Empowering Smart Classroom Efficiency: The Catalytic Role of Academic Support in Higher Education

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ABSTRACT:

While smart classrooms have proliferated in higher education, the mechanisms through which academic support enhances their efficiency remain underexplored. This study investigates the influence of smart classroom (SC), teachers (TE), and teaching methods (TS) on smart classroom efficiency (SCE), and examines the moderating role of academic support (AS) in these relationships. A quantitative survey was conducted with 575 undergraduate students from eight universities in Zhengzhou, China. Data were analyzed using hierarchical regression analysis to test the moderating effects. SC ($\beta = 0.427$, $p < 0.001$), TE ($\beta = 0.241$, $p < 0.001$), and TS ($\beta = 0.151$, $p = 0.006$) significantly influence SCE. Notably, AS significantly moderates all three pathways, with the strongest moderating effect on the TE-SCE relationship ($\beta = 0.219$, $p < 0.001$). This study advances theoretical understanding of academic support as a catalytic mechanism in technology-enhanced learning environments and provides actionable guidance for designing institutional support systems to maximize smart classroom efficiency.

Keywords: Smart Classroom Efficiency, Academic Support, Teacher Factors, Teaching Methods, Higher Education.

1. Introduction

Research context

The rapid advancement of information and communication technologies has precipitated a paradigm shift in higher education, compelling institutions worldwide to rethink traditional pedagogical models and learning environments (United Nations, 2022; Zhu & Yang, 2023). Among the most prominent manifestations of this transformation is the emergence and proliferation of smart classrooms (Huang & Yang, 2022), technology-enhanced learning spaces that integrate interactive displays, collaborative digital tools, learning analytics systems, and flexible physical designs to create dynamic, data-rich educational environments (Bai & Zheng, 2020; He & Huang, 2018).

In China, the development of smart classrooms has been further accelerated by national policy imperatives. The Ministry of Education's "Action Plan for Education Informatisation 2.0" explicitly calls for the widespread deployment of smart learning environments and the deep integration of technology into teaching and learning processes (Ministry of Education of the People's Republic of China, 2018). Consequently, universities across China have made substantial investments in smart classroom infrastructure, with the expectation that these technologically enriched spaces will enhance teaching quality, increase student engagement, and cultivate twenty-first-century competencies such as critical thinking, collaboration, and creativity (Zhang, 2020).

Zhengzhou, as a major educational hub in central China, has been actively implementing this movement. The city's universities have invested heavily in smart classroom construction, aiming to modernise their teaching environments and improve educational outcomes. However, the mere presence of advanced technology does not guarantee its effective use or the realisation of anticipated pedagogical benefits (Liu et al., 2023). This disjuncture between infrastructural investment and educational return (Cao et al., 2025) constitutes the central problematic that motivates the present investigation.

Problem Statement

Despite the substantial financial and institutional resources devoted to smart classroom construction, a significant body of evidence suggests that the potential of these environments remains largely unrealised. This study identifies five interrelated problems that collectively underscore the necessity for the present research.

First, a persistent utilisation gap exists between smart classroom hardware investments and their actual efficiency in teaching. At present, under the premise that the smart teaching environment has been highly emphasised, its use effect has not received corresponding widespread attention. Smart classroom efficiency is not as expected. This gap represents a substantial waste of institutional resources (Alfoudari & Durugbo, 2025). Second, existing academic research on smart classrooms in higher education exhibits a pronounced imbalance. The majority of studies have focused on technological empowerment, examining system architectures, hardware specifications, software functionalities, and technical standards (He & Huang, 2018; Liu et al., 2023). Empirical evidence specifically addressing smart classroom efficiency in higher education contexts remains conspicuously scarce.

Third, a knowledge gap exists concerning the precise nature of the multidimensional influencing factors and their interactions. Existing studies mostly focus on single factors (e.g., teachers' technological proficiency, continuance intentions) (Alfoudari & Durugbo, 2025), yet the smart classroom efficiency may be subject to complex influences from multiple dimensions. Consequently, there is a lack of clarity regarding the relative importance of these factors and the mechanisms through which they exert their influence (Tang, 2025). Fourth, the potential moderating role of academic support has been largely neglected. While post-construction support systems, including technical assistance, pedagogical guidance, evaluation feedback, and peer collaboration, are widely recognised as essential for technology adoption (Shi et al., 2025), their systematic investigation as moderating variables in the relationship between influencing factors and smart classroom efficiency is virtually absent from the literature.

Fifth, there is a lack of localised empirical validation within the specific regional context of Zhengzhou universities. Zhengzhou possesses distinct characteristics in resource allocation, faculty profiles, student demographics, and institutional cultures. This contextual specificity necessitates locally grounded research that can inform evidence-based decision-making for Zhengzhou's higher education institutions. Collectively, these five problems, the utilisation gap, the research imbalance, the unclear multidimensional influences, the neglected moderating role of academic support, and the lack of localised validation, constitute the problem space that this study seeks to address.

The primary purpose of this study is to investigate the factors influencing smart classroom efficiency in Zhengzhou universities and to examine the moderating role of academic support in these relationships. More specifically, this study aims to determine the extent to which smart classroom characteristics, teacher factors, and teaching methods influence smart classroom efficiency, and whether academic support moderates these relationships.

Literature Review

Smart Classroom and Smart Classroom Efficiency

Smart classrooms, as technologically enriched learning spaces, provide affordances that can directly enhance educational outcomes (Ta, 2021). These affordances operate through multiple mechanisms. First, the physical design of smart classrooms enables pedagogical approaches that are difficult to implement in traditional fixed-seating classrooms. Second, the technological infrastructure, interactive displays, collaborative digital workspaces, real-time polling systems, and learning analytics tools, supports active learning pedagogies associated with improved student outcomes. Third, the integration of data collection and visualisation capabilities enables personalised feedback and just-in-time instructional adjustments.

Empirical evidence supports the positive influence of smart classroom characteristics on learning outcomes. Dai et al. (2023) found that classroom design significantly affected student learning behaviours and perceptions, with technology-enhanced active learning classrooms producing higher engagement than traditional lecture halls. Similarly, Li (2025) reported that smart classroom environments positively influenced student attitudes, interest, and learning atmosphere. Zhou (2025) demonstrated that the usability, stability, and usefulness of smart classroom technology directly predicted student satisfaction and perceived learning gains. Therefore:

H1: Smart classroom (SC) has a significant positive influence on smart classroom efficiency (SCE).

Teachers and Smart Classroom Efficiency

The preceding section has examined, from the perspective of the technological environment, the impact of hardware facilities and software systems on smart classroom efficiency. However, technology ultimately serves as an auxiliary tool in teaching, and its actual effectiveness in the classroom largely depends on the primary user of these tools, the teachers.

Teachers are not merely users of smart classroom technology but active agents who interpret, adapt, and leverage technological affordances to create productive learning environments (Cui & Zhu, 2022). Theoretical analyses have clearly indicated that teachers play multiple roles as designers, facilitators, and coordinators in technology-rich learning environments (Kang, 2023). Empirical evidence supports the positive influence of teacher factors on classroom efficiency (Gao, 2023; Guo, 2024; Xu, 2024). In technology-enhanced environments, the importance of teacher factors may be amplified, as teachers must manage the dual demands of content delivery and technology integration. Therefore:

H2: Teachers (TE) has a significant positive influence on smart classroom efficiency (SCE).

Teaching Methods and Smart Classroom Efficiency

From the perspective of static elements, the preceding sections have explored the impact of "things" (smart classrooms) and "people" (teachers) on the effectiveness of smart classrooms. However, whether it is the application of technology or the guidance of teachers, both must ultimately exert their influence on students' learning experiences through specific "teaching activity processes", namely teaching methods. Therefore, after analysing the effects of technology and teachers, it is necessary to further examine the empirical impact of teaching methods as a dynamic process.

Optimised teaching methods, characterised by abundant classroom interaction, diverse instructional approaches, effective learning cooperation structures, and appropriate diversified evaluation, are hypothesised to enhance classroom interaction (Tu, 2022), student learning engagement (Li, 2024), and deep learning (Yao, 2023). While teaching methods are dependent on the enabling infrastructure (smart classroom) and executing agents (teachers), their direct influence on moment-to-moment learning experiences is theoretically significant. Therefore:

H3: Teaching methods (TS) has a significant positive influence on smart classroom efficiency (SCE).

Academic Support as a Moderator of the SC-SCE Relationship

Academic support may moderate the relationship between smart classroom characteristics and efficiency through several mechanisms. Academic support enables students to utilise smart classroom features more effectively, thereby enhancing the educational return on technological investments.

Studies have shown that students' emotional support (Huang et al., 2023), technical support , teacher support (Lu, 2021), peer assistance (Shan et al., 2021) and evaluation feedback (Shi et al., 2025) affect classroom efficiency. Even if teaching is conducted in the same smart classroom, different academic support has a significant difference in the impact on students' deep learning results (Li & Wang, 2023). This has also become the main research idea to examine the effecting elements of smart classroom efficiency. Therefore:

H4: Academic support (AS) positively moderates the relationship between smart classroom (SC) and smart classroom efficiency (SCE).

Academic Support as a Moderator of the TE-SCE Relationship

While teacher factors (TE) are hypothesised to exert a direct positive influence on smart classroom efficiency (SCE), the strength and efficacy of this relationship are unlikely to be uniform across all instructional contexts. Academic support (AS) functions as a critical moderator that amplifies the translation of teacher competence into positive educational outcomes (Lu, 2021).

The moderating role of academic support is grounded in three complementary theoretical mechanisms. First, reduction of extraneous cognitive load. Second, satisfaction of basic psychological needs for competence. Third, enabling the full utilisation of teacher capabilities.

Studies have shown that when academic support is robust, teachers' professional knowledge, teaching skills, and enthusiasm are more effectively translated into classroom efficiency (Shi et al., 2025). When support is inadequate, teacher effectiveness may be constrained by technical difficulties, isolation, and lack of feedback. Therefore:

H5: Academic support (AS) positively moderates the relationship between teachers (TE) and smart classroom efficiency (SCE).

Academic Support as a Moderator of the TS-SCE Relationship

Academic support may also moderate the relationship between teaching methods and smart classroom efficiency. Even well-designed teaching methods depend on implementation conditions for their effectiveness (Sun, 2023). Academic support can enhance or undermine this implementation.

Teaching preparation strategies benefit from learning support that provides access to high-quality digital resources, exemplars of effective practice, and guidance on aligning activities with learning objectives. Teaching implementation strategies benefit from technical support that ensures interactive features function as intended and peer assistance that enables real-time problem-solving and adaptation. Based on these theoretical and empirical foundations, this study hypothesises:

H6: Academic support (AS) positively moderates the relationship between teaching methods (TS) and smart classroom efficiency (SCE).

2. Methodology

Research Design

This study employed a quantitative research design to examine the relationships among variables associated with smart classroom learning in higher education. A cross-sectional survey method was adopted because it allows for the systematic collection of numerical data from a large group of respondents and enables statistical testing of the proposed research framework. The study specifically focused on undergraduate students in Zhengzhou universities who had experience using smart classroom environments.

Participants and Sample

The target population consisted of undergraduate students enrolled in universities in Zhengzhou who had completed at least one semester of coursework in smart classroom environments. This criterion was established to ensure that respondents possessed sufficient experience and familiarity with smart classroom learning systems, enabling them to provide informed evaluations and perceptions. A pilot study was first conducted with 121 undergraduate students selected from institutions outside the universities included in the final survey. The purpose of the pilot study was to assess the clarity, reliability, and suitability of the questionnaire items. Following the pilot test, the formal survey was administered to the main sample using a structured questionnaire.

Research Instruments

Data were collected using a self-administered questionnaire consisting of multi-item measurement scales. All constructs were adapted from previously validated instruments in the educational technology and smart learning literature, with modifications made to ensure suitability for the context of smart classrooms in Zhengzhou universities. The final questionnaire contained 41 measurement items. All items were measured using a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). The questionnaire was designed to measure respondents’ perceptions and experiences related to smart classroom learning environments.

Research Procedure

The study was conducted in several stages. First, relevant measurement items were identified from previous literature and adapted to fit the context of this study. Second, a pilot study involving 121 undergraduate students was carried out to evaluate item clarity, questionnaire structure, and completion time. Feedback from the pilot test and item analysis results were used to refine the questionnaire. After the revision process, the final questionnaire was distributed to undergraduate students in Zhengzhou universities who met the selection criteria. Respondents completed the survey voluntarily, and the collected data were screened and prepared for statistical analysis.

Data Analysis

The collected data were analysed using statistical analysis techniques to evaluate the reliability and validity of the measurement model and to test the proposed research framework. Reliability analysis indicated that Cronbach’s alpha and composite reliability values for all constructs exceeded the recommended threshold of 0.80, demonstrating strong internal consistency.

Confirmatory factor analysis (CFA) was conducted to assess construct validity and model fit. The results indicated a satisfactory model fit with $\chi^2/df = 1.422$, CFI = 0.983, TLI = 0.981, and RMSEA = 0.027. In addition, all factor loadings were statistically significant and exceeded 0.60, confirming convergent validity. Discriminant validity was also supported, as the square root of the average variance extracted (AVE) for each construct was greater than its correlations with other constructs.

3. Results

Data Screening and Preliminary Analysis

In this study, the survey data were cleaned, and the data with basically the same answers to all questions, contradictory answers, and too short answering time were excluded. Following the exclusion of outliers and invalid responses, 575 valid questionnaires remained for statistical analysis, which reflects the rigorous sampling procedure that was formulated in chapter 3. The demographic information is specified in the following table.

Table 1: Demographic Information

Categories	Characteristics	Frequency	Percent
Gender	Male	223	38.8%
	Female	352	61.2%
Grade	First Grade	244	42.4%
	Second Grade	167	29%
	Third Grade	144	25%
	Fourth Grade	20	3.5%
Subject	Liberal Arts	243	42.3%
	Science	86	15%
	Engineering	171	29.7%
	Medicine	4	0.7%
	Arts and Sports	71	12.3%
Experience of learning in smart classroom	More Than One Semester	353	61.4%
	More Than Two Semesters	96	16.7%
	More Than Three Semesters	87	15.1%
	More Than Four semesters	39	6.8%

The reliability of the measurement instrument was then assessed using Cronbach's alpha coefficients for each construct. All constructs, smart classroom, teachers, teaching methods, academic support, and smart classroom efficiency, demonstrated alpha values exceeding the acceptable threshold of 0.70, indicating satisfactory internal consistency reliability.

Following reliability assessment, an exploratory factor analysis (EFA) was conducted to examine the underlying factor structure of the measurement items. The EFA results supported the dimensionality of each construct as theoretically specified, with factor loadings meeting the minimum criterion and no significant cross-loadings identified. Subsequently, a confirmatory factor analysis (CFA) was performed for each construct individually. A comprehensive CFA including all measurement items was also conducted to evaluate the overall measurement model. The"CFA 'esults demonstrated acceptable model fit indices (χ^2/df, CFI, TLI, RMSEA, SRMR) for each construct and for the full measurement model, with all factor loadings being statistically significant and exceeding the recommended threshold, thereby establishing convergent validity.

Discriminant validity was assessed using the Fornell-Larcker criterion, comparing the square root of the average variance extracted (AVE) for each construct with the correlations between constructs. The results confirmed that the square root of AVE for each construct exceeded its correlations with all other constructs, providing evidence of discriminant validity. The correlation analysis further revealed significant positive relationships among the independent variables, moderators, and the dependent variable, consistent with theoretical expectations and providing preliminary support for the hypothesised associations.

Correlation Test

The results of the Pearson correlation analysis indicate that all independent variables, namely Smart Classroom (SC), Teaching Effectiveness (TE), and Technical Support (TS), are positively and significantly correlated with Sports Club Engagement (SCE). Specifically, SC shows the strongest correlation with SCE ($r = 0.568$, $p < 0.01$), followed by TE ($r = 0.522$, $p < 0.01$) and TS ($r = 0.516$, $p < 0.01$). In addition, the correlations among the independent variables range from 0.501 to 0.560, which are considered moderate and below the commonly accepted multicollinearity threshold of 0.80. Therefore, the findings suggest that the independent variables are related to the dependent variable while no serious multicollinearity problem exists. These results provide preliminary support for conducting further regression and structural analyses.

Table 2: Summary of Correlation Analysis

Variables	SCE	SC	TE	TS
SCE	1	.568**	.522**	.516**
SC	.568**	1	.560**	.501**
TE	.522**	.560**	1	–
TS	.516**	.501**	–	1

Note: p < 0.01 (2-tailed), N = 575.**. Correlation is significant at the 0.01 level (2-tailed)

Structural Equation Model

The calculation was carried out using AMOS, and the estimation was conducted using the maximum likelihood method. The results are shown in the following figure.

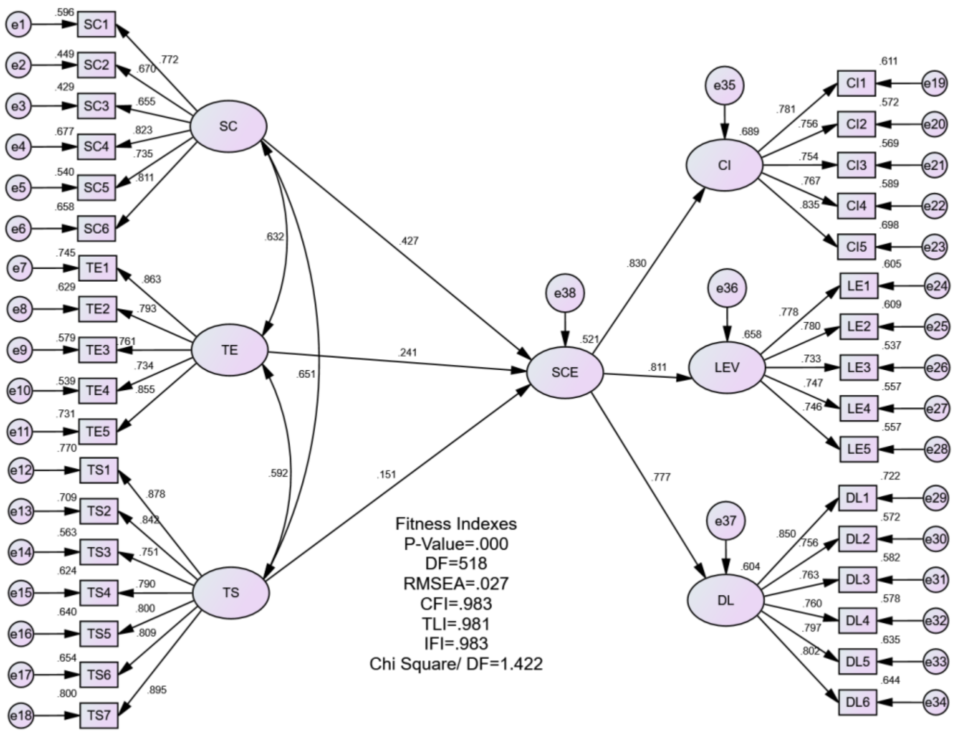

Figure 1: The Structural Equation Model

As presented in the above results, the model fit indices indicate a close alignment between the data and the theoretical framework. The value of CMIN/DF is 1.422, which meets the standard of being less than 3. GFI, AGFI, NFI, TLI, IFI, and CFI all reach above 0.9. RMR is 0.033, which is less than 0.08. RMSEA is 0.027, which is also less than 0.08. Since all indices meet established research thresholds, the model can be considered to demonstrate good fit.

Path Analysis

Based on the research questions and conceptual framework, this study proposed three research hypotheses H1-H3 about the independent variables to the dependent variable, corresponding to the three paths in the structural equation model, namely SC (Smart Classroom) to SCE (Smart Classroom Efficiency), TE (Teachers) to SCE (Smart Classroom Efficiency), and TS (Teaching Methods) to SCE (Smart Classroom Efficiency). According to the analysis results obtained from the AMOS software, the path coefficients and significance levels of the three paths in the structural equation model are shown in the following table.

Table 3: Path Coefficients and Significance of the Structural Equation Model

No.	Paths	B	β	S.E.	C.R.	P
H1	SC--->SCE	0.416	0.427	0.063	6.642	***
H2	TE--->SCE	0.198	0.241	0.046	4.305	***
H3	TS--->SCE	0.108	0.151	0.039	2.751	0.006

*** indicates $P < 0.001$

From the above table, it can be seen that the critical ratios (C.R.) of the three paths, H1, H2, and H3, are all greater than 1.96. The β value of SC on SCE is 0.427, $p < 0.001$. The β value of TE on SCE is 0.241, $p < 0.001$. The β value of TS on SCE is 0.151, $p = 0.006$. This indicates that at the 0.01 significance level, Smart Classroom, Teachers, and Teaching Methods have a significant positive impact on Smart Classroom Efficiency. Paths H1, H2, and H3 have all been verified and the three hypotheses are established.

The Moderating Effect of AS Between SC and SCE

As can be seen from the table above, the interaction term (SC*AS) between the moderating variable AS and the independent variable SC has a significant impact on the dependent variable SCE ($\beta = 0.084$, $p < 0.01$). After adding the interaction terms, the explanatory power of the model significantly improved ($\Delta R^2 = 0.007$, $p < 0.01$).

Table 4: The Moderating Effect Test Result of AS Between SC and SCE

	SCE			
	M1	**M2**	**M3**	**M4**
Gender	0.027	-0.005	-0.009	-0.006
Grade	0.099*	0.077*	0.079*	0.08*
Subject	0.017	0.019	0.03	0.034
Learning Experience	0.094*	0.03	0.002	-0.003
SC		0.557***	0.484***	0.467***
AS			0.345***	0.35***
SC*AS				0.084**
R Square	0.028	0.331	0.443	0.45
R Square Change	0.028	0.303	0.112	0.007
F	4.138**	56.43***	75.421***	66.306***

* indicates $p<0.05$; ** indicates $p<0.01$; *** indicates $P < 0.001$

As shown in the figure above, when the AS level is high, the positive influence of SC on SCE is stronger (with a steeper slope); when the AS level is low, the influence of SC on SCE is weaker (with a flatter slope).Overall, the moderating effect analysis indicates that AS significantly moderates the relationship between SC and SCE ($\beta = 0.084$, $p < 0.01$), and the model's explanatory power increases by 0.7% ($\Delta R^2 = 0.007$). The simple slope analysis shows that at higher AS levels, the promoting effect of SC on SCE is stronger.As a result, it can be concluded that AS has a positive moderating effect between SC and SCE. The hypothesis H4 is thus confirmed.

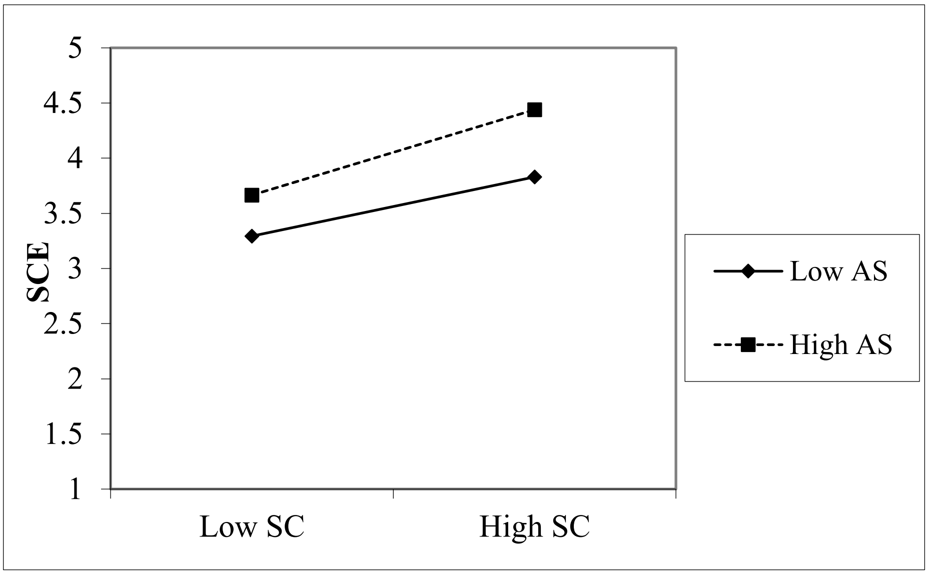

Figure 2: The Moderating Effect Diagram of AS Between SC and SCE

The Moderating Effect of AS Between TE and SCE

Taking gender, grade, subject, and learning experience as control variables, TE as the independent variable, AS as the moderating variable, and SCE as the dependent variable, a moderating effect test is conducted, and the results are shown in the following table.

Table 5: The Moderating Effect Test Result of AS Between TE and SCE

	SCE			
	M1	**M2**	**M3**	**M4**
Gender	0.027	0.026	0.019	0.022
Grade	0.099*	0.085*	0.087*	0.077*
Subject	0.017	0.045	0.05	0.045
Learning Experience	0.094*	0.033	0.011	0.003
TE		0.512***	0.414***	0.395***
AS			0.319***	0.372***
TE*AS				0.219***
R Square	0.028	0.285	0.376	0.421
R Square Change	0.028	0.257	0.091	0.045
F	4.138**	45.407***	57.029***	58.957***

* indicates p<0.05; ** indicates p<0.01; *** indicates P < 0.001

As can be seen from the table above, the interaction term (TE*AS) between the moderating variable AS and the independent variable TE has a significant impact on the dependent variable SCE ($\beta = 0.219$, $p < 0.001$). After adding the interaction terms, the explanatory power of the model significantly improved ($\Delta R^2 = 0.045$, $p < 0.001$).

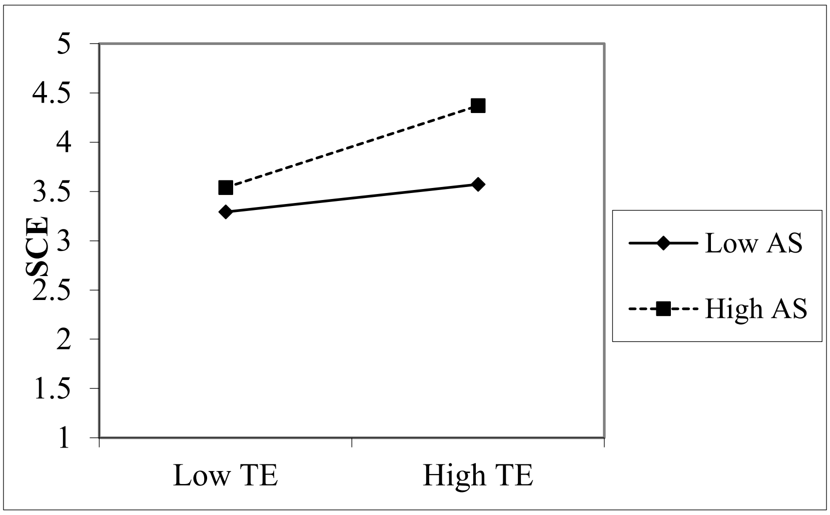

Figure 3: The Moderating Effect Diagram of AS Between TE and SCE

As shown in the figure above, when the AS level is high, the positive influence of TE on SCE is stronger (with a steeper slope); when the AS level is low, the influence of TE on SCE is weaker (with a flatter slope).Overall, the moderating effect analysis indicates that AS significantly moderates the relationship between TE and SCE ($\beta = 0.219$, $p < 0.001$), and the model's explanatory power increases by 4.5% ($\Delta R^2 = 0.045$). The simple slope analysis shows that at higher AS levels, the promoting effect of TE on SCE is stronger. As a result, it can be concluded that AS has a positive moderating effect between TE and SCE.

The Moderating Effect of AS Between TS and SCE

To test the moderating effect of AS on the relationship between TS and SCE, first, the correlation between the independent variable TS, the moderating variable AS, and the dependent variable SCE was calculated. The following table presents the results.

Table 6: Correlation between TS, AS, and SCE

		AS	TS	SCE
AS	Pearson Correlation	1	.239**	.455**
	Sig. (2-tailed)		.000	.000
	N	575	575	575

**. Correlation is significant at the 0.01 level (2-tailed)

From the above results, it can be seen that the moderating variable AS is correlated with the independent variable TS ($r = 0.239$) and the dependent variable SCE ($r = 0.455$), which supports the subsequent test of the moderating effect. Taking gender, grade, subject, and learning experience as control variables, TS as the independent variable, AS as the moderating variable, and SCE as the dependent variable, a moderating effect test is conducted, and the results are shown in the following table.

Table 7: The Moderating Effect Test Result of AS Between TS and SCE

	SCE			
	M1	M2	M3	M4
Gender	0.027	-0.02	-0.021	-0.014
Grade	0.099*	0.093*	0.093*	0.086*
Subject	0.017	0.03	0.039	0.041
Learning Experience	0.094*	0.048	0.019	0.011
TS		0.509***	0.43***	0.407***
AS			0.348***	0.364***
TS*AS				0.131***
R Square	0.028	0.283	0.396	0.412
R Square Change	0.028	0.254	0.113	0.016
F	4.138**	44.818***	62.009***	56.777***

** indicates p<0.05; ** indicates p<0.01; *** indicates P < 0.001*

As can be seen from the table above, the interaction term (TS*AS) between the moderating variable AS and the independent variable TS has a significant impact on the dependent variable SCE ($\beta = 0.131$, $p < 0.001$). After adding the interaction terms, the explanatory power of the model significantly improved ($\Delta R^2 = 0.016$, $p < 0.001$).

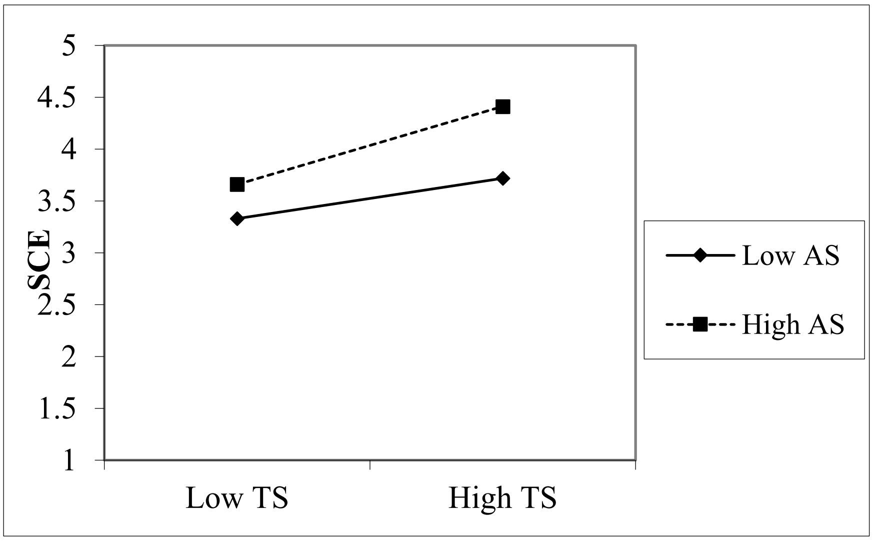

Figure 4: The Moderating Effect Diagram of AS Between TS and SCE

As shown in the figure above, when the AS level is high, the positive influence of TS on SCE is stronger (with a steeper slope); when the AS level is low, the influence of TS on SCE is weaker (with a flatter slope).Overall, the moderating effect analysis indicates that AS significantly moderates the relationship between TS and SCE ($\beta = 0.131$, $p < 0.001$), and the model's explanatory power increases by 1.6% ($\Delta R^2 = 0.016$). The simple slope analysis shows that at higher AS levels, the promoting effect of TS on SCE is stronger. As a result, it can be concluded that AS has a positive moderating effect between TS and SCE.

4. Discussion

The results of this study show that Smart Classroom (SC), Teachers (TE), and Teaching Methods (TS) all have significant positive effects on Smart Classroom Efficiency (SCE). Among the three variables, SC has the strongest influence (β = 0.427), followed by TE (β = 0.241) and TS (β = 0.151). This indicates that the quality of the smart classroom environment plays the most important role in improving learning efficiency, while teachers and teaching methods also contribute positively to students' learning experiences.

The strong effect of SC suggests that a stable and well-designed smart classroom environment is essential for effective learning. Functions such as interactive devices, reliable systems, flexible classroom layouts, and instant feedback can improve classroom participation and student engagement. When students can use the technology smoothly, they are more willing to participate in learning activities and communicate with teachers and classmates. This finding is consistent with previous studies showing that the usability and usefulness of educational technology are important factors influencing learning outcomes (Alfoudari & Durugbo, 2025; Guo, 2023). Teachers also play an important role in improving smart classroom efficiency. The findings show that teachers with strong professional knowledge, teaching skills, and technology literacy are better able to guide students and organise classroom activities effectively. In smart classroom settings, teachers are not only knowledge providers but also facilitators who encourage interaction, collaboration, and active learning. Their support and feedback help students maintain motivation and engagement during the learning process.

Compared with SC and TE, teaching methods have the smallest effect on SCE, although the relationship remains significant. This may be because the effectiveness of teaching methods depends heavily on both the classroom environment and teachers' ability to apply them properly. Methods such as collaborative learning, inquiry-based learning, and diversified assessment can improve students' learning experiences, but these methods require suitable technological support and effective classroom management. Therefore, teaching methods alone may not produce strong outcomes without support from the smart classroom environment and teachers. The moderation analysis further shows that Academic Support (AS) strengthens the relationships between SC, TE, TS, and SCE. Among the three moderating relationships, AS has the strongest effect on the relationship between TE and SCE (β = 0.219). This suggests that students benefit more from teachers when sufficient academic support is available. Guidance, feedback, learning resources, and peer support help students better understand course content and increase their willingness to participate in classroom activities.

AS also strengthens the relationship between TS and SCE (β = 0.131). This means that academic support helps students adapt to different teaching approaches, especially activities requiring collaboration and active participation. However, the moderating effect of AS on the relationship between SC and SCE is weaker (β = 0.084). One possible reason is that modern smart classroom systems are already designed to be user-friendly and easy to operate, reducing students' dependence on additional support for basic learning tasks.

Overall, the findings suggest that improving smart classroom efficiency requires the combined support of technology, teachers, teaching methods, and academic support. Among these factors, the smart classroom environment serves as the foundation, while teachers, teaching methods, and academic support help maximise the effectiveness of the learning process.

5. Conclusion

The findings demonstrate that impacts on smart classroom efficiency are not isolated but represent complex, interactive relationships among multiple factors. This study helps to promote holistic understanding of educational technology. This discovery carries important social implications by clarifying that while smart classrooms serve as carriers of information technology and represent innovation in teaching environments, they are by no means competitions in financial investment or contests of information technology application. The finding that Teacher factors (β = 0.241) and Teaching Methods (β = 0.151) exert independent effects comparable in practical significance to technological factors challenges reductionist views that equate smart classroom effectiveness with hardware sophistication. Similarly, the substantial moderating effects of Academic Support across all pathways demonstrate that organisational and support systems are not peripheral considerations but central determinants of whether technological investments translate into educational improvements.

This study provides society with evidence-based pathways for ensuring that educational technology investments fulfil their promised potential. The findings suggest that closing the utilisation gap of smart classrooms requires coordinated attention to teacher development, pedagogical innovation, management practices, and support systems, not just continued technological investment. This integrated perspective supports more effective allocation of societal resources toward educational improvement and more realistic expectations about the conditions necessary for technology to meaningfully enhance learning outcomes.

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