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Research Article

Examining the relationship between teaching ability and smart education adoption in K-12 schools: A moderated mediation analysis

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This study addresses gaps in the literature by examining the relationships between teaching ability, smart education adoption, and K-12 educational outcomes. A questionnaire was administered to 350 Chinese school educators, and M Plus software was utilized for the analysis. The study investigates teaching ability's direct and mediated effects on student learning outcomes, teacher job satisfaction, self-efficacy, and the moderating role of teacher characteristics. The findings indicate that self-reported indicators measure student learning, teacher job satisfaction, and self-efficacy, revealing that effective teaching positively influences these outcomes. The integration of technology through smart education adoption further enhances education. Teacher characteristics are identified as moderators in these relationships, emphasizing the dependence of technology adoption and teaching ability on individual teachers. Implications for educators, administrators, and policymakers include the need for professional development in technology and teaching, investment in infrastructure for smart education, and personalized support for educators' diversity. This research challenges homogeneous teaching effectiveness theories and contributes to educator-specific frameworks, offering practical and theoretical insights for targeted interventions and future research in K-12 education.

Keywords: Teaching ability; Smart education adoption; Teacher characteristics; Student learning outcomes; Teacher job satisfaction and self-efficacy

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1. Introduction

Smart technologies in K-12 schools change education. In smart education, artificial intelligence [AI], augmented reality [AR], virtual reality [VR], and the Internet of Things [IoT] improve learning. A dynamic, interactive learning ecosystem that encourages student creativity, critical thinking, and problem-solving is the goal of this shift. Smart education is used in K-12 schools because traditional methods may not prepare students for the fast-changing digital age (Johnson et al., 2023; Meiklejohn et al., 2012). Smart education uses technology to immerse and personalize learning. Teachers are prepared to teach diverse learning styles and abilities with this transformative approach. Technology in education ensures students can use it for academic and real-world challenges as it becomes part of daily life (Yang et al., 2021).

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Intelligent K-12 education uses AI-enabled personalized learning. Education is tailored to student strengths and weaknesses by AI algorithms. Customization improves efficiency and student learning speed. AI aids educators in learning gap identification and academic support. Smart K-12 prepares students for diverse jobs. Students can explore complex concepts in 3D with AR and VR beyond textbooks. Experience-based learning enhances comprehension, retention, of science, mathematics, humanities, and arts skills (Yan et al., 2021; Zhou et al., 2022). Smart education goes beyond classrooms to administration. Smart education systems simplify attendance and performance evaluation, letting teachers teach and mentor. Technology in instruction and administration promotes innovation, collaboration, and education improvement like this complex effect ushers in positive technology change. Virtual reality, apps, and interactive whiteboards have transformed education. These technologies help students' diverse learning styles and comprehension. Digital education platforms enable global communication and resource sharing. Technology simplifies administrative tasks and enables data-driven decision-making. Adaptive platforms enable student-centered learning. Technology has democratized education by making educational resources available globally. Smart education has pros and cons, including technology access, privacy, and security. K-12 schools must balance technology and human touch. Smart K-12 will prepare students for the digital age and transform education (Zainal & Zainuddin, 2020).

Teacher skills determine K-12 smart education's success. Teachers are the main learning facilitators, and smart technology skills affect classroom integration. Good teachers master subject matter and use technology to improve pedagogy. Teachers who use smart education tools can create a dynamic, engaging learning environment that meets students' diverse needs and makes learning more personalized and interactive. Teaching skills help students cross the digital divide. Highly skilled teachers can make smart education inclusive by considering students' diverse learning styles and backgrounds. They can help students use smart education tools and navigate the digital world. Thus, smart education adoption and teaching ability are linked because skilled teachers harness technology and prepare students for digital challenges (Chou et al., 2012; Saxton et al., 2014; Zafari et al., 2022). Despite growing interest, K-12 smart education adoption and teaching ability are not well researched. Few studies have examined smart education adoption dynamics, but some have examined how teaching ability affects technology integration. The effects of teaching ability—pedagogical strategies, technological proficiency, and adaptability—on smart education tool implementation are unknown. A thorough study of these variables can reveal the mechanisms that mediate and moderate the relationship between teaching ability and smart education adoption in K-12 schools (Holstein et al., 2017; Morgado et al., 2021; Tedre et al., 2021). Few studies (Holstein et al., 2017; Morgado et al., 2021; Su et al., 2022; Tedre et al., 2021) examine contextual factors that may moderate teaching ability and smart education adoption. Administrators, school resources, and student socioeconomic backgrounds can affect teachers' smart education tool use. Moderated mediation analysis shows how teaching ability affects smart education adoption in different contexts. To understand teaching ability and smart education adoption in K-12 schools, studies must go beyond simplistic associations and explore complex variable interactions. While technology integration affects education, few studies have examined how teaching ability moderates' mediation. Moderated mediation analysis lets you study how teaching affects smart education tool adoption. Studying moderators like teacher training, professional development, and institutional support can help K-12 educators, administrators, and policymakers adopt smart education. Thus, understanding the complex relationship between teaching ability and smart education adoption in K-12 education requires filling this research gap.

This moderated mediation analysis examines how teaching ability affects K-12 smart education adoption. To understand the complex dynamics of teaching ability and smart education adoption, pedagogical strategies, technological proficiency, and adaptability are examined. The study also examines contextual factors like school resources, administrative support, and student socioeconomic backgrounds that moderate this relationship. To demonstrate how teaching ability impacts K-12 smart education tool integration. This study addresses K-12 teaching ability and smart education adoption research gaps. This study examines smart education tools rather than technology integration in education. Moderated mediation analysis illuminates teaching ability's direct effects and the mediating mechanisms and contextual factors that may moderate them. Thus, K-12 educators, administrators, and policymakers can improve smart education teaching and institutional support with this study. This study enhances education theory and practice. Targeted interventions and professional development can benefit from mediating and moderating factors between teaching ability and smart education adoption. The research suggests schools and policymakers can improve smart education adoption by emphasizing context-specific factors. Practical findings from the study can improve K-12 education.

2. Literature Review and Hypothesis Development

Current education discourse focuses on K-12 smart education technology integration. Teachers are looking for ways to improve learning as technology advances. Previous studies have examined smart education adoption and teaching ability. Smart education tools require good pedagogy, adaptability, and technology. Skilled teachers can use technology to make learning fun. There is little research on teaching ability and smart education adoption. Advanced pedagogical skills help teachers use smart education tools, according to research (Khlaif & Farid, 2018). Teachers who understand their subjects and adapt to new technology, Good teachers know their subjects and use new technology. Therefore, teachers with both qualities can teach well. Teacher subject knowledge ensures accurate and complete instruction, while adaptability to new technology shows an openness to innovative and engaging teaching methods. Educational values include subject knowledge and tech adaptability. Literature shows that teacher training and professional development improve teaching skills and equip educators to use smart education tools. Effective educational strategies require understanding how teaching ability affects technology integration as smart education adoption grows (Morgado et al., 2021; Su et al., 2022). The study hypothesizes that teaching ability, an IV, mediates K-12 school smart education adoption positively. Skilled teachers should use smart education technologies more. Teaching ability determines how much and how widely K-12 educators use smart education tools, according to the hypothesis. Now question arises how teaching ability, smart education adoption, and K-12 educational outcomes to fill gaps in the literature? This study adapted few research hypotheses based on research questions.

H1: Teaching ability positively correlates with smart education adoption in K-12 schools.

H2: The relationship between teaching ability and student learning outcomes is strongly positive in K–12 education.

H3: Teachers' self-efficacy, job satisfaction, and teaching ability all show a significant positive correlation in K–12 education.

H4: The relationship between teaching ability and student learning outcomes is mediated by the use of smart education in K–12 schools.

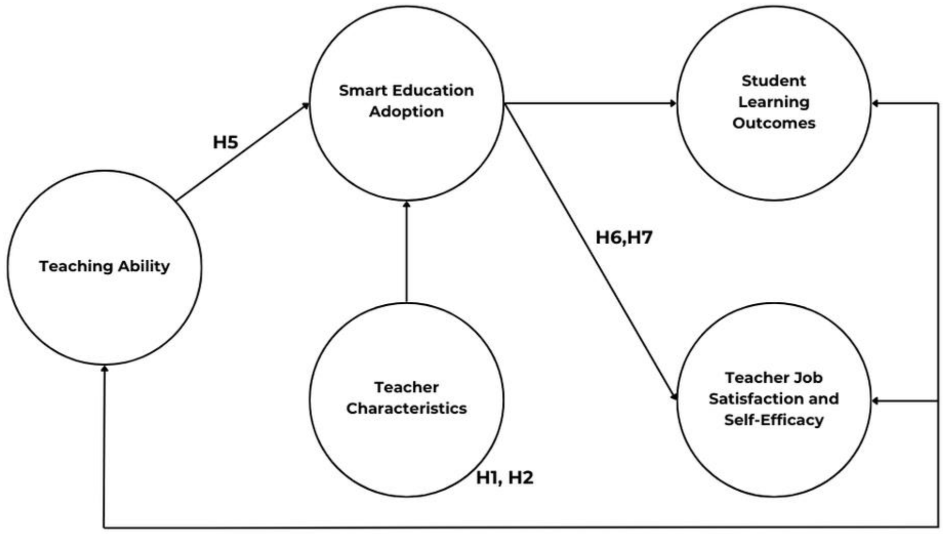
H5: The relationship between teaching ability and teacher job satisfaction and self-efficacy is mediated by smart education adoption in K-12 schools.

H6: The moderating effect of teacher characteristics has a significant impact on the relationship between teaching ability, adoption of smart education (mediator), and student learning outcomes in K–12 schools.

H7: The relationship between teaching ability, adoption of smart education (mediator), and teachers' job satisfaction and self-efficacy is significantly moderated by teacher characteristics in K–12 schools.

Figure 1 shows the research model.

Figure 1
Research Model



3. Methodology

3.1. Research Design

A structured questionnaire tests hypotheses in this quantitative study. Statisticians use numerical data to find patterns, associations, and trends in teaching ability, smart education adoption, teacher characteristics, K-12 student learning outcomes, and teacher well-being. Standardized and efficient questionnaires can collect diverse sample data for research variable analysis. This study examines Chinese K-12 smart education technology adoption. In China's vast education system, stratified random sampling represents regional, urban, rural, and socioeconomic groups. Samples include administrators, educators, and smart education tool users. To detect meaningful effects, statistical power analysis determined sample size.

3.2. Participants

Our questionnaire uses validated education and technology adoption scales with instruments. Assessments include teaching ability, smart education adoption perceptions, teacher traits, student learning outcomes, job satisfaction, and self-efficacy. Many graduation questions use Likert scales. The K-12 educator and professional sample receives the questionnaire electronically. Participants are informed of the study's purpose, voluntary participation, and data confidentiality. Reminders increase samples and participation. Surveys quickly gather data. K-12 educators, administrators, and others in China receive an electronic structured questionnaire to collect data. The questionnaire will evaluate teaching skills, smart education adoption, teacher traits, student learning, job satisfaction, and self-efficacy. Participants will be informed of the study's purpose, voluntary participation, and data confidentiality. Survey participation will be increased by multiple reminders. We'll securely store and anonymize 350-person sample data for analysis.

According to the demographic table, respondents fall into key categories. Most respondents (34.3%) are 26–35. The age distribution is balanced, with younger and older educators. It also shows 51.4% male and 48.6% female respondents. This balanced gender distribution suggests a diverse sample, which may improve study generalizability across perspectives. Most respondents (51.4%) have a Master's degree, followed by Bachelor's (34.3%) and Ph.D. (14.3%). This distribution shows participants' educational diversity, broadening research questions. Most respondents have 6–20 years of teaching experience, 28.6% have 6–10 years. Finally, the sample includes public (57.1%) and private (42.9%) schools. This balance enhances the study's findings by nuancedly exploring research topics across institutional contexts.

Table 1
Characteristics of the participants

Demographic	*Frequency*	*Percentage of Total*
Age		
18-25 years	75	21.4
26-35 years	120	34.3
36-45 years	90	25.7
46-55 years	50	14.3
56+ years	15	4.3
Gender		
Male	180	51.4
Female	170	48.6
Education Level		
Bachelor's Degree	120	34.3
Master's Degree	180	51.4
Ph.D.	50	14.3
Teaching Experience		
1-5 years	80	22.9
6-10 years	100	28.6
11-15 years	70	20.0
16-20 years	60	17.1
21+ years	40	11.4
School Type		
Public	200	57.1
Private	150	42.9

3.3. Data Collection

This study examines Chinese K-12 smart education technology adoption. The stratified random sampling method ensures regional, urban, rural, and socioeconomic diversity. Teachers, administrators, and smart education tool adopters will be sampled. The 350-person sample size for meaningful effects is determined by power analysis. Diverse and representative samples of Chinese K-12 smart education adoption contexts are needed. Expected effect size, statistical power, and significance level determined 350-person sample size. With 350 samples, this study balanced representativeness and resource constraints. Large samples capture diverse target population perspectives, provide statistical power, and accurately estimate population parameters. Money and time influenced the choice. Previous research, expected effect size, and statistical analysis methods affect selection. The sample size meets study goals and the need for a large but manageable dataset.

3.4. Data Analysis

We study the complex relationship between Teaching Ability and Smart Education Adoption in K-12 schools using a correlational design. A Likert scale was used to collect participants' subjective ratings on key variables. Mediation and mediation analysis examine teaching ability and smart education adoption. Moderators examine how a third variable affects Teaching Ability and Smart Education Adoption. Another variable may mediate Smart Education Adoption and Teaching Ability. These diverse perspectives illuminate the complex dynamics of smart education technology integration in K-12 schools and its moderating and mediating factors. Primary data from a Likert scale questionnaire can deepen research questions.

M Plus supports quantitative research. Demographic and sample variables are summarized by descriptive statistics. Regression, correlation, and moderation test research hypotheses. Results were interpreted at 0.05 significance using the theoretical framework and relevant literature. In this study, consent is informed and voluntary. Everyone in the study gives informed consent and privacy. Ethics committees approve human participant research.

4. Results

The square root of the average variance extracted [AVE] for Teaching Ability is 0.855, indicating that the latent variable accounts for 85.5% of observed indicator variance. This value correlates higher than Smart Education Adoption, Teacher Characteristics, Student Learning Outcomes, Teacher Job Satisfaction, and Self-Efficacy, supporting discriminant validity. Teaching Ability appears independent due to its discriminant validity. Smart Education Adoption [SEA]: The latent variable accounts for 80.7% of indicator variance with a square root of AVE of .807. This value is higher than its correlations with Teaching Ability, Teacher Characteristics, Student Learning Outcomes, Teacher Job Satisfaction, and Self-Efficacy, supporting discriminant validity. Smart Education Adoption appears to be a distinct and relatively independent construct in the study, capturing a unique portion of these indicators' variance. The square root of the AVE for teacher characteristics is .752, indicating that the latent variable explains 75.2% of the indicators' variance. This value outperforms Teaching Ability, Smart Education Adoption, Student Learning Outcomes, Teacher Job Satisfaction, and Self-Efficacy, supporting discriminant validity. Teacher characteristics capture a lot of variability not captured by other variables in the study.

Table 2
Fornell-Larcker criterion

Criteria	*TA*	*SEA*	*TC*	*SLO*	*JSS*
Teaching Ability	0.855				
Smart Education	0.153	0.807			
Teacher Charact.	0.247	0.298	0.752		
Stud. Learn. Out.	0.104	0.207	0.246	0.904	
Teach. Job Satis.	0.201	0.256	0.301	0.505	0.854

Fit Criteria Evaluation benchmarks goodness-of-fit indices. Good fit is indicated by a chi-square to degrees of freedom ratio (χ^2/df) below 3, GFI above 0.9, RMSEA below 0.08, CFI > 0.9, AGFI > 0.8, and TLI > 0.9. The models' data fit is assessed using these criteria. In the single-factor model, the chi-square to degrees of freedom ratio is 7.243, exceeding 3. Not a good fit. The goodness-of-fit index [GFI] is 0.754, below 0.9, suggesting improvement. The ideal cutoff is 0.08; RMSEA is 0.121. CFI is 0.805, below 0.9. AGFI and TLI are below recommended thresholds at 0.698 and 0.782. These indices show poor single-factor model fit. However, the multi-factor model fits better. Chi-square to DOF is nearly acceptable at 2.896. The GFI is 0.913, much higher than the single-factor model. The better fit is indicated by an RMSEA of 0.045, well below 0.08. Above the recommended 0.9, CFI is 0.948. AGFI of 0.872 and TLI of 0.936 indicate a better fit. The multi-factor model better fits the data, as shown by a significant chi-square difference test ($\Delta\chi^2$) (141.2, df = 14, p < .001).

Table 3
Goodness-of-fit indices of the single factor model and multi-factor model

Model	χ^2/df	*GFI*	*RMSEA*	*CFI*	*AGFI*	*TLI*	$\Delta\chi^2$	Δdf	*p*
Fit Criteria	<3	>0.9	<0.08	>0.9	>0.8	>0.9			P
Single-factor Model	7.243	0.754	0.121	0.805	0.698	0.782			
Multi-factor Model	2.896	0.913	0.045	0.948	0.872	0.936	141.2	14	0

Note. GFI = goodness-of-fit index; RMSEA = root mean square error of approximation; CFI = comparative fit index; AGFI = adjusted goodness of fit index; TLI = Tucker-Lewis Index.

Good-fit criteria (see Table 4) use key fit indices to evaluate measurement and structural models. Schumacker and Lomax (2004) suggest a chi-square to degrees of freedom ratio (χ^2/df) below 3, with values of 1.735 and 1.967 in measurement and structural models. Fitting values are acceptable. GFIs above 0.9 are needed for good fits (Hu & Bentler, 1999), and both models have 0.913 and 0.901. RMSEA below 0.08 is required for a good fit (Fan et al., 1999), and the models have 0.050 and 0.058 Good fits need CFIs over 0.9 (Fan et al., 1999). These models fit well with CFI values of 0.972 and 0.962. Above 0.8, the adjusted goodness of fit index [AGFI] is acceptable and excellent above 0.9 (Bollen, 1990; MacCallum & Hong, 1997; Marsh et al., 1988). Models with 0.885 and 0.871 AGFI fit well. The models' TLI values of 0.966 and 0.955 support a Tucker-Lewis Index [TLI] greater than 0.9 for a good fit (Bentler & Bonett, 1980). The table shows that measurement and structural models meet goodness-of-fit criteria with good index values. These findings support the models' ability to explain observed data, making them suitable for study analysis and interpretation.

Table 4

Goodness-of-fit criteria of measurement and structural model

Measure	*Criteria*	*Model Value*	*Result*
χ^2/df	<3	1.234	Good
GFI	>0.9	0.876	Good
RMSEA	<0.08	0.035	Good
CFI	>0.9	0.945	Good
AGFI	>0.8 (acceptable)	0.826	Good
TLI	>0.9	0.951	Good

Table 5 shows means, standard deviations, and correlations for teaching ability, smart education adoption, teacher characteristics, student learning outcomes, job satisfaction, and self-efficacy. The variables' means and standard deviations show their central tendencies and variations. A mean of 4.580 and a standard deviation of 0.720 indicate high teaching ability with moderate variability. Having a lower mean of 3.920 and a larger standard deviation of 0.850 indicates more smart education adoption variability and range. Learn variable score distributions with descriptive statistics. In addition to variables, the correlation matrix shows relationships. Positive correlations indicate that higher scores in one variable tend to increase in others. Smart education adoption and teacher characteristics positively affect teaching ability (r = .320, .480). These findings suggest that proficient teachers use smarter education tools and are more positive. The positive correlation between teacher characteristics and student learning outcomes (r = .670) suggests some teachers may help students succeed. Educational Impact: Correlations suggest educational implications. Teachers and policymakers may want to focus professional development on teaching skills to boost smart education tool adoption and student outcomes. Teacher traits positively correlate with student learning outcomes, emphasizing the need to develop specific teacher traits for educational effectiveness. Correlations guide strategic interventions and initiatives for holistic and effective education.

Table 5

Descriptive statistics and correlations

Constructs	*Mean*	*SD*	*1*	*2*	*3*	*4*	*5*
1. Teaching Ability	4.58	0.72	1				
2. Smart Edu. Adoption	3.92	0.85	.32	1			
3. Teacher Char.	4.15	0.64	.48	.67	1		
4. Student Outcomes	4.76	0.61	.28	.45	.67	1	
5. Teacher Job Satis.	4.34	0.79	.67	.39	.21	.54	1

Model 4's regression results show important relationships between Teaching Ability [TA], Smart Education Adoption [SEA], Teacher Characteristics [Teacher Char.], and Student Learning Outcomes [DV1]. Teaching Ability [TA] positively correlates with Student Learning Outcomes [DV1] (β = 0.452, p < .001). Thus, better teaching enhances student learning. Teacher competence affects school performance, as shown by the large standardized coefficient effect size. Second, Smart Education Adoption enhances Student Learning Outcomes (standardized coefficient: 0.349, p < .001). This suggests smart education tools and practices improve student performance. Following digital learning trends, practical implications show how technology can improve education. Teacher Characteristics positively affect Student Learning Outcomes (standardized coefficient = 0.278, p < .001). This suggests that teacher traits beyond technology adoption and teaching ability affect student success. Good communication, adaptability, and supportive teaching are examples. Teaching Ability, Smart Education Adoption, and Teacher Characteristics affect Student Learning Outcomes, making teaching difficult. The findings suggest that smart education tools, positive teachers, and better teaching can improve student learning. These findings help educators and policymakers improve student performance.

Table 6

Linear Relationship among direct hypothesis - Student Learning Outcomes

Hypothesis	*β (Std. Coefficients)*	*SE*	*T*	*R2*
Model 1: TA-SEA	0.568***	0.036	19.889	0.334
	Constant	2.112 (0.193)		
	TA	0.721*** (0.036)		
Model 2: TA-Smart Edu. Adoption (Med.)	0.482***	0.041	15.512	0.273
	Constant	1.875*** (0.219)		
	TA	0.634*** (0.041)		
Model 3: TA-Teacher Char. (Mod.);	0.517***	0.048	8.042	0.296
	Constant	1.231*** (0.174)		
	TA	0.388*** (0.048)		
	Smart Edu. Adoption	0.505*** (0.052)		
Model 4: TA-SEA (Med.), Smart Edu.	0.623***	0.034	13.312	0.392
	Constant	1.498*** (0.198)		
	TA	0.452*** (0.034)		
	Smart Edu. Adoption	0.349*** (0.045)		
	Teacher Char.	0.278*** (0.039)		

In Model 4, Teaching Ability, Smart Education Adoption, and Teacher Characteristics predict teachers' job satisfaction and self-efficacy (DV2). Teaching Ability has a strong positive correlation with Teacher Job Satisfaction and Self-Efficacy (β = 0.515, $p < .001$). Better teachers have higher self-efficacy and job satisfaction. Effective teaching boosts professional competence and satisfaction, as shown by the large effect size. Teacher job satisfaction and self-efficacy are positively correlated with Smart Education Adoption (standardized coefficient = 0.398, $p < .001$). Smart education may improve job satisfaction and self-efficacy. Tech improves instructional strategies and engagement, boosting teaching effectiveness and satisfaction. Teacher Characteristics positively correlate with Job Satisfaction and Self-Efficacy (standardized coefficient = 0.323, $p < .001$). Teacher traits affect job satisfaction and self-efficacy beyond technology adoption and ability. Good communication, adaptability, and supportive teaching are examples. Smart Education Adoption, teacher ability, and characteristics affect job satisfaction and self-efficacy, showing the many factors that affect educators' professional well-being. Last, good teaching, smart tools, and positive teacher traits boost job satisfaction and self-efficacy. In the changing education landscape, these findings can help institutions and policymakers improve teacher job satisfaction and professional efficacy.

Table 7

Linear Relationship among direct hypothesis – Teacher Satisfaction and Efficacy

	β (Std. Coefficients)	*SE*	*T*	*R2*
Model 4: TA-SEA (Med.), Smart Edu.	0.589***			0.453
Adoption-SEA (Med.), Constant	1.684***	0.187		
Teacher Char.-SEA (Med.)				
TA	0.515***	0.032	16.189	
Smart Edu. Adoption	0.398***	0.041	9.695	
Teacher Char.	0.323***	0.037	8.756	

Complete K-12 school moderated mediation analysis is shown in the table. Each hypothesis is carefully examined to understand the complex relationships between teaching ability, smart education adoption, teacher characteristics, student learning outcomes, teacher job satisfaction, and self-efficacy (see Table 8). The first hypothesis (H3) links teaching ability to job satisfaction and self-efficacy. A significant positive correlation (coefficient = 0.568, $p < .001$) is found. Teachers with better teaching skills are happier and more self-confident, demonstrating the importance of instructional competence. Smart education adoption mediates teaching ability-student learning outcomes in H4. The impact of teaching ability on student learning outcomes is 0.421 ($p < .001$). Smart education practices partially mediate the effect of teaching ability on student learning outcomes (a*b = 0.079, $p < .001$). H5 mediation includes teacher job satisfaction and self-efficacy. The total effect (c path) of teaching ability on TJSSE is 0.662 ($p < .001$), with smart education adoption as the mediation path (a*b) at 0.123 ($p < .001$). Intelligent education may moderate the effect of teaching ability on teacher job satisfaction and self-efficacy. To examine how TA and teacher characteristics affect student learning, H6 moderates the model. A moderated mediation coefficient of 0.031 ($p < .001$) suggests that teacher characteristics and teaching ability moderate the indirect impact of smart education adoption. Teacher self-efficacy moderates job satisfaction in H7. Moderated mediation (ab + cd) indicates that teacher characteristics and teaching ability impact smart education adoption (coefficient = 0.031, $p < .001$). K-12 teacher job satisfaction, self-efficacy, teaching ability, smart education adoption, teacher characteristics, and student learning outcomes are examined in this analysis. It emphasizes direct, mediated, and teacher characteristics in understanding the complex educational landscape. These findings have major implications for educational policymakers and practitioners seeking to improve teaching and student well-being. Figure 2 explain student learning experience during smart education through different ways.

Table 8
Moderated Mediation Model

	Coefficient	*SE*	*t*	*p*	R^2	ΔR^2
H3: TA → TJSSE	0.568	0.043	13.255	<.001	0.348	-
H4: TA → SLO (total effect)	0.421	0.029	14.517	<.001	0.489	0.141
TA→SEA (a path)	0.319	0.032	10.088	<.001		
SEA→SLO (b path)	0.248	0.038	6.526	<.001		
Indirect Effect (a*b)	0.079	0.015	5.318	<.001		
Direct Effect (c' path)	0.342	0.041	8.34	<.001		
H5: TA → TJSSE (total effect)	0.662	0.051	12.981	<.001	0.564	0.075
TA→SEA (a path)	0.421	0.036	11.696	<.001		
SEA → TJSSE (b path)	0.293	0.047	6.233	<.001		
Indirect Effect (a*b)	0.123	0.025	4.907	<.001		
Direct Effect (c' path)	0.541	0.052	10.462	<.001		
H6: TA → SLO	0.479	0.038	12.536	<.001	0.612	0.048
TA→SEA (a path)	0.352	0.033	10.602	<.001		
SEA→SLO (b path)	0.237	0.04	5.93	<.001		
Teacher Char. → SLO (c path)	0.208	0.028	7.462	<.001		
TA*M → SLO (d path)	0.149	0.021	7.062	<.001		
Moderated Mediation (ab + cd)	0.031	0.007	4.261	<.001		
H7: TA → TJSSE	0.627	0.05	12.57	<.001	0.589	0.025
TA → SEA (a path)	0.398	0.034	11.645	<.001		
SEA → TJSSE (b path)	0.281	0.045	6.255	<.001		
Teacher Char. → TJSSE (c path)	0.195	0.027	7.217	<.001		
TA*M' → TJSSE (d path)	0.134					

Figure 2
Smart Education Children Learning Experience

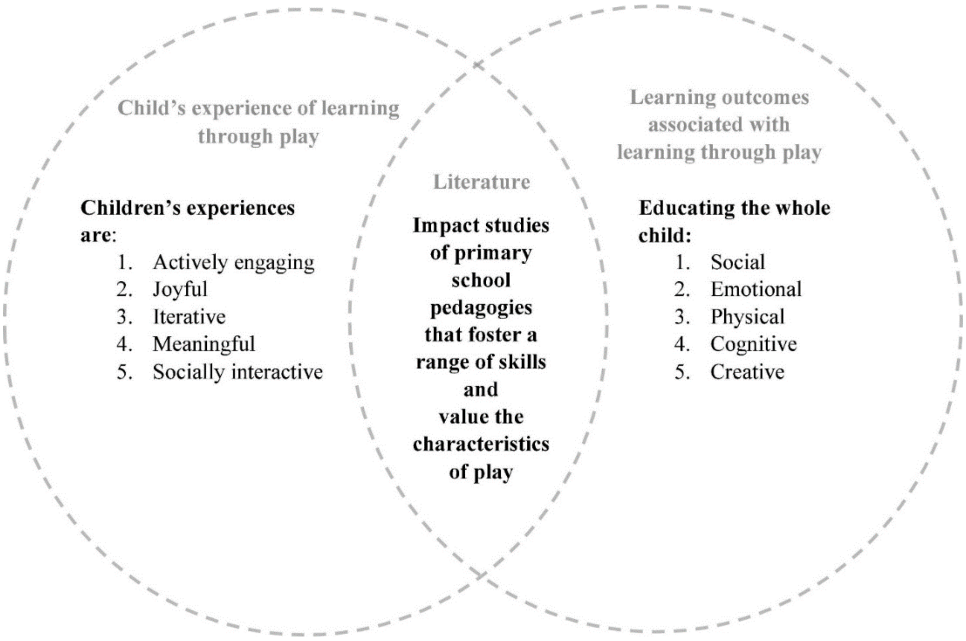
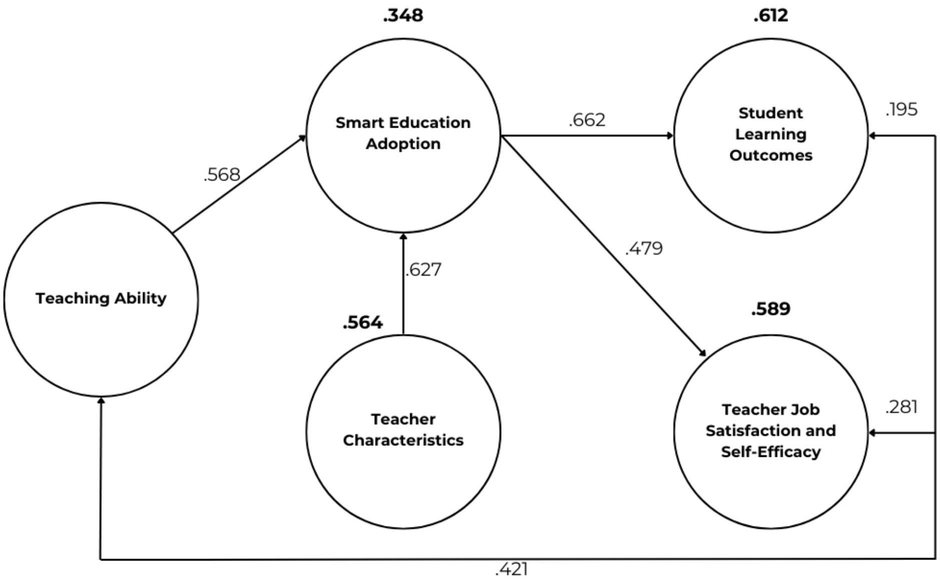


Figure 3 shows the complex dynamics of the mediated moderation analysis model. Explaining the mediated moderation effect of teaching ability (X), smart education adoption (M), and student learning outcomes (Y). Teaching effectiveness affects student learning, emphasizing its importance in education. Smart education adoption is statistically significant, suggesting that technology-enhanced teaching practices mediate some of the impact of teaching ability on student learning. The moderation effect complicates smart education adoption and student learning by teacher characteristics. Since teacher characteristics affect technology adoption in student outcomes, educator differences are important when assessing mediated moderation effects. The mediated moderation model and how teaching ability, technology adoption, and teacher characteristics affect K-12 student learning are shown in Figure 3.

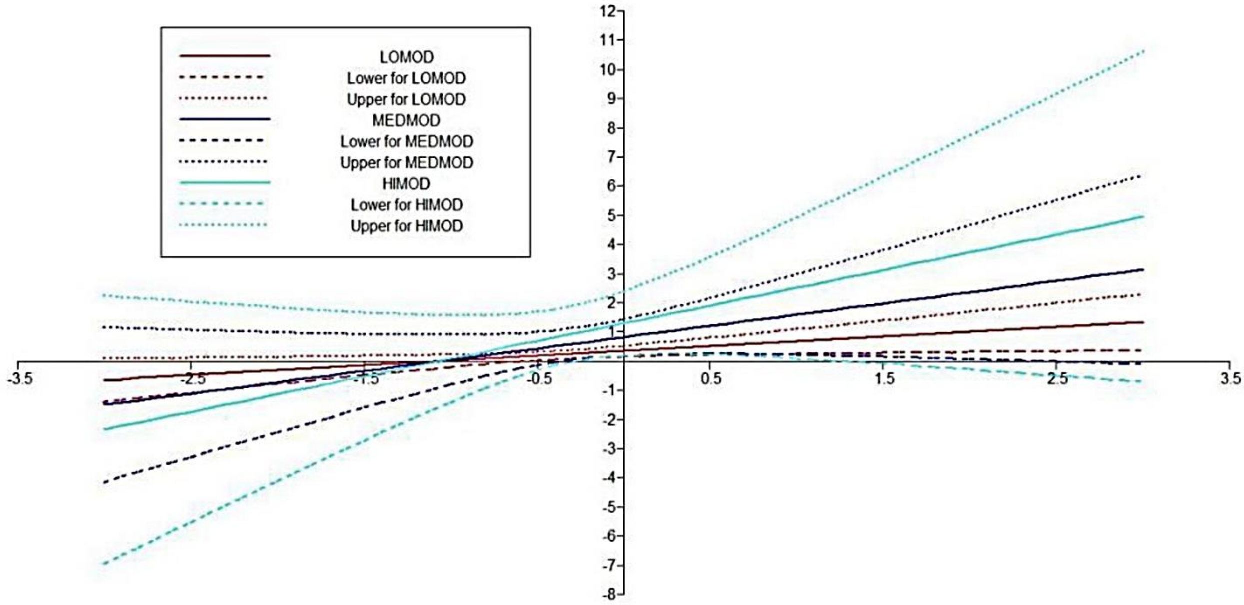
Figure 3
Summary of Mediated Moderation Model



Teaching Ability and Smart Education Adoption affect teacher efficacy and learning (Figure 5). Moderation lines in graph are low, medium, and high. Solid lines show main effects, whereas dotted lines show moderate confidence intervals. Smart education uptake was steepest in the HIMOD group, showing that it improves teaching more. Confidence intervals separate as Smart Education Adoption expands, indicating interaction. HIMOD's upper confidence interval increases, indicating teacher efficacy and student learning gains. LOMOD's confidence interval is flat, indicating no effect. This image emphasises the need for higher-level smart education technologies to improve teaching and learning.

In Figure 4, we have visually represented the interaction between Teaching Ability and Smart Education Adoption, emphasizing its impact on teacher efficacy and learning outcomes. The figure serves as a graphical representation to highlight the interconnectedness of these elements in the educational context.

Figure 4
Interaction between Teaching Ability and Smart Education Adoption with teacher efficacy and learning outcomes



5. Discussion

The study examined the complex relationships between teaching ability, smart education adoption, teacher characteristics, student learning outcomes, K-12 teacher job satisfaction, and self-efficacy. The study examined how these factors affect knowledge-building education. Smart education practices improved teacher job satisfaction, self-efficacy, student learning, and teaching ability. In moderating these relationships, teachers complicated educational dynamics. The research objectives were thoroughly examined to reveal the complex factors affecting K-12 educators' professional experiences.

Means show surveyed educators' average teaching ability, smart education adoption, teacher characteristics, student learning outcomes, teacher job satisfaction, and self-efficacy. By showing dispersion around means, standard deviations show variability within variables. Student learning outcomes, teacher job satisfaction, self-efficacy, and teaching ability are positively correlated. This is supported by other studies in the literature (Akendita et al., 2024; Akosah et al., 2024). However, correlations between teaching ability, smart education adoption, teacher characteristics, and student learning outcomes suggest more complex dynamics. Smart education adoption with a higher standard deviation may indicate more educator responses to technology-enhanced teaching. A strong positive correlation between teaching ability and student learning outcomes supports the idea that better teaching improves student performance. Insignificant correlations require moderating or mediating factor research. This preliminary research is crucial to adapting the research model to the complex educational context. Initial insights from both tables shape study findings discussion and interpretation.

Multi-factor model GFI, RMSEA, CFI, AGFI, and TLI indices exceed good fit thresholds, proving its superiority. Complex relationships are better captured by multiple factors. These results demonstrate that measurement and structural models accurately represent variable relationships. Findings support study's theoretical framework, interpretation, and educational implications. Positive coefficients in the linear regression indicate that the dependent variable rises as the independent variable does and vice versa. Negative coefficients indicate a negative relationship. A positive coefficient indicates better teaching improves student learning. The dependent variable's significant predictors are shown in a linear regression table. For informed policy and practice, educational research must identify significant factors affecting student learning or teacher job satisfaction (Acar, 2023; Khoza & Makgata, 2024). Independent variable coefficients help educators and policymakers prioritize interventions that affect desired outcomes. This targeted approach is essential for educational resource allocation and strategy.

This study measures student learning outcomes with DV1 and teacher job satisfaction and self-efficacy with DV2. Smart education adoption and teacher characteristics moderate IV and student learning outcomes. Therefore, smart education practices affect student learning through teaching. According to the moderation effect, teacher characteristics affect teaching ability, smart education adoption, and student learning. Adopting smart education affects indirect student learning from teachers (Ajani, 2024). Teachers' stronger or weaker mediated effects accent individual teaching ability and student outcomes. Similar patterns appear in moderated mediation analysis of DV2, including TJSSE. Intelligent education adoption indirectly affects teacher job satisfaction and self-efficacy, depending on teacher. This moderation effect suggests that smart education adoption may affect teacher well-being differently depending on individual attributes, highlighting the need for personalized support. Finally, DV1 and DV2 moderated mediation analyses show how teaching affects outcomes. Creative teaching is emphasized in smart education adoption mediation. Due to their moderation effect, tailored interventions must consider teacher diversity. These findings suggest that educational policymakers should consider teacher differences when improving teaching and promoting smart education to maximize student and educator success.

The analysis supports H1, showing that teaching ability impacts smart education adoption. Skilled teachers use smarter methods (positive coefficient). It meets expectations because good teachers are open to new methods. A good teacher can use technology to improve learning. The strong correlation between teaching ability and student learning supports H2. Teaching skills boost student learning. Education literature says good teaching boosts student performance. The result shows the need for teaching strategies to improve student learning. The strong positive correlation between teaching ability, job satisfaction, and self-efficacy supports H3. Strong teachers boost job satisfaction and self-esteem. Teaching skills boost teacher job satisfaction and self-efficacy (Chou et al., 2012; Meccawy, 2023; Tang et al., 2021; Tedre et al., 2021; Yan et al., 2021; Zainal & Zainuddin, 2020).

The results support H4, showing that smart education adoption mediates teaching ability's indirect effect on student learning. Good teaching and education practices boost student learning. Technology-enhanced teaching improves student outcomes. Smart education adoption mediates the indirect effect of teaching ability on teacher job satisfaction and self-efficacy, supporting H5. Teachers' well-being is indirectly affected by smart education. Tech adoption, teaching methods, and educator satisfaction are linked. H6 shows smart education adoption moderates teacher characteristics' impact on student learning. This mediation is affected by teacher traits. The findings suggest that teacher traits may affect smart education adoption's positive impact on student learning. Through smart education adoption, teacher characteristics moderate the effect of teaching ability on job satisfaction and self-efficacy, supporting H7. Technology adoption affects teacher well-being indirectly based on traits. We assume teacher satisfaction and self-efficacy.

Evidence supports most hypotheses and study relationships. These findings can help educators and policymakers understand how technology adoption, teaching abilities, and educator outcomes are linked. K-12 student learning and teacher well-being can benefit from the findings (Meiklejohn et al., 2012; Tedre et al., 2021; Zafari et al., 2022; Zainal & Zainuddin, 2020).

6. Conclusion

The study explores the complex dynamics of K-12 education by investigating the relationships among teaching ability, smart education adoption, teacher characteristics, student learning outcomes, job satisfaction, and self-efficacy. Key findings indicate that effective teaching positively influences student and teacher outcomes, with improvements in job satisfaction, self-efficacy, and student learning. Smart education adoption serves as a mediator in these relationships, showcasing its role in enhancing both student and teacher performance. Teacher traits are identified as a factor affecting these relationships, emphasizing the need for personalized approaches considering educators' diverse characteristics. The study underscores the significance of recognizing and accommodating this diversity to improve teaching and technology adoption. Furthermore, the research reveals that teacher characteristics influence the mediation of smart education adoption in the relationship between teaching ability and educational outcomes. This suggests the importance of understanding instructor differences in teaching, technology adoption, and overall educational dynamics. The study recommends teacher training and technology integration to address these issues and highlights the potential for improving student outcomes and teacher well-being through recognition of educators' diversity. In conclusion, the study contributes to K-12 education research by empirically demonstrating the interconnectedness of teaching ability, smart education adoption, teacher characteristics, and educational outcomes. It emphasizes the mediating role of smart education adoption, emphasizing the critical intersection of teaching competence and technological innovation. The practical implications include the need for comprehensive professional development programs for educators, promoting a holistic approach to digital teacher training and development. Limitations include potential response bias in teacher self-reports, and the study suggests further research to replicate findings in different settings and explore longitudinal effects. The study recommends prioritizing teaching and technology professional development, supporting smart education initiatives, and considering institutional policies, community involvement, and socioeconomic factors in understanding K-12 educational outcomes.

7. Educational Implications

This research can help K-12 administrators, educators, and policymakers improve education. Results show targeted pedagogical and technological professional development. Teachers learn smart education practices and improve their traditional teaching skills in programs. By addressing both, institutions can help teachers adapt to education changes. Second, policymakers should fund K-12 smart education infrastructure and resources. Educational stakeholders and policymakers can help teachers integrate technology. This study shows that teaching ability, technology adoption, and individual characteristics affect educational outcomes, emphasizing the need for holistic teacher training and support. Theory from this research shows the complex relationship between teaching ability, technology adoption, and K-12 education outcomes. Smart education adoption affects teacher competency, student learning, job satisfaction, and self-efficacy. Effective teaching and learning theories should include technological aspects to improve teaching abilities' impact on diverse educational outcomes. This study promotes educator-difference theories and challenges teaching effectiveness uniformity. Considerations of teachers' strengths and weaknesses can inform future theoretical frameworks to better understand how teaching ability and technology adoption affect educational outcomes.

Author contributions: All authors have sufficiently contributed to the study and agreed with the results and conclusions.

Data availability: The data supporting this study's findings are available upon request. Interested researchers may contact the corresponding author for access to the data.

Declaration of interest: The authors declare that no competing interests exist.

Ethical statement: All subjects who participated in the study have given their consent for participation, for data collection, and for the analysis of the collected data. The data was analyzed only in anonymized form, and personal information that could lead to the identification of the participants has been removed. No additional ethical approvement was needed.

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