

Academic Self-Efficacy as a Mediator of the Effect of Personalized Learning on Academic Achievement among Chinese University Students

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ABSTRACT

This study examined academic self-efficacy as a mediator of the effect of personalized learning on academic achievement among graduate students in China. A quantitative cross-sectional survey design was employed. Data were collected from 450 graduate students in China through an electronic questionnaire, and 446 valid responses were retained after Mahalanobis distance screening. The research instrument consisted of 30 items measuring personalized learning, academic self-efficacy, and perceived academic achievement. Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model showed satisfactory reliability and validity, with outer loadings above .70, Cronbach's alpha values ranging from .930 to .934, composite reliability values ranging from .941 to .944, and AVE values ranging from .615 to .628. The structural model explained 66.0% of the variance in academic achievement and 57.4% of the variance in academic self-efficacy. The results showed that personalized learning had a significant positive direct effect on academic achievement ($\beta = .329, t = 6.413, p < .001$) and academic self-efficacy ($\beta = .758, t = 31.583, p < .001$). Academic self-efficacy also significantly predicted academic achievement ($\beta = .534, t = 10.856, p < .001$). Mediation analysis confirmed that academic self-efficacy significantly mediated the relationship between personalized learning and academic achievement ($\beta = .405, t = 10.115, p < .001$). The findings suggest that personalized learning improves graduate students' academic achievement not only by providing flexible and adaptive learning support, but also by strengthening students' confidence in their academic abilities.

Keywords: Personalized learning; academic self-efficacy; academic achievement; graduate students; PLS-SEM; China.

INTRODUCTION

Personalized learning has become an important approach in higher education because it responds to students' different academic needs, learning preferences, abilities, and progress. Instead of assuming that all students benefit equally from the same learning materials, pace, feedback, and instructional support, personalized learning emphasizes flexible and adaptive learning experiences. This approach is particularly relevant for graduate education because postgraduate students differ in their academic background, research skills, learning autonomy, digital competence, and readiness to manage independent academic work. Prior studies have suggested that personalized learning may improve achievement by increasing relevance, engagement, feedback quality, and learner autonomy (Bernacki et al., 2021; Dumont & Ready, 2023; Major et al., 2021).

Despite the growing interest in personalized learning, the mechanism through which it affects academic achievement remains insufficiently explained. Some studies have shown that personalized learning has a positive effect on achievement, while others have argued that its effectiveness depends on students' ability to use personalized resources, feedback, and learning choices effectively (Pane et al., 2015, 2017). Therefore, it is important to examine not only whether personalized learning improves academic achievement, but also how this

effect occurs. One possible mechanism is academic self-efficacy, which refers to students' belief in their ability to complete academic tasks successfully (Bandura, 1997; Schunk & DiBenedetto, 2020).

Academic self-efficacy is a central psychological factor in learning and achievement. According to Social Cognitive Theory, students who believe they can succeed are more likely to set goals, invest effort, persist through difficulties, seek support, and use effective learning strategies (Bandura, 1986, 1997). Previous research has consistently shown that academic self-efficacy is associated with academic performance, persistence, motivation, and learning engagement (Honicke & Broadbent, 2016; Richardson et al., 2012; Robbins et al., 2004). In personalized learning environments, academic self-efficacy may become even more important because students are expected to manage flexible learning opportunities, respond to feedback, and take responsibility for academic progress.

Based on this background, this study examines academic self-efficacy as a mediator of the effect of personalized learning on academic achievement among graduate students in China. The study contributes to the literature by focusing on graduate students, a group that remains less examined in personalized learning research. It also provides a mechanism-based explanation by testing whether personalized learning improves achievement partly through academic self-efficacy.

Problem Statement

Personalized learning has been widely promoted as a student-centred pedagogical approach that improves academic achievement by adapting learning experiences to students' needs, interests, readiness levels, and learning pace. In graduate education, personalized learning is particularly important because students are expected to manage independent reading, academic writing, research tasks, and complex disciplinary learning with greater autonomy. However, the success of personalized learning cannot be explained only by the availability of flexible resources, adaptive tasks, or digital platforms. Prior research suggests that students' internal psychological capacities, especially academic self-efficacy, play a critical role in determining whether they can benefit from personalized learning environments (Bandura, 1997; Honicke & Broadbent, 2016; Richardson et al., 2012). Academic self-efficacy refers to students' belief in their ability to complete academic tasks successfully, and it influences their persistence, effort, help-seeking, and response to academic challenges. This issue is especially important in under-resourced and rural educational contexts such as Qinghai Province, China, where graduate students may face limited digital infrastructure, traditional teacher-centred learning backgrounds, insufficient academic support, and low confidence in managing independent learning demands. Although personalized learning is expected to support academic achievement, its effectiveness may be weakened when students do not believe that they are capable of handling academic tasks independently.

Despite the growing body of research on personalized learning and academic achievement, limited empirical attention has been given to the psychological mechanism through which personalized learning influences achievement among graduate students in non-Western and rural higher education contexts. Most previous studies have examined personalized learning, academic self-efficacy, and academic achievement as separate or direct relationships, while fewer studies have investigated whether academic self-efficacy mediates the relationship between personalized learning and academic achievement. This gap is important because personalized learning may improve achievement not only by providing suitable resources and feedback, but also by strengthening students' confidence in their academic ability. In contexts such as Qinghai, where many graduate students may enter postgraduate study with limited exposure to independent learning, academic self-efficacy may become a key mechanism that determines whether personalized learning can produce meaningful academic outcomes. Therefore, this study examines academic self-efficacy as a mediator of the effect of personalized learning on academic achievement among graduate students in China. By doing so, the study provides evidence on whether personalized learning enhances academic achievement partly by improving students' confidence in their ability to manage academic demands.

Conceptual Framework and Hypotheses

The conceptual framework of this study proposes that personalized learning directly influences academic achievement and indirectly influences academic achievement through academic self-efficacy. Personalized

learning is treated as the independent variable, academic self-efficacy as the mediating variable, and academic achievement as the dependent variable. The framework is grounded in Social Cognitive Theory, which explains that learning outcomes are influenced by the interaction between environmental factors, personal beliefs, and behavioural responses (Bandura, 1986, 1997). In this model, personalized learning represents the learning environment, academic self-efficacy represents the learner's psychological belief in academic capability, and academic achievement represents the learning outcome.

Personalized learning is expected to enhance academic achievement because it provides students with learning experiences that are more relevant, flexible, adaptive, and supportive. Personalized learning may include clear learning objectives, suitable resources, learning recommendations, adaptive activities, flexible pacing, and timely feedback. These features can help students understand academic requirements, monitor progress, and improve performance. Prior research has shown that personalized and technology-supported learning can positively influence academic outcomes when learning experiences are aligned with students' needs and progress (Bernacki et al., 2021; Dumont & Ready, 2023; Major et al., 2021; Pane et al., 2015).

Academic self-efficacy is also expected to directly influence academic achievement. Students with high academic self-efficacy are more likely to approach academic tasks confidently, persist when facing difficulties, and use effective strategies to complete assignments, projects, and assessments. Academic self-efficacy has been identified as a strong psychological predictor of academic performance in higher education (Honicke & Broadbent, 2016; Richardson et al., 2012; Robbins et al., 2004). In graduate education, this belief is especially important because students are required to manage independent reading, academic writing, research tasks, and complex learning demands.

Academic self-efficacy is also expected to mediate the relationship between personalized learning and academic achievement. Personalized learning may strengthen students' academic confidence by providing mastery experiences, constructive feedback, appropriate challenge, and opportunities to progress at a suitable pace. These features align with the sources of self-efficacy proposed by Bandura (1997), particularly mastery experiences and social persuasion. When students feel more capable of managing academic tasks, their achievement is likely to improve. Therefore, personalized learning may influence achievement partly by increasing students' academic self-efficacy.

Accordingly, the following hypotheses were tested:

- **H₁:** Personalized learning has a significant positive effect on academic achievement.
- **H₂:** Academic self-efficacy has a significant positive effect on academic achievement.
- **H₃:** Academic self-efficacy mediates the relationship between personalized learning and academic achievement.

METHODOLOGY

Research design and approach

This study employed a quantitative research design using a cross-sectional survey approach. The quantitative approach was appropriate because the study aimed to test hypothesized relationships among latent constructs using numerical data. The cross-sectional design allowed data to be collected at one point in time from a relatively large sample of graduate students. This approach is commonly used in educational research when the objective is to examine relationships among variables such as learning environment, self-efficacy, and academic achievement (Creswell & Creswell, 2018).

The study adopted a positivist orientation because it tested theoretically derived hypotheses using statistical analysis. The proposed model examined the direct effect of personalized learning on academic achievement, the direct effect of academic self-efficacy on academic achievement, and the mediating role of academic self-efficacy. Since the model involved latent variables measured by multiple indicators, PLS-SEM was used as the main analytical method.

Population and sampling

The target population of the study consisted of graduate students in China. A total of 450 graduate students were randomly selected to participate in the study. Data were collected through an electronic survey distributed to the selected students. Before the main analysis, the dataset was screened for missing data, response quality, and multivariate outliers. Four cases were removed based on Mahalanobis distance screening. Therefore, the final sample used for the analysis consisted of 446 valid responses.

The final sample size was considered adequate for PLS-SEM analysis. PLS-SEM is suitable for models involving latent constructs, mediation effects, and prediction-oriented objectives (Hair et al., 2019; Hair et al., 2022). The sample size of 446 was sufficient for estimating the proposed model, which included three latent constructs and three structural paths.

Instrumentation and measures

Data were collected using a structured questionnaire consisting of 30 items measuring three constructs: personalized learning, academic self-efficacy, and academic achievement. Each construct was measured using 10 items. The personalized learning items measured students' perceptions of adaptive learning resources, learning recommendations, flexible participation, learning pace, feedback, and suitability of learning activities. The academic self-efficacy items measured students' confidence in understanding academic readings, completing academic projects, solving academic difficulties, managing study time, seeking academic support, and succeeding in academic work. The academic achievement items measured perceived academic preparation, assignment completion, assessment performance, subject understanding, application of knowledge, academic participation, problem-solving, progress satisfaction, deadline management, and continuous improvement.

All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. A Likert scale was suitable because it allowed respondents to express the degree of agreement with statements related to their learning experiences, academic confidence, and academic achievement. Before the main data collection, the instrument was reviewed and validated to ensure content relevance, clarity, and suitability for graduate students.

Data analysis method (PLS-SEM)

The data were analysed using Partial Least Squares Structural Equation Modeling. PLS-SEM was selected because the study aimed to explain and predict academic achievement through personalized learning and academic self-efficacy. Compared with covariance-based SEM, which is mainly used for theory confirmation and model fit assessment, PLS-SEM is more suitable for prediction-oriented studies, mediation analysis, and models involving latent constructs (Hair et al., 2019; Hair et al., 2021; Sarstedt et al., 2022).

The analysis followed a two-stage procedure. First, the measurement model was assessed using outer loadings, Cronbach's alpha, composite reliability, Average Variance Extracted, HTMT, and Fornell–Larcker criterion. Second, the structural model was evaluated using collinearity statistics, coefficient of determination, effect size, predictive relevance, model fit, path coefficients, total effects, and indirect effects. Bootstrapping was used to test the significance of the direct and indirect effects.

RESULTS

Measurement Model Assessment

The measurement model was assessed to determine the reliability and validity of the constructs before testing the structural relationships. Indicator reliability was assessed using outer loadings. As shown in Table 1, all outer loadings exceeded the recommended threshold of .70, indicating that the indicators adequately represented their respective constructs (Hair et al., 2019).

Table 1. Outer Loadings of Measurement Items

Item	Academic Achievement	Academic Self-Efficacy	Personalized Learning
ASE01		.787	
ASE02		.802	
ASE03		.787	
ASE04		.784	
ASE05		.745	
ASE06		.787	
ASE07		.794	
ASE08		.803	
ASE09		.820	
ASE10		.798	
PAA01	.782		
PAA02	.805		
PAA03	.803		
PAA04	.804		
PAA05	.796		
PAA06	.778		
PAA07	.760		
PAA08	.792		
PAA09	.787		
PAA10	.729		
PL01			.824
PL02			.746
PL03			.801
PL04			.836
PL05			.764
PL06			.823
PL07			.772
PL08			.778
PL09			.792
PL10			.786

Internal consistency reliability was assessed using Cronbach’s alpha, composite reliability rho_A, and composite reliability rho_C. As presented in Table 2, Cronbach’s alpha values ranged from .930 to .934, rho_A values ranged from .931 to .935, and rho_C values ranged from .941 to .944. These values exceeded the recommended threshold of .70 and remained below .95, indicating strong reliability without serious item redundancy. Convergent validity was assessed using AVE. The AVE values ranged from .615 to .628, exceeding the recommended threshold of .50. Therefore, convergent validity was established.

Table 2. Reliability and Convergent Validity

Construct	Cronbach’s alpha	rho_A	rho_C	AVE
Academic Achievement	.930	.931	.941	.615
Academic Self-Efficacy	.933	.934	.943	.625
Personalized Learning	.934	.935	.944	.628

Discriminant validity was assessed using HTMT and the Fornell–Larcker criterion. The HTMT values were below the recommended threshold of .85, indicating that the constructs were empirically distinct (Henseler et al., 2015). The HTMT value between academic achievement and academic self-efficacy was .840, between academic achievement and personalized learning was .786, and between academic self-efficacy and personalized learning was .811. These results confirmed acceptable discriminant validity.

Table 3. HTMT Results

Construct	Academic Achievement	Academic Self-Efficacy	Personalized Learning
Academic Achievement	—		
Academic Self-Efficacy	.840	—	
Personalized Learning	.786	.811	—

The Fornell–Larcker criterion was also examined. Based on the AVE values, the square roots of AVE were .784 for academic achievement, .791 for academic self-efficacy, and .793 for personalized learning. These values were generally higher than the inter-construct correlations, indicating acceptable discriminant validity.

Table 4. Fornell–Larcker Criterion

Construct	Academic Achievement	Academic Self-Efficacy	Personalized Learning
Academic Achievement	.784		
Academic Self-Efficacy	.784	.791	
Personalized Learning	.734	.758	.793

Collinearity was examined using Variance Inflation Factors. All VIF values ranged from 1.829 to 2.685, which were below the conservative threshold of 3.00 and well below the maximum acceptable threshold of 5.00. Therefore, collinearity was not a concern in the measurement model.

Table 5. VIF Values

Item	VIF	Item	VIF	Item	VIF
ASE01	2.178	PAA01	2.134	PL01	2.528
ASE02	2.308	PAA02	2.319	PL02	1.922
ASE03	2.173	PAA03	2.327	PL03	2.301
ASE04	2.182	PAA04	2.376	PL04	2.685
ASE05	1.915	PAA05	2.241	PL05	2.032
ASE06	2.225	PAA06	2.154	PL06	2.514
ASE07	2.280	PAA07	2.056	PL07	2.075
ASE08	2.286	PAA08	2.238	PL08	2.132
ASE09	2.508	PAA09	2.205	PL09	2.218
ASE10	2.281	PAA10	1.829	PL10	2.183

Model fit was also assessed. The SRMR value was .033 for both the saturated and estimated model, which is below the recommended threshold of .08. The NFI value was .941, indicating acceptable model fit. These results suggest that the measurement and structural model adequately represented the data.

Table 6. Model Fit Indicators

Fit indicator	Saturated model	Estimated model
SRMR	.033	.033
d _{ULS}	.500	.500
d _G	.226	.226
Chi-square	550.252	550.252
NFI	.941	.941

Structural Model Evaluation

The structural model was assessed after confirming the adequacy of the measurement model. The coefficient of determination showed that the model explained 66.0% of the variance in academic achievement and 57.4% of the variance in academic self-efficacy. These values indicate strong explanatory power. Personalized learning

and academic self-efficacy together explained a substantial proportion of academic achievement, while personalized learning explained a substantial proportion of academic self-efficacy.

Table 7. Coefficient of Determination

Endogenous construct	R ²	Adjusted R ²
Academic Achievement	.660	.659
Academic Self-Efficacy	.574	.573

Effect size was assessed using f^2 . Personalized learning had a large effect on academic self-efficacy, $f^2 = 1.348$. Academic self-efficacy had a medium-to-large effect on academic achievement, $f^2 = .357$. Personalized learning had a small-to-medium direct effect on academic achievement, $f^2 = .136$. These results suggest that personalized learning strongly contributes to academic self-efficacy, while academic self-efficacy makes a meaningful contribution to academic achievement.

Table 8. Effect Size Results

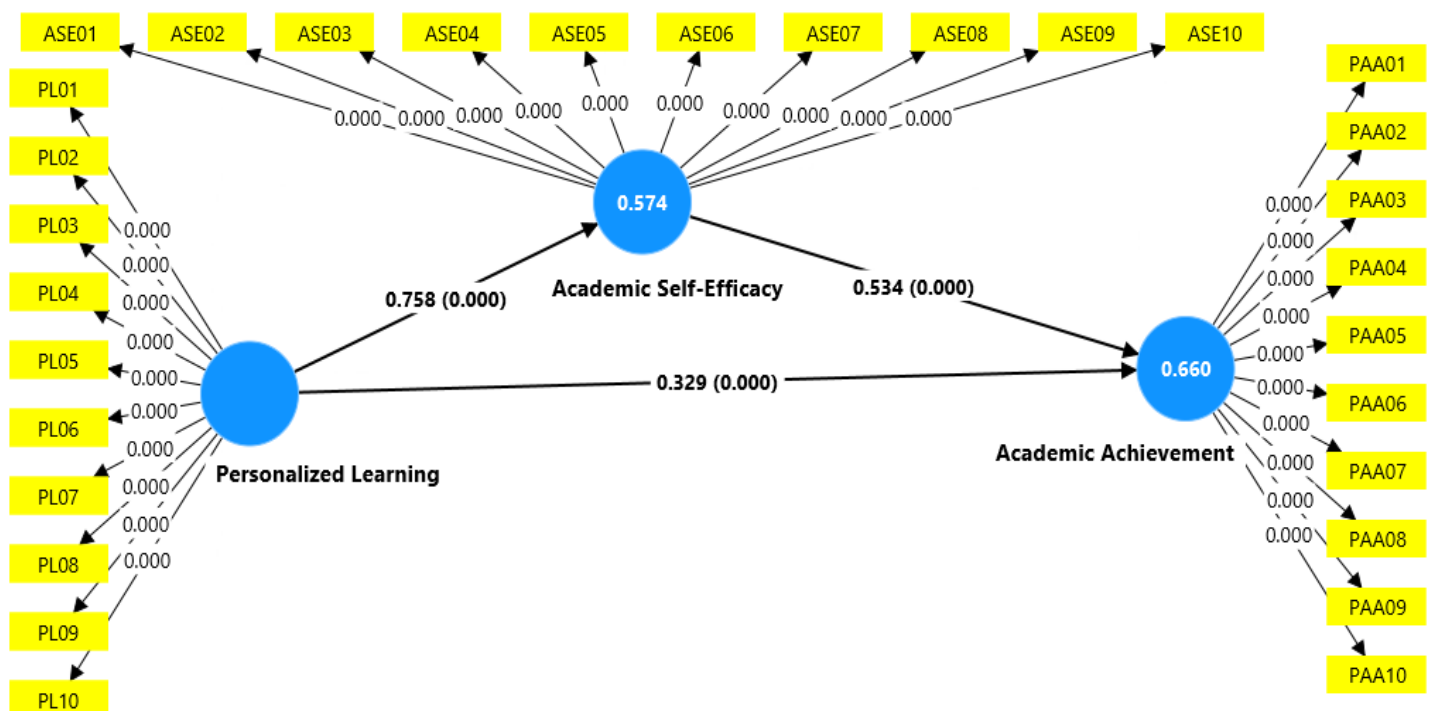
Predictor	Academic Achievement	Academic Self-Efficacy
Academic Self-Efficacy	.357	
Personalized Learning	.136	1.348

Predictive relevance was assessed using $Q^2_{predict}$. Academic self-efficacy recorded $Q^2_{predict} = .572$, while academic achievement recorded $Q^2_{predict} = .536$. Since both values were greater than zero, the model demonstrated predictive relevance for the endogenous constructs.

Table 9. $Q^2_{predict}$ Results

Endogenous construct	$Q^2_{predict}$	RMSE	MAE
Academic Self-Efficacy	.572	.657	.504
Academic Achievement	.536	.684	.515

Path Coefficients and Hypothesis Testing



The direct relationships among the constructs were assessed using bootstrapping. As shown in Table 10, personalized learning had a significant positive effect on academic achievement ($\beta = .329, t = 6.413, p < .001$).

Therefore, H₁ was supported. Academic self-efficacy also had a significant positive effect on academic achievement ($\beta = .534, t = 10.856, p < .001$). Therefore, H₂ was supported. In addition, personalized learning had a significant positive effect on academic self-efficacy ($\beta = .758, t = 31.583, p < .001$), confirming that students who perceived stronger personalized learning also reported higher academic self-efficacy.

Table 10. Direct Path Coefficients

Path	O	M	STDEV	t	p
Academic Self-Efficacy → Academic Achievement	.534	.535	.049	10.856	< .001
Personalized Learning → Academic Achievement	.329	.329	.051	6.413	< .001
Personalized Learning → Academic Self-Efficacy	.758	.758	.024	31.583	< .001

Mediation Analysis

The mediating role of academic self-efficacy was assessed using the bootstrapped indirect effect. The result showed that the indirect effect of personalized learning on academic achievement through academic self-efficacy was significant ($\beta = .405, t = 10.115, p < .001$). Therefore, H₃ was supported. This indicates that personalized learning improves academic achievement partly by strengthening students' academic self-efficacy.

Table 11. Specific Indirect Effect

Indirect path	O	M	STDEV	t	p
Personalized Learning → Academic Self-Efficacy → Academic Achievement	.405	.406	.040	10.115	< .001

The total indirect effect was also significant, as shown in Table 12. Since the direct effect of personalized learning on academic achievement remained significant together with the significant indirect effect, the mediation was interpreted as partial mediation.

Table 12. Total Indirect Effect

Path	O	M	STDEV	t	p
Personalized Learning → Academic Achievement	.405	.406	.040	10.115	< .001

The total effect of personalized learning on academic achievement was strong and significant ($\beta = .734, t = 26.835, p < .001$). This indicates that personalized learning had a substantial overall effect on academic achievement when both the direct and indirect effects were considered.

Table 13. Total Effects

Path	O	M	STDEV	t	p
Academic Self-Efficacy → Academic Achievement	.534	.535	.049	10.856	< .001
Personalized Learning → Academic Achievement	.734	.734	.027	26.835	< .001
Personalized Learning → Academic Self-Efficacy	.758	.758	.024	31.583	< .001

Table 14. Summary of Hypothesis Testing

Hypothesis	Result	Decision
H ₁ : Personalized learning has a significant positive effect on academic achievement.	$\beta = .329, t = 6.413, p < .001$	Supported
H ₂ : Academic self-efficacy has a significant positive effect on academic achievement.	$\beta = .534, t = 10.856, p < .001$	Supported
H ₃ : Academic self-efficacy mediates the relationship between personalized learning and academic achievement.	$\beta = .405, t = 10.115, p < .001$	Supported

DISCUSSION

The findings of this study provide strong evidence that personalized learning contributes to academic achievement among graduate students in China. The direct effect of personalized learning on academic achievement indicates that students who experience more flexible, adaptive, and supportive learning environments tend to report better academic outcomes. This result is consistent with previous research showing that personalized learning improves achievement by aligning learning materials, feedback, and instructional support with students' needs and progress (Bernacki et al., 2021; Dumont & Ready, 2023; Major et al., 2021). It also supports the argument that personalization is especially useful in higher education because students differ in their academic goals, prior preparation, and ability to manage independent learning.

The direct effect of academic self-efficacy on academic achievement was stronger than the direct effect of personalized learning. This finding is consistent with Social Cognitive Theory, which emphasizes that students' beliefs in their own capabilities influence motivation, persistence, strategy use, and performance (Bandura, 1986, 1997). The result also aligns with previous meta-analytic evidence showing that academic self-efficacy is one of the strongest psychological predictors of academic performance in higher education (Honicke & Broadbent, 2016; Richardson et al., 2012; Robbins et al., 2004). For graduate students, academic self-efficacy is particularly important because postgraduate study requires independent reading, academic writing, research design, thesis development, and long-term persistence.

The mediation result provides the most important contribution of the study. Academic self-efficacy significantly mediated the relationship between personalized learning and academic achievement. This means that personalized learning improved achievement partly because it increased students' confidence in their academic abilities. Personalized learning may strengthen academic self-efficacy by providing appropriate challenge, clear learning pathways, timely feedback, opportunities for mastery, and resources that match students' academic needs. These features are consistent with Bandura's sources of self-efficacy, especially mastery experiences and social persuasion (Bandura, 1997). When students feel that they can understand academic content, manage tasks, and succeed in their studies, they are more likely to achieve better academic outcomes.

The finding also helps explain why personalized learning may produce different levels of effectiveness across contexts. Personalized learning may not automatically improve achievement unless it also strengthens students' internal academic resources. If personalized learning provides flexibility without guidance, or resources without feedback, students may not develop stronger confidence. However, when personalized learning provides adaptive support, visible progress, and constructive feedback, it can improve academic self-efficacy and achievement. This interpretation is consistent with prior studies suggesting that the effectiveness of learning environments depends on psychological mechanisms such as motivation, self-efficacy, and self-regulation (Panadero, 2017; Schunk & DiBenedetto, 2020).

The partial mediation result is also important. Since personalized learning continued to have a significant direct effect on academic achievement after academic self-efficacy was included in the model, the relationship was not fully mediated. This means that personalized learning influences academic achievement in two ways. First, it directly supports achievement by providing relevant resources, flexible learning activities, and adaptive feedback. Second, it indirectly supports achievement by strengthening students' academic self-efficacy. Therefore, personalized learning should be viewed as both an instructional support system and a psychological support mechanism.

In the context of Chinese graduate education, these findings are meaningful. Graduate students often face demanding academic expectations related to coursework, research productivity, academic writing, thesis completion, and future career preparation. Personalized learning can help students manage these demands by providing flexible and responsive learning opportunities. However, the findings show that personalized learning becomes more powerful when it builds students' belief that they can succeed. Therefore, universities should design personalized learning environments that intentionally strengthen academic self-efficacy through constructive feedback, achievable milestones, academic mentoring, and opportunities for progressive mastery.

Contributions

This study makes several contributions to research and practice. First, it contributes to personalized learning research by examining its effect among graduate students in China. Much of the existing research on personalized learning has focused on school or undergraduate contexts. This study extends the literature by demonstrating that personalized learning is also relevant to postgraduate education, where independent learning and academic self-management are central.

Second, the study contributes theoretically by integrating personalized learning with Social Cognitive Theory. By showing that academic self-efficacy mediates the relationship between personalized learning and academic achievement, the study confirms that environmental learning conditions influence achievement through students' psychological beliefs. This supports Bandura's view that personal, behavioural, and environmental factors interact in shaping learning outcomes.

Third, the study contributes empirically by providing evidence from a PLS-SEM mediation model. The study showed that the model had strong explanatory power, with personalized learning and academic self-efficacy explaining 66.0% of the variance in academic achievement. This indicates that the proposed model has strong relevance for explaining graduate students' academic achievement.

Fourth, the study provides practical implications for universities, lecturers, and graduate supervisors. The findings suggest that personalized learning should not be limited to offering flexible resources or digital learning platforms. Instead, it should be designed to build students' academic confidence. Instructors and supervisors should provide constructive feedback, scaffold difficult tasks, create achievable milestones, and help students recognize their progress. Such practices can strengthen academic self-efficacy and improve achievement.

CONCLUSION

This study examined academic self-efficacy as a mediator of the effect of personalized learning on academic achievement among graduate students in China. The findings confirmed that personalized learning had a significant positive effect on academic achievement and academic self-efficacy. Academic self-efficacy also had a significant positive effect on academic achievement. Most importantly, academic self-efficacy significantly mediated the relationship between personalized learning and academic achievement.

The study concludes that personalized learning improves academic achievement not only by providing flexible, adaptive, and supportive learning experiences, but also by strengthening students' confidence in their academic abilities. The partial mediation result indicates that personalized learning has both direct and indirect effects on achievement. Therefore, academic self-efficacy should be considered a key psychological mechanism in personalized learning research and practice.

The findings suggest that graduate education should adopt personalized learning approaches that intentionally support students' academic confidence. Universities should design learning environments that provide relevant resources, adaptive feedback, clear learning pathways, and opportunities for mastery. By strengthening academic self-efficacy, personalized learning can become a more effective approach for improving graduate students' academic achievement.

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