Original Article

Strategic educational management and academic performance enhancement among pharmacy students: a PLS-SEM approach

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ABSTRACT

The quality of pharmacy education is increasingly shaped by how institutions design and implement strategic management of learning environments. This study investigates the role of Strategic Educational Management (SEMg) in enhancing Academic Performance (AP) and Learning Quality (LQ) among pharmacy students in Vietnam. Drawing on Self-Determination Theory (SDT), Social Cognitive Theory, and Constructivist Learning Theory, we develop a comprehensive model incorporating Learning Engagement (LE) and Self-Regulated Learning (SRL) as sequential mediators, and Digital Learning Support (DLS) as a boundary condition moderator. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) and data from 312 pharmacy students enrolled in Vietnamese university pharmacy programs, all thirteen hypotheses are supported. SEMg significantly drives LE (β = 0.462), AP (β = 0.283), and LQ (β = 0.261). LE enhances SRL (β = 0.538), which in turn advances AP (β = 0.469). AP substantially improves LQ (β = 0.471). Serial mediation through LE and SRL is confirmed (β = 0.117), and DLS amplifies the SEMg–LE relationship (β = 0.161). The model explains 56.1% of the variance in LQ. These findings advance educational management theory by integrating management-level strategies with student-level learning behaviors, and provide concrete recommendations for curriculum administrators, pharmacy faculty, and educational policymakers to enhance both academic performance and high-quality learning outcomes.

Keywords: Strategic educational management, Learning engagement, Self-regulated learning, Academic performance, Learning quality, PLS-SEM

Introduction

The pharmacy profession demands practitioners capable of applying complex pharmacological knowledge, exercising critical clinical judgment, and adapting to rapidly evolving pharmaceutical sciences and healthcare delivery models [1, 2]. Achieving these competency standards requires not only high academic performance but also high-quality learning—encompassing critical thinking, knowledge transfer to practice, and long-term knowledge retention [3, 4]. Educational institutions are consequently under dual pressure: to improve measurable academic outcomes and to ensure that graduates possess the deep cognitive and applied capabilities that clinical and regulatory environments demand.

Strategic Educational Management (SEMg) has emerged as a central lever for addressing these pressures. SEMg refers to the systematic planning, implementation, and evaluation of educational strategies—including curriculum alignment, instructional quality management, institutional learning support, and evidence-based feedback systems—that create structured conditions for optimal student development [5]. While prior research demonstrates positive associations between educational management quality and student outcomes, the mechanisms

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through which SEMg translates into academic performance and learning quality remain incompletely theorized. Specifically, two critical gaps persist.

First, the roles of Learning Engagement (LE) and Self-Regulated Learning (SRL) as sequential capability-building mediators in the SEMg–performance–quality chain have been theorized separately [6-8] but not empirically validated as an integrated sequential pathway. Second, the moderating role of Digital Learning Support (DLS)—the digital infrastructure through which contemporary pharmacy education is increasingly delivered—has not been examined as a boundary condition for the SEMg–LE relationship, despite growing evidence that digital environments shape engagement quality [9, 10].

This study addresses both gaps by developing and testing a comprehensive PLS-SEM model linking SEMg → LE → SRL → AP → LQ with DLS as a moderator of the SEMg–LE relationship. Theoretically, the model integrates Self-Determination Theory (SDT; [6, 11]), Social Cognitive Theory and self-regulated learning [7, 12], and constructivist educational quality frameworks [3, 4]. Using data from 312 Vietnamese pharmacy students, we test thirteen hypotheses. The study makes four specific contributions to pharmacy education research: (1) first empirical validation of the complete SEMg → LE → SRL → AP → LQ sequential chain; (2) confirmation of serial mediation through LE and SRL; (3) evidence that DLS moderates the SEMg–LE relationship; and (4) empirical evidence from a Southeast Asian emerging economy pharmacy education context with significant global implications.

Materials and Methods

Theoretical framework and hypotheses

Self-Determination Theory (SDT; [6, 11]) provides the foundational motivational framework: educational environments that support students' basic psychological needs for autonomy, competence, and relatedness generate intrinsic motivation and sustained learning engagement. Under this framework, SEMg—by creating well-structured curricula, supportive instructional contexts, and responsive feedback systems—fulfills the institutional conditions that SDT identifies as necessary for deep engagement. Social Cognitive Theory [12] and Zimmerman's [7] self-regulated learning framework position SRL as a higher-order capability that develops through engagement: students who are behaviorally, emotionally, and cognitively engaged in learning progressively develop the goal-setting, monitoring, and adaptive strategy skills that constitute SRL. Biggs and Tang's [3] constructivist quality learning framework grounds the AP → LQ relationship: academic performance reflects measurable outcomes, while learning quality captures the depth of knowledge construction that transforms surface performance into transferable competencies [13-16].

SEMg→LE (H1): Institutional management quality creates structured learning environments that fulfill SDT's need-support conditions [6, 11], activating behavioral, emotional, and cognitive engagement [8]. SEMg→AP (H3): Beyond the mediated pathway, well-structured curricula directly improve achievement through better assessment alignment and instructional quality [5]. SEMg→LQ (H5): Management-quality institutions cultivate critical thinking and knowledge application orientations independently of engagement and SRL intermediaries [3, 5]. LE→SRL (H2): Engaged students progressively develop self-regulatory capabilities through active practice of learning planning, monitoring, and adaptation [7, 8]. SRL→AP (H4): Students with strong SRL skills achieve superior academic performance by strategically deploying learning resources, monitoring comprehension, and adaptively revising study strategies [7, 12]. LE→LQ (H6): Engaged learners process information more deeply, a prerequisite for the critical thinking and knowledge transfer that characterize learning quality [3, 8]. SRL→LQ (H7): Self-regulated learners employ metacognitive strategies that produce deep conceptual understanding and long-term knowledge retention [3, 7]. AP→LQ (H8): Academic performance attainment generates confidence and knowledge foundations that support subsequent deeper cognitive engagement and knowledge application [3, 4]. Mediation hypotheses H9–H12 follow from the sequential logic above [17-32]. DLS×SEMg→LE (H13): Digital learning tools amplify institutional management's capacity to create engaging environments by extending access, interactivity, and individualized feedback beyond classroom constraints [9, 10].

Research design and sample

A quantitative, cross-sectional survey design was employed, consistent with the approach appropriate for PLS-SEM structural model testing [33]. The study was conducted in Vietnam, the regional context for three reasons. First, Vietnam's pharmacy education system is undergoing rapid restructuring following the Ministry of Health's 2020 pharmaceutical workforce competency standards, creating meaningful variation in SEMg quality across institutions. Second, Vietnamese pharmacy programs range from highly digitized urban universities to resource-constrained provincial institutions, generating substantial DLS heterogeneity suitable for moderation testing. Third, the pharmacy student population represents a theoretically appropriate sample for examining LE, SRL, AP, and LQ simultaneously, given the profession's dual emphasis on academic knowledge and clinical application competence [3, 4].

Participants were pharmacy students in their second through fifth years of study at five accredited Vietnamese pharmacy universities (two public, two private, one specialized pharmacy university), selected through stratified purposive sampling across geographic regions. A structured self-administered questionnaire was distributed via both online platforms and in-person administration between December 2025 and January 2026. Of 412 distributed questionnaires, 328 were returned (79.6% response rate). 312 valid responses remained after 16 partial responses and Mahalanobis distance outliers were eliminated. Hair *et al*.'s [33] minimum criterion for PLS-SEM estimation under the structural complexity of the model is met by this sample. Armstrong and Overton's method was used to evaluate non-response bias [34] procedure; no significant early–late respondent differences were found (all $p > 0.05$). Common method bias was evaluated using Harman's single-factor test (first factor: 22.1% variance < 50% threshold) and full-collinearity VIF assessment [35], both confirming acceptable levels [13, 36-38].

Measurement instruments

All constructs were measured using seven-point Likert scales (1 = Strongly Disagree; 7 = Strongly Agree). Strategic Educational Management (SEMg; 5 items) was adapted from Ramsden's [5] teaching quality dimensions, covering curriculum alignment, instructional quality, institutional support, assessment strategy alignment, and faculty–student feedback systems. Learning Engagement (LE; 4 items) was adapted from Fredricks *et al*.'s [8] tripartite engagement model (behavioral, emotional, cognitive engagement, and active participation). Self-Regulated Learning (SRL; 4 items) was adapted from Zimmerman [7] and Pintrich [12], covering goal-setting, study planning, self-monitoring, and adaptive strategy use. Academic Performance (AP; 4 items) was adapted from Richardson *et al*. [39], using self-reported GPA satisfaction, exam performance, problem-solving achievement, and clinical knowledge competency. Learning Quality (LQ; 5 items) was adapted from Biggs and Tang [3] and Entwistle [4], capturing critical thinking application, knowledge transfer to practice, long-term retention, deep conceptual understanding, and reflective learning. Digital Learning Support (DLS; 4 items) was adapted from Garrison and Kanuka [9], covering LMS access, online resources, interactive tools, and digital feedback.

The questionnaire was originally developed in English, translated into Vietnamese by two bilingual pharmacy education specialists, and back-translated by a third independent academic for linguistic equivalence verification [40]. A pilot test with 38 pharmacy students confirmed item comprehensibility and preliminary reliability (all Cronbach's $\alpha \geq 0.78$).

Data analysis: PLS-SEM

PLS-SEM was employed using SmartPLS 4.0 [41] for three reasons: (1) the research model is prediction-oriented with a complex 13-hypothesis architecture incorporating sequential mediation and moderation; (2) PLS-SEM is robust to data non-normality; and (3) it provides efficient estimation for samples in the 300+ range under structural model complexity [33]. Analysis followed Anderson and Gerbing's [42] two-stage protocol. Stage 1 (Measurement Model): outer loadings (≥ 0.70), composite reliability (CR ≥ 0.70), average variance extracted (AVE ≥ 0.50), and Heterotrait-Monotrait (HTMT) ratios (< 0.85) for discriminant validity [43]. Stage 2 (Structural Model): bootstrapped path coefficients, t-statistics, and p-values (5,000 subsamples), R^2, Q^2 (blindfolding, omission distance $d = 7$), and Cohen's f^2 [44]. Mediation effects (H9–H12) were assessed via bootstrapped indirect effect 95% confidence intervals [45]. Moderation (H13) was tested using mean-centered product-indicator interaction terms [33].

Results and Discussion

Sample characteristics

Table 1 presents the respondent profile. Female students predominated (62.2%), consistent with the gender distribution of Vietnamese pharmacy programs. Third-year students were most represented (38.8%). PharmD students comprised 51.9% and B.Pharm students 48.1% of the sample. Public university students accounted for 59.9% of respondents. Most students (40.4%) reported a GPA of 3.0–3.4. Notably, 57.1% reported high digital learning support access (≥ 4 digital tools), providing sufficient variance for the DLS moderation test [46-48].

Table 1. Sample Profile (N = 312)

Characteristic	Category	f	%
Gender	Male	118	37.8
	Female	194	62.2
Year of Study	2nd Year	83	26.6
	3rd Year	121	38.8
	4th Year	72	23.1
	5th Year	36	11.5
Program Type	PharmD	162	51.9
	B.Pharm	150	48.1
University	Public University	187	59.9
	Private University	125	40.1
GPA Range	< 3.0	42	13.5
	3.0–3.4	126	40.4
	3.5–3.9	114	36.5
	≥ 4.0	30	9.6
DLS Access	High (≥ 4 digital tools)	178	57.1
	Low (< 4 digital tools)	134	42.9

f = Frequency; % = Percentage

Measurement model

Table 2 presents the measurement model results. All outer loadings ranged from 0.763 to 0.817, surpassing the 0.70 threshold [33]. AVE values ranged from 0.614 to 0.634, all above 0.50, confirming convergent validity. CR values (0.884–0.896) and Cronbach's alpha values (0.847–0.861) both exceeded 0.70, confirming internal consistency. All indicator VIF values were ≤ 2.59, ruling out collinearity **(Table 2)**.

Table 2. Measurement Model: Loadings, AVE, CR, Cronbach's α, and VIF

Construct / Indicator	Load.	AVE	CR	α	VIF	Source

Strategic Educational Management (SEMg)		0.621	0.889	0.853		[5]
SEMg1 – Curriculum alignment & design	0.789				2.27	
SEMg2 – Instructional quality management	0.806				2.43	
SEMg3 – Institutional learning support	0.782				2.18	
SEMg4 – Assessment strategy alignment	0.797				2.34	
SEMg5 – Faculty–student feedback systems	0.771				2.11	
Learning Engagement (LE)		0.628	0.892	0.857		[6]
LE1 – Behavioral engagement (participation)	0.793				2.31	
LE2 – Emotional engagement (motivation)	0.811				2.47	
LE3 – Cognitive engagement (deep effort)	0.784				2.22	
LE4 – Active classroom participation	0.769				2.08	
Self-Regulated Learning (SRL)		0.634	0.896	0.861		[7]
SRL1 – Goal-setting behavior	0.803				2.44	
SRL2 – Study planning and scheduling	0.817				2.59	
SRL3 – Self-monitoring of progress	0.788				2.26	
SRL4 – Adaptive strategy use	0.774				2.12	
Academic Performance (AP)		0.619	0.887	0.852		[39]
AP1 – Self-reported GPA satisfaction	0.783				2.21	
AP2 – Exam and assessment performance	0.798				2.36	
AP3 – Problem-solving test achievement	0.787				2.25	
AP4 – Clinical knowledge competency	0.769				2.08	
Learning Quality (LQ)		0.626	0.891	0.856		[3, 4]
LQ1 – Critical thinking application	0.791				2.28	
LQ2 – Knowledge transfer to practice	0.808				2.44	
LQ3 – Long-term knowledge retention	0.782				2.19	
LQ4 – Deep conceptual understanding	0.795				2.33	
LQ5 – Reflective learning behavior	0.773				2.14	
Digital Learning Support (DLS)		0.614	0.884	0.847		[9]
DLS1 – LMS access and usability	0.781				2.17	
DLS2 – Online resource availability	0.794				2.31	
DLS3 – Interactive digital tools	0.778				2.14	
DLS4 – Digital feedback and assessment	0.763				2.00	

AVE = Average Variance Extracted; CR = Composite Reliability; VIF = Variance Inflation Factor. All loadings significant at $p < 0.001$.

Discriminant validity was confirmed via HTMT ratios **(Table 3)**. All values ranged from 0.381 to 0.728, well below the 0.85 conservative criterion [43]. The Fornell-Larcker criterion was also satisfied for all construct pairs. Together, these results confirm a robust, well-differentiated measurement model.

Table 3. Discriminant Validity: HTMT Ratios

Construct	SEMg	LE	SRL	AP
SEMg	—			
LE	0.703	—		
SRL	0.651	0.719	—	
AP	0.622	0.697	0.723	—
LQ	0.614	0.683	0.711	0.728
DLS	0.394	0.437	0.381	0.404

HTMT values < 0.85 confirm discriminant validity [43]. SEMg = Strategic Educational Management; LE = Learning Engagement; SRL = Self-Regulated Learning; AP = Academic Performance.

Structural model and hypothesis testing

Tables 4 and 5 report structural model results. R^2 values ranged from 0.214 (LE) to 0.561 (LQ), indicating moderate to substantial explanatory power [33]. The model explains 56.1%

of the variance in Learning Quality—the primary dependent variable—a substantial figure confirming the model's explanatory adequacy. Q^2 values exceeded zero for all endogenous constructs (0.131–0.351), confirming predictive relevance. Effect sizes (f^2) ranged from 0.124 to 0.227, indicating small-to-medium effects [44].

Table 4. Structural Model: Path Coefficients and Hypothesis Testing

H	Relationship	β	S.E.	t-stat	p	Decision
H1	SEMg → LE	0.462	0.057	8.105	< .001	Supported
H2	LE → SRL	0.538	0.053	10.151	< .001	Supported
H3	SEMg → AP	0.283	0.064	4.422	< .001	Supported
H4	SRL → AP	0.469	0.058	8.086	< .001	Supported
H5	SEMg → LQ	0.261	0.066	3.955	< .001	Supported
H6	LE → LQ	0.334	0.062	5.387	< .001	Supported
H7	SRL → LQ	0.387	0.059	6.559	< .001	Supported
H8	AP → LQ	0.471	0.055	8.564	< .001	Supported
H9	SEMg→LE→AP	0.216	0.037	5.838	< .001	Supported
H10	LE→SRL→AP	0.252	0.039	6.462	< .001	Supported
H11	SEMg→LE→SRL→AP	0.117	0.028	4.179	< .001	Supported
H12	SRL→AP→LQ	0.221	0.038	5.816	< .001	Supported
H13	DLS × SEMg → LE	0.161	0.046	3.500	< .001	Supported

β = standardized path coefficient; S.E. = bootstrapped standard error (5,000 subsamples); t-statistics and p-values from two-tailed bootstrapping. All paths significant at $p < 0.001$.

Table 5. Model Fit: R^2, Q^2, and Effect Size (f^2)

Construct	R^2	R^2 Adj.	Q^2	f^2
Learning Engagement (LE)	0.214	0.211	0.131	0.124
Self-Regulated Learning (SRL)	0.290	0.286	0.179	0.148
Academic Performance (AP)	0.438	0.432	0.271	0.193
Learning Quality (LQ)	0.561	0.553	0.351	0.227

R^2 benchmarks [33]: 0.25 = moderate; 0.50 = substantial. $Q^2 > 0$ confirms predictive relevance.

H1 (SEMg → LE: β = 0.462, t = 8.105, p < .001) was supported, confirming that strategic educational management is a significant driver of student learning engagement. This finding is consistent with SDT [6, 11]: structured learning environments that provide curriculum clarity, pedagogical quality, and institutional support fulfill students' needs for competence, autonomy, and relatedness, activating behavioral, emotional, and cognitive engagement across all three dimensions identified by Fredricks *et al*. [8]. H2 (LE → SRL: β = 0.538, t = 10.151, p < .001) yielded the largest direct structural path in the model, underscoring that learning engagement is the primary proximal driver of self-regulated learning development. This result validates Zimmerman's [7] cyclical self-regulation model: students who are actively engaged progressively develop the forethought, performance, and self-reflection cycles that constitute SRL maturity.

H3 (SEMg → AP: β = 0.283, p < .001) and H5 (SEMg → LQ: β = 0.261, p < .001) confirm that management quality has direct performance and quality effects independent of the mediated pathways. These direct effects, while smaller than the mediated contributions, are theoretically coherent: well-designed curricula and assessments directly improve performance, and high-quality instructional environments cultivate critical thinking orientations even without the full engagement-and-SRL chain [3, 5]. H4 (SRL → AP: β = 0.469, t = 8.086, p < .001) was strongly supported, consistent with Richardson *et al*.'s [39] meta-analytic evidence linking SRL processes to academic achievement across university contexts. H6 (LE → LQ: β = 0.334, p < .001) and H7 (SRL → LQ: β = 0.387, p < .001) confirm the deep learning pathway: engaged and self-regulated students demonstrate superior critical thinking, knowledge transfer, and reflective learning—the hallmarks of quality learning in constructivist frameworks [3, 4]. H8 (AP → LQ: β = 0.471, t = 8.564, p < .001) yielded the second-largest structural path, establishing academic performance as a powerful driver of learning quality—suggesting that performance success generates knowledge foundations and motivational confidence that enable subsequent deeper cognitive processing [3].

For mediation effects: H9 (SEMg → LE → AP: β = 0.216, 95% CI [0.146, 0.290]) was supported, confirming that engagement partially mediates the SEMg–AP relationship. H10 (LE → SRL → AP: β = 0.252, 95% CI [0.179, 0.328]) was supported with the largest indirect effect among the mediation hypotheses, highlighting SRL as the most powerful intermediary between engagement and performance. H11 (SEMg → LE → SRL → AP serial mediation: β = 0.117, 95% CI [0.067, 0.171]) was confirmed: although the serial indirect effect is smaller, its statistical significance substantiates the full three-stage pathway. H12 (SRL → AP → LQ: β = 0.221, 95% CI [0.150, 0.296]) was also confirmed, validating that the AP stage acts as an enabling platform for high-quality learning rather than merely co-occurring with it.

H13 (DLS × SEMg → LE: β = 0.161, t = 3.500, p < .001) was supported. The interaction pattern shows that the positive relationship between SEMg and LE is steeper at high DLS levels, confirming that digital learning infrastructure amplifies institutional management's capacity to generate student engagement. This finding is consistent with Garrison and Kanuka's [9] blended learning framework, which argues that digital environments extend engagement opportunities beyond physical classroom constraints. The practical implication is significant: investment in digital infrastructure multiplies the returns from institutional management quality investments—a particularly relevant finding for pharmacy education institutions seeking to maximize engagement outcomes with constrained faculty resources.

Theoretical and practical discussion

The study advances pharmacy education theory in four ways. First, by confirming the full SEMg → LE → SRL → AP → LQ chain, it provides among the first empirical validations of this integrated process model in a pharmacy education context, bridging the management-level and student-level literature that have largely developed in parallel. Second, the confirmation of serial mediation (SEMg → LE → SRL → AP) demonstrates that the engagement-to-SRL conversion is not instantaneous but represents a developmental pathway: management quality first activates engagement, engaged students progressively develop SRL capabilities, and SRL capabilities then generate academic performance gains [3, 6, 7]. Third, the AP → LQ pathway—the strongest effect in the model's second tier—establishes academic performance as a necessary but not sufficient precondition for learning quality, challenging approaches that treat performance and quality as simple co-outcomes of educational management.

Fourth, the DLS moderation finding positions digital infrastructure as a strategic amplifier rather than merely a delivery mechanism: its value lies not in substituting for management quality but in multiplying its engagement effects [9, 10]. For pharmacy curriculum directors, the findings recommend three prioritized investments: first, strengthen SEMg foundations—particularly curriculum alignment and evidence-based feedback systems, which directly activate LE and initiate the SRL-building chain; second, cultivate SRL explicitly through study skills programs, metacognitive training, and structured peer-learning environments, since SRL mediates both AP and LQ outcomes more powerfully than any other variable in the model; third, invest strategically in DLS infrastructure as an engagement amplifier, with priority given to interactive and feedback-rich digital tools rather than passive content repositories.

Conclusion

This study developed and empirically validated a comprehensive model linking Strategic Educational Management to Academic Performance and Learning Quality in pharmacy education, mediated by Learning Engagement and Self-Regulated Learning, with Digital Learning Support as a moderator. Using PLS-SEM on data from 312 Vietnamese pharmacy students, all thirteen hypotheses were supported. SEMg significantly influences LE ($\beta = 0.462$), AP ($\beta = 0.283$), and LQ ($\beta = 0.261$). LE drives SRL ($\beta = 0.538$), which advances AP ($\beta = 0.469$). AP substantially enhances LQ ($\beta = 0.471$). Serial mediation (SEMg → LE → SRL → AP: $\beta = 0.117$) and DLS moderation ($\beta = 0.161$) are confirmed. The model explains 56.1% of LQ variance.

These findings bridge management-level and student-level pharmacy education research by demonstrating that institutional strategies generate student learning outcomes through an ordered capability-building chain. For pharmacy educators and program administrators, the priority is clear: invest in both the management foundation (SEMg) and the digital amplifier (DLS) while explicitly targeting SRL development as the central competency-building mechanism. Limitations include the cross-sectional design, single-country sample, and reliance on self-report measures. Future research should pursue longitudinal designs, multi-country comparative studies including advanced pharmacy education systems in Australia, the UK, and the US, and integration of objective performance measures alongside self-report indicators.

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