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Research Article

Engagement and Secondary English Achievement: A Multi-Method Study of Climate, Family, and Psychological Capital

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Abstract
English-language proficiency gates access to tertiary education, employment, and competitive examinations in India, yet large learning-outcome surveys continue to document wide variation in secondary-stage English achievement. Classroom climate, parental involvement, psychological capital, and student engagement are the constructs most often linked to such achievement, but their joint contribution is usually summarised through a single average-effect model. This study examines how these four constructs relate to English achievement among Indian secondary students, using a variance-decomposition framework that distinguishes unique from shared explanatory variance. Cross-sectional survey data were collected from 1,605 students in classes XI and XII (52.6% female; mean age 16.74 years) drawn from 107 secondary schools in West Bengal, India. Six complementary variance-partitioning analyses were applied to the zero-order correlation matrix: a saturated structural equation model, dominance analysis, commonality analysis, suppression and redundancy diagnostics, mutual-information dependence decomposition, and community-aware bridge centrality. The full model accounted for 31.4% of the variance in English achievement. Engagement showed the strongest direct standardised association (β = .327) and the largest unique variance contribution (43.6% of explained variance). Commonality analysis indicated that only 29.7% of explained variance was uniquely attributable to single predictors, with 70.3% shared among combinations of predictors. Suppression diagnostics revealed no suppression but substantial redundancy for three of four predictors, and engagement showed the highest cross-domain bridge strength (BS = .722). Engagement appears as the most central associational construct in the system, but the four predictors operate substantially as overlapping representations of related learner and contextual processes rather than as independent unique contributors. Convergent associational evidence across multiple methods is stronger than evidence from any single method, but the cross-sectional design precludes causal inference; longitudinal and experimental work is needed before intervention claims can be made.

Keywords: Commonality Analysis, Dominance Analysis, English Achievement, Shared Variance, Student Engagement, Suppression Diagnostics

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1. INTRODUCTION

English-language proficiency in Indian secondary education is a long-standing concern of researchers, policy-makers, and parents. Achievement in English at the higher-secondary stage gates access to many tertiary streams, government employment opportunities, and standardised competitive examinations, and recent learning-outcome surveys continue to document substantial variation across and within Indian states (Banerji & Wadhwa, 2024; National Council of Educational Research and Training, 2023). Understanding which student-level and contextual factors are associated with English achievement

is therefore an enduring practical concern, particularly for school systems in eastern India where rural-urban disparities remain salient.

Four constructs have received the most sustained empirical attention in this literature. Classroom climate (i.e., the perceived quality of teacher support, peer cohesion, and orderliness in the immediate learning environment) has been consistently associated with academic engagement and achievement, with recent reviews and large-scale studies confirming small-to-moderate effect sizes across countries and grade levels (Cohen et al., 2009; Wang & Degol, 2016; Olivier et al., 2021; Daily et al., 2020; Maxwell et al., 2017). Parental involvement, encompassing both home-based and school-based engagement of parents in their child's education, has been the focus of multiple meta-analyses (Jeynes, 2017; Castro et al., 2015), with recent work refining the conditions under which involvement is most strongly associated with achievement (Barger et al., 2019; Kim, 2022). Psychological capital — the constellation of hope, self-efficacy, resilience, and optimism articulated by Luthans and colleagues (2007) — has been elaborated for educational contexts and linked cross-sectionally and longitudinally with engagement and achievement (Carmona-Halty et al., 2021; Skinner et al., 2022; Datu et al., 2018). Student engagement, conceptualised by Fredricks and colleagues (2004) as a multi-dimensional construct combining behavioural, emotional, and cognitive components, is widely treated as the proximal learner-level construct most closely tied to moment-to-moment learning behaviour (Wang & Eccles, 2013; Wong & Liem, 2022; Reschly & Christenson, 2022; Salmela-Aro et al., 2021; Lei et al., 2018).

A common pattern in this literature is to summarise the joint association of these constructs with achievement using a single average-effect lens — typically structural equation modelling (SEM) on cross-sectional data. SEM is informative, but it answers only one question among several that policy actors and educators may ask. It does not, by itself, indicate how much of the explained variance is uniquely attributable to a given predictor across all possible model configurations; it does not decompose the explained variance into unique and shared partitions; it does not diagnose whether the predictors function as unique contributors or as overlapping representations of similar learner processes; it does not quantify dependence reduction in metrics that do not assume linear additive structure; and it does not characterise which constructs occupy the most cross-domain network position. Each of these questions calls for a different statistical lens, and answering them on the same dataset offers a more complete portrait than any single lens alone (Nimon & Reio, 2011; Howard & Hoffman, 2018; Epskamp et al., 2018).

The present study applies a six-method variance-decomposition framework to cross-sectional survey data from 1,605 secondary students nested in 107 schools in West Bengal, India. The study is associational throughout: cross-sectional covariance structure cannot establish causal direction, temporal precedence, or intervention effect, and we use the language of association, conditional independence, and statistical centrality throughout. We do not claim that using multiple methods alone constitutes a contribution; the contribution is transparent triangulation of the same associational structure across complementary lenses. Within these limits, five complementary analyses address five corresponding research questions, and a sixth analysis tests an explicit null hypothesis specified a priori:

RQ1 (relative importance): What is the unique additive contribution of each of the four predictors to the variance in English achievement when all 2^4-1 subset models are considered?

RQ2 (variance partitioning): How is the explained variance in English achievement decomposed into the unique variance attributable to each predictor and the variance shared among combinations of predictors?

RQ3 (construct distinctiveness): Do the predictors function as independent unique contributors to English achievement, or are their full-model coefficients diminished (redundancy) or inflated (suppression) relative to their zero-order correlations?

RQ4 (dependence decomposition): How much of the predictor–outcome statistical dependence is reduced after conditioning on the hypothesised mediators when the dependence metric is mutual information rather than a product of standardised coefficients?

RQ5 (network role): Which constructs occupy the most cross-domain bridge position in the partial-correlation network across school, family, learner, and outcome communities?

2. METHODOLOGY

2.1. Research Design

The study used a quantitative, cross-sectional, correlational survey design, an approach widely employed in educational and psychological research to examine associations among naturally occurring variables when experimental manipulation is neither feasible nor ethical and when the aim is to estimate the structure of relationships at a defined point in time (Setia, 2016; Spector, 2019). Because the design is cross-sectional and units of observation were measured at a single time point, all reported relations are associational, and the manuscript uses the vocabulary of association, partial correlation, conditional independence, and statistical centrality throughout. Causal language ('drives', 'leads to', 'translates into', 'pathway', 'mechanism') is reserved for explicit reference to prior experimental evidence in cited literature, not for the present results. The data are original primary data collected by the corresponding author from 1,605 students; the analytic file used for the present manuscript is a composite-score file computed from those original participant responses, with item-level data retained in secured institutional storage.

2.2. Participants and Sampling

Participants were 1,605 students in classes XI and XII (mean age 16.74 years, SD = 0.44; 52.6% female, 47.4% male) recruited from 107 government and government-aided secondary schools in West Bengal, India. Approximately two-thirds (66.4%) attended rural schools and one-third (33.6%) attended urban schools. Schools were sampled across districts to mirror the regional demographic composition. A target of 20 students per school (2,140 in total) was set in advance, and the participating schools and students were informed accordingly. On the day of administration, one to two students were absent in each school, so 1,950 students (91.1% of the intended sample) actually completed the questionnaires. The returned response sets were then screened for completeness and correctness, and, to preserve a balanced cluster design, 15 complete-record students were retained from each school, yielding a final analytic sample of 1,605 students (1,605 = 107 × 15; 82.3% of the 1,950 respondents). The 345 response sets (17.7%) not carried forward comprised those containing incomplete or incorrect item-level data, together with the small number of complete sets in excess of the balanced 15-per-school quota; no missing-data imputation was applied. Because composite scores were computed only from the retained full-record completers, the composite-level analytic file used in the present study contained no missing values.

Because students were nested within schools, dependency in the data structure cannot be ruled out a priori. Balanced cluster sizes do not by themselves remove or correct intra-class dependency; what they do remove is the additional efficiency loss introduced by unbalanced cluster sizes. School-level identifiers were not retained in the composite-level analytic file; we therefore cannot fit a multilevel model or compute cluster-robust standard errors and report this as a limitation in Section 4. To convey the magnitude of the issue, the design effect for cluster-balanced sampling, $DEFF = 1 + (m - 1)\cdot ICC$ with $m = 15$, lies in the plausible range 1.7–2.4 if the intraclass correlation for student outcomes nested in schools is 0.05–0.10 (the typical range in educational research; Hedges & Hedberg, 2007). Under such ICCs, the effective sample size lies between approximately 670 and 945, and confidence-interval widths reported here may be conservatively narrow by a factor of approximately 1.3–1.55. We therefore interpret all p-values and confidence intervals as approximate, and recommend explicit ICC and design-effect computation in any future hierarchical re-collection of these data.

2.3. Research Instruments

Five composite scores were used. For each construct, we report below the source, item count, response format, the minimum and maximum possible composite score, and the reliability and confirmatory-factor-analysis (CFA) evidence obtained in an independent calibration sample (N = 240) drawn from the same population. All four self-report scales were administered in English, with a Bengali translation available for students who required one. The Bengali version was prepared through a standard back-translation procedure conducted by two independent translators proficient in both English and Bengali: one translator rendered the original English items into Bengali, and the second independently back-translated them into English, after which the few discrepancies that emerged were reconciled by the

research team before administration. Among the four self-report scales, only the Classroom Climate Scale contained negatively worded items (ten in total); these were reverse-scored before composite computation, so that on every scale a higher score consistently indicates a more positive standing on the construct.

Classroom Climate (CC). A 20-item Classroom Climate Scale was administered, refined from Muthee's (2011) 36-item instrument through exploratory and confirmatory factor analysis on an independent calibration sample. Items were rated on a five-point Likert-type scale (1 = strongly disagree to 5 = strongly agree); minimum–maximum possible composite score = 20–100. Example item: "Good discipline is maintained in my class." CFA on the refined scale (N = 240) supported a unidimensional structure with excellent fit (CFI = .989, TLI = .988, RMSEA = .023 [.017, .029], SRMR = .025); Cronbach's α = .94 and composite reliability = .95.

Parental Involvement (PI). The Perceived Parental Involvement Scale was adapted from the standardised Perceived Parental Involvement (PPI) questionnaire developed by Anthonyraj and Sasikala (2021), which measures students' perceptions of cognitive, emotional, and participatory parental engagement in academic affairs. The original 30-item instrument was validated on an independent sample (N = 420): exploratory factor analysis indicated a unidimensional structure accounting for 68.5% of the variance (KMO = .988; Bartlett's test $\chi^2(435) = 8698.93$, $p < .001$; item loadings .62–.81), and confirmatory factor analysis showed excellent fit ($\chi^2/df = 1.096$, RMSEA = .015, GFI = .934, CFI = .995; standardised loadings .694–.769; Cronbach's α = .96). For the present study the scale was systematically refined to a 15-item version, retaining items on the basis of combined statistical (factor loading, item–total correlation) and conceptual (content-domain coverage) criteria, and was re-validated on the independent calibration sample (N = 240). Items were rated on a five-point Likert scale; minimum–maximum possible composite score = 15–75. Example item: "My parents take my opinions seriously while making decisions." CFA on the refined 15-item scale (N = 240) supported a unidimensional structure with excellent fit (CFI = .994, TLI = .993, RMSEA = .019 [.000, .041], SRMR = .049); Cronbach's α = .913, composite reliability = .874.

Psychological Capital (PsyCap). A 15-item Psychological Capital Assessment Scale (refined from the 24-item PCAS by Rani & Choudhary, 2007) measuring four sub-dimensions — hope, self-efficacy, resilience, and optimism — on a five-point Likert scale; minimum–maximum possible composite score = 15–75. Example item: "When I face academic difficulties, I can usually think of many ways to solve them." CFA (N = 240) supported the four-factor structure with excellent fit; dimension-specific Cronbach's α ranged from .931 to .974.

Student Engagement (ENG). A 12-item Student Engagement Scale, refined from the 30-item SES (Sharma & Chowdhry, 2015), measures three sub-dimensions — Learning Strategies / Cognitive Engagement, Social / Emotional Engagement, and Behavioural Engagement / Persistence — on a five-point Likert scale; minimum–maximum possible composite score = 12–60. Example item: "I try my best to do in-depth study of a topic by identifying the key points." CFA (N = 240) supported the three-factor structure with excellent fit (CFI = .998, TLI = .997, RMSEA = .016 [.000, .045], SRMR = .049). Subscale Cronbach's α ranged from .840 to .866; total-scale α was .710 (acceptable). The lower total-scale α reflects the multi-dimensional structure of the construct, which is best summarised at the subscale level.

English Achievement (EAT). A 30-item criterion-referenced English Achievement Test, developed by the corresponding author following item analysis on a 50-item pilot pool (N = 240), and aligned with the West Bengal Council of Higher Secondary Education English syllabus. The test covers grammar, vocabulary, reading comprehension, and short writing items; items were dichotomously scored (correct = 1, incorrect = 0); minimum–maximum possible score = 0–30. Item difficulty (P-values) ranged from .30 to .85 and discrimination (CITC) from .25 to .68. Internal consistency (Kuder–Richardson 20) = .927. Content validity was established through expert-panel review by five subject specialists following the Lawshe (1975) content validity ratio procedure.

2.4. Procedures

All data collection was conducted under institutional ethical clearance from Lovely Professional University (approval number LPU/IEC-LPU/2025/6/4, dated 16 December 2025). Schools were approached through the office of the District Inspector of Schools; written parental consent and student assent were obtained prior to any data collection. The four self-report instruments were administered

together as paper-and-pencil questionnaires in students' regular classrooms, in person and under standardised written instructions; completing the four questionnaires took participants approximately 75–90 minutes. The English achievement test was administered separately under invigilated conditions. All responses were anonymised at entry, with school-level and student-level identifiers replaced by numeric codes prior to any analysis. Composite scores were computed from item-level data following the scoring keys reported in each instrument's validation; the de-identified composite-level data file used in the present analyses contains no information that could re-identify individual schools or students.

2.5. Data Analysis

Univariate distributions were inspected for skew and kurtosis; all five composites had skew < 1 and kurtosis < 2, consistent with approximate normality at the composite level. No transformations were applied to the composites; all six analyses reported below were computed directly from the composite scores and the resulting zero-order correlation matrix. Six analyses were conducted, each connected to one of the research questions stated in Section 1.

Stage 0 — Baseline SEM. A saturated structural model was specified, with classroom climate and parental involvement as exogenous predictors of psychological capital and engagement, and all four predictors as direct predictors of English achievement. Bootstrap procedures with 5,000 resamples furnished bias-corrected confidence intervals for all path coefficients. Because the model is saturated (df = 0), conventional global fit indices (CFI, RMSEA, SRMR) are not informative — a saturated model fits perfectly by construction and 'fit' values cannot be used as evidence of model adequacy (Kline, 2016). Inference therefore focused on standardised path coefficients, bootstrap intervals, and the explained variance R^2 in the criterion.

Stage 1 — Dominance analysis. Following Azen and Budescu (2003) and Budescu (1993), the R^2 for English achievement was decomposed into the unique additive contribution of each predictor across all $2^4-1 = 15$ subset regression models. The general dominance weight of predictor j is the average of its marginal R^2 contributions across all subsets that exclude j; equivalently, it is the Shapley value of j in the cooperative game whose characteristic function is the subset R^2. Dominance weights index relative contribution to prediction; they are not estimates of causal importance.

Stage 2 — Commonality analysis. Following Nimon and Reio (2011) and Ray-Mukherjee et al. (2014), the full-model R^2 was decomposed into $2^4 - 1 = 15$ commonality partitions: four unique components U(·) and 11 shared components C(·) for every nonempty proper subset of the four predictors. Each commonality coefficient was computed via Möbius inversion on the lattice of subset R^2 values; the standard relation $R^2(S) = \Sigma$ over T such that $T \cap S \neq \emptyset$ of c(T) holds, with all 15 commonalities summing exactly to $R^2(P)$. Commonality analysis is mathematically distinct from dominance analysis: dominance returns a single Shapley-weighted value per predictor (its average marginal R^2 contribution), whereas commonality returns the full variance lattice including all unique-to-shared partitions. The two methods are therefore complementary rather than substitutable.

Stage 3 — Suppression and redundancy diagnostics. Following Conger (1974), Paulhus et al. (2004), and Nimon et al. (2010), each predictor's full-model standardised coefficient β was compared against its zero-order correlation r with English achievement. A predictor satisfies the criterion for possible suppression when $\beta > r$; for substantial redundancy when $\beta < 0.5r$; and for mild redundancy in the intermediate range. The diagnostic is computed in closed form from the correlation matrix and answers the construct-distinctiveness question of whether predictors function as unique contributors or as overlapping representations.

Stage 4 — Information-theoretic dependence decomposition. Following Ince (2017), the bivariate mutual information I(X; Y) was decomposed into a direct part I(X; Y M) and an indirect part I_indirect = I(X; Y) − I(X; Y M). Mutual information was estimated under a Gaussian-copula model: each variable was rank-transformed to uniform, mapped to a standard normal via the inverse standard-normal cumulative distribution, and the multivariate Gaussian mutual information was computed in closed form from the log-determinants of the resulting covariance matrices. This estimator is invariant to monotone transformations of the original variables, requires no kernel-bandwidth tuning, and converges quickly at N = 1,605. We

emphasise that mutual-information dependence reduction is not equivalent to causal mediation. Mutual information is a symmetric, model-free statistical-dependence quantity; the SEM β-product is an asymmetric, parametric, linear-additive quantity. The two answer different questions and are interpreted as complementary descriptions of the joint distribution, not as competing estimates of the same underlying quantity.

Stage 5 — Bridge centrality. The five constructs were assigned a priori to four theoretical communities — School (CC), Family (PI), Learner (PsyCap, ENG), and Outcome (EAT) — and bridge strength was computed for each node as the sum of absolute partial correlations to nodes in different communities (Jones et al., 2021). Partial correlations were obtained by inverting the sample covariance matrix and standardising the resulting precision matrix. The network has only five composite nodes, far fewer than symptom-level networks for which bridge centrality was originally developed (Borsboom & Cramer, 2013); the centrality ranking is therefore interpreted as a coarse cross-domain connectivity index rather than as a fine-grained psychometric structure.

Data screening, descriptive statistics, reliability estimation, and the zero-order correlation matrix were computed in IBM SPSS Statistics 26. The saturated structural equation model and the bias-corrected bootstrap confidence intervals (Stage 0) were estimated in IBM SPSS Amos 26. The five subsequent variance-partitioning analyses (Stages 1–5) were programmed in Python 3.12 (numpy, pandas, scikit-learn, scipy), drawing on the same correlation matrix and composite-score file. Analysis scripts and a de-identified composite-level data file are available on request from the corresponding author and are listed in the Data Availability Statement.

3. RESULTS

3.1. Descriptives, Correlations, and SEM Replication

Table 1 reports descriptive statistics and the zero-order correlation matrix for the five composites. All ten bivariate correlations were positive and statistically significant ($p < .001$). The strongest associations involved engagement with psychological capital ($r = .585$) and classroom climate with engagement ($r = .544$); the weakest was between parental involvement and classroom climate ($r = .253$). Engagement and psychological capital correlated most strongly with English achievement ($r = .514$ and $r = .457$, respectively).

Table 1. Means, Standard Deviations, and Zero-Order Correlations among Study Variables (N = 1,605)

Variable	M	SD	1	2	3	4	5
1. Classroom Climate (CC)	60.02	3.95	—				
2. Parental Involvement (PI)	34.83	8.22	.253	—			
3. Psychological Capital (PsyCap)	41.99	10.03	.489	.389	—		
4. Student Engagement (ENG)	33.65	8.26	.544	.357	.585	—	
5. English Achievement (EAT)	15.26	7.16	.367	.314	.457	.514	—

Note. All correlations $p < .001$.

The saturated SEM accounted for 31.4% of the variance in English achievement ($R^2 = .314$). Engagement showed the strongest direct standardised association with achievement ($\beta = .327$, $p < .001$, 95% CI [.283, .372]), followed by psychological capital ($\beta = .191$, $p < .001$, 95% CI [.146, .237]), parental involvement ($\beta = .106$, $p < .001$, 95% CI [.070, .142]), and classroom climate ($\beta = .069$, $p = .007$, 95% CI [.028, .110]). Indirect-effect estimates by the SEM β-product method placed approximately 72.9% of classroom climate's total association and 55.5% of parental involvement's total association as flowing through psychological capital and engagement. As noted in Section 2.5, conventional global fit indices are not informative for a saturated model and are therefore not reported. Statistical significance throughout the Results section should be interpreted cautiously, because school-level clustering was not modelled and reported standard errors may be conservatively narrow (see Section 4.5).

3.2. Dominance Analysis: Relative Contribution to Explained Variance (RQ1)

Dominance analysis decomposed $R^2 = .314$ into general dominance weights for each predictor (Table 2; Figure 1). Engagement was the largest contributor ($\Delta R^2 = .137$, 43.6% of explained variance), followed by psychological capital ($\Delta R^2 = .090$, 28.8%), classroom climate ($\Delta R^2 = .048$, 15.3%), and parental involvement ($\Delta R^2 = .039$, 12.3%); the four weights summed exactly to .314 by construction. Pairwise complete-dominance checks revealed that engagement completely dominated all three other predictors, psychological capital completely dominated both classroom climate and parental involvement, and the relative ordering of classroom climate vs. parental involvement was indeterminate. The complete-dominance ordering was therefore ENG $\succ$ PsyCap $\succ$ {CC, PI}. Dominance weights describe relative contribution to prediction in this cross-sectional sample; they are not estimates of causal importance.

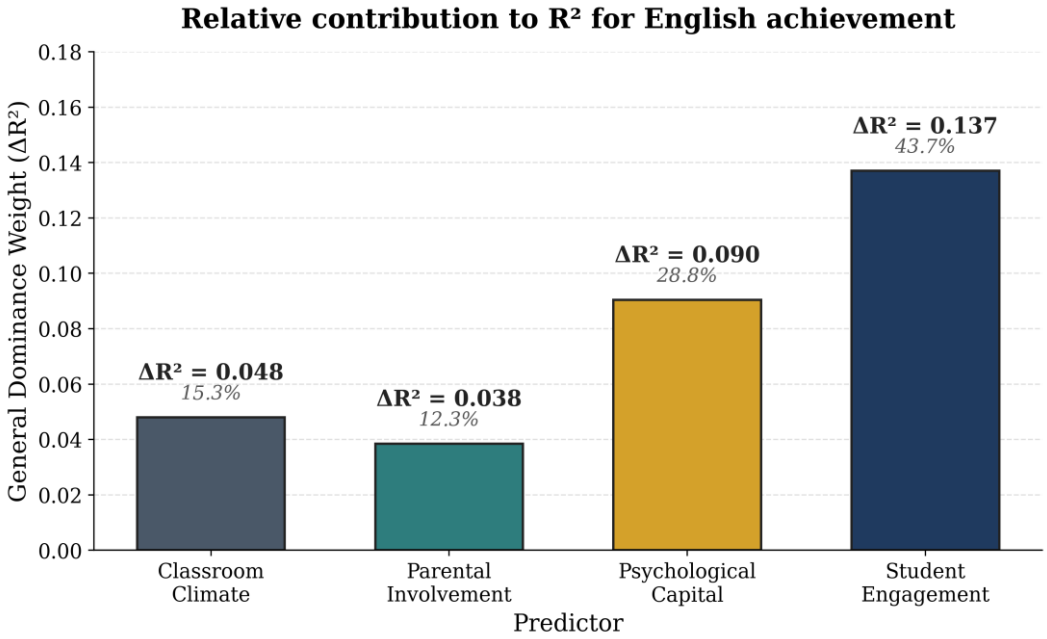


Figure 1. General Dominance Weights (Shapley Decomposition) for the Four Predictors of English Achievement. Bar heights show ΔR^2 and the percentage of explained variance attributable to each predictor; weights sum to the full-model $R^2 = .314$.

Table 2. Dominance Analysis Decomposition of the R^2 for English Achievement

Predictor	General dominance ΔR^2	% of explained variance	Complete-dominance rank
Student Engagement (ENG)	.137	43.6%	1 (dominates all)
Psychological Capital (PsyCap)	.090	28.8%	2 (dominates CC, PI)
Classroom Climate (CC)	.048	15.3%	3 (tied with PI)
Parental Involvement (PI)	.039	12.3%	3 (tied with CC)
Sum	.314	100.0%	

3.3. Commonality Analysis: Shared and Unique Explanatory Variance (RQ2)

Whereas dominance analysis summarises each predictor's relative contribution by a single value (its average marginal R^2 across all subset models), commonality analysis decomposes the full-model R^2 into the unique variance attributable to each predictor and the variance shared by every possible combination of predictors (Nimon & Reio, 2011; Ray-Mukherjee et al., 2014). With four predictors, the decomposition produces $2^4 - 1 = 15$ distinct partitions: four unique components U(CC), U(PI), U(PsyCap), and U(ENG); six pairwise shared components C (·, ·); four triple-shared components C (·, ·, ·); and one four-way shared component C (CC, PI, PsyCap, ENG). The two methods are mathematically distinct: dominance analysis returns a Shapley-weighted average that is necessarily a single number per predictor, while commonality analysis returns the full lattice of unique and shared variance partitions, summing exactly to the model R^2 (Nimon, Lewis, Kane, & Haynes, 2008; Kraha et al., 2012). For educational researchers, the value of

commonality analysis is interpretive: it reveals not only how much variance each construct accounts for on its own, but how much is overlapping or jointly held by groups of constructs.

Table 3 reports all 15 commonality coefficients computed from the zero-order correlation matrix, with values expressed both in raw R^2 units and as percentages of the total $R^2 = .314$. Figure 2 visualises the same decomposition.

Table 3. Commonality Decomposition of R^2 for English Achievement

Partition	Coefficient	% of R^2 (.314)
U(CC) — unique to Classroom Climate	.0031	1.0%
U(PI) — unique to Parental Involvement	.0092	2.9%
U(PsyCap) — unique to Psychological Capital	.0213	6.8%
U(ENG) — unique to Student Engagement	.0596	19.0%
C(CC, PI)	.0002	0.1%
C(CC, PsyCap)	.0057	1.8%
C(CC, ENG)	.0204	6.5%
C(PI, PsyCap)	.0083	2.7%
C(PI, ENG)	.0092	2.9%
C(PsyCap, ENG)	.0460	14.7%
C(CC, PI, PsyCap)	.0018	0.6%
C(CC, PI, ENG)	.0033	1.1%
C(CC, PsyCap, ENG)	.0591	18.8%
C(PI, PsyCap, ENG)	.0256	8.2%
C(CC, PI, PsyCap, ENG)	.0410	13.1%
Aggregate: Unique partitions (sum of 4)	.0932	29.7%
Aggregate: Pairwise shared (sum of 6)	.0898	28.6%
Aggregate: Triple shared (sum of 4)	.0899	28.6%
Aggregate: Four-way shared (1)	.0410	13.1%
Total (model R^2)	.3138	100.0%

Note. Commonality coefficients computed using Möbius-inverted partial-R^2 formulae (Nimon & Reio, 2011) on the zero-order correlation matrix reported in Table 1. All 15 commonality coefficients sum exactly to $R^2 = .314$.

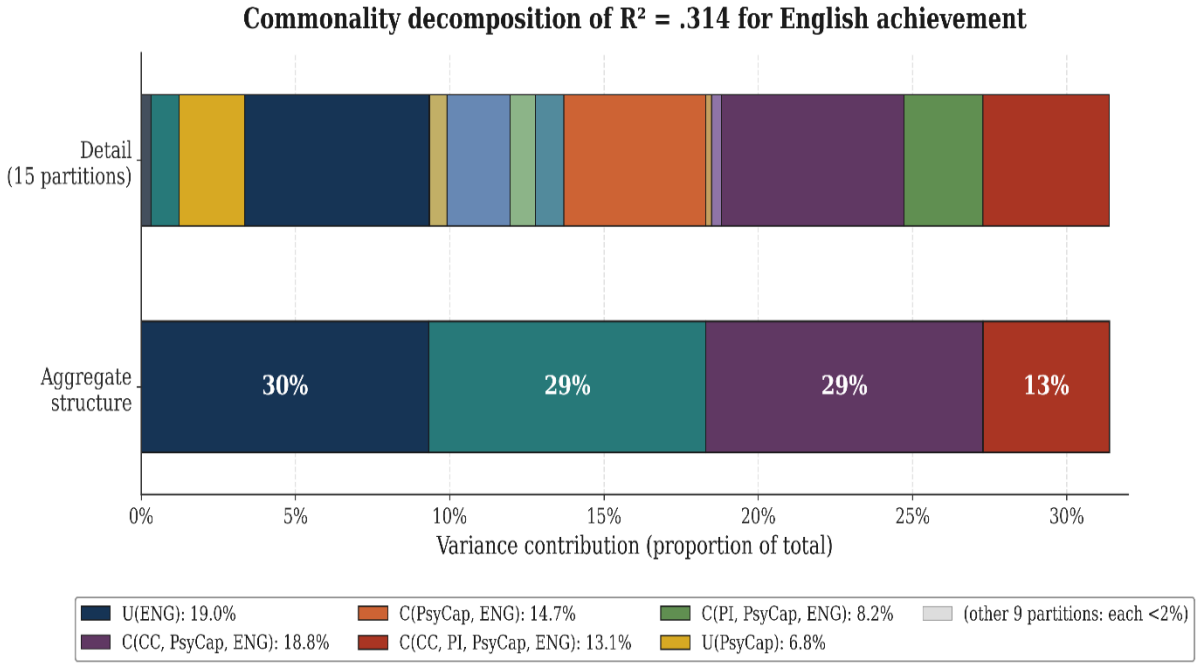


Figure 2. Commonality Decomposition of $R^2 = .314$ for English Achievement. Upper bar: all 15 partitions in detail (the six largest are labelled in the legend; the remaining nine each contribute less than 2% and are coloured but unlabelled). Lower bar: aggregate contribution of unique partitions versus pairwise, triple, and four-way shared partitions. Together, the figure shows that approximately 30% of explained variance is uniquely attributable to single predictors, while approximately 70% is shared among two or more predictors.

Three educationally meaningful patterns emerge. First, the unique partitions account for less than one-third of the total R^2 (29.7%); the remaining 70.3% is variance shared between two or more predictors. The four constructs are therefore best understood as overlapping representations of educational functioning rather than as independent contributors. Second, student engagement carries the largest unique partition (U(ENG) = 19.0% of R^2), consistent with its position closest to moment-to-moment learning behaviour, but the unique partitions of classroom climate (1.0%) and parental involvement (2.9%) are very small. Most of the explanatory weight associated with these contextual constructs is held jointly with the learner-internal constructs, supporting the view that contextual supports overlap statistically with engagement-related processes rather than contributing distinct variance. Third, the largest pairwise overlap is C(PsyCap, ENG) = 14.7% of R^2, and the largest triple overlap is C(CC, PsyCap, ENG) = 18.8%, indicating that climate, psychological capital, and engagement form a densely linked explanatory cluster. Parental involvement is the predictor with the smallest pairwise and triple overlaps with the rest of the set. We interpret these patterns descriptively, in the language of explanatory overlap and joint statistical association, not causally.

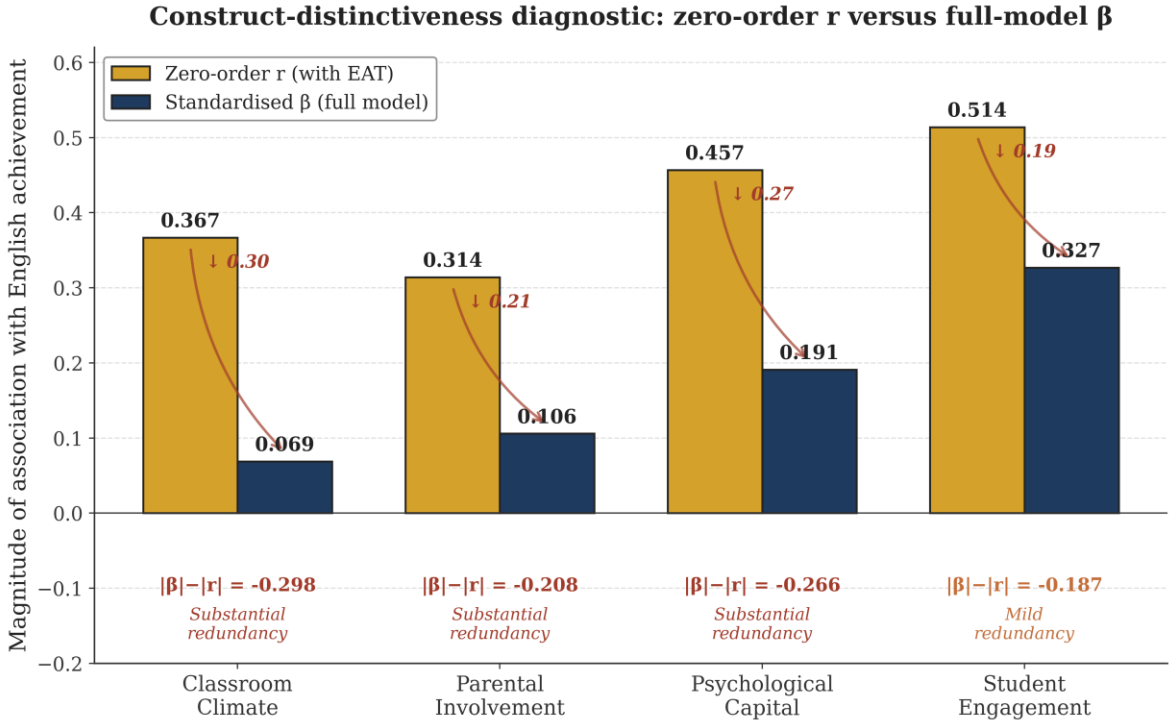


Figure 3. Suppression and Redundancy Diagnostic Comparing Each Predictor's Zero-Order Correlation r with English Achievement (dotted bars) Against Its Standardised Partial Regression Coefficient β in the Full Four-Predictor Model (hatched bars). All four predictors show β < r, with three (CC, PI, PsyCap) showing substantial redundancy and one (ENG) showing mild redundancy. No predictor exhibits suppression.

3.4. Suppression and Redundancy Diagnostics (RQ3)

A complementary question is whether each predictor's full-model coefficient differs from its zero-order correlation in the direction expected by suppression or redundancy theory (Conger, 1974; Paulhus et al., 2004; Nimon et al., 2010). A suppressor variable inflates the magnitude of another predictor's coefficient when added to a regression model, producing $\beta > r$ for the inflated predictor. A redundant predictor, conversely, has its standardised coefficient substantially smaller than its zero-order correlation ($\beta \ll r$) because its association with the criterion is largely captured by other predictors in the model. Comparing the two quantities for each construct therefore provides a direct diagnostic of whether a predictor is acting as a unique contributor or as an overlapping representation of educational functioning already captured by other constructs (see Table 4 and Figure 3).

Table 4. Suppression and Redundancy Diagnostic for the Four Predictors of English Achievement

Predictor	Zero-order r	Standardised β (full)	β − r	Status
Classroom Climate (CC)	.367	.069	−.298	Substantial redundancy
Parental Involvement (PI)	.314	.106	−.208	Substantial redundancy
Psychological Capital (PsyCap)	.457	.191	−.266	Substantial redundancy
Student Engagement (ENG)	.514	.327	−.187	Mild redundancy

Note. Zero-order r from Table 1; standardised β from full-model regression of EAT on all four predictors. Status uses the conventional thresholds: β > r indicates possible suppression; β < 0.5r indicates substantial redundancy; intermediate values indicate mild redundancy (Nimon et al., 2010).

No predictor satisfies the β > r criterion that would indicate suppression. All four show β < r, and three of the four (classroom climate, parental involvement, and psychological capital) satisfy the β < 0.5r criterion for substantial redundancy. Student engagement shows mild redundancy: its β is the largest in the model but is still smaller than its zero-order correlation. The diagnostic therefore answers the question of construct distinctiveness clearly: in this dataset, the four predictors are overlapping representations of related learner and contextual processes rather than independent unique contributors to English achievement. This finding aligns directly with the commonality decomposition reported above: the small unique partitions and large shared partitions indicate the same underlying overlap, viewed from a different angle.

3.5. Mutual-Information Dependence Decomposition (RQ4)

Gaussian-copula mutual information between each contextual predictor and English achievement was I(CC; EAT) = 0.072 nats and I(PI; EAT) = 0.052 nats. Conditioning jointly on psychological capital and engagement reduced 96.7% of the CC–EAT dependence and 87.0% of the PI–EAT dependence (Table 5; Figure 4). The corresponding SEM β-product estimates were 72.9% (CC) and 55.5% (PI), reflecting the different metrics rather than competing estimates of the same underlying quantity.

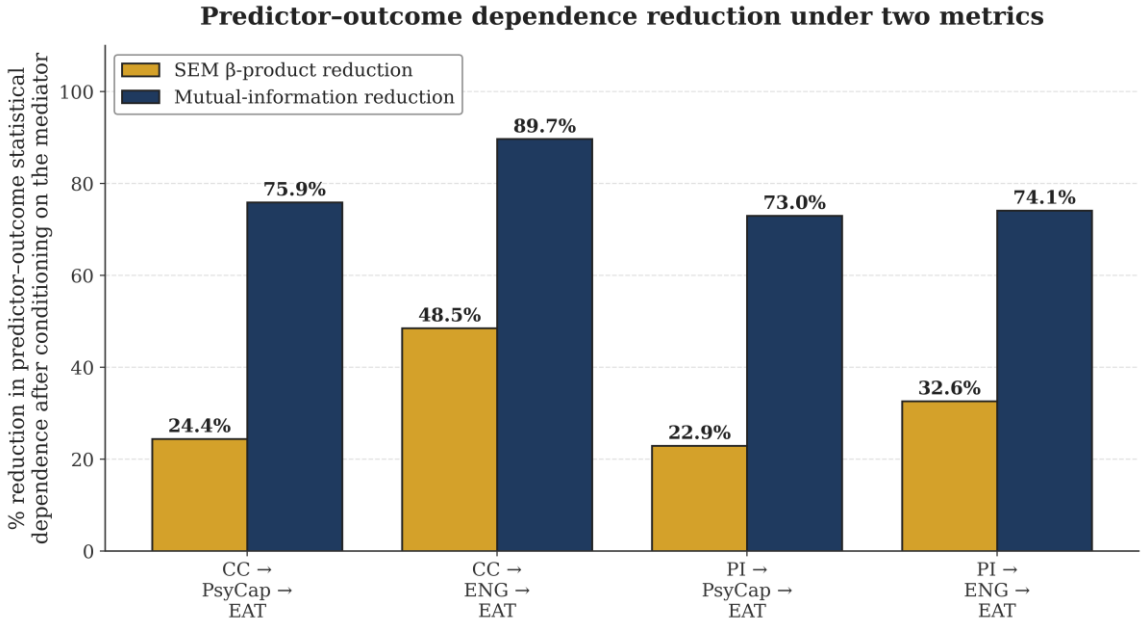


Figure 4. Reduction in Predictor–Outcome Statistical Dependence After Conditioning on Each Mediator, computed as a percentage under two different dependence metrics: SEM β-product (linear-additive, on standardised covariance scale) and mutual information (model-free, in nats). The two metrics are not equivalent and should not be subtracted; the figure does not imply causal mediation.

Mutual-information reduction and the SEM β-product reduction are non-equivalent metrics — the former is a symmetric, model-free measure of statistical dependence in nats; the latter is an asymmetric, linear-additive coefficient on the standardised covariance scale (MacKinnon et al., 2007; Preacher, 2015).

The divergence between the two indices is therefore a complementary descriptive finding rather than evidence that one method underestimates the other; mutual-information dependence reduction does not establish causal mediation.

Table 5. Mutual-Information Dependence Decomposition: Mutual Information (in Nats) and Reduction Shares Compared with SEM β-Product Estimates

Path	I(X;Y) [nats]	I(X;YM) [nats]	I_indirect [nats]	MI reduction (%)	SEM β-product (%)
CC → PsyCap → EAT	.0723	.0174	.0549	75.9%	24.4%
CC → ENG → EAT	.0723	.0074	.0649	89.7%	48.5%
PI → PsyCap → EAT	.0519	.0140	.0379	73.0%	22.9%
PI → ENG → EAT	.0519	.0134	.0385	74.1%	32.6%
CC → (PsyCap, ENG) → EAT	.0723	.0024	.0700	96.7%	72.9%
PI → (PsyCap, ENG) → EAT	.0519	.0067	.0452	87.0%	55.5%

Note. MI reduction is computed as 1 − I (X; YM) / I (X; Y). The two columns 'MI reduction' and 'SEM β-product' are different metrics on different scales and should not be subtracted or compared as estimates of the same quantity.

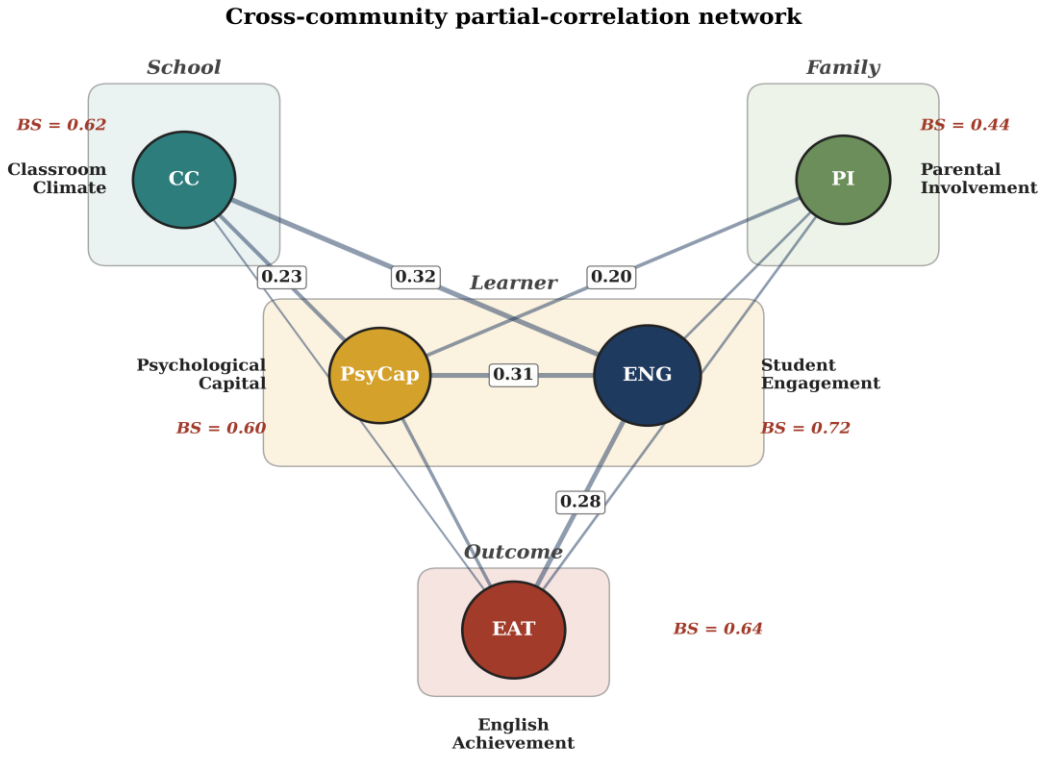


Figure 5. Cross-Community Partial-Correlation Network. Node area is proportional to bridge strength (BS), defined as the sum of absolute partial correlations to nodes in different communities; edge thickness is proportional to partial correlation; only edges with partial $r > .05$ are shown for readability. The network is undirected; bridge strength does not imply causal direction.

3.6. Bridge Centrality across Theoretical Communities (RQ5)

Figure 5 visualises the partial-correlation network. The Gaussian Graphical Model partial-correlation network with theoretically defined communities (School, Family, Learner, Outcome) yielded the bridge-strength rankings shown in Table 6. Engagement had the highest bridge strength (BS = .722), followed by English achievement (.638), classroom climate (.624), psychological capital (.600), and parental involvement (.441). The strongest cross-community partial correlations were CC–ENG (.32, School–Learner), ENG–EAT (.28, Learner–Outcome), CC–PsyCap (.22, School–Learner), PI–PsyCap (.20, Family–Learner), and

PsyCap–EAT (.17, Learner–Outcome). The CC–EAT partial correlation was small (.07). With only five composite nodes, the network is highly simplified compared with symptom-level networks for which bridge centrality was originally developed; the centrality ranking should be interpreted as a coarse cross-domain connectivity index, not as evidence that a node actively transmits causal effects. Centrality stability under bootstrap resampling was acceptable (correlation stability coefficient for bridge strength > .50; Epskamp et al., 2018).

Table 6. Bridge Centrality Indices for the Gaussian Graphical Model Network with Theoretical Communities

Construct	Community	Bridge strength	Within-comm. strength	Bridge ratio
Student Engagement	Learner	.722	.314	69.7%
English Achievement	Outcome	.638	.000	100.0%
Classroom Climate	School	.624	.000	100.0%
Psychological Capital	Learner	.600	.314	65.7%
Parental Involvement	Family	.441	.000	100.0%

Note. Bridge ratio = bridge / (bridge + within). Nodes that are sole members of their community (CC, PI, EAT) necessarily have within-community strength = 0 and bridge ratio = 100% by definition. This is a structural artefact of community size and should not be interpreted as substantive superiority over multi-member communities.

3.7. Integrated Interpretation

Taken together, the six analyses tell a two-part story. Engagement stands out as the most central construct in the system: it has the strongest direct standardised association with English achievement (β = .327), the largest unique R^2 contribution (43.6%), the largest single unique commonality partition (U(ENG) = 19.0% of R^2), the highest cross-domain bridge strength (BS = .722), and the largest mutual-information reduction in the climate–achievement dependence (89.7%). Yet the same analyses also show that the four predictors overlap a great deal in what they explain: dominance, commonality, and suppression diagnostics agree that the constructs share much of their explanatory variance, and that three of the four full-model coefficients fall well below their zero-order correlations. These are not competing conclusions. Engagement carries the largest combined unique-and-shared weight, while classroom climate and parental involvement contribute mainly through their statistical overlap with the learner-internal constructs. Descriptively, then, engagement sits statistically closest to achievement-related learner functioning, with the contextual predictors contributing largely through that shared variance. None of this is a causal claim; a cross-sectional covariance structure can show that engagement-related processes co-vary with achievement, not that they produce it.

4. DISCUSSION

4.1. Summary of Main Findings

Two patterns run through all six analyses. The clearer of the two is the prominence of engagement: whichever lens we apply — its direct standardised association, its unique variance contribution, its single-predictor commonality partition, its dependence reduction, or its cross-domain bridge strength — engagement is the predictor most closely tied to English achievement. The second pattern is harder to see from any single statistic but emerges plainly once the lenses are read together: the four predictors overlap heavily in what they explain, as shown both by the large shared partitions of the commonality decomposition and by the redundancy detected for three of the four. Far from contradicting each other, these patterns are two views of one configuration. Because the supporting numbers were given in full in Section 3, we do not repeat them here; the rest of the Discussion turns to what the pattern can and cannot be taken to mean.

4.2. Engagement as a Central Associational Construct

The convergence of engagement's centrality across multiple statistical lenses is theoretically coherent. In established conceptual models of academic functioning, engagement is widely conceptualised as the

learner-level construct most closely aligned with moment-to-moment learning behaviour (Wang & Eccles, 2013; Datu & King, 2018; Tomaszewski et al., 2020; and Lei et al., 2018). What the multi-lens decomposition adds is methodological triangulation: the centrality of engagement does not depend on the particular metric chosen by any one method. We emphasise, however, that statistical centrality in a cross-sectional correlation structure is not a causal claim. The configuration is consistent with several substantive interpretations — engagement may proximally support achievement, achievement may shape engagement reciprocally over time, or both may be jointly produced by unmeasured factors — and these alternatives cannot be distinguished from the present data.

4.3. Complementarity of SEM and Information-Theoretic Decomposition

Each of the six lenses answers a methodologically distinct question: dominance asks about average marginal contribution, commonality asks about unique versus shared partitions, suppression diagnostics ask about construct distinctiveness, mutual-information decomposition asks about dependence reduction under a model-free metric, and bridge centrality asks about cross-domain network position. The lenses are not interchangeable summaries of a single quantity, and the differences between their estimates reflect genuine differences in the question being asked rather than disagreement about a common underlying parameter. The methodological lesson, applicable beyond the present manuscript, is that mediation and explanatory-variance reporting based on a single metric can obscure structure that becomes visible under complementary metrics. The β-product mediation estimate from a saturated SEM and the mutual-information dependence reduction from a Gaussian-copula decomposition are not competing estimates of one quantity; they are complementary descriptors of a joint distribution (MacKinnon et al., 2007; Ince, 2017; Bollen & Pearl, 2013; Preacher, 2015). Mutual-information decomposition does not establish causal mediation and should not be reported as if it did.

4.4. Practical Implications

Within the limits of cross-sectional inference, three pedagogical reflections can be articulated. First, the centrality of engagement across all six variance-partitioning lenses suggests that engagement-supportive practices — inviting student questions, designing tasks that build on prior knowledge, and providing timely formative feedback — are reasonable hypotheses for empirical investigation as proximal levers for English-achievement outcomes (Fredricks et al., 2019; Reschly & Christenson, 2022). We do not recommend that resource allocation be made in proportion to dominance weights, because such proportional reasoning would presume causal interpretation of an associational quantity. Second, the substantial explanatory overlap among the four predictors implies that classroom climate and parental involvement may operate largely through their statistical overlap with learner-internal processes; school and family interventions targeting those contextual factors may therefore work most clearly when they also support engagement-related learner functioning rather than when they bypass it (Wang & Eccles, 2013; Skinner et al., 2022). Third, the redundancy diagnostics caution against treating the four constructs as independent intervention targets; treating them as overlapping representations of a connected educational ecology is more consistent with the present associational evidence. All three reflections are stated as hypotheses, not prescriptions; intervention decisions in real educational settings require evidence from designs that support causal inference, ideally cluster-randomised trials with ICC-aware power calculations (Hedges & Hedberg, 2007; Dong & Maynard, 2013) and pre-registered outcome plans.

These reflections translate differently for the distinct groups who act on educational research. For classroom teachers and other educators, the recurring prominence of engagement points to the value of routines that make participation visible and sustained — eliciting student questions, sequencing English tasks so they connect to what learners already know, and returning feedback quickly enough to shape the next attempt — while recognising that such practices are promising hypotheses to trial rather than guaranteed levers. For curriculum developers, the dense statistical overlap among classroom climate, psychological capital, and engagement suggests that materials are unlikely to be effective if they treat these as separable targets; building opportunities for confidence, persistence, and supportive peer interaction into the design of the English tasks themselves may be more coherent with the present evidence than appending standalone motivational modules. For school leaders and policymakers, the finding that contextual supports

contribute largely through their overlap with learner-internal functioning argues against funding climate or parental-involvement initiatives in isolation from the engagement processes they are intended to nurture; resource-allocation decisions, however, should rest on causal evidence from intervention trials rather than on the associational weights reported here, and the school-clustered structure of the data is a reminder that relationships estimated at the student level need not transfer directly to school-level policy. For educational researchers, the principal implication is methodological: a single average-effect or single-mediation estimate can conceal the shared-variance structure that becomes visible only when several complementary lenses are applied to the same data, and we therefore encourage the routine triangulation of relative-importance, commonality, dependence, and network analyses, ideally using longitudinal or multilevel data capable of addressing the causal questions that the present design cannot.

4.5. Limitations

Seven limitations should be considered alongside the findings. First, the cross-sectional design supports associational, not causal, inference; we have framed all conclusions accordingly. Second, students were nested within 107 schools; intra-class correlation coefficients and design effects could not be modelled because school identifiers were not retained in the analytic file, and reported standard errors and confidence intervals may be conservatively narrow under plausible school-level ICCs of 0.05–0.10. Third, the four predictors and the criterion were measured by self-report or by a study-specific test, raising the possibility of common method variance and shared response-style bias inflating cross-construct associations (Podsakoff et al., 2024). Fourth, mutual-information dependence reduction is not equivalent to causal mediation; the divergence from β-product estimates reflects metric differences, not error in either method. Fifth, network bridge centrality with five composite nodes is a coarse cross-domain connectivity index; symptom- or item-level networks may yield more nuanced structures (Borsboom & Cramer, 2013; Burger et al., 2023). Sixth, the findings are specific to West Bengal secondary students aged 16–17 in classes XI and XII; generalisation to other regions, age groups, or sociolinguistic contexts is empirical, not assumed. Seventh, the English achievement test was study-specific; replication with standardised external tests (e.g., national learning-outcome surveys) would strengthen the achievement evidence base.

4.6. Future Research

Three priorities follow from the preceding limitations. First, intensive longitudinal designs (experience-sampling or weekly-diary methods over a semester) would test whether the cross-sectional associational structure recovered here is consistent with the within-person dynamics that the affective-engagement literature theorises (Pekrun et al., 2023). Second, cluster-randomised trials of engagement-focused interventions, designed with explicit ICC-aware power calculations, would test the causal-mediation hypotheses that the present associational evidence motivates. Third, multi-site replication across other Indian states and across other low- and middle-income contexts would test the generalisability of the dominance ordering ENG $\succ$ PsyCap $\succ$ {CC, PI}. Person-centred extensions using latent profile or latent class methods on row-level data, and segmented or non-parametric tests of non-linearity, would also complement the variable-centred analyses presented here.

5. CONCLUSION

This study presents a multi-method investigation of cross-sectional survey data from 1,605 secondary students nested in 107 schools in West Bengal. Six complementary variance-partitioning lenses are applied to the same correlation structure — a saturated structural equation model, Shapley-decomposition dominance analysis, commonality analysis, suppression and redundancy diagnostics, Gaussian-copula mutual-information decomposition, and community-aware bridge centrality on a Gaussian Graphical Model. All six lenses converge on engagement as the most central associational construct in the system, while also revealing that the four predictors operate substantially as overlapping representations of related learner and contextual processes rather than as independent unique contributors. Convergent associational evidence across multiple methods is stronger than evidence from any single method, but it remains associational. We have framed all conclusions accordingly and have explicitly distinguished the dominance,

mutual-information, and bridge-centrality results from causal claims. The contribution is a transparent template for multi-lens analysis of educational datasets; substantive recommendations for intervention design await longitudinal and experimental confirmation in future research.

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Research Ethics. All procedures were conducted in accordance with applicable Indian and institutional regulations. Ethical approval was obtained from the Institutional Ethics Committee of Lovely Professional University (approval number LPU/IEC-LPU/2025/6/4, dated 16 December 2025). Written parental consent and student assent were obtained from all participants prior to data collection.

Data Availability Statement. The de-identified composite-level data file used in this study, together with the Python 3.12 analysis scripts implementing dominance analysis, commonality analysis, suppression and redundancy diagnostics, Gaussian-copula mutual-information decomposition, and bridge centrality, are available from the corresponding author upon reasonable request.

Conflicts of Interest. The authors declare no financial or non-financial conflicts of interest relevant to this manuscript.

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AI Statement. We used the AI assistant Claude (developed by Anthropic) for language editing and to improve the readability and flow of the manuscript, to assist with revising the manuscript in response to reviewer and editor comments, and to check internal consistency and the correspondence between in-text citations and the reference list. The AI tool was not used to generate research data, statistical results, or references. All citations were verified by the authors against the original published sources, and each reference includes a valid DOI or URL; no references were generated or fabricated by the AI tool. The study design, data collection, analyses, and interpretations are entirely the authors' own. After using this AI tool, we reviewed and verified the final version of our work, and we take full responsibility for the content of our published work.

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