

From Personalized Care to AI Literacy: The Mediating Role of Peer Support and Organizational Climate

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Abstract

The study overlooked the unclearness of how transformational leadership behaviors influence the development of AI literacy among teachers, with a view to constructing a dual-mediation model of "personalized care—colleague support/AI-supportive organizational climate—teachers' AI literacy." This model combines the personalized care dimension of transformational leadership theory with social support theory and organizational climate theory. 428 valid questionnaires were tested using structural equation modelling and 5000-iteration Bootstrap method. Median scores for all the measures indicated that teachers' AI literacy is moderate, with 47% reporting a score of 5 or above. The median scores for all measures showed that teachers' AI literacy is moderate, with 47% of teachers achieving a score of 5 or more. With the dual mediating variables added, the increase in the explanatory power of the model of teachers' AI literacy from 43.2% to 61.8%, an increase of 18.6 percentage points, shows that organizational contextual mechanisms play a significant enhancing role in explaining the impact of personalized care on teachers' AI literacy.

Keywords: personalized care; teachers' AI literacy; peer support; AI-supportive organizational climate; mediating effect

1 Introduction

As generative AI continues to penetrate educational settings, whether teachers can correctly understand the underlying principles of the technology, identify the limitations of generated content, and effectively integrate it into teaching activities has become a critical issue in the development of digital teaching competencies. Velander et al. (2024) found, from the perspective of teachers' cognition, that teachers' understanding of AI is directly related to their judgments regarding its application in teaching. **Error! Unknown switch argument.** Bower et al. (2024) further noted that generative AI is transforming instructional design and assessment methods, placing higher demands on teachers' technological judgment and curriculum restructuring abilities. Existing research has also begun to focus on the development and measurement of teachers' AI literacy. **Error! Unknown switch argument.** Younis (2024) validated the role of systematic training in developing pre-service teachers' AI literacy through a professional development program. **Error! Unknown switch argument.**, while Göksu and Göksu (2024) examined AI literacy and attitudes toward technology from the perspective of individual teacher differences. **Error! Unknown switch argument.** Uğraş et al. (2024), meanwhile, advanced the standardized measurement of teachers' AI literacy through scale adaptation. **Error! Unknown switch argument.** The aforementioned studies provide a foundation for the conceptual definition, competency development, and measurement and evaluation of AI literacy; however, they still lack a sufficient explanation of its generative mechanisms at the organizational level.

Currently, published work has the following shortcomings: (1) Most of the studies have been conducted at the individual teacher level, and have only examined teachers' cognition, attitude, training outcomes, and measurement tools superficially, not starting from the perspective of how teacher leadership behaviors are manifested as teachers' AI literacy; (2) Limited literature examines teacher leadership behaviors and the role of different channels of support, either peer support or organizational climate, simultaneously; (3) Most studies have only compared variables between teachers or pre- and post-training, and failed to validate teacher leadership behaviors at the same time through different paths. Based on this, we have built a parallel dual-mediation model of "personalized care—colleague support/AI-supportive organizational climate—teachers' AI literacy," and, using a sample of 428 university faculty members, structural equation modeling, and 5,000 Bootstrap tests, we explored the transmission mechanisms. The findings indicate that the dual-mediation model has a significant explanatory effect, and the support for the leadership effect on the AI competence of faculty is improved by 20% ($r^2 = 0.432$ to $r^2 = 0.618$) by this dual mediation.

2 Theoretical Framework

2.1 Personalized Care and Faculty AI Competence

Personalized care is an important aspect of transformational leadership because a leader attends to the

different needs of members and helps them become competent by providing resources, support and guidance. Teachers' AI literacy does not just rely on their individual technical bases, but also on organizational support and learning opportunities⁶. Leaders can address differences among teachers in their AI cognition, tool use, and how they apply the technology by tailoring support and training to their needs, thus improving their willingness to learn and ability to apply technology.

2.2 The Mediating Role of Peer Support

Based on the social support theory, it is believed that the support given to individuals in terms of information, emotion and instrumentality can reduce the stress of learning and help them acquire knowledge. Personalized care can make the sharing of experiences, technical assistance and problem-solving feedback between teachers more intensive and reinforce interaction in teams and the collaborative norms⁷. Practical experience and operational knowledge of the use of AI in the classroom is facilitated through a high level of peer support, which in turn contributes to further translation of leadership support to improved teacher AI literacy.

2.3 The Mediating Role of an AI-Supportive Organizational Climate

Organizational climate reflects members' shared perceptions of organizational systems, resource allocation, and behavioral norms. Leadership's personalized care can foster an organization that values AI-driven learning and instructional innovation by allocating resources, supporting training, and encouraging the adoption of technology⁸. A supportive organizational environment enhances teachers' recognition of the value of technology applications and the degree of organizational support, and encourages them to continue to study, practice, and reflect in order to enhance their AI literacy.

3 Research Design

3.1 Research Hypotheses

It is assumed that according to latent variable structure and the dual-mediation path, personalized care is the input node, teachers' AI literacy is the target node, and peer support and AI-supportive organizational climate are the two parallel mediating nodes. Based on this, the relationships presented below are proposed for testing:

Personalized care positively impacts teachers' AI literacy.

H2: Personalized care has a positive influence on peer support.

Peer support was found to have a positive mediating role in the relationship between personalized care and teachers' AI literacy.

H4: Personalized care can lead to a positive AI-supportive organizational climate.

H5: Organizational climate plays a positive mediating role between personalized care and teachers' AI literacy with the assistance of AI.

3.2 Research Setting, Sample, and Data Collection

This data collection was then performed from March to May 2026 with college faculty who have experience with the use of AI based teaching tools. 450 questionnaires were sent out. 428 valid samples were obtained after data cleaning according to the rules of the presence of missing values, the presence of consecutive identical values, and the abnormal response time. The questionnaire also captured factors like years of teaching experience, professional title, frequency of use of AI tools and digital teaching environment. In addition, 20 faculty members were chosen and subjected to semi-structured interviews for the purpose of the validation of variable definitions, item semantics and the boundaries of the measurement of AI-supported contexts with the aim of defining a data foundation for the subsequent latent variable modeling and SEM parameter estimates.

3.3 Variable Definitions and Measurement

To achieve a computable representation of the dual-mediation structural model, this study defined personalized care as the independent variable X , teacher AI literacy as the dependent variable Y , and colleague support M_1 and AI-supportive organizational climate M_2 as parallel mediating variables. Teaching experience, professional title, frequency of AI tool use, AI training experience, and digital teaching environment were set as control variables. Each latent variable was coded using a five-point Likert scale. After semantic calibration, the observed items were input into the measurement layer of SEM, with the basic mapping represented as $z_{ij} = \lambda_j \eta_i + \varepsilon_{ij}$. Specifically, AI literacy primarily measures understanding of AI knowledge, tool operation, integration into teaching, evaluation of outputs, and ethical and security competencies; the organizational environment focuses on AI resources, technology services, training systems, and application standards. The operational definitions for each variable are given in Table 1, which are used as a uniform input for the subsequent measurement models and the estimation of path parameters.

Table 1: Research Variables and Measurement Design

Variable Type	Variable Symbol	Variable Name	Main Measurement Content	Role in the Model
Independent Variables	X	Personalized Care	AI-driven identification of learning differences, targeted guidance, allocation of technical resources, and support for development opportunities	Exogenous Input Nodes
Mediating Variables	M_1	Colleague Support	AI experience sharing, technical assistance, instructional design feedback,	Individual Interaction Transmission Nodes

			encouragement to apply	
Mediating Variables	M ₂	AI-Supportive Organizational Climate	AI tool and platform support, training services, tolerance for innovation, and ethical and data security guidelines	Organizational Context Transmission Nodes
Dependent variable	Y	Teachers' AI Literacy	Understanding of AI, tool operation, integration into teaching, assessment of outcomes, ethics and security	Target Output Nodes
Control Variables	C	Individual and Digital Environment Characteristics	Years of Teaching Experience, Professional Title, Frequency of AI Tool Use, AI Training Experience, Digital Teaching Environment	Controlling for Heterogeneity Effects

3.4 Data Quality and Methods for Testing the Measurement Model

This study adopted a processing chain of “sample quality control—robust coding—measurement model estimation—validity assessment” to make sure that the data structure of variables is consistent and can be calculated in the dual-mediation SEM11. Based on the five-point Likert-Scale items, a polychoric correlation matrix is constructed, and the validation factor measurement model is estimated with WLSMV estimator:

In the equation, x_{ij} represents the raw score of the i th teacher on the j th item, med_j is the median for that item, MAD_j is the absolute deviation from the median, $z_{ij} = \frac{x_{ij} - med_j}{MAD_j}$ is the robust standardization value, 1.4826 is the normal consistency correction coefficient, and δ is a small stability term to prevent the denominator from approaching zero. A polychoric correlation matrix was further constructed for the five-point Likert-scale items, and the WLSMV estimator was used to estimate the confirmatory factor measurement model:

$$x_i^* = \Lambda \eta_i + \varepsilon_i, \quad \Sigma(\theta) = \Lambda \Phi \Lambda^T + \Theta$$

where x_i^* represents the latent continuous response vector for the item, Λ is the factor loading matrix, η_i consists of personalized care, colleague support, AI-supportive organizational climate, and teacher AI literacy, ε_i represents measurement error, Φ is the latent variable covariance matrix, Θ is the error covariance matrix, and θ denotes the measurement parameters to be estimated. The calculation chain and data flow relationships are shown in Figure 1.

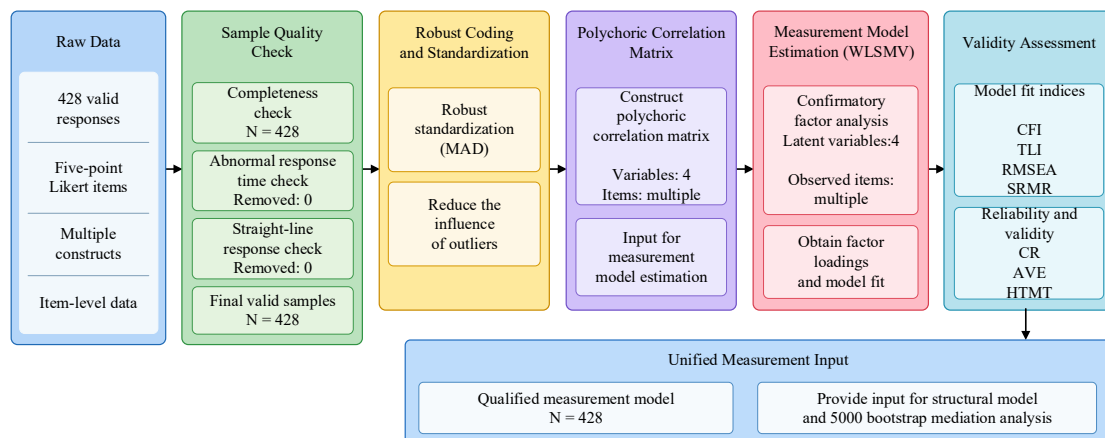


Figure 1: Computational Workflow for Data Quality Control and Measurement Model Validation

Building on this workflow, the covariance reconstruction error and the latent variable separation constraint are further combined into a unified quality function:

where Q represents the measurement model quality loss, S is the sample covariance matrix, $\Sigma(\theta)$ is the model latent covariance matrix, $\|\cdot\|_F$ is the Frobenius norm, ϕ_{ab} is the correlation coefficient between the latent variables a and b , τ is the discrimination constraint threshold, and ω_1 , ω_2 are the weights for the two types of error. Finally, the measurement layer was selected based on CFI, TLI, RMSEA, SRMR, as well as CR, AVE, and HTMT, providing a unified measurement input for the calculation of the dual mediating effects.

3.5 Structural Model and Methods for Testing Mediating Effects

Once the measurement model met the quality criteria, the four types of latent variables were converted into a directed computational graph with an input node being personalized care, and the output node being teachers' AI literacy. Colleague support, and an organizational climate that is AI-supportive, were coded as 2 parallel transmission pathways, and years of teaching experience, professional title, frequency of AI tool usage, AI training experience and digital teaching environment were coded as a control vector¹². All structural parameters are estimated by SEM and 5,000 Bootstrap resamples are conducted to obtain the empirical distribution of indirect effects since the assumption of normal distribution of the mediating

effects is not a requirement in the SEM analysis. The dual-mediation relationship can be represented as:

where X represents personalized care, M_1 and M_2 denote colleague support and AI-supportive organizational climate, respectively, Y represents teachers' AI literacy, C is the control variable vector, a_k , b_k are the coefficients of the two mediation paths, c' is the direct effect after controlling for mediators, γ is the control parameter, ε is the structural residual, and IE_k is the k th indirect effect. To visually illustrate the path calculations, the inclusion of control variables, and the Bootstrap resampling process, the overall testing workflow is shown in Figure 2.

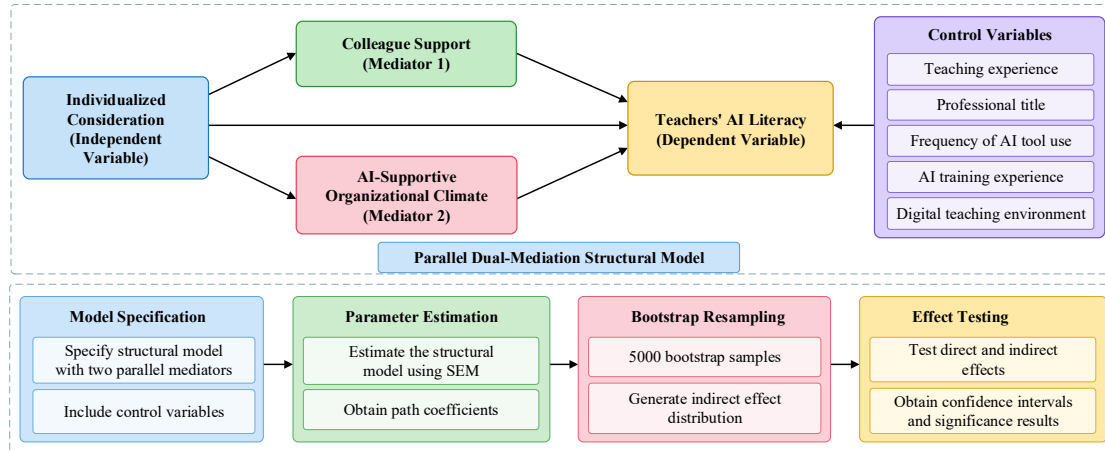


Figure 2: Computational Framework for Testing Parallel Dual-Mediating Structural Models and Bootstrap Effects

4 Empirical Results and Analysis

4.1 Descriptive Statistics and Measurement Model Test Results

We found the statistical distributions and variable correlations of the four variables: personalized care, colleague support, AI support in the organization's atmosphere, and teachers' AI literacy, based on 428 valid samples as seen in Table 2. The mean scores of each variable were between 3.58 and 3.74 and their standard deviations were between 0.61 and 0.70. The values of skewness and kurtosis were both negative and less than 1, which means that the values of the data that entered the SEM did not have significant distribution skewness. Personalized care correlated significantly with teachers' AI literacy with a correlation coefficient of 0.586, and a correlation coefficient of 0.612 and 0.651 was seen between colleague support and teachers' AI literacy and between AI-supportive organizational climate and teachers' AI literacy, respectively. This means that the statistical relationships are present that are consistent with the theoretical pathways between the four latent variables, thus giving a data base for the subsequent structural path analysis.

Table 2: Descriptive Statistics and Correlation Coefficients of Key Variables

Variable	Mean	Standard Deviation	Skewness	Kurtosis	1	2	3	4
1 Personalized Care	3.74	0.66	-0.31	0.24	1			
2 Support from colleagues	3.69	0.63	-0.27	0.18	0.574***	1		
3 AI-Supportive Organizational Climate	3.58	0.7	-0.19	-0.12	0.603***	0.548***	1	
4 Teacher AI Literacy	3.72	0.61	-0.35	0.29	0.586***	0.612***	0.651***	1

Note: N=428, N=428; *** indicates $p < 0.001$.

Based on descriptive statistics, confirmatory factor analysis was also carried out based on the pre-determined measurement hierarchy, and the quality of measurement of the latent variables was explored from four perspectives: item loading, internal consistency, convergent validity, and discriminant validity. The results are given in Table 3.

Table 3: Results of Reliability and Validity Tests for the Measurement Model

Latent Variable	Standardized Load Range	Cronbach's α	CR	AVE	HTMT Maximum Value
Personalized Care	0.718–0.846	0.881	0.887	0.611	0.764
Colleague support	0.701–0.832	0.862	0.871	0.575	0.748
AI-Supportive Organizational Climate	0.726–0.861	0.903	0.91	0.628	0.792
Teachers' AI	0.739–0.874	0.918	0.923	0.657	0.792

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As shown in Table 3, the maximum value of HTMT is 0.792, there is no significant overlap between the latent variables, and the standardized factor loadings of each observed item range from 0.701 to 0.874, Cronbach's α range from 0.862 to 0.918, composite reliability (CR) range from 0.871 to 0.923, and average variance extracted (AVE) range from 0.575 to 0.657, indicating that the four latent variables have stable internal consistency and convergent validity. Further covariance fitting of the overall measurement model proved the latent covariance matrix of the model to be an effective reconstruction of the structure of the sample data, with $\chi^2/df=1.94$, CFI = 0.956, TLI = 0.948, RMSEA = 0.049, and SRMR = 0.041. For that reason, the measurement layer also satisfies the requirements for the subsequent estimation of the structural parameters, for the additional test of the direct path of personalized care and the parallel paths of the mediators colleague support and AI-supportive organizational climate **Error! Unknown switch argument..**

4.2 The Effect of Personalized Care on Teachers' AI Literacy

Following the confirmation of the reliability and validity of the measurement model, personalized care was taken as the exogenous node as input and teachers' AI literacy as the output node. Using SEM, standardized structural paths were estimated while controlling for years of teaching experience, professional title, frequency of AI tool usage, training experience in AI, and digital teaching environment. The results indicate that the standardized path coefficient of personalized care on teachers' AI literacy is $\beta=0.312$, with a standard error of 0.054, $z=5.78$, $p<0.001$, and a 95% confidence interval of [0.206, 0.418], which does not cross zero; when only personalized care and control variables are included, the explanatory power of teachers' AI literacy is $R^2=0.432$. To visually illustrate the parameter directions, effect sizes, and estimation uncertainties of the core input variables and control variables, the structural path results are shown in Figure 3.

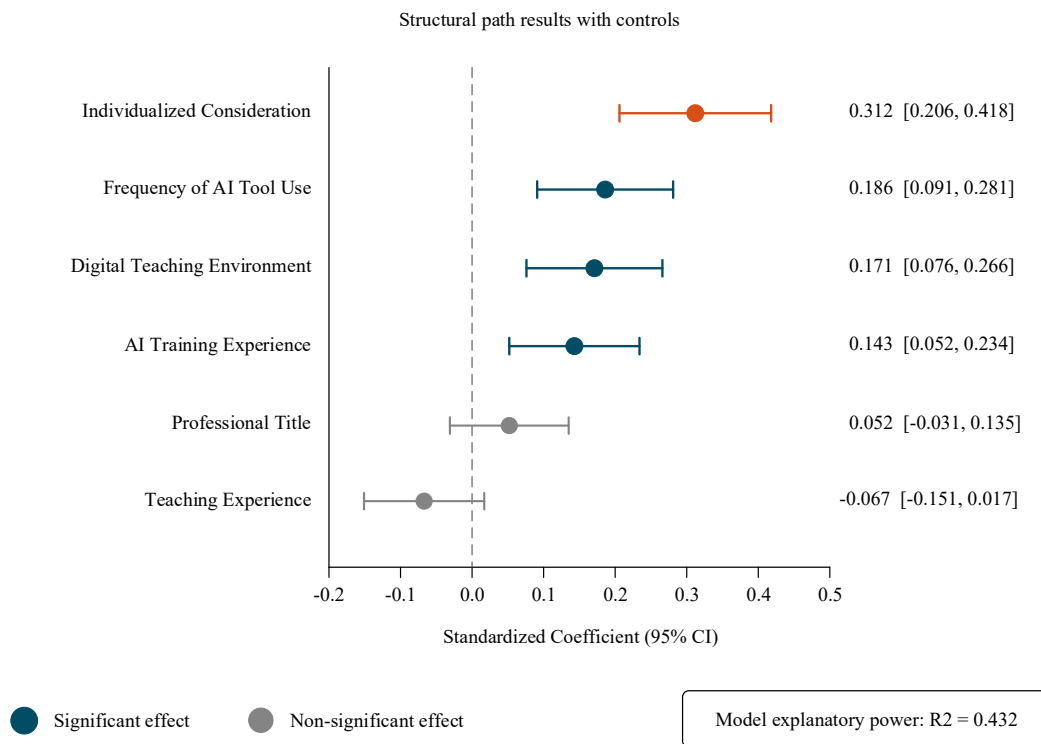


Figure 3: The Effect of Personalized Care on Teachers' AI Literacy

Results show that personalized care can be seen to have a stable positive structural influence after factors such as teachers' individual characteristics and the digital teaching environment are controlled, and the effect size is higher than all the control variables. This indicates that AI learning competency development can be established as an independent pathway, with leaders offering guidance and support for resources based on teachers' differences. Thus, H1 is verified and can serve as a reference point to see how much extra value is added by the additional inclusion of peer support and AI-supportive organizational climate.

4.3 Mediating Effects of Peer Support and an AI-Supportive Organizational Climate

Two parallel mediating nodes—colleague support and an AI-supportive organizational climate—were added to the baseline structural model, and 5, 000 Bootstrap resamples were conducted according to the settings in Section 3.5. The standardized path coefficients for the pathways: “personalized care → colleague support” and “colleague support → teachers' AI literacy” showed values of 0.421 and 0.280, resulting in an indirect effect of 0.118; and “Personalized Care → AI-Supportive Organizational Climate” and “AI-Supportive Organizational Climate → Teachers' AI Literacy” were 0.456 and 0.360, respectively, corresponding to an indirect effect of 0.164. Table 4 shows the two computed pathways and Bootstrap results.

Table 4: Bootstrap Test Results for Parallel Mediation Effects

Mediation Path	Front Path a	Backward Path b	Indirect Effect	Bootstrap SE	95% CI	p
Personalized	0.421	0.28	0.118	0.025	[0.072,	<0.001

Care → Peer Support → Teachers' AI Literacy					0.171]	
Personalized Care → AI-Supportive Organizational Climate → Teachers' AI Literacy	0.456	0.36	0.164	0.029	[0.109, 0.224]	<0.001

To further compare the effect sizes and confidence intervals of the two mediation pathways, the bootstrap results can be visualized in Figure 4.

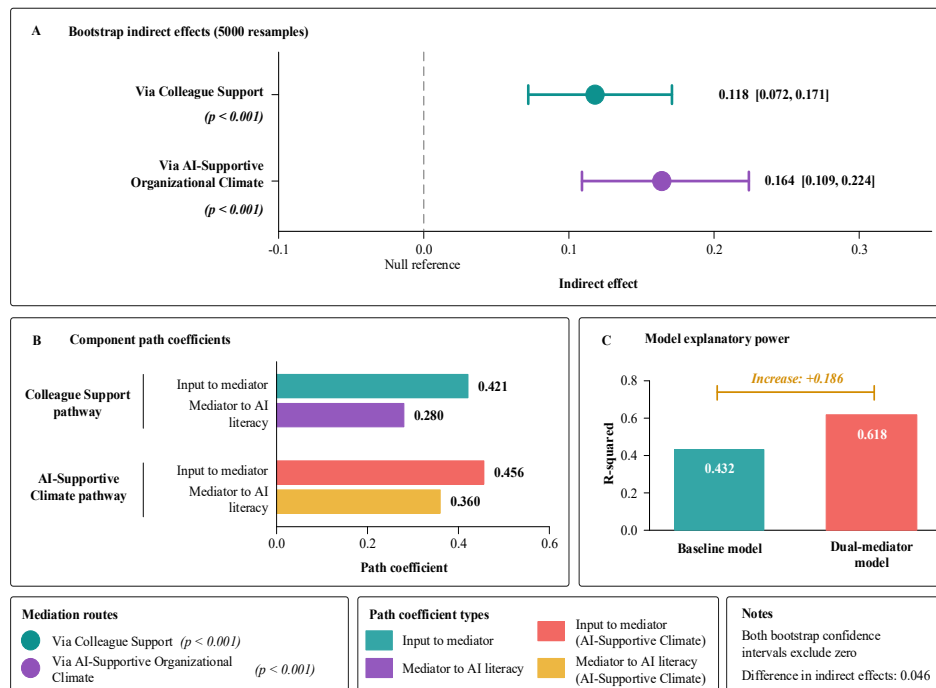


Figure 4: Dual mediation effects and 95% confidence intervals

Figure 4 shows the coefficient plot for the horizontal confidence interval for the indirect effect of colleague support (0.118 [0.072, 0.171]) and the indirect effect of an AI-supportive organizational climate (0.164 [0.109, 0.224]), using a horizontal line representing the value of 0 as a reference point. Both the confidence intervals do not include 0, which means that both the individual interaction channel and the organizational context channel are persistent information transmission channels, with the organizational climate channel path effect being 0.046 larger. The R² value for the two-mediating variables for teachers' AI literacy is 0.432 to 0.618 (a rise of 18.6 percentage points), which indicates that the mediating variables make a significant contribution in explaining the data point in the baseline model. So, hypothesis H3 and H5 are accepted.

4.4 Robustness and Alternative Model Tests

To investigate the sensitivity of the structural parameters to the estimation algorithm and the perturbations of the samples, we changed the original WLSMV model by using the robust maximum likelihood estimation method and reestimated the model after removing some samples with extreme standard residuals, but without changing the coding of control variables and the mapping of latent variables 16. We chose to study the upstream route from personalized care to the two mediating nodes and the findings are displayed in Table 5.

Table 5: Robustness Tests for Key Structural Paths Under Different Estimation Conditions

Testing Approach	Personalized Care → Colleague Support β	95% CI	Personalized Care → AI-Supportive Organizational Climate β	95% CI	Teachers' AI Literacy R ²
Baseline WLSMV	0.421***	[0.329, 0.510]	0.456***	[0.361, 0.547]	0.618
Robust MLR	0.408***	[0.315, 0.498]	0.443***	[0.347, 0.536]	0.607
Re-estimation after residual	0.414***	[0.320, 0.505]	0.449***	[0.353, 0.542]	0.612

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Note: *** indicates $p < 0.001$.

Table 5 reveals that there are only minor variations in both forward paths under the various data perturbations and parameter estimation algorithms and that the direction of the two paths remains the same; moreover, none of the 95 percent confidence intervals intercepts at zero. That is, the path coefficient values between personalized care and colleague support fell within the range of 0.408 to 0.421 and the path coefficient values between personalized care and an AI-supportive organizational climate ranged from 0.443 to 0.456, which means that there is no single estimator or a small number of outlier samples that drive the structural connectivity. Thus, H2 and H4 are accepted and this constitutes evidence from the upstream paths to the stability of the two indirect effects. By further altering the computational topology between the mediating nodes and re-estimating the parallel dual-mediation model alongside the single-mediation and serial-mediation models, the fit results are presented in Table 6.

Table 6: Test Results for Alternative Models with Different Structural Topologies

Model Structure	χ^2/df	CFI	TLI	RMSEA	SRMR	R ²
Parallel Dual-Mediator Model	1.89	0.958	0.951	0.046	0.039	0.618
Only colleagues support the agency	2.47	0.927	0.916	0.059	0.057	0.527
Organizational climate as a mediator only	2.21	0.939	0.93	0.054	0.051	0.566
Serial Mediator Model	2.12	0.944	0.935	0.052	0.048	0.584

As presented in Table 6, when excluding any mediating node, the explanatory power of teachers' AI literacy will also be reduced, and the R² for the serial structure will also be lower than 0.618. The parallel structure, on the contrary, still has CFI = 0.958, RMSEA = 0.046, and SRMR = 0.039, which shows that the two channels of information transmission are peer support and AI-supportive organizational climate, and they are relatively independent of each other. The results of the parameter stability were also examined, and the results showed that the corresponding structural relationships were stable when the estimator is replaced by another estimator and when the sample number is varied, as well as when the model topology is changed, which further proved the stability of the dual-mediation model.

5. Conclusions

Empirical results show that personalized care has two direct pathways that can boost AI literacy of teachers, as well as two relatively independent indirect pathways via peer support and AI-supportive organizational climate. In these, the indirect pathway (organizational climate pathway) made more contributions than the peer support pathway, and by introducing dual mediation, the explanatory power of teachers' AI literacy rose from 43.2% to 61.8%, suggesting that the transformation of leadership support into teachers' digital competence is not a single-mechanism process but rather the result of the combined effects of individual interaction mechanisms and organizational contextual mechanisms. The contribution of the research work is in the integration of transformational leadership and social support with organizational climate within the same structural framework and in the improvement of the rigor of the mechanism identification by means of path stability checking via estimator substitution, outlier detection, and alternative topology tests. With the use of cross-sectional data, self-report scales and faculty from a single educational institution, there are limitations that need to be addressed related to the temporal causal relationships between variables and the applicability of the findings across contexts. Future studies might include a longitudinal design, data from multiple data sources about teacher behaviour and multilevel structures to explore how the path coefficients change depending on the type of school, the digital infrastructure, and leadership context, as well as further identify the boundary conditions for the process of organizational support to teacher AI literacy.

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