve learning outcomes. For example, a study explored the role of information technology in language learning and found that through the practice of smart classrooms, students' oral and listening skills were significantly improved [33]. Another study analyzed the impact of personalized learning platforms on students' autonomous learning abilities and found that these platforms could effectively enhance students' critical thinking and problem-solving skills by providing customized learning resources and activities [35].

In the field of smart education, scholars have also begun to focus on the relationship between core literacy and learning outcomes in the smart classroom environment. For example, a study pointed out that the gamification learning elements integrated into smart classrooms can stimulate students' participation and motivation, thereby improving learning outcomes [9]. Another study analyzed the use of collaborative learning tools in smart classrooms and found that these tools can promote communication and cooperation among students, helping to enhance team collaboration abilities and collective learning outcomes [13].

This study will further explore, based on existing literature, how smart English classrooms enhance learning outcomes by improving core literacies. This will help to more comprehensively understand the teaching effects of smart English classrooms and provide guidance for future educational practice and research.

3. The impact of smart classrooms on the core literacy of college English learners

3.1. Core explanatory variables

3.1.1. Construction of the index system

The core explanatory variable of this paper is the core literacy of college English learners. Constructing this index system first requires determining the framework of the indicators. This study takes the "Overall Plan for the Reform of Educational Evaluation in the New Era" as the policy guidance, and in conjunction with the spirit of important documents such as the "Undergraduate English Major Teaching Guidelines" and "China English Proficiency Scale" issued by the Ministry of Education in 2020, uses a theoretical deduction method to focus on combining relevant theoretical research results and preliminarily establish an evaluation index framework for the core literacy of English learners. Subsequently, based on the Delphi method, two educational technology experts and ten college English teaching experts were invited to conduct semi-structured interviews to jointly discuss opinions and judgments on the indicators related to the core literacy of English learners. The advantage of the Delphi method is that it can reduce the influence of individuals with strong leadership or persuasive power on others' opinions in face-to-face meetings while allowing experts enough time to think carefully [25]. Before the forecast, the author explained the relevant national policy documents, the purpose of the index system construction, and the research objectives one by one. Experts provided judgments and opinions through anonymous feedback and, after repeated communication and confirmation, summarized the expert opinions and fed the results back to all experts. Experts can revise their opinions after seeing the judgments and opinions of other experts. After three rounds of surveys and feedback, the expert opinions converged, the differences gradually narrowed, and a consensus was reached, determining four first-level indicators, sixteen second-level targets, and seventy-two third-level targets, and describing specific observation points, as shown in the figure 1.

3.1.2. Determination of index weights

Based on the established index system, this paper employs the Analytic Hierarchy Process (AHP) software (Mesh) to develop a hierarchical AHP questionnaire for the core literacy evaluation index system, incorporating a 1-9 scale method and forming a judgment matrix. Once the judgment matrix is formed, the relative importance weight of one element of a certain layer to an element of the upper layer can be calculated by determining the maximum eigenvalue of the judgment matrix and its corresponding eigenvector. After calculating the single sorting weights of a certain layer relative to various factors of the upper layer, the overall sorting weights can be calculated by weighting and synthesizing them with the weights of the factors themselves from the upper layer. In multi-objective decision-making, complex systems with numerous variables, complex structures, and significant uncertain factors are encountered. It is necessary to make a correct estimation of the relative importance of the targets described in these complex systems. The importance of each factor varies, and to reflect the importance of the factors, it is necessary to estimate the relative importance (i.e., weights) of the factors. The collection composed of

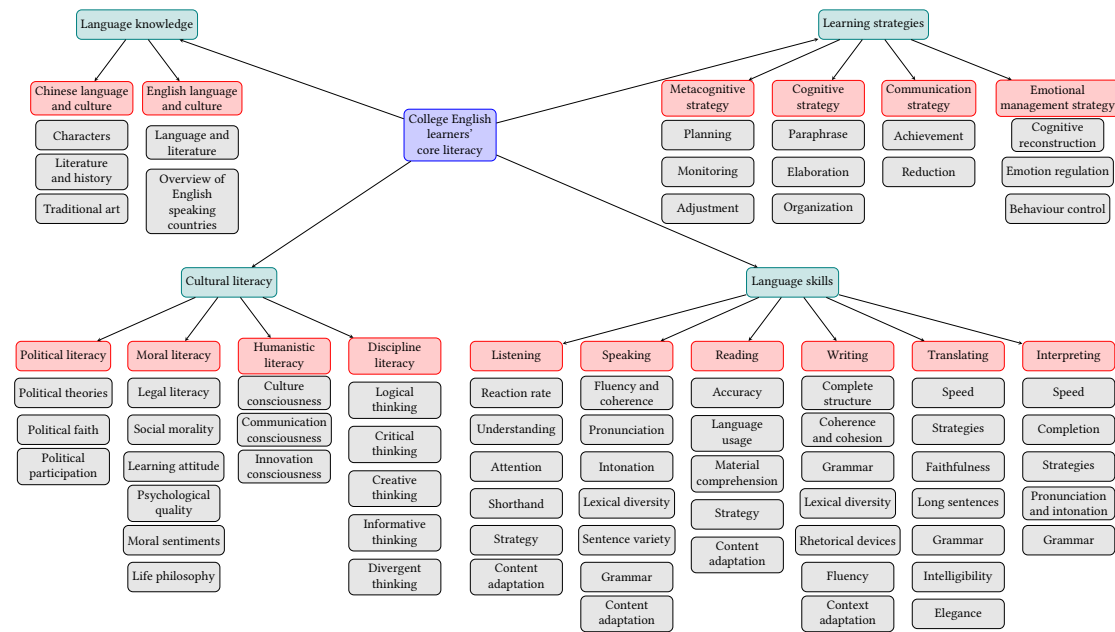


Figure 1: Construction of core literacy indicators for college English learners.

the weights of each factor is the weight set. Weights are the objective reflection of the physical properties of the index itself and are the result of a combination of subjective and objective measurements. The Analytic Hierarchy Process (AHP) is a good method for determining weights. It is a multi-objective, multi-criteria decision-making method that organizes various factors in a complex problem into an ordered hierarchy, combining quantitative analysis with qualitative analysis. The AHP first places the decision problem within a larger system, where multiple factors interact with each other. These problems are hierarchically structured to form a multi-layered analytical structural model. Then, by combining mathematical methods with qualitative analysis through layer-by-layer sorting, the weights calculated for each scheme are used to assist in decision-making.

The steps to determine weights using the Analytic Hierarchy Process (AHP) are as follows:

1. Construct the judgment matrix. A denotes the target, u_i, u_j ($i, j = 1, 2, \dots, n$) denote the factors. u_{ij} denotes the relative importance of u_i to u_j . And by u_{ij} form $A - U$ judgment matrix P .

$$P = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{n1} & u_{n2} & \dots & u_{nn} \end{bmatrix}$$

2. Calculate the importance ranking. Based on the judgment matrix, find the eigenvector w corresponding to its largest eigenroot $\lambda_{\max}$. The equation is as follows:

$$P_w = \lambda_{\max} \cdot w$$

The normalized feature vector w is the importance ranking of each evaluation factor, i.e., the weight assignment.

3. Consistency test. Whether the above weights are reasonable or not, it is also necessary to test the consistency of the judgment matrix. The test uses the formula

$$CR = \frac{CI}{RI}$$

where CR is the random consistency ratio of the judgment matrix, and CI is the consistency index of the judgment matrix. The following equation gives it:

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

RI is the average stochastic consistency index of the judgment matrix, and the RI values of the judgment matrices of order 1 to 9 are shown in table 1.

Table 1

RI values of the matrix.

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46

P is considered to have satisfactory consistency when the CR of the judgment matrix $P < 0.1$ or when $\lambda_{\max} = n$, $CI = 0$. Otherwise, the elements of P need to be adjusted to have satisfactory consistency.

Due to the strong subjectivity in the expert scoring of the Analytic Hierarchy Process (AHP), the scoring matrix often exhibits inconsistencies or omissions. This study employs Particle Swarm Optimization (PSO) to correct the expert scoring matrix. The core of PSO is to utilize the sharing of information among individuals within a group, thereby enabling the entire group's movement to evolve from disorder to order in the problem-solving space and thus obtaining the optimal solution to the problem. PSO is initialized with a group of random particles (random solutions). Then, through iteration, the optimal solution is found. In each iteration, particles update themselves by tracking two "extreme values" ($pbest$, $gbest$). After finding these two optimal values, particles update their velocity and position using the following formula:

$$V_{i+1} = V_i + c_1 \times rand(0 \sim 1) \times (pbest_i - x_i) + c_2 \times rand(0 \sim 1) \times (gbest_i - x_i)$$

$$x_{i+1} = x_i + V_i$$

where $i = 1, 2, \dots, M$, M is the total number of particles in the population; V_i is the velocity of the particles; $pbest$ is the individual optimum; $gbest$ is the global optimum; $rand(0 \sim 1)$ is a random number between (0, 1); x_i is the current position of the particle. c_1 and c_2 are the learning factors, usually taking $c_1 = c_2 = 2$. In each dimension, the particle has a maximum limiting velocity V_{max} ; if the velocity in a dimension exceeds the set V_{max} , then the velocity in this dimension is limited to V_{max} .

This study invited a total of 12 experts in college English teaching to provide a detailed introduction to the content of the index system. Based on the aforementioned evaluation scale, they formed the final judgment values through pairwise comparisons, as shown in the following tables 2, 3, and 4.

Table 2

Group decision-making underlying weights.

Primitive element	Concluding value (global weight)	Peer weighting	Superiors
Political theories	0.0972	0.5366	Political literacy
Political faith	0.0476	0.2628	
Political participation	0.0363	0.2005	
Legal literacy	0.0294	0.2344	Moral literacy
Social morality	0.0258	0.2053	
Learning attitude	0.023	0.183	
Psychological quality	0.0193	0.1534	
Moral sentiments	0.0151	0.1199	
Life philosophy	0.013	0.1039	Humanistic literacy
Cultural consciousness	0.0308	0.4683	
Communication consciousness	0.0205	0.3113	
Innovation consciousness	0.0145	0.2204	Discipline literacy
Logical thinking	0.0144	0.3034	
Critical thinking	0.0111	0.2336	
Creative thinking	0.0088	0.1847	
Informative thinking	0.0075	0.1572	
Divergent thinking	0.0058	0.1211	Chinese language and culture
Characters	0.1006	0.5132	
Literature and history	0.0515	0.2627	
Traditional art	0.0439	0.224	English language and culture
Language and literature	0.0587	0.6424	
Overview of English-speaking countries	0.0327	0.3576	Listening
Reaction rate	0.0133	0.2841	
Understanding	0.0091	0.1947	
Attention	0.008	0.1694	
Shorthand	0.007	0.1496	
Strategy	0.0051	0.1078	
Context adaptation	0.0044	0.0944	
Fluency and coherence	0.0077	0.1997	Speaking
Pronunciation	0.0067	0.1741	
Intonation	0.0065	0.1686	
Lexical diversity	0.0052	0.1333	
Sentence variety	0.0043	0.1102	
Grammar	0.0032	0.0838	
Strategy	0.0027	0.0707	
Context adaptation	0.0023	0.0596	Reading
Speed	0.0089	0.3029	

Continued on next page

Table 2 – continued from previous page

Primitive element	Concluding value (global weight)	Peer weighting	Superiors
Accuracy	0.0062	0.2111	
Language usage	0.0049	0.1672	
Material comprehension	0.0035	0.1194	
Strategy	0.0032	0.1076	
Context adaptation	0.0027	0.0918	
Complete structure	0.0055	0.2475	Writing
Coherence and cohesion	0.0043	0.197	
Grammar	0.0038	0.1703	
Lexical diversity	0.0027	0.1236	
Rhetorical devices	0.0024	0.1107	
Fluency	0.0017	0.0769	
Context adaptation	0.0016	0.074	
Speed	0.0044	0.2684	Translating
Strategies	0.0033	0.2045	
Faithfulness	0.0024	0.1485	
Long sentences	0.0019	0.1141	
Grammar	0.0016	0.1008	
Intelligibility	0.0014	0.0851	
Elegance	0.0013	0.0787	
Speed	0.0038	0.313	Interpreting
Completion	0.0027	0.2268	
Strategies	0.0024	0.2008	
Pronunciation and intonation	0.0016	0.1321	
Grammar	0.0015	0.1273	
Planning	0.0261	0.4899	Metacognitive strategy
Monitoring	0.0161	0.3026	
Adjustment	0.011	0.2074	
Paraphrase	0.0153	0.488	Cognitive strategy
Elaboration	0.009	0.2857	
Organization	0.0071	0.2263	
Achievement	0.0166	0.6819	Communication strategy
Reduction	0.0077	0.3181	
Cognitive reconstruction	0.0095	0.5224	Emotional management strategy
Emotion regulation	0.0054	0.2998	
Behaviour control	0.0032	0.1777	

Subsequently, the research team of this study adopted a nationwide survey method, covering 600 higher education institutions across thirty provinces in China and tracking over four semesters. The measurement was conducted on the current students of each university in the aforementioned manner, and the final weighted average was used to determine the English core literacy situation of the students at each school, ultimately obtaining 2400 samples.

Table 3

Group decision-making intermediate layer weights.

Node	Concluding value (global weight)	Peer weighting	Superiors
Political literacy	0.1811	0.431	Cultural literacy
Moral literacy	0.1256	0.2989	
Humanistic literacy	0.0659	0.1568	
Discipline literacy	0.0476	0.1133	
Chinese language and culture	0.1961	0.6819	Language knowledge
English language and culture	0.0914	0.3181	
Listening	0.047	0.2841	Language skills
Speaking	0.0386	0.2338	
Reading	0.0294	0.1778	
Writing	0.0221	0.1336	
Translating	0.2162	0.0982	
Interpreting	0.012	0.0726	
Metacognitive strategy	0.0532	0.4189	Learning strategies
Cognitive strategy	0.0314	0.2471	
Communication strategy	0.0243	0.1915	
Emotional management strategy	0.0181	0.1425	

Table 4

Group decision-making intermediate layer weights.

Node	Concluding value (global weight)	Peer weighting	Superiors
Cultural literacy	0.4201	0.4201	Core literacy
Language knowledge	0.2875	0.2875	
Language skills	0.1653	0.1653	
Learning strategies	0.1271	0.1271	

3.2. Core explained variables

To measure the implementation of smart English classrooms, this paper designed a simple binary variable, where “1” represents that the university has implemented the smart English classroom teaching model, and “0” indicates that the model has not been implemented. This binary coding method provides a clear distinction for analysis, enabling the research team to track the prevalence of smart classroom teaching models effectively and to associate it with the development of students’ English core literacy.

3.3. Control variables

Control variables are examined from three dimensions: learner background, learning time and frequency, and individual psychological factors. Learner background includes age, gender, native language background, and previous English learning experiences, which may affect the development of the learner’s core literacy and English proficiency. Learning time and frequency refer to the time and frequency that learners invest in English learning, including

both classroom and self-study time outside of class. Individual psychological factors, such as the learner's confidence, anxiety level, motivation, and expectations, should also be considered as control variables because they may affect the learner's learning behaviour and outcomes.

Before starting data analysis, this study performed a series of preprocessing and cleaning steps on the initial data to ensure the accuracy and stability of the data. Firstly, to reduce the dimensional effect between different indicators, the initial data was normalized. This paper refers to the research of [18, 25] for the normalization of the original data. Normalization is a common data preprocessing method that eliminates the impact of dimensions on the analysis results by converting various indicators to the same scale range, making different indicators comparable. Data processed in this way is more convenient for subsequent statistical analysis and modelling.

$$X_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})}$$

3.4. Model construction

Base regression model:

$$CE_{it} = \alpha_0 + \alpha_1 SC_{it} + Control_{it}\alpha_2 + C_i + \lambda_t + \varepsilon_{it}$$

where SC denotes whether the smart English classroom is adopted or not, CE denotes the core English literacy of college students, α represents the regression coefficient, and C_i denotes individual effect, CE denotes college students' English core literacy, and λ_t represents the time effect, the ε_{it} represents random error, i represents subject students, and t represents year. This paper focuses on the regression coefficients of the core explanatory variables, and if they are significantly positive, it means that the smart English classroom can significantly improve college students' English literacy.

In order to explore the mediating effects of Enriched Academic Resources (EAR) and Real-Time Feedback and Evaluation ($RTFE$), this paper constructs the following model for validation.

$$CE_{it} = \alpha_0 + \alpha_1 SC_{it} + Control_{it}\alpha_2 + C_i + \lambda_t + \varepsilon_{it}$$

$$EAR_{it} = \beta_0 + \beta_1 SC_{it} + Control_{it}\beta_2 + C_i + \lambda_t + \varepsilon_{it}$$

$$CE_{it} = \gamma_0 + \gamma_1 SC_{it} + \gamma_2 EAR_{it} + Control_{it}\gamma_3 + C_i + \lambda_t + \varepsilon_{it}$$

$$RTFE_{it} = \beta_0 + \beta_1 SC_{it} + Control_{it}\beta_2 + C_i + \lambda_t + \varepsilon_{it}$$

$$CE_{it} = \gamma_0 + \gamma_1 SC_{it} + \gamma_2 RTFE_{it} + Control_{it}\gamma_3 + C_i + \lambda_t + \varepsilon_{it}$$

3.5. Empirical results

3.5.1. Basic regression

In this section, basic regression analysis is employed, utilizing both Ordinary Least Squares (OLS) and fixed effects (or random effects) regression models. The reason for choosing these two models is their respective adaptability to the data. The OLS model assumes that all observations are independent of each other, while fixed effects or random effects models can account for

differences among individuals in cross-sectional data. By comparing the results of these two models, the importance of individual effects can be assessed, thus determining whether to use fixed effects or random effects models. Moreover, the OLS model may produce biased estimation results in the presence of individual-specific, time-invariant factors, while the fixed effects model can provide more consistent estimates by eliminating these time-invariant individual characteristics. In terms of efficiency, if the fixed effects model is more suitable, but the individual effects are uncorrelated with the explanatory variables, the random effects model may be more efficient due to its smaller standard errors. Before starting the analysis, the Hausman test was first conducted to determine whether the fixed effects or random effects model should be chosen for this paper. The test result was $\chi^2 = 561.1$, $p > \chi^2 = 0.0000$, thus rejecting the null hypothesis and opting for the fixed effects model. The results of the basic regression analysis are presented in table 5.

Table 5

Basic regression results.

	(1) OLS	(2) OLS	(3) FE	(4) FE
SC_{it}	0.2770*** [3.7363]	0.2326*** [19.2162]	0.2405*** [7.4721]	0.2152** [2.2905]
_cons	0.7036*** [49.7066]	0.7135*** [79.5620]	0.7096*** [59.8935]	0.7402*** [76.3360]
N	2400	2400	2400	2400
r^2	0.8715	0.8477	0.8625	0.8041
F	525.3714	1100	880.4862	1000
p	0.0000	0.0000	0.0000	0.0000
Control	NO	YES	NO	YES
FE	NO	NO	YES	YES
Year	NO	NO	YES	YES

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Models (1) to (4) report the basic regression results, with Models (1) and (3) not including control variables, while Models (2) and (4) include control variables. The reason for this approach is as follows: First, control variables may influence the relationship between smart English classrooms and college students' English core literacy, but they are not the core of the study. Therefore, Models (1) and (3) focus on the direct relationship between the core variables, while Models (2) and (4) examine whether these core relationships remain robust after controlling for other relevant factors by including control variables. By comparing the models without control variables to those with control variables, this paper can assess the robustness of the relationship between the main explanatory variables and the dependent variable. If the effect size and statistical significance of the main explanatory variables do not change significantly after the inclusion of control variables, it indicates that the results are more robust, enhancing the credibility of the study's findings. Both Models (3) and (4) take into account individual fixed effects and time fixed effects. The introduction of individual fixed effects is to control for

unobservable factors that may not change much over time but can vary significantly between individuals. Specifically, Model (1) reports the OLS regression results of smart English classrooms on college students' core literacy, showing that smart English classrooms can effectively improve college students' core literacy. The regression result of smart English classrooms on college students' core literacy is 0.2770 and is significant at the 1% level. That is, by adopting the smart English teaching model, college students' core literacy can be increased by $0.2770 \times 100\%$. Model (2) reports the OLS regression results of smart English classrooms on college students' core literacy after including control variables, showing that smart English classrooms can effectively improve the level of college students' core literacy. Specifically, the regression result of smart English classrooms on college students' core literacy is 0.2326 and is significant at the 1% level. That is, by adopting the smart English teaching model, college students' core literacy can be increased by $0.2326 \times 100\%$. Model (3) reports the fixed effects regression results of smart English classrooms on college students' core literacy, showing that enhancing smart English classrooms can effectively improve the level of college students' core literacy. Specifically, the regression result of smart English classrooms on the level of college students' core literacy is 0.2405 and is significant at the 1% level. That is, by adopting the smart English teaching model, the level of college students' core literacy can be increased by $0.2405 \times 100\%$. Model (4) reports the fixed effects regression results of smart English classrooms on the level of college students' core literacy after including control variables. The results show that even after including control variables, smart English classrooms can still effectively improve the level of college students' core literacy. Specifically, the regression result of smart English classrooms on the level of college students' core literacy is 0.2152 and is significant at the 5% level. That is, by adopting the smart English teaching model, college students' core literacy can be increased by $0.2152 \times 100\%$.

3.5.2. Robustness Test and Endogeneity Analysis

Step 1: Modify the static model to a dynamic model.

Static models may not take into account the impact of time factors on the relationships between variables. By introducing a dynamic model, the relationships between variables that change over time can be examined. Dynamic models, by incorporating lagged variables, can better simulate and understand this temporal dependency, thereby providing more accurate estimates and predictions. From the perspective of robustness testing, if the results of the static model remain consistent after being converted to a dynamic model, it enhances the credibility of the original findings. Therefore, this paper modifies the static model to a dynamic model. The benchmark regression model for the research design referred to in this paper is shown in the following formula, and table 6 reports the regression results after converting the static model to a dynamic model.

$$CE_{it} = \alpha_0 + \alpha_1 CE_{it-1} + \alpha_2 SC_{it} + Control_{it} \alpha_3 + C_i + \lambda_t + \varepsilon_{it}$$

It can be observed that when the model is transitioned from a static to a dynamic model, the conclusions remain robust. Specifically, Model (1) reports the OLS estimation results of the dynamic effect model of smart English classrooms on college students' core literacy without

Table 6

Transition from static to dynamic model.

	(1) OLS	(2) OLS	(3) FE	(4) FE
SC_{it}	0.2434*** [5.8880]	0.2544*** [22.2037]	0.2591*** [10.7831]	0.2162** [2.4165]
CE_{it-1}	0.0263*** [3.7722]	0.0242*** [4.7213]	0.0313*** [5.4871]	0.0235*** [4.5944]
_cons	0.7203*** [51.5287]	0.6988*** [77.5402]	0.6901*** [57.6600]	0.7315*** [74.9966]
N	2400	2400	2400	2400
r^2	0.8100	0.8883	0.8016	0.8438
F	646.2347	13e00	1100	1300
p	0.0000	0.0000	0.0000	0.0000
Control	NO	YES	NO	YES
FE	NO	NO	YES	YES
Year	NO	NO	YES	YES

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

including control variables. The results show that smart English classrooms can effectively improve college students' core literacy. Specifically, the regression result of smart English classrooms on college students' core literacy is 0.2434 and is significant at the 1% level. That is, by adopting the smart English teaching model, college students' core literacy can be increased by $0.2434 \times 100\%$. Model (2) reports the OLS estimation results of the dynamic effect of smart English classrooms on college students' core literacy after introducing control variables. The results show that smart English classrooms can effectively improve the level of college students' core literacy. Specifically, the regression result of smart English classrooms on college students' core literacy is 0.2544 and is significant at the 1% level. That is, by adopting the smart English teaching model, the level of college students' core literacy can be increased by $0.2544 \times 100\%$. Model (3) reports the fixed effects regression results of the dynamic model of smart English classrooms on the level of college students' core literacy without including control variables. The results show that enhancing smart English classrooms can effectively improve the level of college students' core literacy. Specifically, the regression result of smart English classrooms on the level of college students' core literacy is 0.2591 and is significant at the 1% level. That is, by adopting the smart English teaching model, the level of college students' core literacy can be increased by $0.2591 \times 100\%$. Model (4) reports the fixed effects regression results of the dynamic model of smart English classrooms on the level of college students' core literacy after including control variables. The results show that improving smart English classrooms can effectively improve the level of college students' core literacy. Specifically, the regression result of smart English classrooms on the level of college students' core literacy is 0.2162 and is significant at the 5% level. That is, by adopting the smart English teaching model, the level of college students' core literacy can be increased by $0.2162 \times 100\%$.

Step 2: Lagging the core explanatory variable by one order.

In conducting robustness checks, this study adopts a common strategy of lagging the core explanatory variable by one order to address potential endogeneity issues and confirm the directionality of the causal relationship, thereby enhancing the robustness of the model estimation. This approach helps to resolve issues that may lead to inaccurate model estimation results. Here is the missing text formatted in LaTeX:

The study lags the core explanatory variable, smart English classrooms, by one order for robustness testing. The benchmark regression model referred to in the research design is as follows, and table 7 reports the regression results after lagging the core explanatory variable by one order.

$$CE_{it} = \alpha_0 + \alpha_1 SC_{it-1} + \alpha_2 SC_{it} + Control_{it}\alpha_3 + C_i + \lambda_t + \varepsilon_{it}$$

Table 7

Lagging the core explanatory variable by one order.

	(1) OLS	(2) OLS	(3) FE	(4) FE
SC_{it}	0.2196*** [2.7317]	0.2818*** [10.5185]	0.2234*** [3.8697]	0.2150** [2.3625]
SC_{it-1}	0.1677*** [22.1846]	0.1478*** [25.7272]	0.1425*** [22.4773]	0.0448*** [6.7056]
_cons	-0.0225 [-1.5210]	-0.0084 [-0.7877]	-0.0260* [-1.8759]	0.0628*** [4.4804]
N	2400	2400	2400	2400
r^2	0.9108	0.8530	0.8602	0.8614
F	778.1317	1100	935.7911	231.8614
p	0.0000	0.0000	0.0000	0.0000
Control	NO	YES	NO	YES
FE	NO	YES	NO	YES
Year	NO	YES	NO	YES
Standard errors in brackets				
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

Model (1) reports the OLS estimation results of the lagged model of smart English classrooms on college students' English core literacy without including control variables. The results show that smart English classrooms can effectively improve college students' English core literacy. Specifically, the regression result of smart English classrooms on college students' English core literacy is 0.2196 and is significant at the 1% level. That is, by adopting the smart English teaching model, college students' English core literacy can be increased by $0.2196 \times 100\%$. Model (2) reports the OLS estimation results of the lagged model of smart English classrooms on college students' English core literacy after introducing control variables. The results show that smart English classrooms can effectively improve the level of college students' English core literacy. Specifically, the regression result of smart English classrooms on college students'

English core literacy is 0.2818 and is significant at the 1% level. That is, by adopting the smart English teaching model, the level of college students' English core literacy can be increased by $0.2818 \times 100\%$. Model (3) reports the fixed effects regression results of the lagged model of smart English classrooms on the level of college students' English core literacy without including control variables. The results show that enhancing smart English classrooms can effectively improve the level of college students' English core literacy. Specifically, the regression result of smart English classrooms on the level of college students' English core literacy is 0.2234 and is significant at the 1% level. That is, by adopting the smart English teaching model, the level of college students' English core literacy can be increased by $0.2234 \times 100\%$. Model (4) reports the fixed effects regression results of the lagged model of smart English classrooms on the level of college students' English core literacy after including control variables. The results show that improving smart English classrooms can effectively improve the level of college students' English core literacy. Specifically, the regression result of smart English classrooms on the level of college students' English core literacy is 0.2150 and is significant at the 5% level. That is, by adopting the smart English teaching model, the level of college students' English core literacy can be increased by $0.2150 \times 100\%$. The results are consistent with the basic regression, thus indicating that the conclusions are robust.

3.5.3. Mechanism analysis

Table 8 reports the regression results of the mediating mechanism of academic resources. Model (1) reports the basic regression results from table 6, while Model (2) reports the regression results of the core explanatory variable, smart English classrooms, on academic resources. It can be observed that smart English classrooms can enrich academic resources. The regression coefficient of smart English classrooms on academic resources is 0.1281, significant at the 1% level, indicating that the emergence of smart English classrooms can enhance the improvement of academic resources by 12.81%. Model (3) reports the regression results between academic resources and college students' English core literacy. The results show that enriched academic resources significantly improve college students' English core literacy. Specifically, the regression coefficient between academic resources and college students' English core literacy is 0.5502 and is significant at the 1% level, indicating that for every unit increase in academic resources, the level of college students' English core literacy will increase by 0.5502 units. Model (4) is the basic regression result after the inclusion of the mediating variable. Since the regression coefficient and significance level of the core explanatory variable have both decreased (the regression coefficient decreased from 0.2520 to 0.2290; the significance level decreased from 5% to 10%), it indicates that academic resources play a partial mediating role, and the mediating effect is $\frac{0.1281 \times 0.5502}{0.2290} = 30.78\%$.

4. Research on the relationship between core literacy and learning outcomes

Before delving into the relationship between core literacy and learning outcomes, it is essential to understand the importance of multimodal data in educational evaluation. Multimodal data

Table 8
Mechanism analysis.

	(1) <i>CE</i>	(2) EAR	(3) <i>CE</i>	(4) <i>CE</i>
<i>SC_{it}</i>	0.2520** [2.2905]	0.1281*** [8.2267]		0.2290* [1.8029]
<i>EAR</i>			0.5502*** [27.4339]	0.4935*** [58.5804]
_cons	0.7402*** [76.3360]	0.6818*** [32.9375]	0.6164*** [24.5652]	0.6990*** [61.1052]
<i>N</i>	2400	2400	2400	2400
<i>r</i> ²	0.8041	0.2576	0.2691	0.2063
<i>F</i>	1000	331.0509	273.2582	743.8179
<i>p</i>	0.0000	0.0000	0.0000	0.0000
Control	YES	YES	YES	YES
FE	YES	YES	YES	YES
Year	YES	YES	YES	YES

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

encompasses various types of information, including text, images, audio, and physiological data, originating from both online and offline learning environments. This provides a comprehensive and three-dimensional view of the learning process. The diversity and richness of this data enable more precise capture and analysis of learners' behavioural patterns, engagement, and cognitive activities, thereby offering a more nuanced and dynamic perspective for evaluating learning outcomes. Driven by multimodal data, it is possible to more accurately pinpoint learning states, assess learning processes and results, and reveal how core literacy affects learning outcomes.

4.1. Collection of multimodal learning data

Based on three characteristic dimensions of offline learning data, online learning data, and learning performance, this study collected the following four types of data from the "Smart Classroom College English" course:

1. Theoretical teaching data, which is teaching video data collected from theoretical classrooms through an automatic recording and broadcasting system. This study used a semi-automatic method to randomly select teaching videos from 8 class periods, encoding and annotating learning data such as attention, learning notes, and interaction of 500 college students to form structured classroom learning data.
2. Practical exercise data, collected using recording equipment in a micro-teaching classroom environment, mainly comes from teaching simulation practice, lecture exercises, and course teaching design.
3. Online learning data, which is the online learning process data of students automatically

stored by the online learning platform, mainly involving course teaching video learning, topic discussions, chapter learning, etc.

4. End-of-semester test data, which is the students' scores in the end-of-semester test for this course.

4.2. Data preprocessing of multimodal learning data

Data is anonymized and cleaned, removing incomplete learning data, such as data from students who were absent from class or missed exams, to ensure the completeness and validity of the data. Secondly, the students' end-of-semester test scores are discretized. Finally, the data is normalized, mapping it to a range of 0 to 1. This study uses the L2 norm normalization method, normalizing the vector x to a unit vector, that is, establishing a mapping from x to x' so that the norm of x' is 1. After multiple verifications and processing of the data, this study ultimately extracted valid data from 400 college students as the research sample.

4.3. Multimodal data-driven learning outcome evaluation model

A deep neural network is a neural network with a certain level of complexity and more than two layers. Deep neural networks use sophisticated mathematical modelling to process data in complex ways. This study constructed a deep neural network model for evaluating and predicting students' learning outcomes. The training and validation sets were allocated in a 7:3 ratio. Multiple hidden layers were introduced in the model, and the number of neurons in each layer was increased to enhance the model's learning capacity and predictive accuracy. To reduce overfitting, dropout layers were added to the network; at the same time, batch normalization layers were introduced to accelerate the model's training process. By employing various activation functions, such as RELU, and using mean squared error (MSE) as the loss function in the output layer, along with the mean absolute error (MAE) as an evaluation metric, the model's performance and the accuracy of the evaluation were further improved.

Table 9 displays the basic information of the independent and dependent variables, where the independent variables encompass multiple dimensions, including political literacy, moral literacy, cultural literacy, and subject literacy, while the dependent variable is the learning outcomes of students driven by multimodal data. The statistical description of these data provides a quantitative perspective for understanding students' learning performance. Table 10 describes the structure of the deep neural network, including the type, output shape, and number of parameters of each layer, clearly showing the complexity and depth of the model. Figure 2 shows the loss situation of the training and validation sets; after 50 rounds of training of the deep neural network, the training set and validation set losses MSE were 38.72 and 42.83, respectively. These results indicate that the model fits the training data quite well and also shows good generalization ability on unseen data. Although the MSE of the validation set is slightly higher than that of the training set, this difference is within an acceptable range, indicating that the model has not overfitted the training data. Figure 3 shows a comparison between the model's predicted learning outcomes and the actual outcomes. It can be seen that there is a small deviation between the model's predicted values and the actual values, and the predicted curve closely follows the actual value curve, showing a high degree of consistency.

Specifically, the average error of the multimodal data-driven learning outcome evaluation model in this study is only 2.55%, and the predicted curve highly coincides with the actual value curve, demonstrating a high degree of consistency and verifying the positive impact of core literacy on students' learning outcomes.

Table 9

Basic information of independent and dependent variables.

	Variables	count	Mean	σ	min	25%	50%	75%	max
Independent variable	Political literacy	400	3.97	2.00	1	2	4	6	7
	Moral literacy	400	4.01	1.99	1	2	4	6	7
	Humanistic literacy	400	4.00	2.01	1	2	4	6	7
	Discipline literacy	400	4.03	2.00	1	2	4	6	7
	Chinese language and culture	400	4.06	2.02	1	2	4	6	7
	English language and culture	400	3.98	2.02	1	2	4	6	7
	Listening	400	4.03	2.01	1	2	4	6	7
	Speaking	400	4.02	2.00	1	2	4	6	7
	Reading	400	3.94	2.02	1	2	4	6	7
	Writing	400	4.03	2.00	1	2	4	6	7
	Translating	400	4.00	1.98	1	2	4	6	7
	Interpreting	400	3.97	2.02	1	2	4	6	7
	Metacognitive strategy	400	4.01	2.01	1	2	4	6	7
	Cognitive strategy	400	4.05	1.97	1	2	4	6	7
	Communication strategy	400	4.02	1.99	1	2	4	6	7
	Emotional management strategy	400	4.04	1.99	1	2	4	6	7
Dependent variable	Learning effect (Multimodal learning data)	400	73.52	10.68	32	66	74	81	100

Table 10

Deep neural network architecture.

Layer (type)	Output shape	Parameters number
dense (Dense)	(None, 128)	2816
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 256)	33024
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896
batch_normalization (BatchNormalization)	(None, 128)	512
dense_3 (Dense)	(None, 64)	8256
dense_4 (Dense)	(None, 1)	65

5. Conclusions and recommendations

The empirical analysis of this study shows that smart English classrooms have a significantly effective impact on improving college students' core literacy. After numerous model tests, including Ordinary Least Squares (OLS) regression under different conditions, fixed effects model

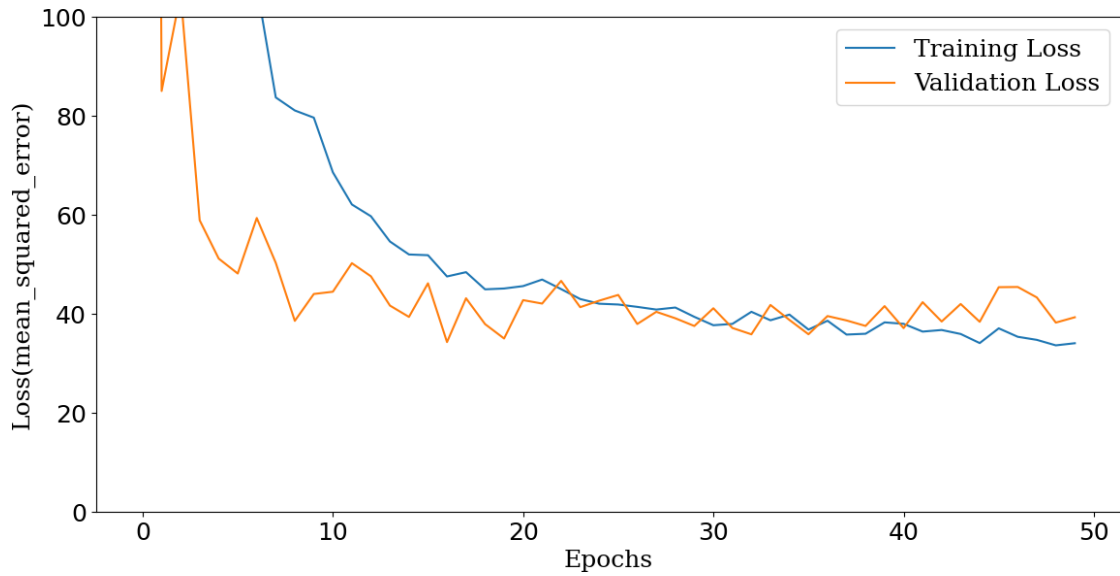


Figure 2: Training and validation set losses.

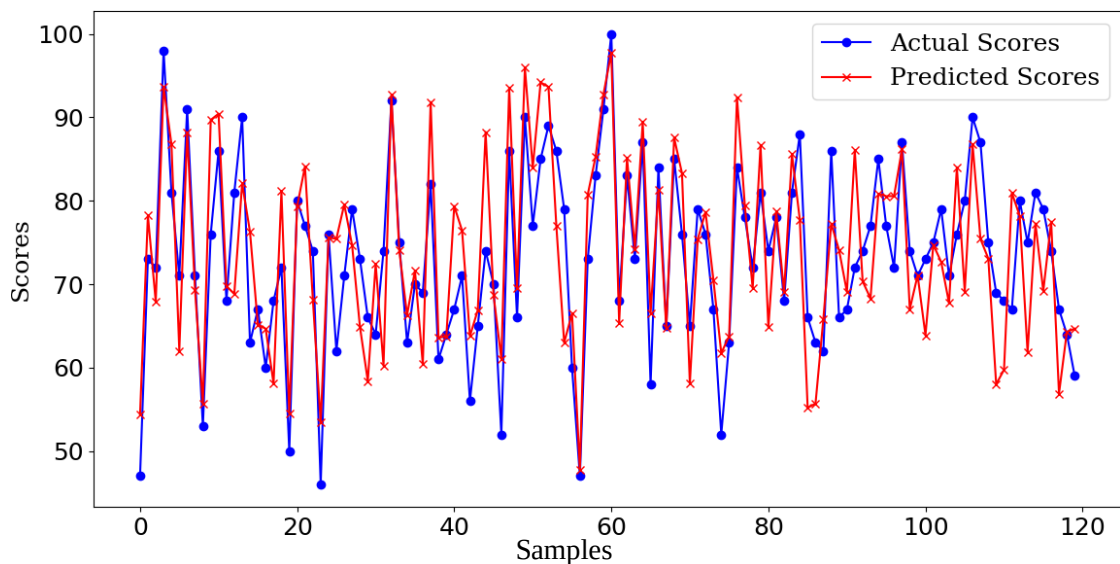


Figure 3: Comparison of actual and predicted learning outcomes.

regression, and fixed effects regression of dynamic lag models, the results consistently point out that adopting the smart English teaching model can significantly promote the improvement of college students' core literacy. The regression coefficients of different models range from 0.2150 to 0.2818, and both are significant at the 1% level, indicating that the positive effect of smart English classrooms on students' core literacy is robust and reliable. In addition, the paper

also considers the possibility of academic resources as a mediating mechanism. Through the diagnosis from Model (2) to Model (4), it is found that smart English classrooms do have an impact on college students' English core literacy through the pathway of enriching academic resources. Smart English classrooms significantly increase academic resources (regression coefficient 0.1281, at a significance level of 1%), and the increase in academic resources can significantly improve students' English core literacy (regression coefficient reaching 0.5502, at a significance level of 1%). By comparing the basic regression with the one considering the mediating effect, academic resources have a mediating effect of 30.78% on the core explanatory variable of smart English classrooms affecting college students' English core literacy level. This study uses a deep neural network to explore further the complex relationship between core literacy and learning outcomes. By constructing a deep learning model with multiple hidden layers combined with students' multimodal learning data, the multidimensional characteristics of core literacy can effectively predict students' learning outcomes. In summary, the study shows that smart English classrooms not only directly promote the improvement of college students' core literacy, but also this positive effect is partly derived from the enhancement of technological resources. It can be seen that smart English classrooms, as an emerging teaching model, can significantly improve students' English core literacy with its extensive application in classroom teaching.

Based on the research conclusions, this paper puts forward the following suggestions:

1. *Promote smart English classrooms*: Given the significant positive effect of smart English classrooms on improving students' core literacy, it is recommended that universities and other educational institutions widely introduce and apply smart teaching models. Upgrade existing English classroom teaching and integrate smart teaching concepts and technology.
2. *Invest in teaching resources and technology*: To make smart English classrooms more effective, it is recommended that relevant schools and institutions invest in modern teaching software and hardware facilities, teaching management systems, and online resources to build and improve the smart classroom environment.
3. *Train teachers' professional skills*: Professional training activities should be organized to enhance English teachers' teaching capabilities and technical application levels in the smart classroom environment, enabling them to use smart classrooms to promote students' literacy improvement more effectively.
4. *Enrich academic resources*: Given that the study shows an increase in academic resources can significantly improve students' English core literacy, it is recommended to strengthen the construction and utilization of academic resources, such as increasing online lectures, professional English reading materials, English learning software, and multimedia interactive materials.
5. *Innovate teaching methods*: Encourage and guide teachers to use smart classroom technology to innovate teaching methods, such as personalized learning plans based on data analysis, interactive learning activities, augmented reality (AR/VR) and other teaching tools.
6. *Continuous monitoring and feedback*: Establish a mechanism for monitoring and evaluating the practical effects of smart English classrooms, collect feedback for timely improvements,

and ensure that the teaching model always fits students' learning needs and teaching objectives.

7. *Support at the policy level*: It is recommended that relevant educational management departments introduce policies to increase the promotion and support for smart English classrooms, such as providing financial subsidies and reforming curriculum systems and assessment mechanisms, in order to systematically promote the implementation of smart English teaching on a wider scale.

References

- [1] Angrist, J., Chin, A. and Godoy, R., 2008. Is Spanish-only schooling responsible for the Puerto Rican language gap? *Journal of development economics*, 85(1), pp.105–128. Available from: <https://doi.org/10.1016/j.jdeveco.2006.06.004>.
- [2] Bansal, G., 2022. The hegemony of English in science education in India: a case study exploring impact of teacher orientation in translating policy in practice. *Cultural Studies of Science Education*, 17(2), pp.439–466. Available from: <https://doi.org/10.1007/s11422-021-10068-2>.
- [3] Benzie, H.J., 2010. Graduating as a 'native speaker': international students and English language proficiency in higher education. *Higher Education Research & Development*, 29(4), pp.447–459. Available from: <https://doi.org/10.1080/07294361003598824>.
- [4] Chang, B.M., 2011. The Roles of English Language Education in Asian Context. *Journal of Pan-Pacific Association of Applied Linguistics*, 15(1), pp.191–206. Available from: <https://eric.ed.gov/?id=EJ939947>.
- [5] Do, T.T.T., Sellars, M. and Le, T.T., 2022. Primary English Language Education Policy in Vietnam's Disadvantaged Areas: Implementation Barriers. *Education Sciences*, 12(7), p.445. Available from: <https://doi.org/10.3390/educsci12070445>.
- [6] Duckworth, A., 2016. *Grit: The power of passion and perseverance*. New York, NY: Scribner, vol. 234, pp.19–23.
- [7] Dweck, C.S., 2012. *Mindset: The new psychology of success*. Random House Digital, Inc., pp.77–91.
- [8] Ge, N., Wang, E. and Li, Y., 2023. Foreign Language Education for Sustainable Development in China: A Case Study of German Language Education. *Sustainability*, 15(8), p.6340. Available from: <https://doi.org/10.3390/su15086340>.
- [9] Hamari, J., Shernoff, D.J., Rowe, E., Coller, B., Asbell-Clarke, J. and Edwards, T., 2016. Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning. *Computers in human behavior*, 54, pp.170–179. Available from: <https://doi.org/https://doi.org/10.1016/j.chb.2015.07.045>.
- [10] Hamid, M.O., 2024. World Englishes, secularisation, and de-secularisation: examining English language textbooks in a Muslim society from the perspective of language as situated practice. *Journal of Multilingual and Multicultural Development*, 45(3), pp.739–757. Available from: <https://doi.org/10.1080/01434632.2022.2159419>.
- [11] Hattie, J., 2008. *Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement*. London: Routledge, pp.113–124. Available from: <https://doi.org/10.4324/9780203887332>.

- [12] Hu, G. and McKay, S.L., 2012. English language education in East Asia: some recent developments. *Journal of Multilingual and Multicultural Development*, 33(4), pp.345–362. Available from: <https://doi.org/10.1080/01434632.2012.661434>.
- [13] Johnson, D.W., Johnson, R.T. and Holubec, E.J., 1998. *Cooperation in the classroom*. 7th ed., Edina, MN: Interaction Book Co., pp.102–117.
- [14] Kobayashi, P.I., 2023. From a Foreign Language to own Language: Resolving Conflicts Over English Education in Japan. *Asian Englishes*, 25(2), pp.234–247. Available from: <https://doi.org/10.1080/13488678.2023.2214773>.
- [15] Kobul, M.K. and Saraçoğlu, İ.N., 2020. Foreign Language Teaching Anxiety of Non-Native Pre-Service and In-Service EFL Teachers. *Journal of History Culture and Art Research*, 9(3), pp.350–365. Available from: <https://www.researchgate.net/publication/344709754>.
- [16] Li, X., 2022. Preschool English language provision in China under the government ban. *Cogent Education*, 9(1), p.2152257. Available from: <https://doi.org/10.1080/2331186X.2022.2152257>.
- [17] Liddicoat, A.J., 2022. Language planning for diversity in foreign language education. *Current Issues in Language Planning*, 23(5), pp.457–465. Available from: <https://doi.org/10.1080/14664208.2022.2088968>.
- [18] Liu, X., Li, N., Liu, S., Wang, J., Zhang, N., Zheng, X., Leung, K.S. and Cheng, L., 2019. Normalization Methods for the Analysis of Unbalanced Transcriptome Data: A Review. *Frontiers in Bioengineering and Biotechnology*, 7. Available from: <https://doi.org/10.3389/fbioe.2019.00358>.
- [19] López Gándara, Y. and Rendón-Romero, S.I., 2023. Critical approaches to English language teacher education: A narrative inquiry into trainee teachers' experiences as speakers of English. *Heliyon*, 9(12), p.e22882. Available from: <https://doi.org/10.1016/j.heliyon.2023.e22882>.
- [20] MacDonald, N.I., 2023. Why Inuit culture and language matter: decolonizing English second language learning. *AlterNative: An International Journal of Indigenous Peoples*, 19(4), pp.794–803. Available from: <https://doi.org/10.1177/11771801231197841>.
- [21] Marzano, R.J., 2007. *The Art and Science of Teaching: A Comprehensive Framework for Effective Instruction*. Association for Supervision and Curriculum Development, pp.189–231.
- [22] Morse, Z. and Nakahara, S., 2001. English language education in Japanese dental schools. *European Journal of Dental Education*, 5(4), pp.168–172. Available from: <https://doi.org/10.1034/j.1600-0579.2001.50405.x>.
- [23] Ortiz, A.A. and Robertson, P.M., 2018. Preparing Teachers to Serve English Learners With Language- and/or Literacy-Related Difficulties and Disabilities. *Teacher Education and Special Education*, 41(3), pp.176–187. Available from: <https://doi.org/10.1177/0888406418757035>.
- [24] Pan, L., 2015. *English as a Global Language in China: Deconstructing the Ideological Discourses of English in Language Education*, *English Language Education*, vol. 2. Springer Cham. Available from: <https://doi.org/10.1007/978-3-319-10392-1>.
- [25] Pei, J., Liu, W. and Han, L., 2019. Research on Evaluation Index System of Chinese City Safety Resilience Based on Delphi Method and Cloud Model. *International Journal of Environmental Research and Public Health*, 16(20), p.3802. Available from: <https://doi.org/>

- 10.3390/ijerph16203802.
- [26] Rivers, D.J., 2012. Modelling the perceived value of compulsory English language education in undergraduate non-language majors of Japanese nationality. *Journal of Multilingual and Multicultural Development*, 33(3), pp.251–267. Available from: <https://doi.org/10.1080/01434632.2012.661737>.
 - [27] Roberts, N. and Mort, T., 2023. Designing an English language and literacies knowledge and skills test for Initial Teacher Education students in South Africa. *Journal of Education*, 2023(90), pp.32–48. Available from: <https://doi.org/10.17159/2520-9868/i90a02>.
 - [28] Rojas, R., Iglesias, A., Bunta, F., Goldstein, B., Goldenberg, C. and Reese, L., 2016. Interlocutor differential effects on the expressive language skills of Spanish-speaking English learners. *International Journal of Speech-Language Pathology*, 18(2), pp.166–177. Available from: <https://doi.org/10.3109/17549507.2015.1081290>.
 - [29] Salaberri-Ramiro, M.S. and Sánchez-Pérez, M.d.M., 2022. Students' Perceptions of the Use of English in Higher-Education Bilingual Programs. *Latin American Journal of Content & Language Integrated Learning*, 14(2), p.263–291. Available from: <https://doi.org/10.5294/laclil.2021.14.2.4>.
 - [30] Simie, T. and McKinley, J., 2024. English medium instruction in Ethiopian university mission statements and language policies. *Language Policy*. Available from: <https://doi.org/10.1007/s10993-024-09693-8>.
 - [31] Walt, C. van der, 2021. Training multilingual English language teachers: challenges for higher education. *ELT Journal*, 76(2), pp.218–226. Available from: <https://doi.org/10.1093/elt/ccab088>.
 - [32] Wang, Y., Weng, H. and Li, Y., 2020. Language ideologies and English in Chinese primary education. *Asian Englishes*, 22(2), pp.179–194. Available from: <https://doi.org/10.1080/13488678.2019.1681719>.
 - [33] Wei, L. and Liu, B., 2022. Smart Classroom College English Listening Teaching System Based on Virtual Environment Technology. *Journal of Cases on Information Technology*, 24(5), p.1–18. Available from: <https://doi.org/10.4018/jcit.302246>.
 - [34] Weiyu Zhang, S.X. and Cheung, Y.L., 2022. Vocational English language education in multilingual context: the case of Singapore. *Research in Post-Compulsory Education*, 27(3), pp.436–453. Available from: <https://doi.org/10.1080/13596748.2022.2076056>.
 - [35] Xu, X., Li, Z., Hin Hong, W.C., Xu, X. and Zhang, Y., 2024. Effects and side effects of personal learning environments and personalized learning in formal education. *Education and Information Technologies*. Available from: <https://doi.org/10.1007/s10639-024-12685-0>.
 - [36] Yang, Y. and Zhou, W., 2022. Research on the reform of English teaching mode and analysis of teaching efficiency based on QFD theory model. *International Journal of Continuing Engineering Education and Life Long Learning*, 32(4), pp.474–487. Available from: <https://doi.org/10.1504/IJCEELL.2022.124970>.