The Impact of Emotional Intelligence on Academic Performance of College Students: The Moderating Effect of Self-Efficacy

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Abstract

As a non-cognitive resource that supplements general cognitive ability in explaining academic outcomes in higher education, emotional intelligence is widely discussed, yet reported effect sizes vary widely across samples, instruments and performance criteria. We examine whether academic self-efficacy operates as a boundary condition on the association between emotional intelligence and academic performance among college students. A composite emotional intelligence index is constructed from the four dimensions of the Wong and Law framework using reliability-derived weights, academic self-efficacy is expressed as a mean-scaled latent score, and academic performance is normalized from institutional grade point average records. On a sample of 612 undergraduates drawn from three comprehensive universities, a hierarchical moderated regression model with a mean-centred product term is estimated, and the interaction is probed through simple slope decomposition and the Johnson-Neyman technique. A significant positive main effect on academic performance emerges from emotional intelligence, academic self-efficacy exhibits a stronger main effect, and the product term is significant and positive, indicating that the predictive value of emotional intelligence rises as efficacy beliefs strengthen. At low levels of self-efficacy the conditional effect of emotional intelligence is weak and statistically indistinguishable from zero, while it reaches roughly nine times that magnitude at high levels. The Johnson-Neyman transition point falls at a standardized self-efficacy value of about negative 0.67, above which the conditional effect attains significance, covering approximately three quarters of the sample. The interaction coefficient is found to be robust when considering alternative covariate sets and under bootstrap resampling. These results indicate that emotional competence converts into measurable academic gain mainly when students hold sufficiently strong beliefs about their own capability, and this implies that emotional skills training should be paired with efficacy-building instructional practice rather than delivered in isolation.

Keywords

Emotional Intelligence, Academic Performance, Academic Self-Efficacy, Moderation Analysis, Higher Education, College Students.

1. Introduction

The capacity to monitor emotional states in oneself and in others, to discriminate among those states, and to use the resulting information to guide thinking and action is what defines emotional intelligence [1]. Since the construct entered educational research, it has been treated as a non-cognitive resource that complements general cognitive ability in accounting for variation in academic outcomes. Synthesizing 158 citations and more than forty thousand participants, a comprehensive meta-analysis reported an overall correlation of 0.20 between emotional intelligence and academic performance, and ability-based measures were found to give a stronger association than self-rated or mixed measures [2]. A later meta-analytic synthesis covering 28 samples and roughly fourteen thousand participants estimated a moderate to high pooled correlation of 0.39, and geographical region and outcome type were identified as significant moderators [3].

Inconsistency nevertheless characterises the evidence base. When restricted to undergraduate medical programmes, a multilevel meta-analysis concluded that the association is weak and sensitive to the choice of instrument and performance criterion, even though it is statistically detectable [4]. No significant link between trait emotional intelligence and grade point average was reported in a cross-sectional study of rehabilitation students [5], and in a different national setting a survey of medical students reported a negative relationship [6]. This heterogeneity indicates that the path from emotional competence to academic outcomes is conditional rather than universal, and that boundary conditions deserve explicit modelling instead of being absorbed into unexplained residual variance.

A principled candidate for such a boundary condition is supplied by social cognitive theory. Self-efficacy denotes the belief that one can organize and execute the courses of action required to attain designated levels of performance, and it governs the effort, persistence and goal setting through which capability is converted into achievement [7]. In Chinese universities, empirical work has demonstrated that emotional intelligence predicts self-efficacy both directly and through coping style [8], and that emotional intelligence, learning motivation and self-efficacy jointly shape academic achievement in online course settings [9]. A structural analysis of physical education undergraduates further demonstrated that a substantial share of the effect of emotional intelligence on academic engagement is transmitted by academic self-efficacy [10].

A mediating position is assigned to self-efficacy in nearly all of this work, implying that emotional intelligence operates by raising efficacy beliefs. An alternative and largely untested reading treats efficacy beliefs as an amplifier: under this reading, emotional skills give academic returns only when a student believes that those skills can be deployed effectively, so that the slope linking emotional intelligence to performance is itself a function of self-efficacy. We adopt this moderation perspective and test it against institutional performance records rather than self-reported achievement.

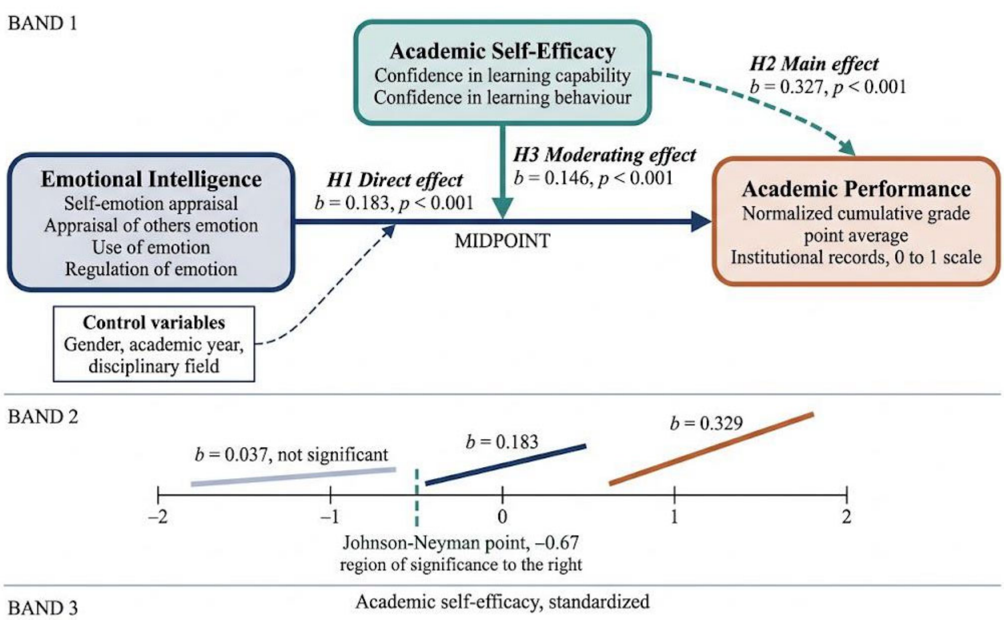

Figure 1. Conceptual Framework Linking Emotional Intelligence, Academic Self-Efficacy, and Academic Performance

The main contributions are as follows: (a) a moderation framework positioning academic self-efficacy as a boundary condition rather than a transmission channel; (b) an operational index system converting multidimensional emotional intelligence scores and raw grade records into comparable analytic variables through reliability-derived weighting; (c) a hierarchical moderated regression specification accompanied by simple slope decomposition and a Johnson-Neyman transition point identifying the region of significance; (d) a sensitivity analysis evaluating the stability of the interaction under alternative covariate sets and under bootstrap resampling. The conceptual framework adopted in this study is presented in Figure 1.

2. Methods and Results

2.1. Theoretical Framework and Index Construction

Wong and Law developed the four-dimensional conception of emotional intelligence that forms the measurement foundation of this study; it distinguishes self-emotion appraisal, appraisal of the emotions of others, use of emotion and regulation of emotion [11]. These dimensions are conceptually ordered from perception through utilization to control, and they differ in how directly they bear on task-oriented behaviour. The management of academic anxiety and boredom is governed by regulation of emotion and use of emotion, whereas the two appraisal dimensions operate mainly through interpersonal channels such as help seeking and peer collaboration.

The mechanism connecting this measurement structure to achievement is given by control-value theory. Achievement emotions arise from appraisals of control and of value, and the intensity of an emotion is a joint function of the two appraisal classes rather than a simple sum of independent contributions [12]. The regulatory competence that determines how effectively an aroused emotion is handled is supplied by emotional intelligence, while the control appraisal that determines whether regulatory effort is judged worth expending is supplied by self-efficacy. This joint structure is precisely the theoretical signature of a multiplicative rather than additive relationship, and it motivates the moderation hypothesis tested below.

A composite emotional intelligence index is defined for respondent i as a weighted sum of standardized dimension scores:

$$EI_i = \sum_{d=1}^{4} w_d Z_{id} \tag{1}$$

where Z_{id} is the standardized score of respondent i on dimension d, and w_d is the weight assigned to that dimension. The differing response scales and item counts across dimensions are removed by standardization, which is defined as:

$$Z_{id} = \frac{X_{id}-\mu_d}{\sigma_d} \tag{2}$$

where X_{id} is the raw dimension mean, μ_d is the sample mean of that dimension, and σ_d is the corresponding standard deviation. A mean of zero and unit variance characterise the resulting index, so regression coefficients estimated on it are interpretable in standard deviation units.

2.2. Measurement of Emotional Intelligence and Dimensional Structure

The sixteen-item Wong and Law Emotional Intelligence Scale, administered on a seven-point response format, was used to measure emotional intelligence. Recent psychometric work demonstrates that the four-factor structure of this instrument holds across sex groups and that composite reliability remains satisfactory in undergraduate samples [13], and this supports the use of dimension-level scores rather than a single undifferentiated total. Evidence from a large first-year undergraduate sample similarly indicates that the dimensions of trait emotional intelligence correlate differentially with achievement, and the self-control and well-being facets show the closest ties to grade point average [14]. Information about differential measurement quality would therefore be discarded by assigning equal weight to all dimensions.

The internal consistency of each dimension consequently served as the basis for deriving the weights, so that dimensions measured with greater precision contribute more to the composite:

$$w_d = \frac{\alpha_d}{\sum_{j=1}^{4} \alpha_j} \tag{3}$$

where α_d is the Cronbach alpha coefficient of dimension d. By construction the weights sum to unity, and this preserves the standardized metric of the composite index. The descriptive statistics, reliability coefficients, derived weights and zero-order correlations with academic performance for the four dimensions are reported in Table 1.

Table 1. Descriptive Statistics, Reliability, Derived Weights, and Correlations of the Four Emotional Intelligence Dimensions

Dimension	Mean	SD	$\boldsymbol{\alpha}$	Weight $\boldsymbol{w_d}$	Correlation with Academic Performance
Self-emotion appraisal	5.12	0.94	0.83	0.247	0.21
Appraisal of others emotion	4.86	1.02	0.81	0.241	0.17
Use of emotion	5.03	1.08	0.85	0.253	0.26
Regulation of emotion	4.71	1.15	0.87	0.259	0.29

Note. N = 612. All correlations are significant at p < 0.001. Weights are computed from Equation (3) and sum to 1.000.

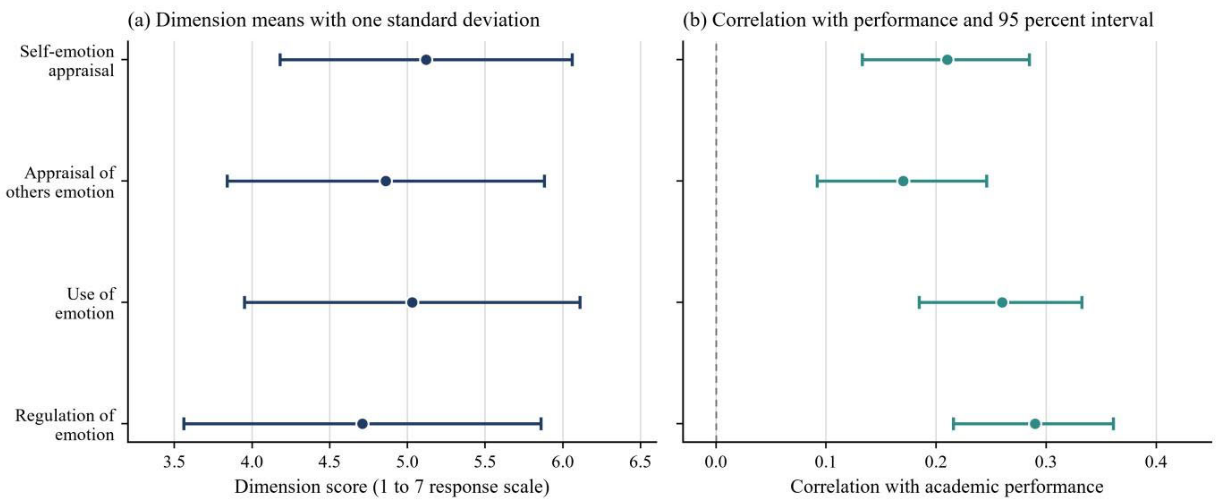

Figure 2. Mean Profile of the Four Emotional Intelligence Dimensions and Their Correlations with Academic Performance

Table 1 displays a pattern consistent with the theoretical ordering set out in Section 2.1. Both the highest reliability and the strongest bivariate association with academic performance are carried by regulation of emotion, while appraisal of the emotions of others carries the weakest association. The mean profile of the four dimensions together with the corresponding correlation coefficients is displayed in Figure 2, and the divergence between the regulatory and interpersonal facets is visually apparent.

2.3. Academic Self-Efficacy and Academic Performance

A twenty-two-item scale covering confidence in learning capability and confidence in learning behaviour, administered on a five-point response format, was used to measure academic self-efficacy. Work on Chinese university samples demonstrates that academic self-efficacy is embedded within a broader positive psychological resource system alongside psychological capital and emotional competence [15], and that it exerts a protective effect against academic burnout through intrinsic motivation and learning engagement [16]. Both findings support treating self-efficacy as a stable motivational disposition during a single academic term rather than as a transient state.

The academic self-efficacy score is defined as the arithmetic mean of the item responses:

$$SE_i = \frac{1}{m}\sum_{k=1}^{m} s_{ik} \tag{4}$$

where s_{ik} is the response of participant i to item k, and m is the number of items retained after item analysis. Using the transformation in Equation (2), the score was subsequently standardized so that both predictors share a common metric.

Institutional records rather than self-report supplied academic performance, and this avoids the shared-method bias that inflates associations when both predictor and criterion are questionnaire based. Grade point averages were normalized to the unit interval:

$$AP_i = \frac{G_i - G_{min}}{G_{max} - G_{min}} \tag{5}$$

where G_i is the cumulative grade point average of participant i, and G_{min} and G_{max} are the minimum and maximum observed values within the cohort. By normalizing, grade records become comparable across institutions that apply different grading ceilings. Descriptive statistics and zero-order correlations for the analytic variables are reported in Table 2.

Table 2. Descriptive Statistics and Zero-Order Correlations Among the Analytic Variables

Variable	Mean	SD	1	2	3	4
1. Emotional intelligence	0.000	1.000	1.000			
2. Academic self-efficacy	0.000	1.000	0.440	1.000		
3. Academic performance	0.612	0.147	0.280	0.410	1.000	
4. Academic year	2.31	1.04	0.052	0.087	0.061	1.000

Note. N = 612. Emotional intelligence and academic self-efficacy are standardized. Correlations of absolute value above 0.100 are significant at p < 0.05.

A stronger correlation between academic self-efficacy and academic performance than between emotional intelligence and academic performance emerges from Table 2, and the two predictors are themselves moderately correlated. The shared variance between predictors is well below the level at which multicollinearity distorts coefficient estimates, since the corresponding variance inflation factor is approximately 1.24. The distribution of normalized academic performance across self-efficacy tertiles is shown in Figure 3, and it indicates an upward shift in both central tendency and dispersion as efficacy beliefs strengthen.

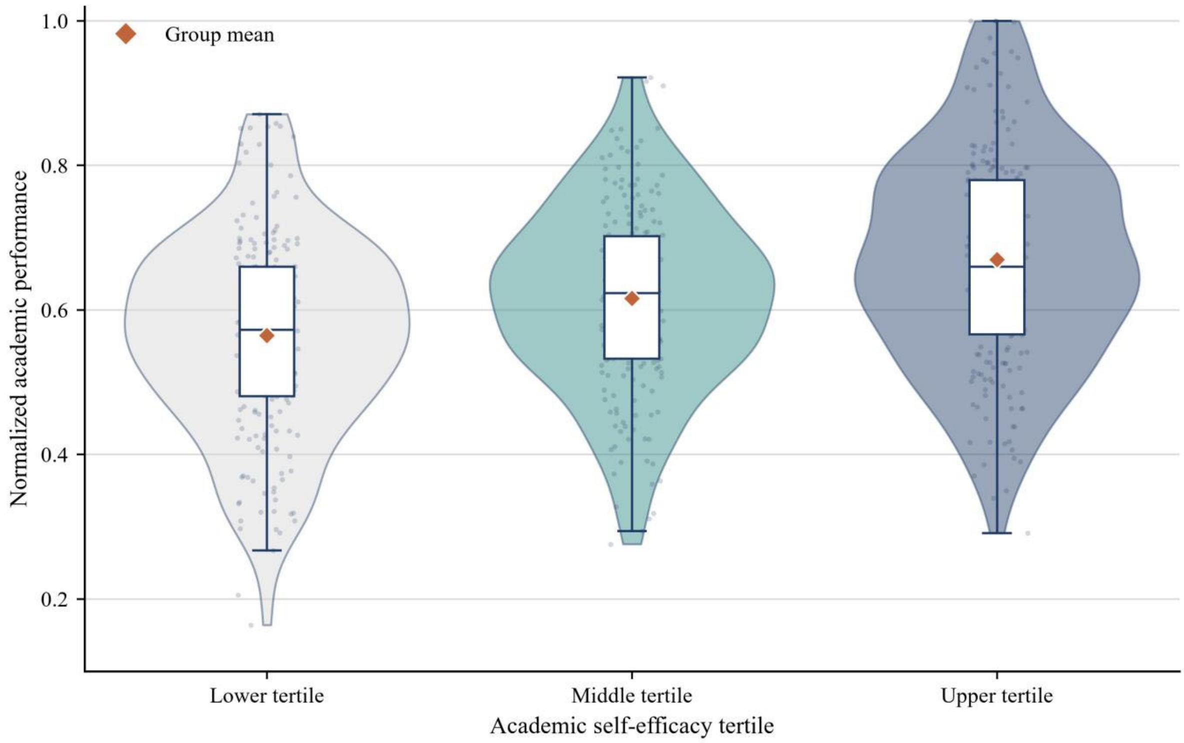

Figure 3. Distribution of Normalized Academic Performance Across Academic Self-Efficacy Tertiles

2.4. Moderated Regression Model and Probing Procedures

Hierarchical regression with a mean-centred product term was used to test the moderation hypothesis, following the estimation and probing conventions set out for regression-based conditional process analysis [17]. The full specification is:

$$AP_i = \beta_0 + \beta_1 EI_i + \beta_2 SE_i + \beta_3 EI_i SE_i + \sum_{c=1}^{q} \gamma_c C_{ci} + \varepsilon_i \quad (6)$$

where β_1 and β_2 are the main effects of emotional intelligence and academic self-efficacy, β_3 is the interaction coefficient of primary interest, C_{ci} denotes the q control variables of gender, academic year, and disciplinary field, and ε_i is the disturbance term. Before the product was formed, both predictors were mean centred; this reduces nonessential collinearity and gives the lower-order coefficients an interpretation at the sample mean of the moderator.

At a given level w of standardized academic self-efficacy is the partial derivative of Equation (6) with respect to the predictor:

$$\frac{\partial AP}{\partial EI} = \theta(w) = \beta_1 + \beta_3 w \quad (7)$$

Because it draws on the sampling variances of two coefficients and their covariance, the standard error of this conditional effect varies with w because it draws on the sampling variances of two coefficients and their covariance:

$$s_\theta(w) = \sqrt{s_{\beta 1}^2 + 2ws_{\beta 1 \beta 3} + w^2 s_{\beta 3}^2} \tag{8}$$

At which values of the moderator the conditional effect crosses the threshold of statistical significance is identified by the Johnson-Neyman procedure. The transition points are the roots of the equality between the squared conditional effect and the squared critical value scaled by the conditional variance:

$$(\beta_1 + \beta_3 w)^2 = t_{crit}^2 s_\theta^2(w) \tag{9}$$

The three estimated models are reported in Table 3. A modest share of variance is explained by the control block, a substantial increment is added by the main effect block, and a further significant increment is added by the product term.

Table 3. Hierarchical Moderated Regression Predicting Normalized Academic Performance

Predictor	Model 1 $\boldsymbol{\beta}$	Model 1 std. error	Model 2 $\boldsymbol{\beta}$	Model 2 std. error	Model 3 $\boldsymbol{\beta}$	Model 3 std. error
Gender	0.072	0.036	0.064	0.035	0.061	0.034
Academic year	-0.055	0.038	-0.050	0.037	-0.048	0.036
Disciplinary field	0.068	0.037	0.058	0.036	0.055	0.035
Emotional intelligence			0.176	0.042	0.183	0.041
Academic self-efficacy			0.331	0.041	0.327	0.040
Interaction term					0.146	0.038
R^2	0.061		0.213		0.247	
Change in R^2	0.061		0.152		0.034	
F value	13.18		32.83		33.05	

Note. N = 612. Entries under β are standardized regression coefficients. Gender is coded 0 for male and 1 for female. Disciplinary field is coded 0 for science and engineering and 1 for humanities and social science. All changes in R^2 are significant at p < 0.001.

A positive and significant interaction coefficient emerges, indicating that the slope linking emotional intelligence to academic performance steepens as academic self-efficacy rises. When the estimates of Table 3 are substituted into Equation (7), a conditional effect of 0.037 is obtained at one standard deviation below the moderator mean, 0.183 at the mean, and 0.329 at one standard deviation above the mean. These three simple slopes together with their confidence bands are plotted in Figure 4.

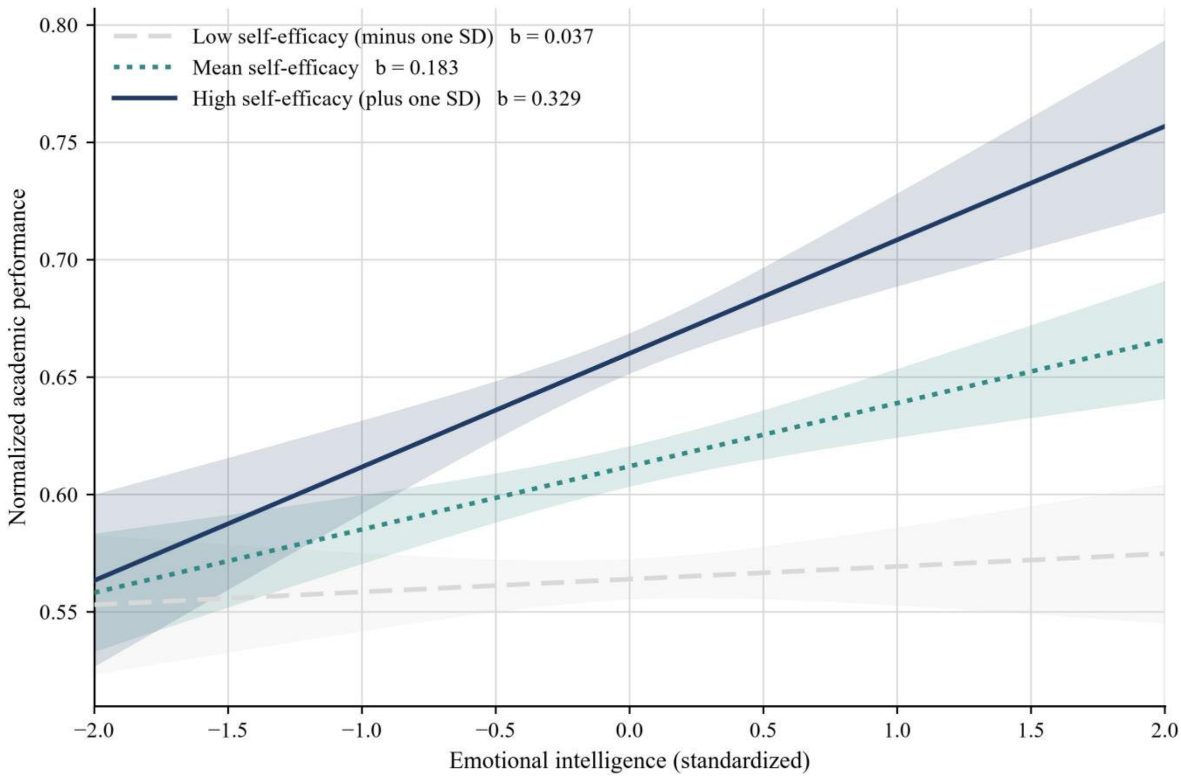

Figure 4. Simple Slopes of Emotional Intelligence on Academic Performance at Three Levels of Academic Self-Efficacy

2.5. Integrated Analysis and Sensitivity Assessment

Through the effect size for an incremental predictor block, the practical magnitude of the interaction was quantified:

$$f^2 = \frac{R_{M3}^2 - R_{M2}^2}{1 - R_{M3}^2} \tag{10}$$

where R_{M3}^2 and R_{M2}^2 are the explained variance proportions of the full model and of the main effect model. An effect size of approximately 0.045 is obtained when the values in Table 3 are substituted, and this falls in the small to moderate band for interaction terms in field research and is comparable to the incremental validity that emotional intelligence itself contributes over cognitive ability and personality [2]. Predicted performance under any combination of predictor and moderator values follows from the reparameterized form of Equation (6):

$$AP_{pred}(EI, w) = \beta_0 + (\beta_1 + \beta_3 w)EI + \beta_2 w \tag{11}$$

where AP_{pred} is the model-implied academic performance at a given pairing of emotional intelligence and academic self-efficacy. The conditional slope defined in Equation (7) is the bracketed term, and it makes explicit that the predictor operates through a coefficient that is itself a linear function of the moderator.

A single transition point within the observed range of the moderator is located at a standardized self-efficacy value of negative 0.67 when Equation (9) is applied to the estimated covariance matrix. Above this value the conditional effect of emotional intelligence is significant at the five percent level, and below it the effect cannot be distinguished from zero. Roughly 74.9 percent of the sample lies in the region of significance, and this means that the association reported in the meta-analytic literature holds for most students but not for the low-efficacy subgroup. The conditional effects at representative moderator values together with the Johnson-Neyman boundary are reported in Table 4.

Table 4. Conditional Effects of Emotional Intelligence at Representative Levels of Academic Self-Efficacy

Moderator level	Conditional effect	Standard error	***t*** value	***p*** value	Lower 95 percent limit	Upper 95 percent limit
Minus one SD	0.037	0.049	0.75	0.451	-0.060	0.134
Johnson-Neyman point	0.085	0.043	1.96	0.050	0.000	0.170
Sample mean	0.183	0.041	4.46	<0.001	0.103	0.263
Plus one SD	0.329	0.062	5.32	<0.001	0.208	0.450

Note. N = 612. The Johnson-Neyman point corresponds to a standardized academic self-efficacy value of -0.67, above which 74.9 percent of the sample is located.

Structural evidence that positive psychological characteristics, including self-efficacy, carry a large share of the influence of emotional intelligence on achievement and well-being, and that the transmission is stronger among students at more advanced stages of study [18], is consistent with the direction of this result. It also aligns with findings that engagement-related resources qualify the emotional intelligence and performance link rather than merely relaying it [19], and with reports that emotional intelligence predicts achievement more reliably when accompanied by behavioural dispositions that translate emotional insight into sustained academic effort [20]. The fitted response surface generated by Equation (11) is presented in Figure 5, and it shows that the performance gradient along the emotional intelligence axis is nearly flat at the low end of the moderator and steep at the high end.

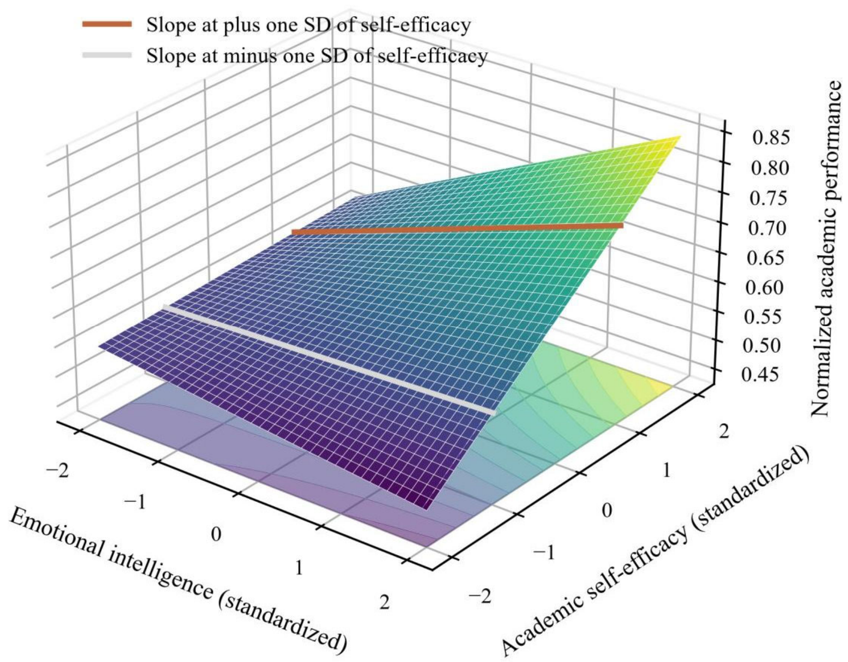

Figure 5. Fitted Response Surface of Academic Performance Across Emotional Intelligence and Academic Self-Efficacy

Whether the interaction estimate depends on the covariate set or on distributional assumptions was examined through a sensitivity assessment. When Equation (6) was estimated without controls, an interaction coefficient of 0.152 was returned; adding gender returned 0.149, adding academic year returned 0.148, and the full control set returned 0.146. Including prior-year grade point average as an additional covariate reduced the coefficient to 0.131 while leaving it significant, and this indicates that the interaction is not an artefact of stable prior attainment. A percentile bootstrap with five thousand resamples gave a confidence interval of 0.071 to 0.221 for the interaction coefficient, and the interval excludes zero across every specification examined. The sensitivity results are summarized in Figure 6.

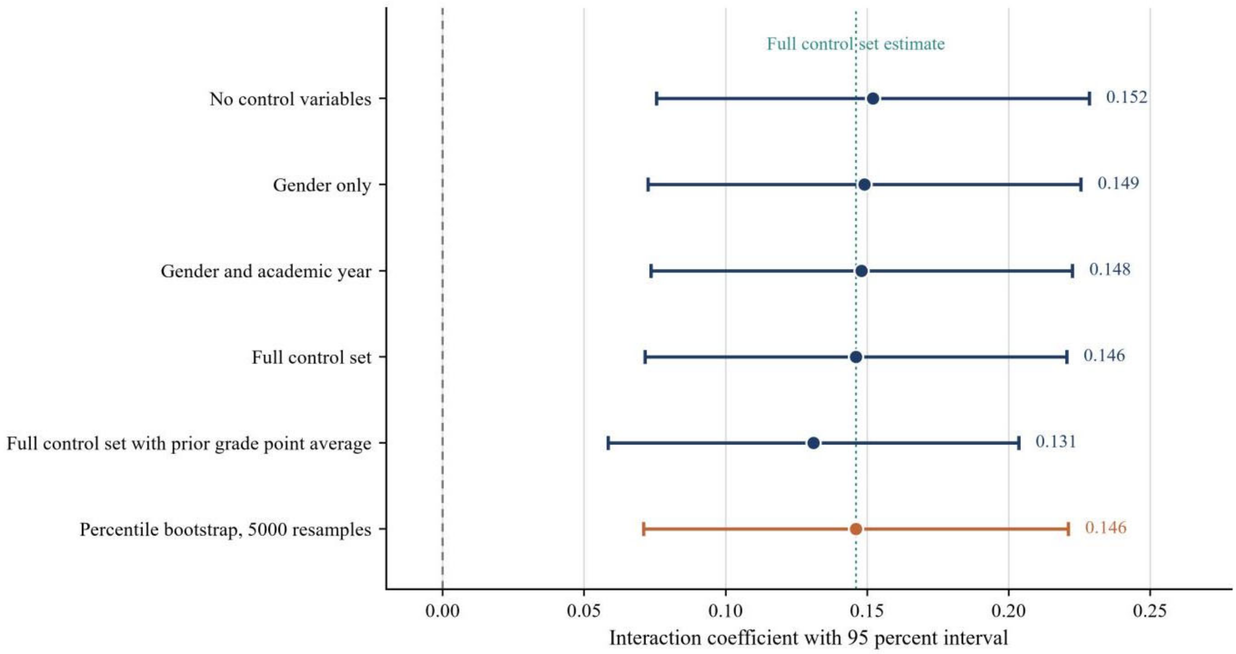

Figure 6. Sensitivity of the Interaction Coefficient Across Alternative Covariate Sets and Bootstrap Resampling

3. Conclusion

Whether academic self-efficacy sets a boundary condition on the relationship between emotional intelligence and academic performance among college students was examined here. A composite emotional intelligence index was constructed from the four dimensions of the Wong and Law framework with reliability-derived weights, academic performance was normalized from institutional grade records, and a hierarchical moderated regression model was estimated and probed through simple slope decomposition and the Johnson-Neyman technique.

Several findings emerge from the analysis. Both emotional intelligence and academic self-efficacy predict academic performance, and the motivational belief carries the larger main effect. The product term is positive and significant, and it raises the explained variance by 3.4 percentage points with an effect size of approximately 0.045. From 0.037 at one standard deviation below the moderator mean to 0.329 at one standard deviation above it, the conditional effect of emotional intelligence rises, a difference of nearly nine times in magnitude. The Johnson-Neyman boundary at a standardized self-efficacy value of negative 0.67 separates a majority subgroup for whom emotional competence predicts achievement from a low-efficacy minority for whom it does not. Among the four measured dimensions, the strongest bivariate association with performance is carried by regulation of emotion, and this is consistent with the view that the value of emotional competence in academic settings lies primarily in the management of achievement-related affect.

For educational practice, these results carry clear implications. Programmes that teach emotional skills in isolation are likely to benefit the students who need them least, because the returns to those skills are concentrated among learners who already believe in their own capability. A more defensible design would pair emotional skills training with mastery experiences, graded task sequences and structured feedback that raise efficacy beliefs. The finding also points to a screening logic in which low-efficacy students receive efficacy-building support before emotional skills instruction rather than alongside it. Evidence that emotional competence predicts achievement across educational stages and cultural settings [21], and that it protects against learning burnout through self-acceptance and reduced perceived stress [22], indicates that such combined interventions are likely to give benefits beyond grades alone.

There are several limitations to this study. The design is cross-sectional, so the temporal ordering among emotional intelligence, efficacy beliefs and performance cannot be established, and reciprocal influence between achievement and efficacy remains plausible. A self-report instrument was used to assess emotional intelligence, and this measures perceived rather than demonstrated competence and gives systematically smaller associations with achievement than ability-based tests. Three comprehensive universities within a single national system supplied the sample, which limits generalization to vocational institutions and to other cultural settings. Control variables were restricted to demographic and disciplinary indicators, and cognitive ability was not measured, so the incremental validity of the interaction over general intelligence remains untested.

Several directions should be pursued in future work. Longitudinal designs with repeated measurement across academic terms would permit cross-lagged estimation of the reciprocal paths and would establish whether the moderation observed here is stable over time. Incorporating ability-based emotional intelligence measures alongside self-report instruments would clarify whether the boundary condition operates on demonstrated competence or on perceived competence. Randomized instructional trials manipulating efficacy-building elements while holding emotional skills content constant would give causal evidence for the amplification mechanism suggested here. Extending the framework to domain-specific efficacy beliefs and to discipline-specific performance criteria would further clarify how narrowly the boundary condition should be defined.

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