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EDITED BY
Emilio Jesús Lizarte,
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REVIEWED BY
Abdulelah S. Alshehri,
King Saud University, Saudi Arabia
Meriem Khaled Gijón,
University of Granada, Spain

*CORRESPONDENCE
Heping Zhang
✉ 445390696@qq.com

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The impact of teachers' teaching strategies on students' deep learning in online learning environments: the mediating role of learning interaction

Zhaojia Xu[1], Junjie Yang[2], Heping Zhang[2]* and Ting Liu[3]

[1]Hubei Provincial Collaborative Innovation Center for Basic Education Digitization, Hubei University of Education, Wuhan, China, [2]Normal School of Vocational Techniques, Hubei University of Technology, Wuhan, China, [3]School of Teacher Education, Hubei University of Education, Wuhan, China

Introduction: The COVID-19 pandemic accelerated global online education, which faces "shallow learning" challenges. Deep learning is key to student competencies. Based on sociocultural theory, this study explored how teachers' teaching strategies affect online deep learning and the mediating role of learning interactions.
Methods: Stratified cluster sampling was used to select students from six central Chinese provinces, yielding 10,028 valid samples. The instruments included a revised NSSE scale (deep learning, $\alpha = 0.889$), the PISA2018 questionnaire (teaching strategies, $\alpha = 0.790$), and 2-item learning interaction test. Data were analyzed using descriptive statistics, regression, SEM, and Bootstrap tests; no significant common method bias existed.
Results: All scales had good reliability and validity. SEM showed that teaching strategies positively predicted deep learning ($\beta = 0.216$) and learning interaction ($\beta = 0.561$), and that learning interaction positively predicted deep learning ($\beta = 0.746$). Learning interaction partially mediated the relationship (indirect effect = 0.418, 65.93% of the total effect). Gender had no moderating effect, and the effect of grade was negligible.
Discussion: The study supports sociocultural theory by extending offline research to online settings and clarifying the "teaching strategies→learning interaction→deep learning" mechanism. This suggests that teachers prioritize interactive online designs. Limitations include self-reported data, brief interaction scales, cross-sectional data, and regional generalizability.

KEYWORDS

sociocultural theory, online learning, teaching strategy, deep learning, learning interaction

Introduction

The growth of information technology and Internet accessibility has established online learning as a vital part of education (Gao et al., 2021). The COVID-19 pandemic (2020–2023) accelerated a global shift toward technology-driven education, posing unprecedented challenges to the education sector (Turnbull et al., 2021). This transition overcame the traditional teaching constraints of time and space while reshaping pedagogical opportunities and demands. In China, the Ministry of Education enforced the "suspending classes without suspending learning" policy (Ministry of Education of the People's Republic of China, 2020), prompting online teaching across all educational levels.

However, the efficacy of online learning remains a topic of debated. Studies indicate persistent issues: many online courses exhibit suboptimal quality, prioritizing superficial content delivery over engagement (Demir Kaymak and Horzum, 2022). Instruction often mirrors passive lecture-based formats, described as "more didactic, less interactive" (Zhu and Zhang, 2021), with limited teacher-student interaction and feedback exacerbating student distraction and uneven progress (Saraç and Dogan, 2023). Learners frequently report poorer outcomes and experiences than in traditional settings, raising concerns about online environments fostering "shallow learning" (Alarifi and Song, 2024).

Introduced by Marton and Säljö (1976), deep learning emphasizes conceptual understanding rather than rote memorization. Since 2013, China's Ministry of Education has promoted deep learning through initiatives such as the Instructional Improvement for Deep Learning Project (Institute of Curriculum Textbook Research, 2024), which was formalized in 2017 with theoretical frameworks and teaching guidelines (Liu, 2021). Deep learning is increasingly recognized as essential for cultivating core student competencies (Torshizi and Bahraman, 2019).

Current research on online deep learning focuses on conceptual frameworks such as teacher-student interaction dynamics (Guaña-Moya et al., 2024; Wong and Chapman, 2023) and factors shaping online engagement (Abrami et al., 2011). However, teachers' instructional strategies critically influence the quality and satisfaction of online learning (Zhang et al., 2024b). This study investigates the mechanisms through which teachers' strategies affect deep learning in online environments. Using sociocultural theory and large-scale survey data from Chinese schools and universities, this study analyzes these relationships and their operational pathways.

Theoretical basis and research hypothesis

Sociocultural theory and deep learning

Building on Bloom's taxonomy, learning is divided into basic (memorization-focused) and deep (higher-order cognitive processing, such as analysis and application) types, with the latter requiring knowledge transfer to real-world contexts (Adams, 2015).

Deep learning represents active, comprehension-driven cognition, in contrast to passive memorization (Warburton, 2003). It emerges not through isolated studies but via collaborative social engagement within supportive networks, rejecting atomized individualism (Zhang G. et al., 2024).

Vygotsky's sociocultural theory identifies language as a form of cultural and psychological scaffolding (Mercer, 2019). Social interactions, particularly with more competent peers, drive advanced cognitive skill development through knowledge co-construction and discourses (Mercer and Howe, 2012). This positions interpersonal communication as foundational for internalizing complex thinking skills.

Thus, the evaluation of educational effectiveness must extend beyond individual aptitude and teaching methods to prioritize interaction quality. Stimulating deep learning requires enhancing teacher-student and peer communication dynamics.

Teacher teaching strategies and deep learning

In the process of implementing teaching strategies, teachers engage in a dynamic interplay of interpersonal communication and collaborative activities, which is inherently cultural. Deep learning requires students to participate in authentic and meaningful tasks involving communication, collaboration, and problem-solving rooted in real-world contexts. To facilitate this, teachers must design learning environments that support these experiences. Achieving deep learning necessitates that teachers establish goals aimed at fostering higher-order thinking, integrate meaningful content, create authentic scenarios, and employ assessment methods that emphasize sustained engagement (Man, 2023). Additionally, teachers should cultivate students' intrinsic motivation while judiciously leveraging extrinsic motivators and combining diverse strategies to promote deep learning (Meyer and McNeal, 2011). For instance, incorporating critical questioning can enhance instructional approaches, leading to the development of new and effective teaching strategies (Tofade et al., 2013).

Therefore, the successful implementation of online teaching hinges on whether the instructional strategies employed by teachers can effectively support students' learning processes rather than merely transmitting knowledge (Roddy et al., 2017). Effective teaching strategies are better equipped to address students' developmental needs, thereby fostering deep learning.

Based on this, this study proposes research hypothesis

H1: in the online learning environment, teachers' teaching strategies have a significant positive impact on students' deep learning.

Learning interaction and deep learning

Sociocultural theory emphasizes the critical impact of meaningful interaction on academic performance and student satisfaction while fostering deep learning (Anderson, 2003). As a cornerstone of education, interaction determines the effectiveness of online teaching and learning outcomes. Effective teaching emerges from dynamic exchanges between instructors and learners and among peers (Yakovleva and Yakovlev, 2014).

Quality teacher-student interactions directly influence instructional effectiveness, enhancing both motivation and academic achievement (Pennings et al., 2014). These interactions also serve as catalysts for deep learning. Research on the English subject shows that improving the frequency and extent of interaction between teachers can promote deep learning among students (Shi and Lan, 2024).

Collaborative learning is particularly effective in digital environments. Peer learning, evaluation, and feedback stimulate deep learning through enhanced cognitive processing of content, simultaneously increasing the authenticity of online learning (Gijbels et al., 2009). Thus, both vertical (teacher-student) and horizontal (peer) interactions function as essential mechanisms for achieving profound educational outcomes (Horn et al., 2014).

Based on this, this study proposes research hypothesis

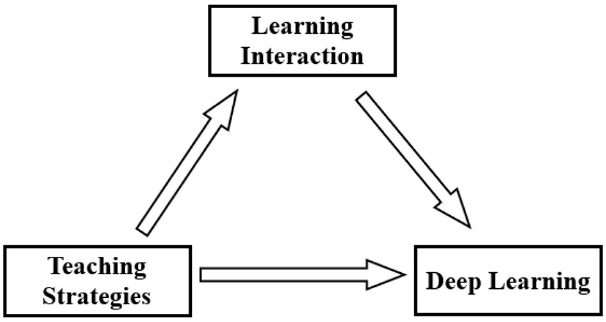

FIGURE 1
Theoretical analysis framework.

H2: in the online learning environment, learning interaction has a significantly positive impact on students' deep learning.

Teachers' teaching strategies and learning interaction

Education is essentially an interactive process, and teachers' teaching strategies not only affect the learning effect but also affect the construction of benign learning interactions (Zhang et al., 2024a). In classroom teaching, the key behavior is learning interaction to complete common tasks (Hamre et al., 2013). Teachers' teaching types and strategies directly affect the quality of interaction and students' learning methods, which in turn affects students' learning quality and teachers' teaching quality (Pol et al., 2010).

Specifically, teachers can promote effective learning interactions by creating teaching situations, mobilizing students' enthusiasm, and constructing reasonable peer interaction groups (Kang and Yang, 2023). Teachers' teaching strategies and effective learning interactions are key to successful teaching (Hofkens et al., 2023). Teacher-student interaction in online learning includes teachers' direct teaching, dialogue promotion, feedback, teaching support, and teachers' presence (Tsingos et al., 2015). It can be seen that successful teaching strategies essentially work through learning interaction.

Based on this, this study proposes research hypothesis

H3: in the online learning environment, teachers' teaching strategies have a significantly positive impact on learning interactions.

Teacher teaching strategies, learning interaction, and deep learning

In terms of teaching strategies, deep learning encourages teachers to transform teaching content into guided learning themes (Smith and Colby, 2007) and promotes students to move from individual learning to cooperative communication, from simple memory to thinking and application, realizing the transformation from teaching to learning (Muniasamy and Alasiry, 2020). Deep learning also emphasizes the importance of guidance from teachers. In the network environment, teaching objectives, activities, and evaluation tasks must be consistent to enhance students' in-depth understanding (Zhou, 2022).

At the level of learning interaction, some studies have shown that deep teaching interaction is conducive to the effect of online deep learning, and effective teacher-student interaction is the key guarantee of deep learning (Rose, 2004). Simultaneously, diversified interactive methods can enhance cognition, teaching, and social presence in blended teaching, thus having a positive impact on learning quality (Yang and Ghislandi, 2024).

In summary, teachers' teaching strategies greatly affect the quality of learning interaction and deep learning, and deep learning itself is the result of effective learning interaction.

Based on this, this study proposes research hypothesis

H4: in the online learning environment, learning interaction has a mediating effect between teachers' teaching strategies and deep learning.

Based on the above theoretical hypotheses, we constructed the following theoretical analysis framework (Figure 1).

Methods

Participants

This study employed stratified cluster sampling to select participants from primary, secondary, and tertiary educational institutions across six provinces in central China, resulting in a sample of 198 class participants. A questionnaire survey was administered to all students in the selected classes, spanning four educational levels: university (first to fourth year), high school (grades 10–12), junior high school (grades 7–9), and primary school (grades 3–6). The questionnaires were distributed online, with content primarily focusing on students' online learning experiences during the pandemic, including their family environment, personal characteristics, learning behaviors, and teachers' teaching behavior.

After eliminating missing answers, repeated answers, and extreme values, 10,028 valid survey samples were obtained. Among them, 4,801 (47.9 %) were males and 5,227 (52.1 %) were females. Of the total, 4,854 (48.4 %) were in the third grade of primary school or above, 2,826 (28.2 %) were in middle school, 1,294 (12.9 %) were in high school, and 1,054 (10.5 %) were in college. There were 5,995 (59.8%) in urban areas, 2,522 (25.1%) in rural areas, and 1,511 (15.1%) in townships. Table 1 presents the sample description.

Instruments

Deep learning

The commonly used tools to measure deep learning are Biggs' Learning Process Scale (SPQ), Entwistle and Ramsden's Learning Method Scale (ASI), Student Learning Inventory, and Forlanca's Assessment of SPQ and Strategies for Learning and Teaching (ASSIST) (Bellanca, 2014). They all contain three dimensions: deep, shallow, and policy methods. Deep learning methods belong to the process-level problem, and the application of cognitive strategy methods is more important. The National Survey of Students' Learning Engagement (NSSE) in the United States also measures

TABLE 1 Sample description ($N = 10,028$).

Attributes	Items	Frequency	Percent (%)
Gender	Female	5,227	52.1
	Male	4,801	47.9
Educational levels	Primary school	4,854	48.4
	Junior high school	2,826	28.2
	High school	1,294	12.9
	University	1,054	10.5
Location of family	countryside	2,522	25.1
	Townships and towns	1,511	15.1
	City	5,995	59.8

deep learning, which is based on the measurement indicators proposed by Bloom's taxonomy of educational goals from the dimensions of application, analysis, evaluation, creation, and other higher-order thinking.

This study is based on the NSSE deep learning questionnaire, combined with the cultural characteristics of the respondents in this study, and integrated multiple classic scales to revise and improve the NSSE questionnaire, so that the item setting and expression are more in line with the Chinese cultural characteristics and the learning situation of students in each segment. The revised scale contains eight items covering six dimensions: reflection, evaluation, connection, application, analysis, and creation. The total scores of each item were averaged, and the higher the mean value, the higher the level of deep learning. In this study, the internal consistency of the scale was tested, and the Cronbach's α coefficient was 0.889, the KMO value was 0.911, and the Bartlett's sphericity test was $P < 0.001$, $\chi^2 = 1{,}743.587$, RMR $= 0.017$, RMSEA $= 0.044$, TLI $= 0.948$, and CFI $= 0.969$. The GFI was 0.968, indicating good reliability and validity.

Teachers' teaching strategies

In this study, the Program for International Student Assessment (PISA2018) questionnaire on the application of teachers' teaching strategies was selected as the measurement tool. The scale contains seven items covering the dimensions of goal setting, inspiration, oral assessment, in-depth teaching, and so on. For each item, a four-level forward scoring system of "very inconsistent, not very consistent, relatively consistent, and very consistent" is used (represented by 1–4 respectively). The average score of each item was calculated, and the higher the mean value, the higher the degree of teachers' use of teaching strategies. The internal consistency of the scale was tested in this study using Cronbach's alpha. The Cronbach's α coefficient was 0.790, the KMO value was 0.831, and the Bartlett's sphericity test was $P < 0.001$, $\chi^2 = 674.36$, RMR $=$ 0.026, RMSEA $= 0.071$, TLI $= 0.968$, CFI $= 0.980$. The GFI was 0.981, and the scale had good reliability and validity.

Learning interaction

Learning interaction includes teacher-student interaction and student-student interactions. The degree of interaction between students and teachers is measured by the item "I often communicate with teachers online (such as answering questions, asking questions, discussing, sharing, etc.)." The degree of student-student interaction was measured using the item "I often share or discuss problems in study with my classmates online." The options for both are "very inconsistent, not very consistent, relatively consistent, and very consistent," which are represented by values 1–4, respectively.

Data analysis and research results

Common method bias test

In this study, three subscales were used to conduct a questionnaire survey on the same sample. Prior to data analysis, we performed CMB tests on the sample. Harman's single-factor test was used to conduct exploratory factor analysis (EFA) on 17 items, including three sub-scales. KMO $= 0.926$, Bartlett's sphericity test $P < 0.001$; Harman's single-factor method analysis results show that three factors with eigenvalues greater than 1 are extracted, and these factors explain 66.084% of the total variance, among which the variance explained by the first factor is 31.841%, less than half of the total variance. This indicates that there was no obvious common method bias problem in this study.

Reliability and convergent validity tests were constructed

With the help of SPSS and AMOS software, construct reliability and convergent validity tests were conducted on the sample data of deep learning and its sub-dimensions, teaching strategies and its sub-dimensions, and learning interaction and its sub-dimensions (Table 2). The Average Variance Extracted (AVE) was used to conduct confirmatory factor analysis (CFA) on 17 items, including three subscales. The greater the AVE value, the stronger the ability of the latent variable to simultaneously explain its corresponding items. The stronger the ability of the item to express the nature of the latent variable (converging to a point), the better the convergent validity.

When the standardized loading on each factor is observed, if it exceeds 0.5, the common variance between the observed variable and the latent variable requires a larger load than the common variance between the observed variable and the error variance, which is in line with convergent validity. The standardized loading value of each item in this study under its common factor was greater than 0.5, which shows that this study has good convergent validity.

Construct Reliability (CR) reflects whether all items in each latent variable consistently explain the latent variable. The value of each item in this study was greater than 0.7, indicating good convergent validity.

Descriptive analysis and regression analysis were performed

The results of the descriptive analysis are presented in Table 3. The average score for deep learning was 2.811, the average score

TABLE 2 Reliability and validity test results of key variables.

Variables	Indication	Estimate	M	SD	Cronbach'α	CR	AVE
Deep learning	Reflection	0.682	2.77	0.594	0.889	0.888	0.574
	Evaluation	0.848	2.73	0.685			
	Connection	0.719	2.90	0.733			
	Application	0.709	2.85	0.760			
	Analysis	0.764	2.85	0.783			
	Creation	0.802	2.76	0.807			
Learning interaction	Teacher-student	0.817	2.67	0.842	0.798	0.798	0.663
	Students-students	0.812	2.69	0.835			
Teachers' teaching strategies	Goal setting	0.815	3.284	0.668	0.790	0.827	0.516
	Inspirational guidance	0.869	3.32	0.661			
	Oral assessment	0.823	3.33	0.658			
	Deep teaching	0.849	3.24	0.704			
	Tutoring and question resolution	0.544	2.92	0.800			
	Assignment design	0.083	2.61	0.705			
	Tests and examinations	0.146	2.40	0.777			

TABLE 3 Mean, standard deviation and correlation analysis of key variables.

Variables	M	SD	1	2	3
Deep learning	2.811	0.59	1		
Teachers' teaching strategies	3.015	0.76	0.577***	1	
Learning interaction	2.684	0.47	0.676***	0.499***	1

M is the mean, SD is the Standard Deviation.
***$p < 0.001$.

of teaching strategies 3.015, and the average score of learning interaction 2.684. The results of the correlation analysis showed that teachers' teaching strategies were significantly positively correlated with deep learning ($r = 0.577$, $p < 0.001$), teachers' teaching strategies were significantly positively correlated with learning interaction ($r = 0.499$, $p < 0.001$), and learning interaction was significantly positively correlated with deep learning ($r = 0.676$, $p < 0.001$).

Table 4 shows the results of the multiple linear regression analysis with deep learning as the dependent variable and teachers' teaching-learning interaction and learning interaction as the independent variables. Model 2, which adds gender and grade as control variables, shows that teachers' teaching interaction has a significant positive impact on deep learning, which can explain 53.8% of the variation in deep learning.

Teaching strategies, learning interaction, and deep learning

Structural equation model

In this study, AMOS software was used to build the structural equation model. Among them, teachers' teaching strategies were considered the independent variable, and deep learning was considered the dependent variable to obtain the overall model test results, as shown in Figure 2.

The fitting test data of the structural equation model are CMIN/df = 40.973, RMSEA = 0.063 (LO90% = 0.061; HI90% = 0.065), CFI = 0.960, TLI = 0.950, RFI = 0.949, NFI = 0.959, and SRMR = 0.0527, respectively. Due to the large sample size, the chi-square value is too sensitive; therefore, the quality of the model is judged comprehensively by referring to other fitting indicators (Wu, 2013). According to the research results on the reliability and validity of the scale (Louangrath, 2018; Trindade et al., 2021), the RMSEA of this model is no more than 0.08, and all other items are greater than 0.9, which meets the psychological measurement standards, indicating that this measurement model has a good fit with the actual data.

The direct effect test

There are three direct effect paths among the three latent variables in this study: teacher teaching strategies → learning interaction, learning interaction → deep learning, and teacher teaching strategies → deep learning. The analysis results show that the standardized coefficients of each path are 0.561, 0.746, and 0.216, respectively, and all of them are statistically significant ($p < 0.001$), indicating that teachers' teaching strategies have a significant positive impact on learning interaction, and both learning interaction and teachers' teaching strategies have a significant positive impact on deep learning (Table 5). Accordingly, H1, H2, and H3 were verified.

Mediating effect test

This study uses the bootstrapping method proposed by Preacher & Hayes to test the mediating effect of learning interaction

TABLE 4 Multiple linear regression analysis of deep learning.

Model	Variables	beta	Sb	B′	*t*	*P*
1	Constant	0.560	0.026		21.739	<0.001
	Teacher’s teaching strategies	0.395	0.010	0.320	40.627	<0.001
	Learning Interaction	0.395	0.006	0.516	65.582	<0.001
2	Constant	0.645	0.028		23.363	<0.001
	Teacher’s teaching strategies	0.389	0.010	0.315	40.129	<0.001
	Learning interaction	0.392	0.006	0.512	65.300	<0.001
	Gender	0.008	0.008	0.007	1.020	0.308
	Grade	−0.012	0.001	−0.067	−9.779	<0.001

Model 1: $R^2 = 0.533$, adjusted $R^2 = 0.533$, $F = 5727.623$, $P < 0.001$; Model 2: $R^2 = 0.538$, adjusted $R^2 = 0.538$, $F = 50.469$, $P<0.001$, DW = 1.953.

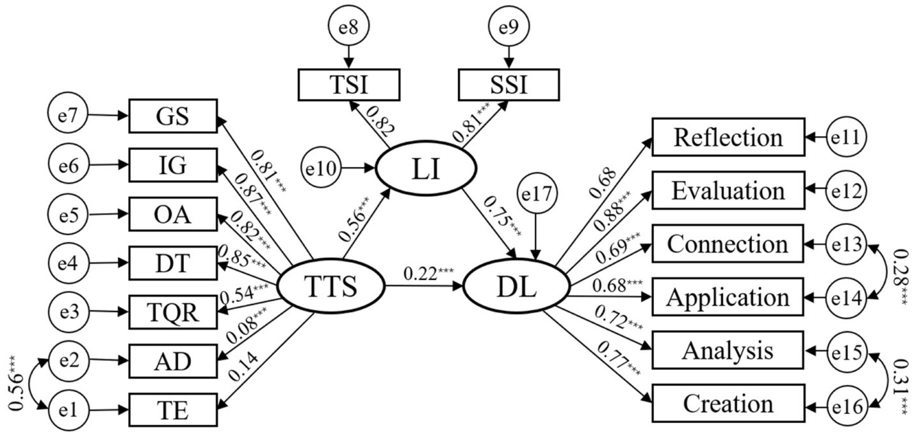

FIGURE 2
Structural equation model of the relationship between teaching strategies, learning interaction and deep learning. DL, Deep learning; TTS, Teachers’ teaching strategies, GS, Goal setting, IG, Inspiration guidance, OA, Oral assessment, DT, Deep teaching, TQR, Tutoring and question resolution, AD, Assignment design, TE, Tests and examinations; LI, learning interaction, TSI, Teacher-students interaction, SSI, Students-students interaction; the coefficients marked in the figure are standardized coefficients; ***$p < 0.001$.

on the path “teacher teaching strategies → deep learning.” Through repeated random sampling, 5,000 samples were drawn from the original data ($N = 10{,}028$) to form the test sample.

The test results are presented in Table 6. In the influence path of “teacher teaching strategies → learning interaction → deep learning” the direct path value of teachers’ teaching strategies is 0.216, $p < 0.001$, and the direct effect accounts for 34.07% of the total effect. The proportion of direct and indirect effects indicates the existence of an indirect effect (mediating effect). The point estimate of the mediating effect of learning interaction was 0.418 ($p < 0.001$), accounting for 65.93% of the total effect. The 95% confidence intervals obtained by the bias-corrected percentile method and the percentile method are (0.398, 0.440) and (0.398, 0.440), respectively, excluding 0, indicating that the mediating effect of “teacher’s teaching strategies → learning interaction → deep learning” is significant. Therefore, H4 is established, and combined with the analysis results of the direct effect in the structural equation model, it can be seen that learning interaction has a mediating effect between teachers’ teaching strategies and deep learning, and there is a partial mediating effect.

Moderated mediation effect test

The moderating effect analysis was conducted based on Model 14 of SPSS Process, in which the moderating variables moderated the relationship between the mediating and dependent variables.

The results of the data analysis show that in the relationship between learning interaction and deep learning, when gender is used as a moderator, the effect value is not significant ($p > 0.5$). When grade was used as a moderator variable, it had certain significance ($p < 0.05$), but the effect size was small.

Discussion

Relationship between teachers‘ teaching strategies and students’ deep learning in online learning environment

The SEM analysis results of this study (Figure 2) support H1: teachers‘ teaching strategies are significantly positively correlated with students’ deep learning in the online environment ($\beta = 0.216$, $p < 0.001$). This means that when teachers adopt effective

TABLE 5 Path test of direct effects among variables.

Paths	Unstandardized regression coefficient	Standardized regression coefficient	S.E.	C.R.	*P*
TTS → LI	3.615	0.561	0.265	13.266	<0.001
TTS → DL	0.790	0.216	0.069	11.534	<0.001
LI → DL	0.437	0.746	0.008	51.407	<0.001

DL, Deep learning; TTS, Teachers' teaching strategies; LI, learning interaction.

TABLE 6 Mediating effect test of learning interaction.

Types of effects	Effect	S.E.	Bias-corrected 95%CI			Percentile 95%CI		
			Lower	Upper	*P*	Lower	Upper	P
Indirect effect	0.418	0.011	0.398	0.440	<0.001	0.398	0.440	<0.001
Direct effect	0.216	0.013	0.190	0.241	<0.001	0.190	0.241	<0.001
Total effect	0.634	0.009	0.615	0.651	<0.001	0.616	0.651	<0.001

teaching strategies, such as goal setting, heuristic guidance, and oral assessment, students can show a higher level of deep learning, specifically reflected in the improvement of the ability to reflect, analyze, and apply knowledge.

This finding is consistent with the core views of sociocultural theory and can build a scaffold for students' cognitive development by selecting appropriate teaching strategies, thus promoting deep learning (Mahn and John-Steiner, 2012). Accordingly, Budhai and Skipwith (2021) pointed out that the use of active and experiential learning methods, such as simulation teaching, gamified design, and social media integration in the online environment, can cultivate learners' problem-solving abilities and critical thinking. Both are important components of deep learning.

It is worth noting that existing research focuses more on the promotion effect of effective teaching strategies on deep learning in the offline environment (Smith and Colby, 2007), while this study extends this cognition to the online environment covering primary schools, middle schools, and universities based on the large-scale data of China ($N = 10{,}028$). In addition, this study fills a key gap in the existing research: previous studies have not clarified the specific mechanism by which teaching strategies affect deep learning, while the empirical results of this study show that there is a mediating variable of "learning interaction" in the relationship between the two.

Mediating role of learning interaction

The results of the SEM also support hypotheses H2 and H3: Teachers' teaching strategies positively predicted learning interaction ($\beta = 0.561$, $p < 0.001$), and learning interaction positively predicted deep learning ($\beta = 0.746$, $p < 0.001$), and learning interaction played a partial mediating role between teachers' teaching strategies and deep learning (indirect effect value $= 0.418$, $p < 0.001$) 65.93% of the total effect (Table 6).

First, there was a significant positive relationship between teachers' teaching strategies and the learning interactions. In other words, teachers who adopt effective teaching strategies are more likely to create effective teacher-student interactions (Liu et al., 2025). The possible mechanism is that strategies such as heuristic guidance and verbal evaluation contain interactive attributes, such as real-time feedback in online discussions and collaborative goal setting, which promote the occurrence of deep learning (Yakovleva and Yakovlev, 2014). This suggests that teachers should take the initiative to build a strategically designed supportive interactive environment.

Second, the results of this study show that there is a significant positive relationship between teaching interaction and deep learning, which supports the understanding of deep learning from the sociocultural theory perspective. Studies from different sources have enhanced the explanatory power of this theory. Japanese empirical researchers Takase et al. (2020) also proposed that learning activities supported by appropriate teachers (learning activities are naturally interactive) can promote students' deep learning. In addition, active and experiential learning strategies, such as project learning and contextualization learning, can increase the interaction between teachers and students in the online environment, which can be used as a means to promote critical thinking and deep learning (Abdul Razzak, 2016). The above also allows us to explain the low effect sizes of the subdimensions of the two teaching strategies, assignment design ($\beta = 0.08$) and test and exam ($\beta = 0.14$): they are strategies that lack interaction and therefore have a weak relationship with deep learning.

Third, learning interaction partially mediates the relationship between teachers' teaching strategies and students' deep learning. This provides a new perspective on previous research on teaching strategies to improve the effects of deep learning (Weng et al., 2022). Vygotsky points out that perhaps the change in teaching strategies and the elevation of deep learning is due to its inclusion of activities of a sociocultural nature.

Additionally, the moderated mediation model analysis showed that gender had no significant moderating effect on the relationship between learning interaction and deep learning ($p > 0.05$). Although the moderating effect of grade was statistically significant ($p < 0.05$), its effect size was very small ($\beta = -0.004$; Table 7), and its significance in educational practice was limited. This may imply that educators who wish to promote deep learning should focus more on improving interaction quality and less on gender or grade-differentiated designs.

TABLE 7 Moderated mediation analysis.

Variables	Model 1 (DV = deep learning)	Model 2 (DV = deep learning)
Teachers' teaching strategies	0.395***	0.389***
Learning interaction	0.391***	0.411***
Gender	−0.001	
Learning interaction * gender	0.007	
Grade		−0.002
Learning interaction * grade		−0.004*
F	2,866.317	2,919.571
R^2	0.534	0.534

*$p < 0.05$.
***$p < 0.001$.

Practical enlightenment for teachers' professional development

This study concludes that teachers need to be deeply aware of the key role of learning interaction in promoting students' deep learning in an online learning environment. Therefore, professional development should emphasize teachers' ability to design and guide interactions. In the process of online learning, teachers consciously use teaching strategies to provide dialogue mode or structure for online interaction, encouraging students to actively share ideas, discuss problems, explore new knowledge, and monitor group cooperation, which strongly supports improving the quality of teacher-student interaction experience.

In the online learning environment, teachers need to design effective teaching activities according to the teaching resources and interactive advantages of different environments before, during, and after class, through the selection of appropriate teaching strategies and methods, and guide students to carry out interactions such as inquiry, discussion, questioning, and evaluation, to improve the depth of interaction, and to finally provide students with a highly engaged learning experience.

Therefore, in the network environment, teachers should not only pay attention to how they speak well, but also pay special attention to how students learn well, so that their teaching behavior can more effectively promote students' deep learning.

Theoretical contribution

This study proposes and tests the mediating effect of learning interaction between teachers' teaching strategies and deep learning in an online environment. This study reveals the internal mechanism by which teaching strategies affect deep learning and provides a new theoretical perspective for online education. The inclusion of learning interactions as a partial mediator (65.93% of the total effect) between teaching strategies and deep learning in the online environment resolves a priori ambiguity regarding the mechanism of the teaching strategies.

Implications for practice

Emphasizes the critical role of teacher-student and peer interactions in online learning. It recommends designing guiding questions, collaborative tasks, and authentic scenarios to foster deep learning (Kwon et al., 2019). The study proposes the pathway "instructional strategies → learning interaction → deep learning," providing actionable guidance for optimizing online course design. For example, enhancing feedback mechanisms and reducing one-way lecturing are recommended (Li et al., 2019).

Conclusion

In the context of Chinese culture and based on a large sample of questionnaires ($N = 10{,}028$), this study advances the understanding of the relationship between instructional strategies, deep learning, and learning interactions through a large-scale questionnaire survey and data analysis of online learning for college and primary and secondary school students. The structural equation model reflects the partial mediating effect of "learning interaction" between teachers' teaching strategies and deep learning and clarifies the mechanism of the effectiveness of teaching strategies in the online environment. In online learning, if teachers adopt teaching strategies that can enhance the depth of teacher-student interaction, it is easier to promote the generation of students' deep learning.

Limitations

First, the study relied on self-reported questionnaire data, which may have been biased. Second, in this study, a micro-scale containing two items was used to measure the degree of student learning interaction. Although it has good reliability and does not affect the core issues discussed in this study, the content validity of its measurement has some limitations due to the small number of items on the scale. A more comprehensive scale may provide richer insights. Third, the cross-sectional data collected during the pandemic may have limited causal inferences. The actual situation may have changed after the pandemic. Finally, the data analyzed in this study were all from China, and it is uncertain whether the results can be generalized to other cultures and educational systems.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by School of Teacher Education Academic Committee, Hubei University of Education. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

ZX: Data curation, Funding acquisition, Methodology, Writing – original draft. JY: Formal analysis, Project administration, Supervision, Validation, Visualization, Writing – review & editing. HZ: Conceptualization, Data curation, Resources, Supervision, Writing – review & editing. TL: Data curation, Investigation, Methodology, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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