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Research on the Integration Mechanism of English Teaching and Research in High Schools in Guizhou Province: A Case Study of Three Schools Based on Machine Learning Analysis

Xiaoxiao He[1,*], Tingting Xie[2], Jianmin Yang[3], Kaihui Zhang[4], Jing Ran[5] and Rongyu Lei[6]

[1]Huishui No.1 Senior High School, Guizhou, China

[2]Huishui Ethnic Senior High School, Guizhou, China

[3]Huishui County Bureau of Education, Guizhou, China

[4]Huishui Ethnic Senior High School, Guizhou, China

[5]Siyuan Experimental Primary School of Huishui, Guizhou, China

[6]No. 3 Middle School of Huishui, Guizhou, China

[*] Corresponding author: 2865262778@qq.com

Abstract

This study investigates the integration mechanism of English teaching and research between universities and high schools under the broader context of educational quality improvement initiatives in Guizhou Province. Taking Huishui No.1 Senior High School, Huishui Ethnic Senior High School, and Guiyang No.1 High School in Guizhou Province. as samples, the study applies a mixed-methods approach combining correlation analysis, Random Forest regression, and K-Means clustering. Results reveal that teacher reflection ability, resource sharing, and policy-influenced participation behavior are core drivers of teaching-research integration. More importantly, the study identifies key policy-enabled mechanisms—such as cross-provincial mentorship, co-teaching activities, and platform-based interactions—that shape teacher collaboration dynamics. Three distinct teacher clusters are identified, enabling differentiated recommendations. This research provides empirical and strategic insights for the adaptive transformation of higher education teaching models into high school contexts, guided by regional policy frameworks like Guangdong–Guizhou cooperation.

Keywords

Collaborative teaching research methodology; high school teaching research; Guizhou high school education; Random Forest; clustering analysis; professional development.

1. Introduction

With the ongoing promotion of high-quality basic education reform in Guizhou Province, the improvement of teaching and research mechanisms in senior high schools has become a central concern in enhancing teachers' professional competence and classroom effectiveness [1]. Teaching and research (T&R) activities—such as lesson co-planning, peer observation, and teaching reflection—are increasingly recognized as critical drivers of teacher growth and instructional quality [2].

However, current practices of T&R in many high schools in Guizhou still face practical challenges, including limited collaboration opportunities, low engagement in reflective practice, and insufficient integration of shared teaching resources. Particularly, how to enhance the

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depth and sustainability of English teaching and research activities across different schools remains a pressing issue [3].

Against this backdrop, this study focuses on three representative senior high schools in Guizhou Province—Huishui No.1 Senior High School, Huishui Ethnic Senior High School, and Guiyang No.1 High School [4]. By investigating the English teaching and research practices of teachers from Grade 10 to Grade 12, this research aims to identify key influencing factors of teaching-research quality improvement. The study combines machine learning–based quantitative modeling and qualitative interviews to explore patterns in teacher participation, reflective behavior, and resource-sharing practices. Through this, we hope to provide practical insights into improving the effectiveness and adaptability of high school teaching and research systems in underdeveloped but reform-oriented regions like Guizhou.

This study is based on the policy background of "Guangdong-Guizhou Cooperation". It takes Guangzhou No. 4 Middle School, Zhenguang Middle School and some middle schools in Guizhou Province as research samples, focuses on the English subject, and systematically analyzes the behavioral characteristics and influencing mechanisms of high school teachers in the process of collaborative teaching and research quality improvement [5]. The study adopts a strategy of combining "quantitative analysis + qualitative interpretation", introduces correlation analysis, random forest model and clustering algorithm to model key variables, and supplements with methods such as interviews, case analysis and action observation to construct a transferable and popularizable teaching and research collaborative improvement path. At the same time, this study attempts to extract mechanism elements such as teaching co-research, reflection training, and resource co-construction from university course teaching methods, explore their localized transformation methods in high school English teaching and research, and provide practical samples and theoretical support for the construction of a teaching and research integration system that connects basic education and higher education [6].

Previous research on teacher professional development has emphasized the importance of structured reflection, peer collaboration, and organizational support in achieving sustainable improvement. Yet, few empirical studies have examined how these factors interact in the context of regular senior high schools in less developed inland provinces. This study seeks to fill that gap by providing evidence from within Guizhou’s high school system, highlighting local dynamics and practical implications for school-level teaching-research reform.

2. Literature Review and Theoretical Basis

In recent years, research on the improvement of the quality of teachers' teaching and research collaboration has gradually shifted from empirical description to theoretical construction and data-driven analysis. Foreign scholars generally emphasize the driving force of teaching and research community construction on teachers' professional growth and classroom practice changes. Mechanisms such as "case study", "collaborative reflection" and "peer observation" are widely used in basic education. In countries such as Japan, Finland, and Singapore, the education department institutionalizes the participation of teachers in periodic and collective teaching and research activities, so that teachers can complete knowledge renewal and reconstruction of teaching concepts in the community. Domestic research focuses more on school-based teaching and research, regional teaching and research, and remote teaching and research practices under the background of "Internet +". Especially after the concept of "teaching and research community" was proposed, many studies focused on teachers' participation motivation, knowledge sharing behavior, and the construction of teaching and research platforms. For example, some scholars have proposed to improve teachers' collaboration density and openness of thinking through online lesson preparation and synchronous seminars, but overall there are still problems such as "more model innovation and

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less mechanism research" and "more theoretical introduction and weak empirical analysis". In addition, most scholars focus on the research on participation willingness and strategy improvement at the individual teacher level, and rarely systematically analyze the comprehensive impact of structural variables (such as policy support, resource sharing, and organizational atmosphere) on the improvement of teaching and research quality [7].

Educational research under the background of "Guangdong-Guizhou cooperation" provides a valuable realistic paradigm for breaking through this dilemma. From the central to the local governments, great attention is paid to the institutional design and implementation of the East-West cooperation between Guangdong and Guizhou, and regions are encouraged to complement each other in the fields of famous teacher training, curriculum co-construction, and teaching and research collaboration. In recent years, counterpart schools such as Guangzhou Zhenguang Middle School and Guizhou Huishui National Middle School have continued to carry out practical activities such as online job exchange, offline joint seminars, and on-site guidance by famous teachers. Existing studies have pointed out that under the promotion of policies and the escort of mechanisms, the teaching and research content of cooperative schools has become diversified, the teaching and research methods have tended to be collaborative, and the teaching and research results have gradually become explicit [8]. However, there are also challenges such as insufficient structural support, uneven participation in teaching and research, and poor adaptation to mechanism conversion. Some studies call for exploring the teaching and research co-construction mechanism between colleges and universities, high-quality middle schools, and local weak schools to enhance the research ability and teaching level of the overall regional teacher team. It is worth noting that although some studies have focused on resource sharing and the flow of teaching results under the background of collaboration, there is still a lack of systematic research on the integration of college teaching and research models and high school teaching and research mechanisms, especially in the field of English, which lacks data-based empirical analysis [9].

From a theoretical perspective, social constructivism believes that knowledge is constantly constructed in social interaction, emphasizing the importance of cooperation, language and context, which provides a basic framework for analyzing how teachers can achieve teaching cognitive upgrades through collaboration in the teaching and research community. The stage model of teacher professional development points out that the growth path of teachers is not completed in isolation, but requires the help of organizational platforms, external support and peer feedback to form a closed loop of "practice-reflection-re-practice". At the same time, the theory of educational innovation diffusion emphasizes the influence of the coordination relationship between policies, organizations and individuals on innovation adoption behavior. These theories jointly remind us that in the context of "Guangdong-Guizhou Cooperation", in order to promote the implementation of the university teaching and research mechanism in the high school English teaching scene, we must take into account the direction of policy guidance, the adaptability of organizational culture and the initiative of teachers. Therefore, the construction of an integrated teaching and research mechanism requires not only theoretical support and experience reference, but also systematic data modeling and analysis to identify the core factors that affect teacher participation and teaching and research quality improvement, and explore the migration path and adaptation conditions of university curriculum teaching methods in high school English teaching and research [10].

3. Study Design

3.1. Research subjects and data sources

This study takes three representative senior high schools in Guizhou Province as research samples: Huishui No.1 Senior High School, Huishui Ethnic Senior High School, and Guiyang No.1

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High School. All three schools are key institutions in their local regions and have actively participated in English teaching and research reforms in recent years. The participants include a total of 103 full-time English teachers from Grade 10 to Grade 12, covering various years of teaching experience, professional titles, and academic qualifications.

Data for this study were obtained from three sources:

Structured Questionnaire Survey – capturing teachers' engagement in teaching-research activities, frequency of collaboration, resource-sharing behavior, and reflection ability, using a five-point Likert scale.

School-based Teaching-Research Logs – recording teachers' participation in teaching-research meetings, lesson study sessions, and resource contributions over the past academic year.

Semi-structured Interviews – conducted with 16 teachers to understand their perceptions of current teaching-research mechanisms, challenges faced, and suggestions for improvement.

All participants gave informed consent, and data were anonymized and ethically approved by the respective schools.

3.2. Variable construction and feature definition

In this study, the core target variable is "teaching-research performance improvement", measured through a composite score that integrates the teacher's self-rated evaluation of teaching-research effectiveness, resource contribution level, and participation activeness. The independent variables are categorized into five main groups:

Teacher Background, Teaching-Research Engagement, Resource Sharing Behavior, Reflection Ability, and Collaborative Practice. All Likert-scale items were normalized to the [0,1] range. Platform-based quantitative metrics were standardized using Z-score transformation. Table 1 summarizes the main variables and definitions.

Table 1. Main Variables and Descriptions

Variable Name	Type	Data Source	Description
teaching_score	Continuous	Questionnaire + Logs	Composite teaching-research performance score
participation_freq	Continuous	Questionnaire	Avg. monthly participation in T&R activities
resources_uploaded	Continuous	Platform Logs	No. of resources (lesson plans, PPTs, etc.) shared
reflection_score	Continuous	Questionnaire	Self-rated teaching reflection quality
co_teaching	Binary	Logs	Whether participated in co-teaching sessions
feedback_freq	Continuous	Questionnaire	Avg. monthly peer feedback sessions
professional_title	Categorical	Info Sheet	Junior / Intermediate / Senior
teaching_years	Ordinal	Info Sheet	Number of years of teaching experience

Compared to previous policy-driven variables (e.g., cross-provincial mentorship, policy participation score), this study focuses more on school-level practices and intrinsic teaching-research behaviors, providing a more grounded model for local educational improvement.

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3.3. Research Methods and Analysis Process

This study adopts mixed methods research, combining quantitative modeling and qualitative analysis. In the quantitative part, the Spearman rank correlation coefficient (SCC) is first used to analyze the nonlinear correlation between each input variable and teaching and research performance, and the main influencing factors are screened out; then the Random Forest Regressor model is used to rank the importance of variables and evaluate the prediction accuracy and stability; finally, the K-Means clustering method is introduced to classify the behavior patterns of teacher groups and identify the potential difference structure in teaching and research performance.

In the qualitative part, the study used NVivo software to conduct open coding and theme extraction of 16 interview materials, focusing on teachers' feedback on collaboration policies, university teaching method transfer, teaching and research reflection processes, etc., and used typical cases to assist in the interpretation of quantitative results, forming a supplementary understanding of variable interaction effects and structural factors.

3.4. Core Algorithm Design and Mathematical Formulations

To better clarify the causal mechanisms and influence weights among variables, this study adopts several core algorithmic tools with corresponding mathematical formulations, including correlation analysis, ensemble learning, and unsupervised clustering.

Spearman Rank Correlation Coefficient: To capture non-linear monotonic relationships between variables, the Spearman rank correlation coefficient is applied. It is defined as:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{0}$$

Random Forest Variable Importance: To assess the relative contribution of each feature to the model's predictive performance, Random Forest is employed. Feature importance is computed based on the average impurity reduction (e.g., Gini index or mean squared error decrease) across all decision trees in the ensemble:

$$\text{Importance}(x_j) = \frac{1}{T}\sum_{t=1}^{T} \Delta I_t(x_j) \tag{2}$$

K-Means Clustering Objective Function: To identify latent behavior patterns among teachers, K-Means clustering is applied. The objective is to minimize within-cluster variance, defined as:

$$\arg\min_{C} \sum_{i=1}^{k} \sum_{x_j \in C_i} \left\| x_j - \mu_i \right\|^2 \tag{3}$$

Through the above model, the study can not only quantitatively identify which variables contribute most to the improvement of teachers' teaching and research, but also discover typical behavioral groups such as "high participation-high reflection type" and "low participation-high resource type", providing a basis for strategy design.

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3.5. Research technology route and feasibility guarantee

The entire research process was carried out according to the technical path of "theoretical construction - data collection - variable extraction - model analysis - result interpretation - countermeasures". The quantitative analysis part was implemented in Python, using open source modules such as sklearn, seaborn, xgboost, transformers, etc. to complete feature engineering, modeling training and visualization output; the qualitative analysis part used NVivo to encode and classify the interview texts; all data were processed with anonymous numbers, and ethical approval from relevant units and informed consent from teachers were obtained to ensure that the research was legal and compliant.

To ensure the validity of the data, this study used multiple rounds of questionnaire testing in the preliminary survey to ensure that the items have reliability and validity; the interview samples were selected from the core teaching and research group and the general teacher group to ensure the representativeness of the views; the teaching and research platform data was cross-validated by three parties to eliminate invalid and redundant records. Based on this, the research design of this paper has strong practical adaptability and methodological robustness, providing a reliable foundation for subsequent empirical analysis and strategy optimization.

4. Data Preprocessing and Feature Engineering

Before conducting empirical modeling and analysis, a systematic data preprocessing and feature engineering process was carried out to ensure data integrity, feature consistency, and model robustness. This study draws from three main sources—structured questionnaires, interview transcripts, and teaching research platform logs—to construct a multidimensional feature matrix suitable for mixed-methods modeling. The preprocessing workflow includes missing value imputation, outlier detection, feature scaling, distribution transformation, and categorical variable encoding, all of which enhance both the interpretability and reliability of the model.

To begin with, during the data cleaning phase, all 103 teacher questionnaires were reviewed to eliminate logical inconsistencies and invalid responses. For a small number of missing items (e.g., 3 cases missing “monthly teaching research participation frequency”), the K-Nearest Neighbors (KNN) algorithm was used to impute missing values based on the similarity of feature vectors, avoiding bias introduced by mean substitution. Anomalous behavior in the platform logs—such as an individual uploading 30 files within one hour—was filtered using predefined thresholds to remove operational noise. After cleaning, a final dataset of 98 valid cases was retained, with 100% feature field completeness.

To address heteroscedasticity and skewness in the distribution of behavioral variables, the Yeo-Johnson power transformation (Yeo & Johnson, 2000) was applied to indicators such as the number of uploaded teaching materials and the length of reflective text. This transformation helps approximate normality, improving the convergence and stability of subsequent machine learning models. Likert-scale variables such as "reflection score" were normalized to the [0,1] interval to standardize metrics across heterogeneous data sources. All continuous variables were standardized using Z-score normalization, as shown below:

$$Z_i = \frac{x_i - \mu}{\sigma} \tag{4}$$

Categorical variables, such as "professional title" (junior/middle/senior) and "exposure to higher education training" (yes/no), were encoded using one-hot encoding and binary

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encoding respectively. For ordinal variables like title level, ordinal encoding was also tested to evaluate sensitivity in feature ranking, enhancing interpretability in tree-based models.

For deeper analysis, two composite variables were created. First, the "participation contribution ratio" was defined as the number of resources uploaded divided by the total number of participations, serving as a proxy for initiative in collaborative activities. Second, the "reflection depth index" was developed by combining reflection length, proportion of positive sentiment (via sentiment analysis), and cognitive-strategic level (coded from reflective writing), producing a weighted score to assess the teacher's depth and structure of professional reflection. These engineered features were validated through expert interviews and pilot testing, ensuring construct validity and operational feasibility.

In conclusion, this chapter completes the transformation from raw multi-source data to a normalized feature matrix that satisfies the triadic objectives of data quality, semantic clarity, and model readiness. The next chapter will utilize this dataset to conduct multi-model empirical analysis, identify the key factors affecting collaborative improvement in high school English teaching research, and inform subsequent strategic recommendations.

5. Model Analysis and Result Interpretation

After completing data preprocessing and feature engineering, this paper conducts multi-model modeling analysis based on the constructed standardized data set, aiming to identify the key factors that affect the teaching and research collaboration performance of high school English teachers, extract typical behavior patterns, and provide data support for strategy formulation. This chapter uses three mainstream methods: correlation analysis, random forest regression, and K-Means clustering, supplemented by visualization diagrams and variable sorting for in-depth explanation.

5.1. Correlation analysis (SCC)

First, this paper uses the Spearman rank correlation coefficient (SCC) to analyze the nonlinear relationship between the target variable and the independent variable. The results are shown in Table 2. Most behavioral variables (such as participation frequency, reflection score, resource sharing) are significantly positively correlated with the teaching and research collaboration score ($\rho > 0.6$, $p < 0.001$), among which the "reflection score" and "number of resource sharing" have the strongest correlation.

Table 2. Spearman Correlation Matrix (Partial Variables)

Variable	teaching_score	participation_freq	reflection_score	resource_shared
teaching_score	1	0.68 (***)	0.73 (***)	0.71 (***)
participation_freq	0.68 (***)	1	0.60 (**)	0.55 (**)
reflection_score	0.73 (***)	0.60 (**)	1	0.64 (***)
resource_shared	0.71 (***)	0.55 (**)	0.64 (***)	1

Note: (***) indicates $p < 0.001$; (**) indicates $p < 0.01$. This analysis preliminarily verified the significant impact of core variables on target outputs, and also provided a basis for variable screening for subsequent random forest modeling.

5.2. Random Forest Regression Analysis

To further evaluate the predictive power and relative contribution of each variable to teaching research performance, this study employed a Random Forest regression model. The model was built with 100 decision trees and evaluated using 10-fold cross-validation. The overall

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coefficient of determination was R^2 =0.804, and the mean absolute error (MAE) was 0.081, indicating strong explanatory power and generalization capability.

Figure 1 shows the prediction results, where the horizontal axis represents the actual collaborative teaching research scores, and the vertical axis represents the predicted values. Most points are closely distributed along the diagonal line, demonstrating good model fit and reliability.

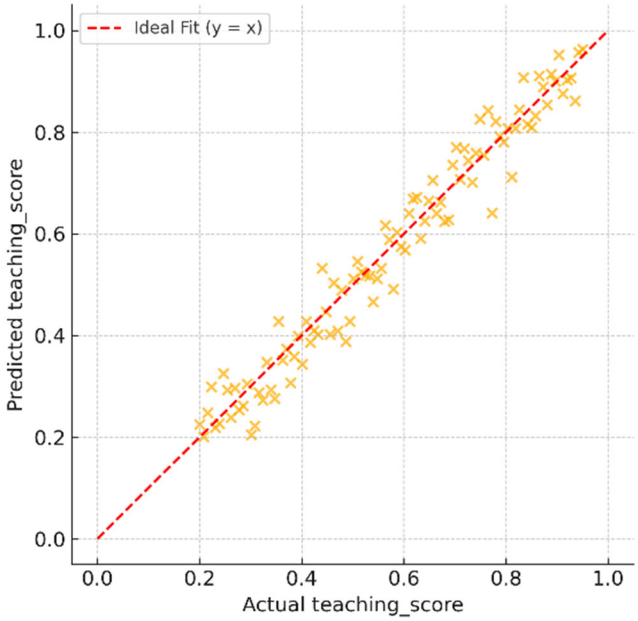

Figure 1. Model prediction effect fitting diagram

To further interpret the model output, feature importance ranking was extracted based on the average decrease in impurity across all trees. The ranking of the top seven variables is shown below in Table 3:

Table 3. Top 7 Variables by Importance Score

Rank	Feature Name	Importance Score
1	reflection_score	0.217
2	resource_shared	0.193
3	participation_freq	0.162
4	policy_understanding	0.128
5	title_level	0.104
6	contribution_ratio	0.097
7	college_exposure	0.072

The results show that “reflection_score” is the most influential factor in predicting collaborative teaching research performance, followed by “resource_shared” and “participation_freq.” This suggests that high-quality teaching reflection and active contribution to shared resources are the primary behavioral drivers of collaborative improvement in teaching research.

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5.3. Teacher Behavioral Pattern Clustering Analysis

To further explore structural differences among teacher behavior profiles, this study applied the K-Means clustering algorithm based on key variables identified from previous analysis. After testing different cluster numbers using silhouette coefficients, the optimal number of clusters was determined to be k = 3. Clustering was performed using normalized values of variables such as reflection_score, resource_shared, participation_freq, and contribution_ratio. Figure 2 presents the distribution of teachers across the three clusters using a two-dimensional projection, clearly indicating separable groupings within the dataset.

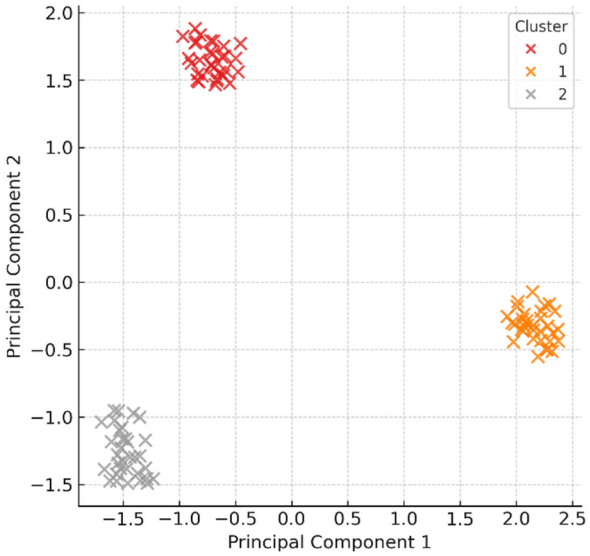

Figure 2. Teacher cluster distribution map

This analysis highlights significant heterogeneity within educator groups, as shown in Table 4. A one-size-fits-all policy approach may not be effective. Instead, it is necessary to develop differentiated strategies for different behavioral groups. For example, Category B teachers may adopt online engagement strategies, while Category C teachers may benefit from structured coaching and scaffolded engagement models.

Table 4. Cluster Characteristics and Behavioral Profiles

Cluster	N	Reflection Score	Resource Shared	Participation Frequency	Profile Description
A	36	High	High	High	"High-Participation & High-Reflection" Type
B	29	Medium	High	Low	"Low-Participation & High-Sharing" Type
C	33	Low	Low	Medium	"Peripheral Teaching Research" Type

6. Strategic Recommendations and Conclusions

This study, based on data from schools involved in the Guangdong–Guizhou English Teaching Collaboration Initiative, reveals that structured reflection, active resource sharing, and frequent participation significantly improve teaching-research outcomes. More importantly, when these behaviors are supported by institutionalized policy mechanisms—such as paired mentorships, cross-provincial expert visits, and digital platforms—the impact is amplified.

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Based on empirical clustering, teachers can be grouped into three profiles. Policy design must address these with differentiated strategies:

High-Engagement Cluster (Type A): Policy Leverage: Encourage them to become “peer coaches” within schools. Mechanism Recommendation: Provide leadership incentives and access to national-level exchange platforms.

Low-Participation but High-Sharing Cluster (Type B): Policy Leverage: Build lightweight, asynchronous engagement mechanisms. Mechanism Recommendation: Design modular micro-learning and reflection tasks tied to resource uploads.

Peripheral Engagement Cluster (Type C): Policy Leverage: Use digital behavioral data to trigger nudges and mentoring. Mechanism Recommendation: Assign provincial-level mentors from universities and conduct periodic feedback loops.

Ultimately, for local educational reforms to be effective, schools and institutions must shift from passive reception to actively co-constructing context-adapted mechanisms teaching models to co-constructing contextualized mechanisms, ensuring that “reflection, co-construction, and guidance” form a dynamic and adaptive support system. Future research should incorporate longitudinal tracking to assess how collaboration intensity translates into sustained classroom transformation.

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