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

Wang YuanYuan[1], Mohammed Y.M. Mai[2]

[1]PhD Candidate, Faculty of Human Development, Sultan Idris Education University, Tanjung Malim, Perak, Malaysia

[1,2]Associated Professor, Educational Studies Department, Faculty of Human Development, Sultan Idris Education University, Tanjung Malim, Perak, Malaysia

DOI: https://doi.org/10.47772/IJRISS.2026.100500090

Received: 30 April 2026; Accepted: 06 May 2026; Published: 23 May 2026

ABSTRACT

This study examined self-regulated learning 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, self-regulated learning, and perceived academic achievement. Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model demonstrated satisfactory reliability and validity, with all outer loadings exceeding .70, Cronbach's alpha values ranging from .930 to .937, composite reliability values ranging from .941 to .947, and AVE values ranging from .615 to .640. The structural model explained 65.4% of the variance in academic achievement and 51.6% of the variance in self-regulated learning. The results showed that personalized learning had a significant positive direct effect on academic achievement ($\beta = .386$, $t = 8.101$, $p < .001$) and self-regulated learning ($\beta = .718$, $t = 25.018$, $p < .001$). Self-regulated learning also significantly predicted academic achievement ($\beta = .486$, $t = 10.138$, $p < .001$). Mediation analysis confirmed that self-regulated learning significantly mediated the relationship between personalized learning and academic achievement ($\beta = .349$, $t = 9.629$, $p < .001$). The findings suggest that personalized learning improves graduate students' academic achievement partly by enhancing students' ability to regulate their learning process.

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

INTRODUCTION

Personalized learning has become an important pedagogical approach in higher education because it responds to students' different academic needs, learning preferences, readiness levels, and progress. Rather than applying a uniform model of teaching, personalized learning provides learning experiences that are more flexible, adaptive, and responsive to individual students. In graduate education, this approach is particularly relevant because students are expected to engage in independent learning, research activities, academic writing, complex reading tasks, and long-term academic projects. Previous studies have shown that personalized learning can improve academic outcomes when learning materials, feedback, instructional support, and learning pathways are aligned with students' needs and progress (Bernacki et al., 2021; Dumont & Ready, 2023; Major et al., 2021; Pane et al., 2015).

However, personalized learning does not automatically lead to higher academic achievement. Students must know how to use personalized opportunities effectively. Flexible resources, adaptive feedback, and learning choices can support achievement only when students are able to plan their learning, monitor progress, manage study time, seek help, and revise strategies. Therefore, self-regulated learning is a critical mechanism in personalized learning environments. Zimmerman (2000, 2002) explained that self-regulated learners are active participants who set goals, apply strategies, monitor performance, and reflect on outcomes. Similarly, Pintrich (2000, 2004) emphasized that self-regulated learning involves the regulation of cognition, motivation, behaviour, and learning context.

Self-regulated learning has been consistently associated with academic achievement in higher education, online learning, and blended learning environments. Systematic reviews and meta-analyses have shown that students who use self-regulated learning strategies such as time management, metacognitive monitoring, effort regulation, help-seeking, and strategy adjustment tend to perform better academically (Broadbent & Poon, 2015; Dent & Koenka, 2016; Theobald, 2021; Xu et al., 2023). This is especially important for graduate students, whose academic success depends heavily on independent study, research management, and sustained academic effort.

Based on this background, this study examines self-regulated learning as a mediator of the effect of personalized learning on academic achievement among graduate students in China. The study contributes to the literature by testing a mechanism-based model in which personalized learning influences academic achievement both directly and indirectly through self-regulated learning.

Problem Statement

Personalized learning is increasingly viewed as a transformative approach for improving academic achievement because it provides students with flexible learning pathways, adaptive resources, timely feedback, and opportunities to learn according to individual needs and progress. However, personalized learning also places greater responsibility on students to manage their own learning. This creates a major challenge in graduate education, where students are expected to regulate complex academic tasks such as research reading, proposal writing, data analysis, academic writing, and thesis development. Self-regulated learning is therefore central to the success of personalized learning because it involves students' ability to set goals, plan learning activities, monitor progress, manage time, seek help, and adjust strategies when difficulties arise (Zimmerman, 2002; Pintrich, 2004; Panadero, 2017). In under-resourced and rural contexts such as Qinghai Province, China, the challenge is more serious because students may have limited access to digital learning infrastructure, limited prior experience with learner-centred education, and weaker preparation for autonomous learning. As a result, personalized learning may not automatically improve academic achievement unless students have sufficient self-regulated learning skills to use personalized learning opportunities effectively.

Although previous research has shown that personalized learning and self-regulated learning are associated with academic success, the mediating role of self-regulated learning remains insufficiently examined among graduate students, especially in rural and non-Western higher education settings. Many personalized learning frameworks assume that learners already possess the metacognitive and behavioural skills needed to benefit from autonomy, flexibility, and adaptive learning resources. This assumption is problematic for students who were previously educated in teacher-centred systems and may struggle with goal setting, self-monitoring, feedback use, and independent academic planning. In such cases, personalized learning may provide learning opportunities, but students may fail to convert these opportunities into academic achievement without strong self-regulated learning. Therefore, this study examines self-regulated learning as a mediator of the effect of personalized learning on academic achievement among graduate students in China. The study addresses an important gap by explaining whether personalized learning improves academic achievement partly through students' ability to regulate their own learning, thereby offering evidence for designing personalized learning environments that actively support learner autonomy, strategic learning, and academic success.

Conceptual Framework and Hypotheses

The conceptual framework of this study proposes that personalized learning directly influences academic achievement and indirectly influences academic achievement through self-regulated learning. Personalized learning is treated as the independent variable, self-regulated learning as the mediating variable, and academic achievement as the dependent variable. The model is grounded in self-regulated learning theory, which argues that students' academic outcomes depend not only on learning conditions but also on their ability to control and manage their own learning processes (Zimmerman, 2000, 2002; Pintrich, 2000, 2004).

Personalized learning is expected to influence academic achievement because it provides learning environments that are more flexible, relevant, adaptive, and supportive. Personalized learning may include clear learning objectives, learning recommendations, differentiated resources, flexible participation formats, learning pace options, adaptive learning activities, and timely feedback. These features can help students understand learning requirements and improve their academic performance. Therefore, personalized learning is expected to have a direct positive effect on academic achievement.

Self-regulated learning is also expected to directly influence academic achievement. Students who can set goals, organize their learning environment, use different strategies, monitor progress, adjust learning methods, seek help, collaborate with peers, review previous materials, and manage time effectively are more likely to complete academic tasks successfully. This is particularly important in graduate education because students are expected to manage independent and complex academic responsibilities.

Self-regulated learning is also expected to mediate the relationship between personalized learning and academic achievement. Personalized learning gives students more learning opportunities, but self-regulated learning determines whether students can use these opportunities effectively. A personalized learning environment may encourage students to plan their learning, use feedback, monitor academic progress, and adjust their strategies. Therefore, personalized learning may improve achievement partly through self-regulated learning.

Accordingly, the following hypotheses were tested:

- **H_1:** Personalized learning has a significant positive effect on academic achievement.
- **H_2:** Self-regulated learning has a significant positive effect on academic achievement.
- **H_3:** Self-regulated learning 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-step approach. First, the measurement model was assessed using outer loadings, Cronbach's alpha, composite reliability, Average Variance Extracted, HTMT, Fornell–Larcker criterion, and VIF values. Then, the structural model was analyzed by evaluating the coefficient of determination, effect size, model fit, path coefficients, indirect effects, and total effects. Bootstrapping was utilized to determine the significance of both direct and indirect effects.

RESULTS

Measurement Model Assessment

The measurement model was scrutinized to confirm that the indicators accurately and consistently measured their designated constructs. The reliability of the indicators was evaluated through outer loadings. As shown in Table 1, all outer loadings exceeded the suggested threshold of .70, indicating that the indicators effectively represented their respective constructs.

Table 1. Outer Loadings of Measurement Items

Item	Academic Achievement	Personalized Learning	Self-Regulated Learning
PAA01	.781		
PAA02	.805		
PAA03	.801		
PAA04	.807		
PAA05	.796		
PAA06	.778		
PAA07	.760		
PAA08	.792		
PAA09	.787		
PAA10	.728		

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

PL01		.824	
PL02		.742	
PL03		.802	
PL04		.836	
PL05		.762	
PL06		.823	
PL07		.774	
PL08		.779	
PL09		.791	
PL10		.786	
SRL01			.833
SRL02			.824
SRL03			.827
SRL04			.807
SRL05			.772
SRL06			.767
SRL07			.799
SRL08			.793
SRL09			.785
SRL10			.791

Internal consistency reliability was evaluated 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 .937, rho_A values ranged from .931 to .938, and rho_C values ranged from .941 to .947. These values surpassed the recommended threshold of .70 and remained below .95, indicating robust internal consistency without significant item redundancy. Convergent validity was assessed through the Average Variance Extracted (AVE). The AVE values ranged from .615 to .640, exceeding the recommended threshold of .50. Consequently, convergent validity was established.

Table 2. Construct Reliability and Convergent Validity

Construct	Cronbach's alpha	rho_A	rho_C	AVE
Academic Achievement	.930	.931	.941	.615
Personalized Learning	.934	.935	.944	.628
Self-Regulated Learning	.937	.938	.947	.640

Discriminant validity was evaluated using the HTMT criterion. As presented in Table 3, the HTMT values were below the recommended threshold of .85. Specifically, the HTMT value between academic achievement and personalized learning was .786, between academic achievement and self-regulated learning was .816, and between personalized learning and self-regulated learning was .766. These findings suggest that the constructs were empirically distinct.

Table 3. HTMT Results

Construct	Academic Achievement	Personalized Learning	Self-Regulated Learning
Academic Achievement	—		
Personalized Learning	.786	—	
Self-Regulated Learning	.816	.766	—

The Fornell–Larcker criterion was evaluated. As shown in Table 4, the square roots of the Average Variance Extracted (AVE) were .784 for academic achievement, .793 for personalized learning, and .800 for self-regulated learning. These values exceeded the correlations between the constructs, thereby affirming discriminant validity.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

Table 4. Fornell–Larcker Criterion

Construct	Academic Achievement	Personalized Learning	Self-Regulated Learning
Academic Achievement	.784		
Personalized Learning	.735	.793	
Self-Regulated Learning	.763	.718	.800

Collinearity was assessed through the application of Variance Inflation Factors (VIF). As indicated in Table 5, the VIF values ranged from 1.829 to 2.685. Given that all values were below the conservative threshold of 3.00 and significantly below the maximum threshold of 5.00, collinearity was not deemed problematic.

Table 5. VIF Values

Item	VIF	Item	VIF	Item	VIF
PAA01	2.134	PL01	2.528	SRL01	2.665
PAA02	2.319	PL02	1.922	SRL02	2.553
PAA03	2.327	PL03	2.301	SRL03	2.611
PAA04	2.376	PL04	2.685	SRL04	2.425
PAA05	2.241	PL05	2.032	SRL05	2.085
PAA06	2.154	PL06	2.514	SRL06	2.056
PAA07	2.056	PL07	2.075	SRL07	2.292
PAA08	2.238	PL08	2.132	SRL08	2.234
PAA09	2.205	PL09	2.218	SRL09	2.169
PAA10	1.829	PL10	2.183	SRL10	2.252

Model fit was assessed using SRMR, d_ULS, d_G, chi-square, and NFI. As shown in Table 6, the SRMR value was .032 for both the saturated and estimated models, which is below the recommended threshold of .08. The NFI value was .944, indicating acceptable model fit. Therefore, the model demonstrated adequate fit.

Table 6. Model Fit Indicators

Fit indicator	Saturated model	Estimated model
SRMR	.032	.032
d_ULS	.491	.491
d_G	.215	.215
Chi-square	531.790	531.790
NFI	.944	.944

Structural Model Evaluation

Following the confirmation of the measurement model's adequacy, the structural model was subsequently assessed. The coefficient of determination revealed that personalized learning and self-regulated learning accounted for 65.4% of the variance in academic achievement. Furthermore, personalized learning accounted for 51.6% of the variance in self-regulated learning. These findings suggest that the model possesses substantial explanatory power.

Table 7. Coefficient of Determination

Endogenous construct	R^2	Adjusted R^2
Academic Achievement	.654	.652
Self-Regulated Learning	.516	.514

The effect size was evaluated using f^2. Personalized learning demonstrated a substantial effect on self-regulated learning, with $f^2 = 1.064$. Self-regulated learning exhibited a medium-to-large effect on academic achievement, with $f^2 = .330$. Additionally, personalized learning had a medium effect on academic achievement, with $f^2 = .208$.

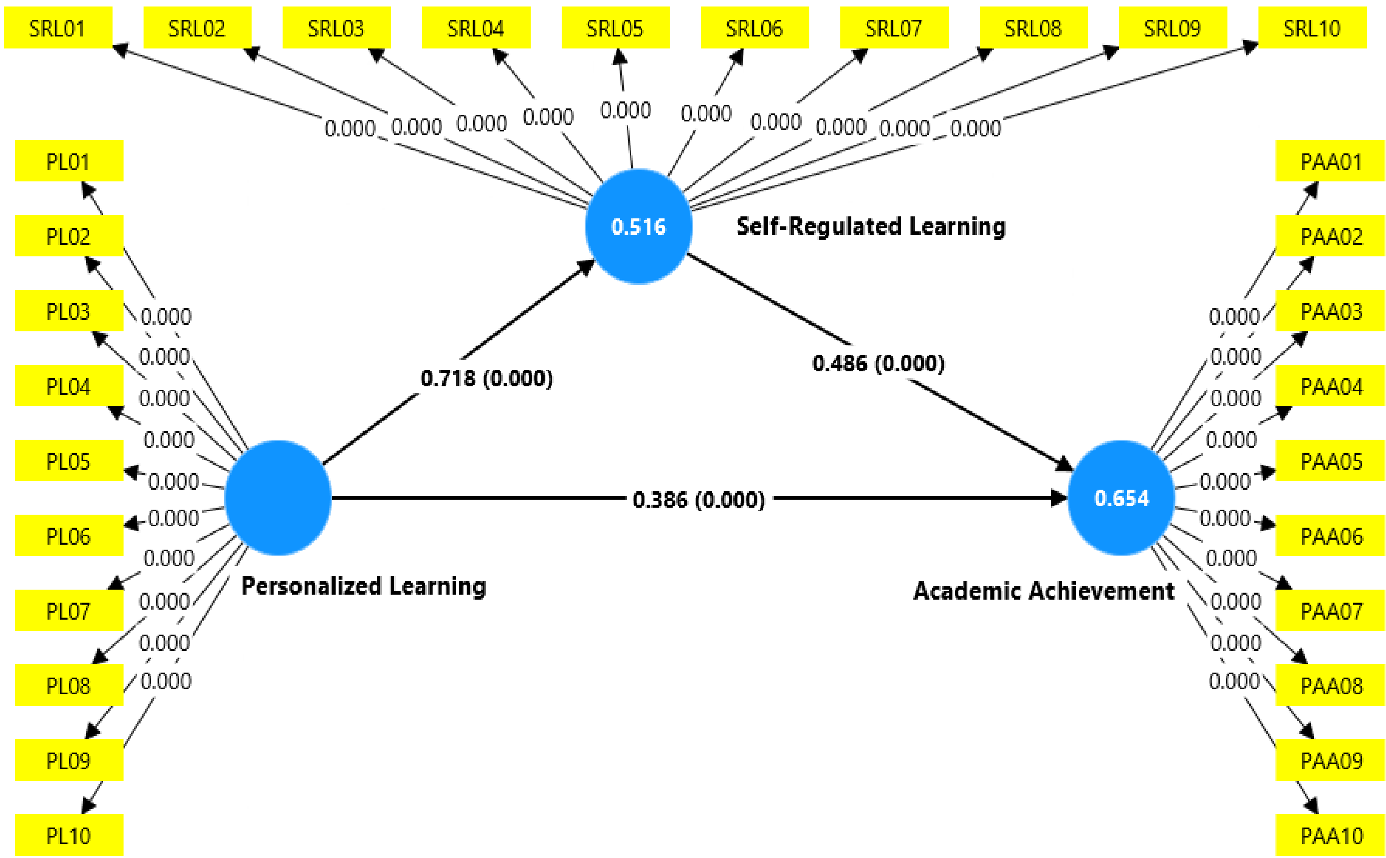
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

These findings suggest that personalized learning significantly enhances self-regulated learning, while both personalized learning and self-regulated learning contribute meaningfully to academic achievement.

Table 8. Effect Size Results

Predictor	Academic Achievement	Self-Regulated Learning
Personalized Learning	.208	1.064
Self-Regulated Learning	.330	

Path Coefficients and Hypothesis Testing



Bootstrapping was employed to evaluate the significance of the direct relationships. As indicated in Table 9, personalized learning exerted a significant positive influence on academic achievement (β = .386, t = 8.101, p < .001), thereby supporting H_1. Similarly, self-regulated learning demonstrated a significant positive impact on academic achievement (β = .486, t = 10.138, p < .001), thus supporting H_2. Furthermore, personalized learning significantly positively affected self-regulated learning (β = .718, t = 25.018, p < .001), corroborating that students who perceived a higher degree of personalized learning also reported enhanced self-regulated learning.

Table 9. Direct Path Coefficients

Path	O	M	STDEV	*t*	*p*
Personalized Learning → Academic Achievement	.386	.385	.048	8.101	< .001
Personalized Learning → Self-Regulated Learning	.718	.719	.029	25.018	< .001
Self-Regulated Learning → Academic Achievement	.486	.488	.048	10.138	< .001

Mediation Analysis

The mediating role of self-regulated learning was assessed using bootstrapping. The specific indirect effect of personalized learning on academic achievement through self-regulated learning was significant (β = .349, *t* =

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

9.629, $p < .001$). Therefore, H_3 was supported. This result indicates that personalized learning improved academic achievement partly by enhancing students' self-regulated learning.

Table 10. Specific Indirect Effect

Indirect path	O	M	STDEV	*t*	*p*
Personalized Learning → Self-Regulated Learning → Academic Achievement	.349	.350	.036	9.629	< .001

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

Table 11. Total Indirect Effect

Path	O	M	STDEV	*t*	*p*
Personalized Learning → Academic Achievement	.349	.350	.036	9.629	< .001

The total effect of personalized learning on academic achievement was strong and significant ($\beta = .735$, $t = 26.944$, $p < .001$). This indicates that personalized learning had a substantial overall effect on academic achievement when both the direct and indirect effects were considered.

Table 12. Total Effects

Path	O	M	STDEV	*t*	*p*
Personalized Learning → Academic Achievement	.735	.735	.027	26.944	< .001
Personalized Learning → Self-Regulated Learning	.718	.719	.029	25.018	< .001
Self-Regulated Learning → Academic Achievement	.486	.488	.048	10.138	< .001

Table 13. Summary of Hypothesis Testing

Hypothesis	Result	Decision
H_1: Personalized learning has a significant positive effect on academic achievement.	$\beta = .386$, $t = 8.101$, $p < .001$	Supported
H_2: Self-regulated learning has a significant positive effect on academic achievement.	$\beta = .486$, $t = 10.138$, $p < .001$	Supported
H_3: Self-regulated learning mediates the relationship between personalized learning and academic achievement.	$\beta = .349$, $t = 9.629$, $p < .001$	Supported

DISCUSSION

This study investigated the role of self-regulated learning as a mediator in the relationship between personalized learning and academic achievement among graduate students in China. The findings revealed that personalized learning exerted a significant positive direct effect on academic achievement. This outcome corroborates previous research indicating that personalized learning can enhance student outcomes when learning activities, resources, feedback, and support are tailored to students' needs, progress, and learning preferences (Bernacki et al., 2021; Dumont & Ready, 2023; Major et al., 2021; Pane et al., 2015). In the context of graduate education, personalized learning may be particularly beneficial, as graduate students require flexible support to manage independent reading, research activities, academic writing, and long-term academic tasks.

The results also demonstrated that self-regulated learning had a significant positive direct effect on academic achievement. This finding aligns with self-regulated learning theory, which conceptualizes students as active learners who set goals, monitor progress, regulate effort, employ strategies, and reflect on outcomes (Pintrich, 2000, 2004; Zimmerman, 2000, 2002). It is further supported by empirical evidence indicating that self-regulated learning strategies are positively associated with academic performance in higher education, online learning, and blended learning contexts (Broadbent & Poon, 2015; Dent & Koenka, 2016; Theobald, 2021; Xu et al., 2023). For graduate students, self-regulated learning is particularly crucial, as academic success necessitates independence, planning, persistence, and strategic use of learning resources.

The most significant finding of this study is that self-regulated learning significantly mediated the relationship between personalized learning and academic achievement. This suggests that personalized learning enhances achievement partly by bolstering students' ability to regulate their own learning. Personalized learning offers students flexibility, feedback, adaptive resources, and learning choices. However, students require self-regulated learning skills to effectively utilize these opportunities. Without planning, monitoring, time management, help-seeking, and strategy adjustment, students may not fully benefit from personalized learning. This finding supports the argument that personalized learning should not be perceived as a passive instructional arrangement. Instead, it should be designed to cultivate students' active learning management.

The mediation results further clarify the differential impact of personalized learning across various educational settings. Personalized learning may prove less effective when students are granted flexibility without sufficient structure or guidance. Conversely, when personalized learning facilitates students' goal setting, progress monitoring, feedback utilization, and reflection, it can enhance self-regulated learning and improve academic achievement. This interpretation aligns with Nicol and Macfarlane-Dick's (2006) assertion that feedback can support self-regulation by helping students understand standards, monitor performance, and identify subsequent steps. It also concurs with Wong et al. (2019), who emphasized that online and flexible learning environments require explicit support for self-regulated learning.

The partial mediation result is also noteworthy. Since personalized learning continued to exert a significant direct effect on academic achievement after self-regulated learning was incorporated into the model, self-regulated learning partially mediated the relationship. This indicates that personalized learning influences academic achievement in two ways. First, it directly supports achievement by providing relevant learning resources, adaptive learning activities, and feedback. Second, it indirectly supports achievement by enhancing students' ability to regulate their own learning. Therefore, personalized learning is most effective when it integrates adaptive instructional support with the development of students' self-regulatory capacity.

In the context of Chinese graduate education, these findings have significant implications. Graduate students are expected to manage complex academic demands, including coursework, research proposal writing, data analysis, academic publication, thesis development, and supervisor feedback. Personalized learning can offer the flexible support necessary for these demands, but students also require self-regulated learning to translate such support into achievement. Consequently, universities should design personalized learning environments that incorporate structured goal-setting, formative feedback, progress monitoring, reflective learning activities, and support for time management and help-seeking.

Contributions

This study offers several significant contributions to both research and practice. Firstly, it advances the field of personalized learning research by investigating its impact on graduate students in China. While previous research has predominantly concentrated on school students, undergraduate learners, or technology-based personalized learning systems, this study broadens the scope by demonstrating the applicability of personalized learning to postgraduate education.

Secondly, the study makes a theoretical contribution by integrating personalized learning with self-regulated learning theory. The findings reveal that personalized learning enhances achievement not only directly but also indirectly through self-regulated learning. This supports the perspective that learning environments affect achievement via students' active regulation of their learning processes.

Thirdly, the study provides empirical contributions by employing a mediation model using PLS-SEM. The model accounted for 65.4% of the variance in academic achievement and 51.6% of the variance in self-regulated learning. These figures suggest that the proposed model possesses substantial explanatory power in elucidating graduate students' academic achievement.

Lastly, the study offers practical contributions by illustrating that personalized learning should be structured to foster self-regulated learning. It is recommended that universities, lecturers, and supervisors equip students with tools and support for goal setting, time management, strategy use, progress monitoring, feedback utilization, and reflective learning. Such support can enable students to more effectively leverage personalized learning opportunities and enhance their academic performance.

CONCLUSION

This study investigated the role of self-regulated learning as a mediator in the relationship between personalized learning and academic achievement among graduate students in China. The results demonstrated that personalized learning exerted a significant positive influence on both academic achievement and self-regulated learning. Furthermore, self-regulated learning was found to have a significant positive impact on academic achievement. Crucially, self-regulated learning significantly mediated the relationship between personalized learning and academic achievement.

The study concludes that personalized learning enhances academic achievement not only by offering flexible, adaptive, and supportive learning experiences but also by bolstering students' capacity to regulate their own learning. The partial mediation result suggests that personalized learning has both direct and indirect effects on achievement. Consequently, self-regulated learning should be regarded as a key behavioral mechanism in personalized learning research and practice.

The findings imply that graduate education should incorporate personalized learning approaches that deliberately support students' self-regulation. Universities should design learning environments that provide clear learning goals, adaptive resources, progress monitoring, constructive feedback, reflective activities, and structured opportunities for students to manage their learning. By enhancing self-regulated learning, personalized learning can become a more effective strategy for improving graduate students' academic achievement.

REFERENCES

1. Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose(s)? Educational Psychology Review, 33, 1675–1715.
2. Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies and academic achievement in online higher education learning environments: A systematic review. The Internet and Higher Education, 27, 1–13.
3. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE.
4. Dent, A. L., & Koenka, A. C. (2016). The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. Educational Psychology Review, 28, 425–474.
5. Dumont, H., & Ready, D. D. (2023). On the promise of personalized learning for educational equity. npj Science of Learning, 8, Article 26.
6. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE.
7. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.
8. Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2022). Advanced issues in partial least squares structural equation modeling (2nd ed.). SAGE.
9. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.
10. Honicke, T., & Broadbent, J. (2016). The influence of academic self-efficacy on academic performance: A systematic review. Educational Research Review, 17, 63–84. https://doi.org/10.1016/j.edurev.2015.11.002

11. Major, L., Francis, G. A., & Tsapali, M. (2021). The effectiveness of technology-supported personalised learning in low- and middle-income countries: A meta-analysis. British Journal of Educational Technology, 52(5), 1935–1964.
12. Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. Studies in Higher Education, 31(2), 199–218.
13. Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. Frontiers in Psychology, 8, Article 422. https://doi.org/10.3389/fpsyg.2017.00422
14. Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2015). Continued progress: Promising evidence on personalized learning. RAND Corporation.
15. Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), Handbook of self-regulation (pp. 451–502). Academic Press.
16. Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. Educational Psychology Review, 16(4), 385–407. https://doi.org/10.1007/s10648-004-0006-x
17. Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. Psychological Bulletin, 138(2), 353–387. https://doi.org/10.1037/a0026838
18. Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2022). Estimation issues with PLS and CBSEM: Where the bias lies! Journal of Business Research, 69(10), 3998–4010.
19. Theobald, M. (2021). Self-regulated learning training programs enhance university students' academic performance, self-regulated learning strategies, and motivation: A meta-analysis. Contemporary Educational Psychology, 66, Article 101976.
20. Wong, J., Baars, M., Davis, D., Van Der Zee, T., Houben, G.-J., & Paas, F. (2019). Supporting self-regulated learning in online learning environments and MOOCs: A systematic review. International Journal of Human–Computer Interaction, 35(4–5), 356–373.
21. Xu, Z., Zhang, Y., & Li, H. (2023). A meta-analysis of the efficacy of self-regulated learning interventions on academic achievement in online and blended environments in K–12 and higher education. Behaviour & Information Technology, 42(16), 2911–2928.
22. Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), Handbook of self-regulation (pp. 13–39). Academic Press.
23. Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory Into Practice, 41(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2