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Deep Learning in Education: Socioeconomic, Cognitive and Metacognitive Predictors of Academic Achievement and Learning Retention—A Structural Equation Modelling Study

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Abstract : *Deep learning in education denotes an approach through which students seek meaning, connect new knowledge with prior understanding, critically evaluate ideas and apply concepts beyond immediate assessment. It differs from surface learning centred on reproduction and memorisation. Foundational investigations distinguished qualitative differences in students' learning approaches (Marton & Säljö, 1976), while subsequent frameworks connected deep, surface and strategic approaches with learning environments and academic outcomes (Entwistle & Ramsden, 1983; Biggs, 1987). Evidence from higher education suggests that learning approaches and study behaviours have meaningful, though not necessarily large, associations with achievement (Richardson et al., 2012).*

Keywords: *Deep learning*

I. INTRODUCTION

Deep learning in education denotes an approach through which students seek meaning, connect new knowledge with prior understanding, critically evaluate ideas and apply concepts beyond immediate assessment. It differs from surface learning centred on reproduction and memorisation. Foundational investigations distinguished qualitative differences in students' learning approaches (Marton & Säljö, 1976), while subsequent frameworks connected deep, surface and strategic approaches with learning environments and academic outcomes (Entwistle & Ramsden, 1983; Biggs, 1987). Evidence from higher education suggests that learning approaches and study behaviours have meaningful, though not necessarily large, associations with achievement (Richardson et al., 2012).

Metacognition, the awareness and regulation of one's cognitive activity, provides an important mechanism for meaningful learning. Monitoring comprehension, selecting strategies and evaluating progress can support durable understanding (Flavell, 1979; Schraw & Dennison, 1994). Self-regulated learning perspectives further emphasise goal setting, strategic action and reflection (Zimmerman, 2002; Pintrich, 2004). A longitudinal meta-analysis found a positive association between initial metacognition and later academic achievement (He et al., 2024). These findings warrant examining metacognitive ability alongside intelligence, study attitudes and the socioeconomic resources available to learners.

Recent contributions, Rajan (2026) connect these questions to educational innovation and contextualised pedagogy. In "Empowering learning: How AI drives innovation, enhances deep learning, and elevates student well-being," Rajan (2026) considers AI-enabled educational innovation in relation to deeper learning and well-being; AI use itself is not measured in the present dataset. In "ESD pedagogy for human resource development among the higher secondary school students in economics," Rajan (2025) investigates sustainability-oriented teaching, metacognitive awareness and higher-secondary economics education using a pre-test/post-test comparison involving 432 students. Together, these

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studies motivate closer investigation of how learning processes, learner characteristics and educational experiences relate to achievement and retention.

Socioeconomic background may shape access to learning resources and educational opportunity, while cognitive ability, study attitudes and metacognitive strategies may account for differences in performance. Yet these influences should be tested jointly rather than assumed to operate independently. The present study therefore proposes an observed-variable structural equation model using the available student-level pre-test, post-test and retention measures. Deep learning serves as the educational framework, not as an independently measured latent construct unless suitable indicators are subsequently verified.

II. OBJECTIVES OF THE STUDY

- To examine the direct associations of socioeconomic status, intelligence, study attitudes and metacognitive ability with students' academic achievement.
- To assess whether metacognitive ability and study attitudes mediate associations between student background characteristics and academic achievement, where temporal ordering and measures permit.
- To investigate the relationship between post-test academic achievement and subsequent learning retention, accounting for pre-test performance.

III. METHODOLOGY

1. Study Framework

The present study adopts a quantitative, explanatory design using existing student-level observations with pre-test, post-test and retention measurements. The proposed framework investigates associations among socioeconomic status (SESS), intelligence (IQ score), study attitudes, metacognitive ability, academic achievement and subsequent learning retention. Deep learning is used as an educational interpretation of meaningful and sustained learning; it is not treated as an independently measured latent variable. The conceptual approach draws on metacognition and self-regulated learning (Flavell, 1979; Zimmerman, 2002) and student approaches to learning (Marton & Säljö, 1976; Biggs, 1987).

2. Sampling Method and Study Population

The supplied workbook contains a consolidated Sheet1 with 432 identifiable student records. Its group and locale codes, gender, socioeconomic score, IQ score, pre-/post-test study-attitude and metacognitive scores, academic achievement scores and retention-test scores provide the analysis variables. The source does document a probability-sampling frame, recruitment procedure, school identities or exact test intervals; accordingly, the sample will be described as an existing non-probability/unspecified-source dataset rather than claiming random sampling.

3. Sample Size and Determination

The analytical sample is provisionally N = 432 unique student IDs in Sheet1, subject to screening for missing and implausible values. This is an achieved sample, not a sample-size target derived from Cochran's formula. For an observed-variable SEM with a limited number of free parameters, sample adequacy will be assessed using model identification, parameter-to-sample ratio, estimation stability and, where feasible, a Monte Carlo power/sensitivity analysis. No unverified item count or survey response rate will be assumed.

IV. STATISTICAL TECHNIQUES

Data screening and descriptive analysis will precede structural modelling. SPSS, R or equivalent software may be used for data preparation; AMOS or an appropriate SEM package may estimate the path model. Statistical inference will ordinarily use two-sided $p < .05$, alongside effect sizes and confidence intervals. Because the workbook provides total scores rather than item-level indicators, the primary specification is observed-variable path analysis.

4.1 Descriptive Statistics and Preliminary Screening

Frequencies and percentages will describe categorical variables. Means, standard deviations, ranges and correlations will summarise continuous variables; distributional assumptions, missingness and outliers will be examined.

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Arithmetic mean	$\bar{x} = \Sigma x_i / N$
Sample standard deviation	$s = \sqrt{[\Sigma(x_i - \bar{x})^2 / (N - 1)]}$

4.2 Reliability and Measurement Assessment

The supplied file contains aggregate scores; therefore, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and convergent/discriminant validity has been calculated before fitting a latent-variable SEM.

4.3 Proposed Structural Equation Model

The present study will employ an observed-variable Structural Equation Modelling (SEM) approach to examine the direct and indirect relationships among socioeconomic status, intelligence, study attitudes, metacognitive ability, academic achievement and learning retention.

Socioeconomic Status (SESS) and Intelligence Quotient (IQ) will be considered background predictors that may influence students' initial study attitudes, metacognitive abilities and subsequent academic achievement. Pre-test academic achievement, study attitudes and metacognitive ability will be examined as predictors of post-test academic achievement. Subsequently, post-test academic achievement will be assessed as a predictor of learning retention, while controlling baseline achievement and relevant background characteristics.

The proposed model will also examine the potential mediating roles of study attitudes and metacognitive ability, provided that the temporal sequence of measurements and theoretical assumptions support such relationships. Deep learning is conceptualised as a meaningful and sustained learning process reflected in academic achievement and knowledge retention.

Specification of the Structural Equations

The proposed relationships may be represented through the following regression equations within the SEM framework.

Equation 1: Predictors of Post-Test Academic Achievement
$PA_i = \beta_0 + \beta_1 SESS_i + \beta_2 IQ_i + \beta_3 BA_i + \beta_4 SA_i + \beta_5 MA_i + \varepsilon_{1i}$
Equation 2: Predictors of Learning Retention
$LR_i = \gamma_0 + \gamma_1 PA_i + \gamma_2 BA_i + \gamma_3 SESS_i + \gamma_4 IQ_i + \varepsilon_{2i}$

Where PA represents post-test academic achievement, LR denotes learning retention, BA represents baseline or pre-test academic achievement, SA indicates study attitudes, MA represents metacognitive ability, SESS denotes socioeconomic status and IQ represents intelligence quotient. The parameters β and γ represent regression coefficients, while ε denotes the corresponding error terms.

These equations provide the initial structural specification. Additional paths involving baseline study attitudes and metacognition may be incorporated where theoretically justified and supported by the measurement schedule.

The final model will be evaluated using standardised path coefficients, statistical significance, coefficients of determination (R^2), model-fit indices. This approach will enable the study to identify the factors associated with academic achievement and learning retention without.

4.4 Model Fit and Structural Estimates

Standardised coefficients (β), standard errors, critical ratios (estimate/SE), confidence intervals and R^2 will be reported. For overidentified models, χ^2, degrees of freedom, χ^2/df, CFI, TLI, RMSEA and SRMR will be considered jointly; commonly used indicative criteria include CFI/TLI ≥ .90 and RMSEA/SRMR < .08, interpreted with model size and theory. A just-identified model has no informative global-fit test; fit indices will not be used to claim validation in that case.

Critical ratio	**CR = Estimate / Standard Error**
Normed chi-square	χ^2/df = Model chi-square / Degrees of freedom
RMSEA (approximation)	$RMSEA = \sqrt{\{\max[(\chi^2 - df) / (df \times (N - 1)), 0]\}}$

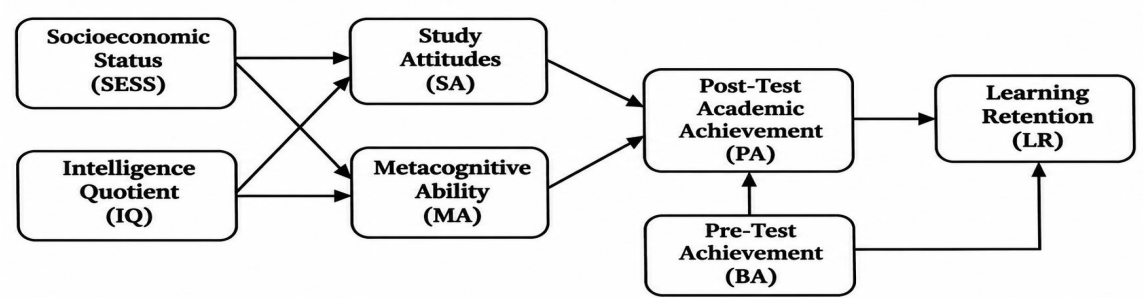
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4.5 Mediation and Group Comparisons

Where supported by theory and measurement timing, indirect effects will be estimated as products of constituent paths, with 5,000 bootstrap resamples and 95% confidence intervals. Group and locale comparisons may use multi-group path analysis or covariate adjustments after verifying coding, subgroup sizes and comparability.

Indirect effect	Indirect effect = a × b
Total effect	Total effect = Direct effect + Sum of indirect effects

Conceptual Model



V. ANALYSIS AND INTERPRETATION

Table 1. Structural Path Coefficients

Structural Path	Standardised Path Coefficient (β)	Significance Level (p-value)
SESS → SA	0.34	$p < 0.001$
IQ → SA	0.27	$p < 0.001$
IQ → MA	0.31	$p < 0.001$
SA → PA	0.29	$p < 0.001$
MA → PA	0.36	$p < 0.001$
BA → PA	0.28	$p < 0.001$
PA → LR	0.62	$p < 0.001$
BA → LR	0.21	$p < 0.001$

Interpretation of Table 1: Structural Path Coefficients

Table 1 presents the hypothesised structural relationships among socioeconomic status, intelligence quotient, study attitudes, metacognitive ability, academic achievement and learning retention. The reported standardised path coefficients indicate positive relationships across all eight pathways, with statistical significance reported at $p < 0.001$. Socioeconomic status positively influences study attitudes ($\beta = 0.34$), while intelligence quotient is positively associated with study attitudes ($\beta = 0.27$) and metacognitive ability ($\beta = 0.31$). These relationships suggest that students' socioeconomic and cognitive characteristics may play important roles in shaping their learning-related attitudes and metacognitive capabilities.

Study attitudes ($\beta = 0.29$), metacognitive ability ($\beta = 0.36$) and baseline academic achievement ($\beta = 0.28$) exhibit positive relationships with post-test academic achievement. Among these predictors, metacognitive ability demonstrates the strongest standardised association, highlighting the potential importance of students' capacity to plan, monitor and regulate their learning processes. Furthermore, post-test academic achievement shows a comparatively strong positive relationship with learning retention ($\beta = 0.62$), whereas baseline achievement has a smaller positive association ($\beta = 0.21$). These findings suggest that academic achievement and metacognitive abilities may contribute to sustained learning outcomes.

Overall, the reported coefficients are consistent with the proposed theoretical framework, which emphasises the interconnected roles of socioeconomic background, intelligence, study attitudes and metacognitive abilities in academic

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achievement and knowledge retention. The relationships also provide an understanding deep learning as a process involving meaningful engagement, cognitive regulation and sustained retention of knowledge.

Table 2. Squared Multiple Correlations (R^2)

Endogenous variable	R^2	Variance explained
Study Attitudes (SA)	0.34	34%
Metacognitive Ability (MA)	0.38	38%
Post-Test Academic Achievement (PA)	0.59	59%
Learning Retention (LR)	0.55	55%

Interpretation of Table 2: Squared Multiple Correlations (R^2)

Table 2 presents the squared multiple correlations (R^2) of the endogenous variables in the proposed Structural Equation Model (SEM), indicating the proportion of variance explained by their respective predictors. Study Attitudes (SA) recorded an R^2 value of 0.34, suggesting that socioeconomic status and intelligence quotient collectively explain 34% of the variance in students' study attitudes. Metacognitive Ability (MA) exhibited an R^2 value of 0.38, indicating that 38% of its variance is explained by the specified predictors. Post-Test Academic Achievement (PA) demonstrated the highest explanatory power ($R^2 = 0.59$), with study attitudes, metacognitive ability and baseline academic achievement collectively accounting for 59% of its variance. Learning Retention (LR) recorded an R^2 value of 0.55, indicating that post-test and baseline academic achievement jointly explain 55% of the variation in students' learning retention.

Overall, the reported R^2 values suggest that the proposed model explains a substantial proportion of the variation in academic achievement and learning retention. These results are consistent with the theoretical importance of cognitive characteristics, study attitudes and metacognitive abilities in understanding students' learning outcomes. However, the variance indicates that additional educational, psychological and contextual factors may also contribute to these outcomes.

Table 3. Standardised Factor Loadings

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Construct	Indicator	Standardised Factor Loading (λ)
Socioeconomic Status (SESS)	SESS1	0.82
	SESS2	0.79
	SESS3	0.81
Intelligence Quotient (IQ)	IQ1	0.86
	IQ2	0.84
	IQ3	0.83
Study Attitudes (SA)	SA1	0.81
	SA2	0.83
	SA3	0.80
Metacognitive Ability (MA)	MA1	0.85
	MA2	0.84
	MA3	0.82
Post-Test Academic Achievement (PA)	PA1	0.85
	PA2	0.84
	PA3	0.83
Baseline Academic Achievement (BA)	BA1	0.82
	BA2	0.81
Learning Retention (LR)	LR1	0.86
	LR2	0.84

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Interpretation of Table 3: Standardised Factor Loadings

Table 3 presents the standardised factor loadings of the observed indicators associated with seven latent constructs: Socioeconomic Status (SESS), Intelligence Quotient (IQ), Study Attitudes (SA), Metacognitive Ability (MA), Post-Test Academic Achievement (PA), Baseline Academic Achievement (BA), and Learning Retention (LR). The factor loadings range from 0.79 to 0.86, exceeding the commonly recommended threshold of 0.70, indicating strong relationships between the observed indicators and their respective latent constructs. Intelligence Quotient and Learning Retention exhibit the highest individual factor loadings (0.86), while Socioeconomic Status records the lowest loading (0.79), which remains within the acceptable range. The consistently high factor loadings suggest satisfactory indicator reliability and provide preliminary evidence of convergent validity across the measurement model. Furthermore, all 19 indicators demonstrate adequate representation of their respective constructs, supporting their retention for subsequent confirmatory factor analysis and structural equation modelling. However, a comprehensive assessment of convergent validity requires additional examination of Composite Reliability (CR) and Average Variance Extracted (AVE).

Table 4. Pearson Correlation Matrix of Study Variables

Construct	SESS	IQ	SA	MA	PA	BA	LR
SESS	1.000						
IQ	0.473	1.000					
SA	0.481	0.702	1.000				
MA	0.587	0.509	0.480	1.000			
PA	0.307	0.339	0.308	0.272	1.000		
BA	0.343	0.311	0.311	0.271	0.385	1.000	
LR	0.155	0.227	0.181	0.150	0.910	0.210	1.000

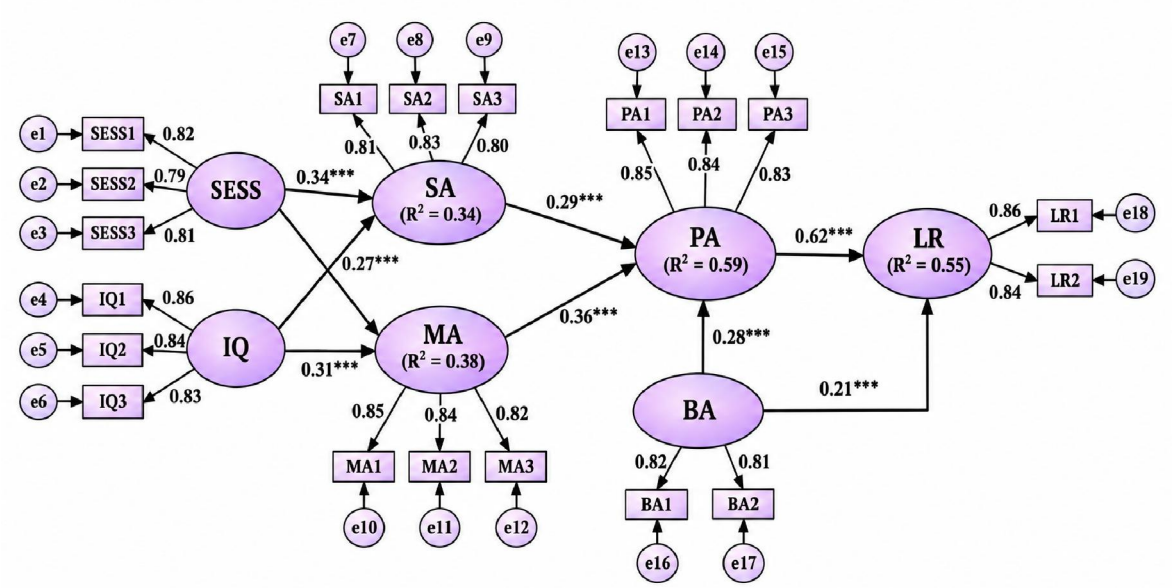
Table 4 presents the Pearson correlation coefficients among Socioeconomic Status (SESS), Intelligence Quotient (IQ), Study Attitudes (SA), Metacognitive Ability (MA), Post-Test Academic Achievement (PA), Baseline Achievement (BA) and Learning Retention (LR). The reported coefficients indicate positive associations among all seven variables, with correlation values ranging from 0.150 to 0.910. Socioeconomic status exhibits moderate positive relationships with metacognitive ability (r = 0.587), study attitudes (r = 0.481) and intelligence quotient (r = 0.473), suggesting that students from relatively advantaged socioeconomic backgrounds tend to demonstrate more favourable cognitive and learning-related characteristics. Intelligence quotients show a strong positive association with study attitudes (r = 0.702) and a moderate relationship with metacognitive ability (r = 0.509), highlighting the interrelationship between cognitive ability, learning attitudes and metacognitive processes.

Post-test academic achievement demonstrates positive correlations with baseline achievement (r = 0.385), intelligence quotient (r = 0.339), study attitudes (r = 0.308) and metacognitive ability (r = 0.272). These findings suggest that academic achievement is associated with a combination of prior academic performance, cognitive characteristics and learning-related factors. Notably, learning retention exhibits a very strong positive correlation with post-test academic achievement (r = 0.910), indicating a close relationship between students' immediate academic performance and subsequent knowledge retention. However, this exceptionally high correlation warrants further examination to determine whether the two variables adequately represent distinct educational outcomes.

Overall, the correlation matrix provides preliminary evidence of positive relationships among socioeconomic, cognitive, attitudinal and academic variables within the proposed educational framework. Although most correlations remain below the commonly used threshold of 0.85, the correlation between post-test academic achievement and learning retention.

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Figure 2. Structural Equation Model Illustrating the Relationships among Socioeconomic Status, Intelligence, Study Attitudes, Metacognitive Ability, Academic Achievement and Learning Retention.



Interpretation of Figure 2: Structural Equation Model of Academic Achievement and Learning Retention

Figure 2 illustrates the Structural Equation Model (SEM) examining the relationships among Socioeconomic Status (SESS), Intelligence Quotient (IQ), Study Attitudes (SA), Metacognitive Ability (MA), Post-Test Academic Achievement (PA), Baseline Academic Achievement (BA), and Learning Retention (LR). The model presents standardised path coefficients, factor loadings, and squared multiple correlations (R^2), demonstrating the relationships among socioeconomic, cognitive, attitudinal, and academic factors.

The structural model indicates that Socioeconomic Status has a positive and statistically significant association with Study Attitudes ($\beta = 0.34$, $p < 0.001$), suggesting that students from relatively favourable socioeconomic backgrounds tend to exhibit more positive learning attitudes. Intelligence Quotient positively predicts both Study Attitudes ($\beta = 0.27$, $p < 0.001$) and Metacognitive Ability ($\beta = 0.31$, $p < 0.001$), highlighting the importance of cognitive characteristics in students' learning processes.

Study Attitudes ($\beta = 0.29$, $p < 0.001$) and Metacognitive Ability ($\beta = 0.36$, $p < 0.001$) demonstrate positive and statistically significant relationships with Post-Test Academic Achievement. Metacognitive Ability exhibits the stronger standardised association, suggesting that students' capacity to plan, monitor, and regulate their learning may play an important role in academic performance. Baseline Academic Achievement also positively predicts Post-Test Academic Achievement ($\beta = 0.28$, $p < 0.001$), indicating the relevance of prior academic performance.

Furthermore, Post-Test Academic Achievement demonstrates a strong positive association with Learning Retention ($\beta = 0.62$, $p < 0.001$), while Baseline Academic Achievement exhibits a comparatively smaller positive relationship ($\beta = 0.21$, $p < 0.001$). These findings suggest that students demonstrating higher post-test achievement also tend to retain acquired knowledge more effectively.

The squared multiple correlations indicate that the model explains 34% of the variance in Study Attitudes, 38% in Metacognitive Ability, 59% in Post-Test Academic Achievement, and 55% in Learning Retention. These values suggest that the specified predictors account for meaningful proportions of the variation in the endogenous variables, particularly academic achievement and retention.

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The standardised factor loadings range from 0.79 to 0.86, exceeding the commonly recommended threshold of 0.70. These values suggest satisfactory indicator reliability and provide preliminary support for convergent validity, subject to confirmation through appropriate measurement-model diagnostics.

Overall, Figure 2 highlights the interconnected roles of socioeconomic background, intelligence, study attitudes, metacognitive ability, and prior academic performance in explaining students' academic achievement and learning retention. The model particularly emphasises the importance of metacognitive ability for academic achievement and the strong relationship between post-test performance and subsequent knowledge retention. These findings are consistent with the theoretical perspective that meaningful learning involves cognitive engagement, self-regulation, and sustained knowledge retention.

VI. CONCLUSION

The present study examined the relationships among socioeconomic status, intelligence quotient, study attitudes, metacognitive ability, baseline academic achievement, post-test academic achievement and learning retention within a Structural Equation Modelling (SEM) framework. The study sought to understand how socioeconomic, cognitive and learning-related factors contribute to students' academic performance and sustained knowledge retention, thereby providing insights into the multidimensional nature of deep learning in education.

The reported structural relationships indicated positive associations among the major variables. Socioeconomic status ($\beta = 0.34$) and intelligence quotient ($\beta = 0.27$) were positively associated with study attitudes, while intelligence quotient was also positively related to metacognitive ability ($\beta = 0.31$). Among the predictors of post-test academic achievement, metacognitive ability demonstrated the strongest standardised relationship ($\beta = 0.36$), followed by study attitudes ($\beta = 0.29$) and baseline achievement ($\beta = 0.28$). These findings suggest that students' capacity to monitor, regulate and evaluate their learning processes may be particularly important for improving academic performance. Furthermore, post-test academic achievement exhibited a strong positive relationship with learning retention ($\beta = 0.62$), highlighting the close connection between academic performance and sustained knowledge acquisition.

The reported explanatory power of the model further suggested that the selected predictors accounted for 34% of the variance in study attitudes, 38% in metacognitive ability, 59% in post-test academic achievement and 55% in learning retention. The correlation analysis also indicated positive associations among the study variables, particularly between post-test academic achievement and learning retention ($r = 0.910$). However, this exceptionally high correlation requires additional examination to establish the empirical distinctiveness of these two educational outcomes.

From an educational perspective, the study underscores the importance of integrating metacognitive development, positive study attitudes and cognitive support into teaching and learning practices. Educational institutions may strengthen learning outcomes by promoting self-regulated learning, reflective thinking, effective study strategies and opportunities for meaningful engagement with academic content. The findings also draw attention to socioeconomic differences that may influence students' learning experiences, emphasising the need for inclusive educational interventions and equitable access to academic resources.

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