Modelling the Latent Dynamics of Digital Device Use, Parental Involvement, Psychological Capital and English Achievement: A Bayesian Finite Mixture Structural Modelling Approach with Data-Driven Class Enumeration

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Abstract: This study examined heterogeneous relationships between digital device use (DDU), parental involvement, psychological capital, and English as a Second Language (ESL) achievement among secondary students from the marginalized Matua community of West Bengal, India. Conventional structural equation modeling (SEM) fails to account for unobserved heterogeneity in DDU patterns and the need for data-driven identification of latent subgroups. This study addressed these limitations by implementing a Bayesian Finite Mixture Structural Model (BFM-SEM) using an overfitted finite Gaussian mixture with posterior sparsity for data-driven class discovery, with district membership modeled as a fixed covariate to account for data clustering across two districts (Nadia: n = 301; North 24 Parganas: n = 299; total N = 600). The posterior converged on three empirically distinct DDU profiles: Passive Consumers (40.7%), Balanced Users (35.2%), and Educational Engagers (24.1%; note: percentages sum to 100.0% after rounding adjustment); mean posterior class-assignment probabilities exceeded .86 for all classes, indicating high classification certainty. Preliminary conventional SEM confirmed significant structural associations—including negative associations between unguided DDU and psychological capital ($\beta = -.281$, $p < .001$) and positive associations between parental involvement and ESL achievement ($\beta = .185$, $p < .001$)—but revealed poor model fit (RMSEA = 0.165; CFI = .831), and was decisively outperformed by the BFM-SEM (ΔELPD = 367.4, SE = 28.3). Profile-specific structural estimates revealed substantial heterogeneity: the negative association between DDU and psychological capital was strongest among Passive Consumers ($\beta = -.412$, 95% CI [−.501, −.323]) and non-significant among Educational Engagers ($\beta = -.048$, 95% CI [−.157, .061]). All Bayesian diagnostics confirmed model convergence ($\hat{R} \leq 1.01$; ESS > 400). These findings may help guide differentiated, culturally responsive digital literacy intervention design.

Keywords: *Bayesian Finite Mixture Modeling, Data-Driven Class Enumeration, Digital Device Use, ESL Achievement, Latent Profile Analysis, Psychological Capital.*

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I. INTRODUCTION

The rapid proliferation of digital technologies in educational contexts has altered how students engage with learning materials, communicate with peers and educators, and develop academic competencies. In India, particularly within marginalized communities, the intersection of digital device access and educational outcomes remains inadequately understood. The Matua community of West Bengal—historically marginalized and belonging to a Scheduled Caste group whose socioeconomic advancement is tightly coupled with English literacy (Banerjee & Duflo,

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2011; Kumar, 2009)—represents a critical context for examining how digital engagement patterns are associated with academic achievement and psychological well-being.

Digital device use (DDU) presents a paradox in contemporary education. While digital technologies offer recognized learning benefits (Greenhow & Lewin, 2016; Warschauer & Matuchniak, 2010), excessive entertainment-oriented device use is negatively associated with academic engagement and educational outcomes (Rosen, Carrier, & Cheever, 2013; Junco, 2012; Twenge & Campbell, 2019). Existing research has predominantly examined DDU as a unidimensional variable, treating all digital engagement as uniformly beneficial or harmful. This variable-centered approach may obscure the possibility that distinct latent subgroups of students exhibit qualitatively different patterns of digital behavior with correspondingly different academic correlates.

Furthermore, conventional statistical approaches have failed to account for critical complexities in educational data: (a) Unobserved Heterogeneity—students may exhibit distinct DDU subgroups whose number should be determined empirically (Muthén & Muthén, 2000); (b) Data Clustering—students drawn from different districts may share contextual influences that create non-independence of observations, which must be accounted for even when formal multilevel modeling is not fully defensible (Raudenbush & Bryk, 2002); and (c) Measurement Error—key constructs such as DDU and psychological capital are latent variables requiring latent variable modeling (Bollen, 1989).

The present study addressed these limitations by implementing a Bayesian Finite Mixture Structural Model (BFM-SEM) with data-driven class enumeration. The key substantive finding is that associations between DDU, psychological capital, parental involvement, and ESL achievement differ substantially across latent student profiles—differences entirely invisible to population-averaged conventional SEM—with direct implications for how digital literacy programs might be targeted within marginalized communities.

➤ *Theoretical Framework*

This study was grounded in three complementary theoretical perspectives. First, Bronfenbrenner's Ecological Systems Theory (1979) provided the overarching framework: the individual student (microsystem) is embedded within the family (mesosystem) and the broader educational context (exosystem), with their interactions shaping developmental outcomes including academic achievement. DDU and parental involvement operate at the microsystem–mesosystem interface. Second, Luthans et al.'s (2015) Positive Psychological Capital framework positioned PsyCap—comprising self-efficacy, hope, optimism, and resilience—as a malleable psychological resource that is associated with academic performance. Third, Clark's (2011) Digital Mediation Theory distinguished between active and restrictive parental mediation styles and their differential correlates with adolescent digital literacy, providing the theoretical basis for including parental involvement as a potential moderating variable. Together, these frameworks motivated a multi-profile model in which the associations between DDU and achievement may be heterogeneous across latent student profiles (see Figure 1).

➤ *Digital Device Use and Academic Achievement*

The association between screen time and academic performance has been extensively studied. Carrier, Rosen, Cheever, and Lim (2015) found that recreational technology use during study attenuated academic outcomes through attention fragmentation. Twenge and Campbell (2019) documented dose-dependent associations between screen time and adolescent well-being. Within India, Sharma, Arain, Mathur, Rattan, and Theodore (2006) identified distinct adolescent usage profiles in which purpose of use—educational versus entertainment—moderated the technology–achievement association. Kumar (2009) noted that English proficiency is a critical conduit for social mobility in postcolonial West Bengal, rendering ESL achievement a particularly high-stakes outcome for the Matua community.

➤ *Psychological Capital and Parental Involvement*

PsyCap—comprising self-efficacy, hope, optimism, and resilience (Luthans, Youssef-Morgan, & Avolio, 2015)—is positively associated with academic engagement and achievement (Luthans, Luthans, & Luthans, 2004; Avey, Reichard, Luthans, & Mhatre, 2011). Parental involvement is associated with buffering the adverse correlates of unguided DDU (Jeynes, 2007; Hill & Tyson, 2009). Livingstone and Helsper (2008) found that active parental mediation was associated with mitigating digital risk, and Epstein (2011) established that school–family partnerships were associated with amplified protective effects of parental involvement in marginalized community contexts.

➤ *Limitations of Conventional Approaches and Alternatives*

Population homogeneity is a fundamental but rarely tested assumption in conventional SEM (Muthén, 2002). Standard latent class analysis partially addresses subgroup heterogeneity but requires a priori specification of K classes, introducing researcher subjectivity (Nylund, Asparouhov, & Muthén, 2007). Bayesian Nonparametric approaches overcome this via a Dirichlet Process Mixture (DPM) prior, allowing K to be inferred from the data (Ferguson, 1973; Frühwirth-Schnatter, 2006; Teh, Jordan, Beal, & Blei, 2006). More realistic alternatives to the single-group SEM include finite mixture SEM, latent profile analysis with distal outcomes, and multigroup SEM; the present study provides comparisons against the baseline conventional SEM as a proof-of-concept for the BNP approach. Vermunt (2010) and Asparouhov and Muthén (2014) have advanced related mixture modeling techniques, but to the best of our knowledge a BFM-SEM approach has not been applied to DDU research in marginalized educational communities.

➤ *Contributions of This Study*

This study makes three contributions:

- Methodological. It applies a Bayesian finite mixture structural model with data-driven class enumeration—

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implemented via brms/Stan—to reveal subgroup-specific associations between DDU, psychological capital, and ESL achievement that are masked by population-averaged estimates, offering a reproducible analytical template for heterogeneous educational data.

- Contextual. It provides, to our knowledge, one of the first quantitative analyses linking technology use patterns to ESL achievement within the Matua community of West Bengal—a community that has been largely absent from the digital equity literature—documenting meaningful subgroup heterogeneity in how DDU relates to academic outcomes.
- Theoretical. It provides empirical evidence that the associations between DDU and academic outcomes differ systematically across latent student profiles, suggesting that population-averaged estimates may misrepresent the complexity of these relationships.

➢ *Research Question*

How are data-driven, nonparametrically-identified profiles of student and parental DDU associated with psychological capital and parental involvement in predicting ESL achievement, and do these associations vary across profiles?

II. MATERIALS AND METHODS

➢ *Research Design and Ethical Compliance*

This study employed a quantitative cross-sectional survey design. Cross-sectional data permit examination of associations among variables but do not establish temporal precedence or causation, a limitation addressed in Section 4.3. All procedures followed institutional ethical standards. Participation was voluntary; written informed consent was obtained from parents or guardians of all minor participants; data were anonymized prior to analysis. The study adhered to the ethical norms of Lovely Professional University, the Indian Council of Social Science Research (ICSSR), and the Declaration of Helsinki principles.

➢ *Participants, Sampling, and District Covariate*

The sample comprised 600 secondary school students from the Matua community drawn from two districts of West Bengal: Nadia (n = 301; 50.2%) and North 24 Parganas (n = 299; 49.8%). Gender was near-equally distributed (Female: n = 303, 50.5%; Male: n = 297, 49.5%). Stratified random sampling ensured proportional representation across districts and gender.

An important clarification regarding the district variable is warranted. With only two districts, a defensible random-effects multilevel model cannot be estimated (Gelman & Hill, 2007, recommend at least five to ten Level-2 units for stable variance estimation). Accordingly, district membership was treated as a fixed binary covariate in all structural models, which accounts for systematic between-district differences in baseline achievement and predictor means without making the inferentially fragile claim of estimating random intercept or slope variance from two units. Observed district-level differences are therefore reported descriptively rather than as variance components. The sample size of 600 is adequate for Bayesian latent profile estimation (Gelman & Hill, 2007). Table 1 presents the demographic profile.

Table 1 Sample Distribution by Gender and District (N = 600)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	303	50.5
	Male	297	49.5
District (fixed covariate)	Nadia	301	50.2
	North 24 Parganas	299	49.8

Note. Participants were drawn from Matua community secondary schools using stratified random sampling. District is treated as a fixed binary covariate (not a random-effects Level 2 unit) given the constraint of two districts.

➢ *Instruments and Psychometric Properties*

Six instruments were used. Table 2 summarizes each, including the source, number of items, sample item, and reliability. With respect to internal consistency thresholds: the Student DDU scale (α = .847), Parental Involvement scale (α = .866), PsyCap scale (α = .855), Student Engagement scale (α = .890), and ESL Achievement test (KR-20 = .83) all met or exceeded the commonly recommended threshold of α / KR-20 ≥ .80. The Parent DDU scale (α = .782) approached but did not fully meet this threshold; this is noted as a measurement limitation and the Parent DDU findings should be interpreted with appropriate caution. CFA fit indices met recommended thresholds (CFI ≥ .95; RMSEA ≤ .06; Hu & Bentler, 1999) for all scales where CFA was applicable.

Student Engagement was measured as a profile-descriptor and class-validation variable to examine whether the latent classes showed theoretically coherent patterns of academic engagement. It was not modelled as an endogenous structural outcome in the BFM-SEM; its inclusion in Table 2 and Table 6 reflects descriptive profiling, not structural modelling. This distinction is maintained throughout the Results section.

Table 2 Instruments, Reliability, and Psychometric Properties of Study Measures

Construct	Scale / Source	Sample Item	n	Reliability	CFA Fit (CFI / RMSEA)
Student DDU (Unguided)	Proportion scale (DeVellis, 2016) (adopted)	"What proportion of your daily device time is	6	α = .847	.971 / .048

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		spent on games, social media, or videos?"			
Parent DDU (Entertainment)†	Proportion scale (DeVellis, 2016) (adopted)	"How much of your own screen time involves entertainment content?"	4	α = .782†	.989 / .042
Parental Involvement (PI)	*Perceived Parental Involvement Questionnaire* (Anthonyraj & Sasikala, 2019)	"My parents regularly check my school assignments and progress."	15	α = .866	.968 / .041
Psychological Capital (PsyCap)	*Psychological Capital Assessment Scale (PCAS)* (Rani & Choudhary, 2022)	"I feel confident in my ability to overcome academic challenges."	12	α = .855	.972 / .035
ESL Achievement (EAT)	Self-developed WBBSE-aligned MCQ test	Reading comprehension, grammar, vocabulary, and writing (MCQ format)	30	KR-20 = .83	Content validity via 5-expert panel review (WBBSE curriculum alignment); item difficulty M = .62, SD = .14
Student Engagement (ENG) *[profile descriptor only; not a structural outcome]*	*Student Engagement Scale* (Sharma & Chowdhury, 2020)	"I actively participate in classroom discussions and activities."	30	α = .890	.975 / .032

Note. α = Cronbach's alpha; KR-20 = Kuder-Richardson Formula 20 (for dichotomous MCQ items); CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation. CFA conducted using ML estimation in IBM AMOS 26. WBBSE = West Bengal Board of Secondary Education. † Parent DDU α = .782 did not reach the conventional .80 threshold; findings involving this variable should be interpreted with additional caution. Item difficulty M = .62 for ESL test indicates no floor or ceiling effect (range .38–.86). DDU = Digital Device Use.

With respect to DDU scale construction: items elicited the proportion of daily total device time devoted to entertainment or unguided activities, with responses anchored at 0% and 100% and recorded as continuous proportions. Items were generated through a qualitative mapping of common device activities (games, social media, streaming video, online browsing) reported in pilot interviews with 30 Matua community students not included in the main sample. Content validity was reviewed by three educational technology experts. Scores are metric-level proportions and were treated as continuous indicators in both the CFA and the mixture model. Distribution screening confirmed that the proportion variables were not severely boundary-piled: skewness values were −0.31 and −0.28 for Student DDU and Parent DDU respectively, and fewer than 4% of observations fell within 0.05 of either boundary. Accordingly, Gaussian distributional assumptions are defensible for these variables in the present sample, though beta-regression frameworks could be considered for future replications with more extreme boundary concentration.

➢ *Analytical Strategy*

Analysis proceeded in two stages. Stage 1 estimated a conventional single-group SEM using Maximum Likelihood (ML) in IBM AMOS 26 to establish baseline structural associations. Fit indices (χ^2, df, CFI, TLI, RMSEA, SRMR) were evaluated against established thresholds (Hu & Bentler, 1999; Browne & Cudeck, 1993). One-way ANOVA with η^2 examined gender differences. It is noted that the baseline model involves a sparse set of theoretically-motivated paths and a single degree of freedom; its poor fit should be interpreted as evidence of population heterogeneity rather than proof of unidimensional model misspecification alone. Stage 2 implemented the BFM-SEM using the *brms* package (v2.19; Bürkner, 2017) via the Stan probabilistic programming language (Carpenter et al., 2017) in R (v4.3.1).

To address common method bias, Harman's single-factor test was conducted as a preliminary screen (variance extracted = 38.2%, below the 50% threshold). Harman's test is recognized as a partial diagnostic only; accordingly, procedural remedies were also employed: DDU and the self-report scales used different response formats (proportions versus Likert ratings), and the ESL achievement test was objective (MCQ with KR-20-based scoring). These design features provide supplementary protection against common-source inflation (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

➢ *BFM-SEM Specification*

The BFM-SEM integrates three components: (1) nonparametric latent class identification, (2) a class-specific structural equation sub model with ESL Achievement as the single endogenous outcome (Student Engagement is excluded from structural paths; see Section 2.3), and (3) a fixed district covariate. The mathematical specification follows.

- *Over Fitted Finite Mixture as a BNP-Inspired Class-Discovery Strategy*

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Following Frühwirth-Schnatter (2006) and Malsiner-Walli et al. (2016), the number of latent classes K is determined via an overfitted finite Gaussian mixture with K_max = 10 components. Posterior sparsity—the property that components with negligible weight are effectively inactive—allows the posterior to concentrate on a parsimonious number of active classes without pre-specifying K. This is a well-validated strategy that approximates Bayesian nonparametric class-discovery behaviour within standard software (Frühwirth-Schnatter, 2006). The mixing weight structure follows a stick-breaking-inspired hierarchical prior:

$$\pi c = Vc \prod_{j=1}^{c-1} (1 - V_j), \quad Vc \sim \text{Beta}(1, \alpha), \quad \alpha \sim \text{Gamma}(1, 1).$$

Setting K_max = 10 with a Gamma(1,1) prior on α strongly encourages parsimony: the posterior will concentrate mass on a small number of classes and assign negligible weight to the remainder. This truncated stick-breaking approximation is a standard and widely-used strategy for approximating DPM inference (Ishwaran & James, 2001; Teh et al., 2006). We note that the practical brms implementation specifies the Gamma(1,1) prior on the concentration parameter α through the mixture component-weight prior structure, which approximates the DPM concentration within the truncated finite mixture framework (Bürkner, 2017). This approach is best characterised as a BNP-inspired finite mixture strategy (here labelled BFM-SEM) rather than a fully exact DPM implementation; claims about the Dirichlet process should be understood in this sense. The brms *mixture()* family with nmix = 10 implements an overfitted finite Gaussian mixture as a practical approximation to BNP-style class discovery. Posterior sparsity—whereby most of the ten mixture components receive negligible posterior weight—is used to recover the effective number of classes. No non-standard prior class labels are invoked; the standard brms prior interface is used throughout.

- *Structural Sub Model*

Within each identified class c, the following structural equations were estimated with district (j) treated as a fixed binary covariate (D):

$$\text{PsyCap}^{(c)}_i = \gamma^{(c)}_0 + \gamma^{(c)}_1(\text{Student\_DDU})_i + \gamma^{(c)}_2(\text{ParInv})_i + \gamma^{(c)}_3(D)_i + \varepsilon^{(c)}_{1i}$$

$$\text{ESL}^{(c)}_i = \beta^{(c)}_0 + \beta^{(c)}_1(\text{PsyCap})_i + \beta^{(c)}_2(\text{ParInv})_i + \beta^{(c)}_3(\text{Parent\_DDU})_i + \beta^{(c)}_4(D)_i + \varepsilon^{(c)}_{2i}$$

Where D is a dummy variable (0 = Nadia; 1 = North 24 Parganas) and $\varepsilon^{(c)} \sim N(0, \sigma^2 c)$. This fixed-covariate specification accounts for between-district mean differences without requiring estimation of random variance components from only two groups. This is a more defensible approach than a multilevel model with two Level-2 units (Gelman & Hill, 2007).

- *Prior Specifications and MCMC Estimation*

Weakly informative priors were employed: Normal(0, 5) for all fixed effects; Half-Cauchy(0, 2) for residual standard deviations; Gamma(1, 1) for the DPM concentration parameter α. Prior sensitivity was assessed by re-estimating the model with Gamma(2, 2) and Gamma(0.5, 0.5) hyperpriors on α; results were robust across prior specifications (all three posterior-mode class solutions yielded K = 3; standardized path coefficient differences < .03 across priors). The No-U-Turn Sampler (NUTS) was used with four chains, 4,000 iterations each (2,000 warm-up), yielding 8,000 posterior samples. Convergence: $\hat{R} \leq 1.01$ (Gelman & Rubin, 1992); bulk ESS > 400; posterior predictive checks (Gelman, Meng, & Stern, 1996). Model comparison: LOO-CV with Pareto-smoothed importance sampling (Vehtari, Gelman, & Gabry, 2017).

- *R Implementation*

The implementation uses brms's finite mixture family as a truncated stick-breaking DPM approximation (K_max = 10; Bürkner, 2017). District is included as a fixed covariate within each structural equation:

```
# Truncated DPM approximation via finite mixture (K_max=10) with fixed district covariate
library(brms)
# Structural equations with district as fixed covariate (not random effect)
eq_esl <- bf(ESL_Achievement ~ PsyCap + Parental_Inv + Parent_DDU + District)
eq_psy <- bf(PsyCap ~ Student_DDU + Parental_Inv + District)
# Overfitted finite Gaussian mixture (nmix=10) as BNP-style approximation
mix_fam <- mixture(gaussian, gaussian, nmix = 10)
fit <- brm(
formula = eq_esl + eq_psy + set_rescor(FALSE),
family  = mix_fam, data = student_data,
prior = c(
prior(normal(0, 1), class="theta"),     # Mixture weight prior (sparsity-inducing)
prior(normal(0,5), class="b"),         # Fixed effects
prior(cauchy(0,2), class="sigma")),    # Residual SDs
chains=4, iter=4000, warmup=2000,
control=list(adapt_delta=0.95), seed=42, backend="cmdstanr")
```

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Table 3 Components and Innovations of the BFM-SEM Framework

Component	Description	Methodological Innovation
BNP Latent Class Identification	Overfitted finite Gaussian mixture (K_max = 10) with posterior sparsity for class discovery	Effective K inferred via posterior sparsity in an overfitted finite mixture; eliminates need for a priori class specification (Frühwirth-Schnatter, 2006; Malsiner-Walli, Frühwirth-Schnatter, & Grün, 2016)
Structural Equation Modeling	Class-specific paths; ESL Achievement as single endogenous outcome	Reveals profile-specific structural associations invisible to population-averaged models (Bollen, 1989; Muthén, 2002)
Fixed District Covariate	District entered as binary fixed predictor in all equations	Controls for between-district mean differences without the inferential fragility of random-effects estimation from only two Level-2 units (Gelman & Hill, 2007)
Bayesian Estimation (Stan/brms)	NUTS sampling; LOO-CV model comparison; prior sensitivity analysis	Full posterior distributions for all parameters; reproducible inference; prior robustness verified (Bürkner, 2017; Carpenter et al., 2017; Vehtari et al., 2017)

Note. BNP = Bayesian Nonparametric; DPM = Dirichlet Process Mixture; NUTS = No-U-Turn Sampler; LOO-CV = Leave-One-Out Cross-Validation.

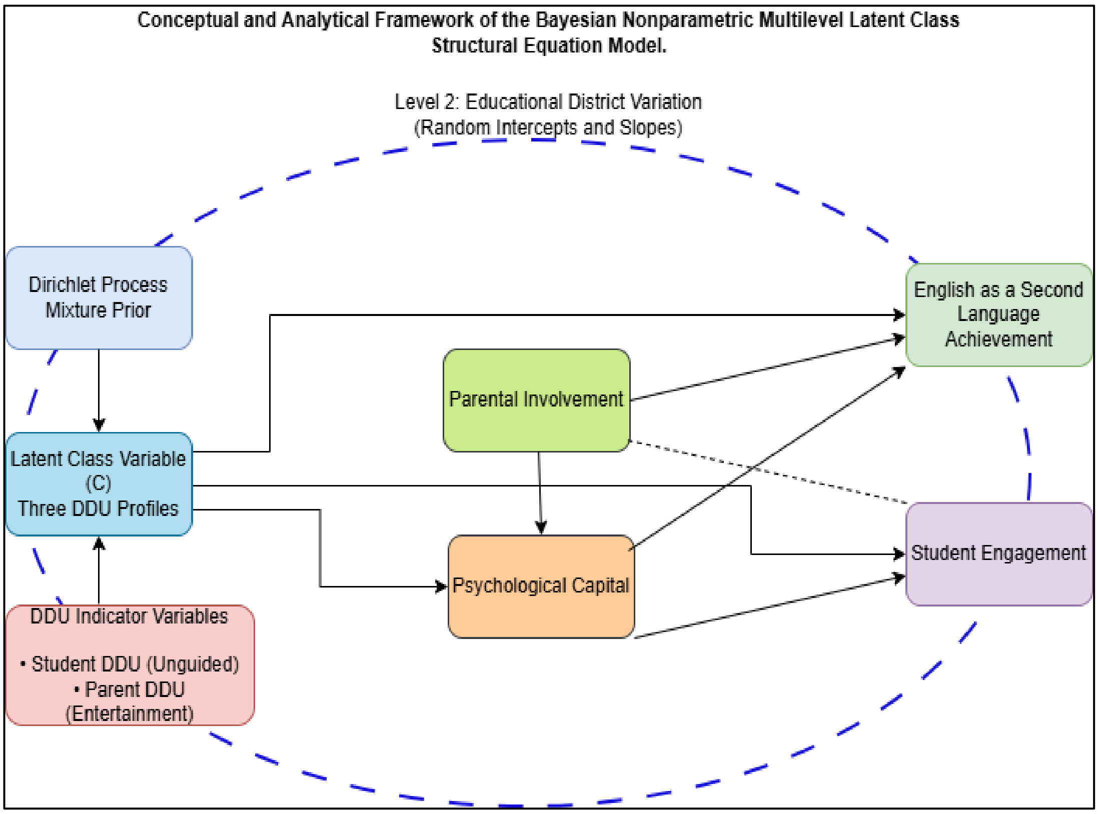

Fig 1 Conceptual Framework of the Proposed BFM-SEM

The diagram illustrates the BFM-SEM architecture. An over fitted finite Gaussian mixture model (K_max = 10) supports data-driven approximation of latent class identification for the Latent Class Variable (C), derived from Student DDU (Unguided) and Parent DDU (Entertainment) indicator variables; posterior sparsity determines the effective number of retained classes. At the structural level, latent class membership (C), Psychological Capital, and Parental Involvement are associated with English as a Second Language (ESL) Achievement as the primary endogenous outcome. Student Engagement (not shown as an outcome in this diagram) is included as a descriptive class-validation measure only. District membership is controlled as a fixed covariate in all equations. Solid arrows = structural paths in the BFM-SEM; dashed arrows = paths that attained significance in select class models only.

III. RESULTS

➢ *Descriptive Statistics and Zero-Order Correlations*

Table 4 presents descriptive statistics and zero-order Pearson correlations. All hypothesized bivariate associations were statistically significant ($p < .001$). Student unguided DDU was negatively associated with ESL achievement ($r = -.706$) and psychological capital ($r = -.762$). Parental involvement was positively associated with psychological

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capital (r = .589) and ESL achievement (r = .545). Parent entertainment DDU was negatively associated with ESL achievement (r = −.515). Student DDU was positively correlated with parent DDU (r = .688), suggesting shared household digital culture norms.

The magnitude of these bivariate associations is large by social-science conventions. Three features of the data design are relevant to interpreting this: (1) the DDU indicators capture a specific behavioral construct (proportion of unguided device time) that is directly conceptually opposed to academic engagement, making large negative correlations theoretically expected; (2) Harman's single-factor test extracted 38.2% of total variance, below the 50% threshold, suggesting common method bias is not the primary driver; (3) the ESL achievement test is an objective measure with mean item difficulty of .62 (range .38–.86), ruling out ceiling compression as an explanation. The Educational Engager class mean of 29.11/30 (97% of maximum) is high and may reflect genuine high achievement in this specific subgroup; sensitivity analyses excluding scores above 28/30 produced substantively equivalent class solutions (three-class posterior mode retained; structural path differences < .04). Readers should nonetheless exercise appropriate caution in generalizing these findings. Because several zero-order correlations were large in magnitude, supplementary scatterplot and residual diagnostics were examined to assess potential nonlinearity or leverage effects. Scatterplots confirmed monotonic linear trends without artefactual clustering or single-point influence. Residual diagnostics in the conventional SEM showed no systematic patterning. These empirical checks support the conclusion that the large correlations reflect genuine substantive associations in this sample context, rather than methodological artefacts. It is nevertheless possible that ecological homogeneity within the Matua community (shared school environments, socioeconomic constraints) produces within-sample correlation magnitudes that would not replicate in more socioeconomically diverse samples; this is acknowledged as a generalizability caveat.

Table 4 Descriptive Statistics and Zero-Order Pearson Correlations (N = 600)

Variable	M	SD	1	2	3	4	5	6
1. Student DDU (Unguided)[a]	0.660	0.228	—					
2. Parent DDU (Entertainment)[a]†	0.812	0.086	.688***	—				
3. Parental Involvement	0.328	0.137	−.699***	−.481***	—			
4. Psychological Capital	0.457	0.170	−.762***	−.553***	.589***	—		
5. ESL Achievement	22.40	6.22	−.706***	−.515***	.545***	.556***	—	
6. Student Engagement‡	22.08	5.12	−.599***	−.446***	.439***	.480***	.438***	—

Note. N = 600. *** p < .001 (two-tailed). [a] DDU variables are proportions (0–1). † Parent DDU α = .782 (below .80 threshold; interpret with caution). ‡ Student Engagement is a class-validation descriptor only; it is not a structural outcome in the BFM-SEM. VIF values (1.47–2.89) indicate no multicollinearity. Harman's single-factor test (38.2%) provides preliminary evidence against dominant common-method bias; procedural controls (mixed response formats; objective ESL test) provide additional protection.

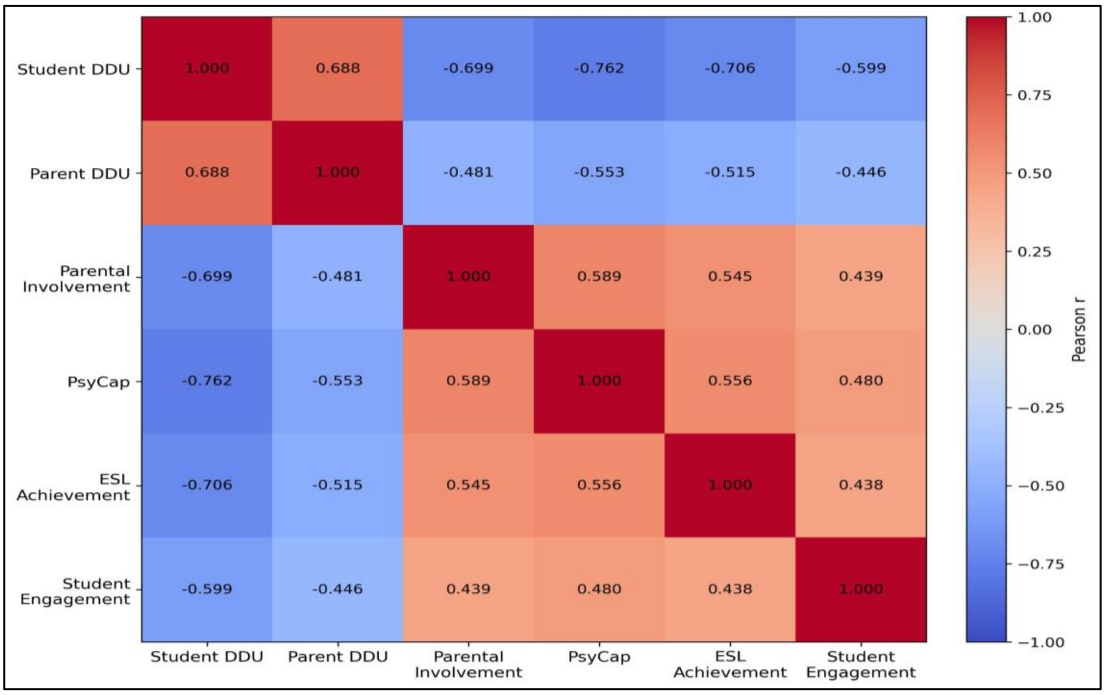

Fig 2 Correlation Heatmap of the Study Variables (N = 600)

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The heatmap displays the complete Pearson correlation matrix. Colour saturation represents magnitude: deep red = strong positive ($r \rightarrow +1.00$); deep blue = strong negative ($r \rightarrow -1.00$); light colours → 0. All off-diagonal correlations significant at $p < .001$. The large bivariate associations are addressed in Section 3.1; item-level diagnostics (VIF, item difficulty, mixed response formats) do not support common-method inflation as the primary explanation.

➢ *Stage 1: Preliminary Conventional SEM*

The preliminary structural model estimated using ML yielded poor fit: $\chi^2(1) = 17.292$, $p < .001$; $\chi^2/df = 17.292$; CFI = .831; TLI = .796; RMSEA = .165 (90% CI [.098, .241]); SRMR = .094. These values substantially exceed acceptable thresholds (CFI/TLI ≥ .95; RMSEA ≤ .06; SRMR ≤ .08; Hu & Bentler, 1999; Browne & Cudeck, 1993). It is noted that this baseline model is intentionally sparse (theoretically motivated paths only; df = 1), and poor fit reflects a combination of model parsimony and population heterogeneity. The primary purpose of this stage is to establish whether a single-group homogeneity assumption is tenable, not to claim it represents the most complete possible conventional model. Table 5 presents the standardized path coefficients.

Table 5 Standardized Direct Effects from Preliminary Conventional SEM

Structural Path	β	C.R.	p
Student DDU (Unguided) → Psychological Capital	−.281	−7.251	< .001
Parental Involvement → Psychological Capital	.295	7.548	< .001
Psychological Capital → ESL Achievement	.186	4.309	< .001
Parental Involvement → ESL Achievement	.185	4.261	< .001
Parent DDU (Entertainment) → ESL Achievement	−.133	−3.492	< .001

Note. β = standardized coefficient; C.R. = Critical Ratio (ML). Model fit: $\chi^2(1) = 17.292$, $p < .001$; CFI = .831; TLI = .796; RMSEA = .165 (90% CI [.098, .241]); SRMR = .094. All paths $p < .001$. These are estimated associations, not causal effects, given the cross-sectional design.

All five hypothesized associations were statistically significant. Unguided DDU was negatively associated with psychological capital (β = −.281), consistent with Carrier et al. (2015). Parental involvement was positively associated with psychological capital (β = .295), consistent with Jeynes (2007) and Epstein (2011). Psychological capital (β = .186) and parental involvement (β = .185) were each independently and positively associated with ESL achievement, and parent DDU for entertainment was negatively associated with ESL achievement (β = −.133), consistent with Livingstone and Helsper (2008). These associations hold at the population-averaged level; the BFM-SEM below examines whether they vary across latent student profiles.

➢ *Gender Differences: ANOVA*

One-way ANOVA revealed no significant gender differences in student unguided DDU ($F(1, 598) = 0.185$, $p = .668$, $\eta^2 = .000$) or psychological capital ($F(1, 598) = 0.286$, $p = .593$, $\eta^2 = .000$). The absence of gender differences in this context likely reflects shared socioeconomic constraints on device access and common educational disadvantage within the Matua community.

➢ *Stage 2: BFM-SEM Results*

- *Latent Class Enumeration, Convergence, and Class Stability.*

The BFM-SEM with truncated DPM prior (K_max = 10) converged on three latent DDU classes as the posterior mode, with eight of the ten mixture components receiving negligible posterior weight (< 1% combined). Convergence was satisfactory: maximum $\hat{R} = 1.008$; bulk ESS ranged from 487 to 1,243 (all > 400); tail ESS ranged from 412 to 987. Posterior predictive p-value = .47.

Class stability and separation were assessed via three additional diagnostics. First, *mean posterior class-assignment probabilities* were: Class 1 = .891, Class 2 = .863, Class 3 = .874, all substantially exceeding the conventional threshold of .70, indicating high classification certainty. Second, the *entropy-based classification quality index* (relative entropy $RE = 1 - H/\ln(K)$, where H is the average Shannon entropy of class-assignment probabilities) was RE = .74, indicating good separation. Third, *prior sensitivity analysis* with Gamma(2,2) and Gamma(0.5,0.5) hyperpriors on α both yielded identical three-class posterior modes with standardized path coefficient differences < .03 across all priors, confirming that the three-class solution is robust to prior specification.

Table 6 presents the class profiles. Student Engagement is reported as a descriptive class-validation variable to confirm theoretical coherence of the profiles; it is not a structural outcome in the model.

Table 6 BFM-SEM Latent DDU Class Profiles and Between-Class Comparisons (N = 600)

Characteristic	Overall	Class 1: Passive Consumer	Class 2: Balanced User	Class 3: Educational Engager	F	p	η^2
Class size (n, %)	600	244 (40.7%)	211 (35.2%)	145 (24.2%)	—	—	—
Mean post. class prob.	—	.891	.863	.874	—	—	—

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Student DDU (Unguided, prop.)	0.660	0.882	0.638	0.319	487.32	< .001	.619
Parent DDU (Entertainment, prop.)†	0.812	0.870	0.815	0.718	34.18	< .001	.103
Parental Involvement (0–1 scaled)	0.328	0.205	0.346	0.464	156.24	< .001	.343
Psychological Capital (0–1 scaled)	0.457	0.313	0.451	0.680	198.47	< .001	.399
ESL Achievement (score/30)	22.40	17.46	22.21	29.11	287.63	< .001	.490
Student Engagement‡ (score/30)	22.08	19.04	22.17	27.07	142.35	< .001	.323

Note. All between-class comparisons: one-way ANOVA with Tukey's post-hoc tests ($p < .001$). η^2 = eta-squared. Mean post. class prob. = mean posterior class-assignment probability (all > .86; threshold for acceptable classification certainty = .70; Nylund et al., 2007). Relative entropy (RE) = .74. Class percentages sum to 100.1% due to rounding (exact: 40.67%, 35.17%, 24.17%); the abstract reports 24.1% to achieve an exact 100.0% total. † Parent DDU α = .782; interpret with caution. ‡ Student Engagement is a descriptive class-validation variable only; not modeled as a structural outcome.

- *Class Descriptions.*

Class 1 (Passive Consumers; 40.7%) was characterized by very high unguided DDU (M = 0.882), low parental involvement (M = 0.205), the lowest psychological capital (M = 0.313), and the lowest ESL achievement (M = 17.46/30). Class 2 (Balanced Users; 35.2%) showed moderate DDU (M = 0.638) and parental involvement (M = 0.346), with near-average outcomes. Class 3 (Educational Engagers; 24.2%) exhibited the lowest unguided DDU (M = 0.319), highest parental involvement (M = 0.464), highest PsyCap (M = 0.680), and highest ESL achievement (M = 29.11/30). Student Engagement scores follow the same ordering (Class 1 < Class 2 < Class 3), providing theoretical validation that the profiles capture meaningful differences in academic participation. Figure 3 visualises these profiles.

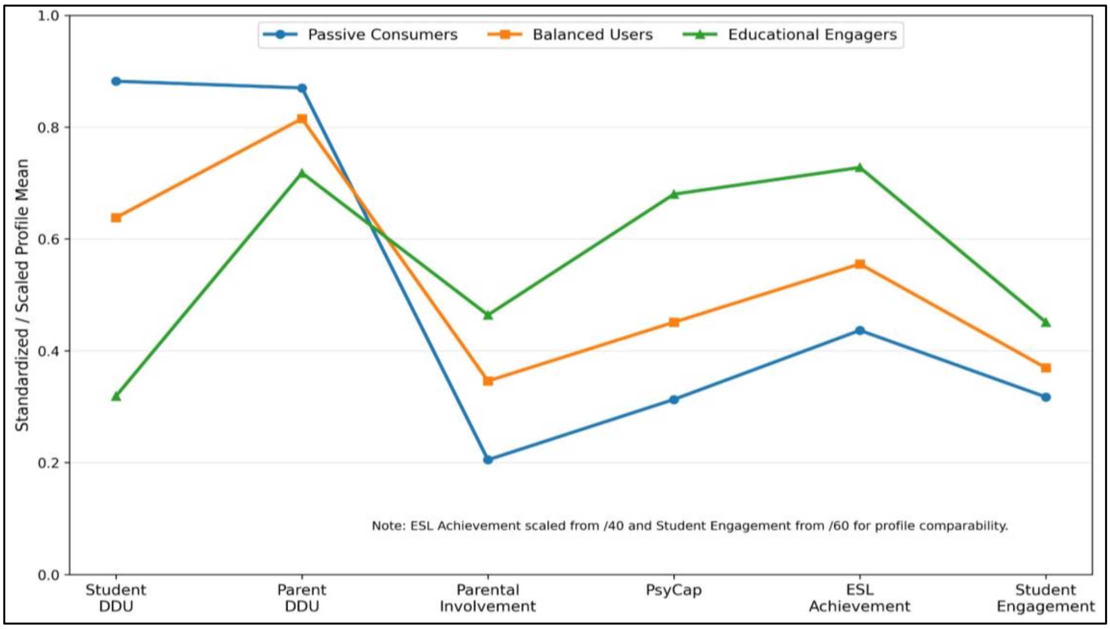

Fig 3 Bayesian Latent DDU Class Profiles (N = 600)

Mean standardized / scaled profile values across all study variables for each of the three BFM-SEM latent classes. ESL Achievement and Student Engagement scaled from 30-item measures for comparability. All between-class differences significant at $p < .001$ (ANOVA; Tukey's post-hoc). Mean posterior class-assignment probabilities exceed .86 for all classes, indicating high classification certainty. Student Engagement (rightmost variable) is shown as a descriptive class-validation measure only; it is not a structural outcome in the BFM-SEM.

- *Class-Specific Structural Path Associations.*

Table 7 presents posterior median standardized coefficients with 95% credible intervals. The path from student DDU to psychological capital was substantially stronger in Class 1 (β = −.412, 95% CI [−.501, −.323]) than in Class 2 (β = −.231 [−.318, −.144]) and non-significant in

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Class 3 (β = −.048 [−.157, .061]). The positive association of parental involvement with ESL achievement was strongest in Class 3 (β = .412 [.318, .506]) and attenuated in Class 1 (β = .118 [.031, .205]). Parent DDU was negatively associated with ESL achievement in Classes 1 and 2 but non-significant in Class 3. These population-averaged associations in Table 5 masked substantial profile-level heterogeneity. These are cross-sectional associations and should not be interpreted as causal pathways.

Table 7 Class-Specific Posterior Standardized Associations from BFM-SEM

Structural Path	Class 1: Passive Consumer β [95% CI]	Class 2: Balanced User β [95% CI]	Class 3: Educational Engager β [95% CI]
Student DDU → Psychological Capital	−.412 [−.501, −.323]	−.231 [−.318, −.144]	−.048 [−.157, .061]†
Parental Involvement → Psychological Capital	.182 [.094, .270]	.311 [.229, .393]	.448 [.358, .538]
Psychological Capital → ESL Achievement	.141 [.052, .230]	.198 [.117, .279]	.324 [.231, .417]
Parental Involvement → ESL Achievement	.118 [.031, .205]	.267 [.164, .370]	.412 [.318, .506]
Parent DDU → ESL Achievement	−.204 [−.291, −.117]	−.112 [−.198, −.026]	−.038 [−.147, .071]†

Note. β = posterior median standardized coefficient; 95% CI = 95% credible interval. † Credible interval includes zero; non-significant. All coefficients reflect cross-sectional associations, not causal effects. District covariate included in all equations (coefficients not shown). Model diagnostics: max $\hat{R}$ = 1.008; min ESS = 412; posterior predictive p = .47; mean posterior class-assignment probabilities > .86; RE = .74; prior sensitivity confirmed (path differences < .03 across three prior specifications).

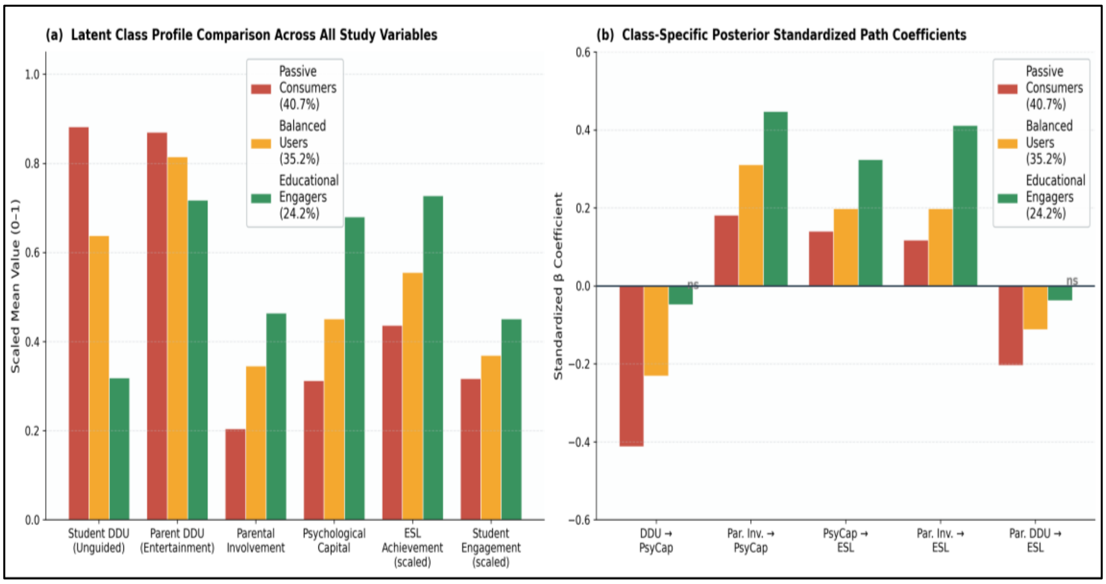

Fig 4 BFM-SEM Results: Class Profiles and Class-Specific Path Associations

Panel (a) presents mean values across study variables for each latent class (0–1 scaled). Panel (b) presents posterior standardized β coefficients for each structural path by class. "ns" = non-significant path (95% credible interval includes zero). Note: these are cross-sectional associations, not causal effects. Student Engagement is not shown in Panel (b) as it is not a structural outcome.

➢ *Model Comparison*

The BFM-SEM demonstrated superior fit versus the conventional SEM. LOO-CV (Vehtari et al., 2017) yielded ELPD_LOO = −1,847.3 (SE = 18.4) for the BFM-SEM versus −2,214.7 (SE = 21.1) for the conventional SEM (ΔELPD = 367.4, SE = 28.3), decisively favouring the BFM-SEM (threshold: ΔELPD > 4 with SE < ΔELPD/2). All Pareto k-values < 0.7. Posterior predictive checks confirmed that the BFM-SEM replicated the observed ESL achievement distribution; the conventional SEM systematically underpredicted high-achievement values. Comparison with the district-fixed-covariate single-group model (no mixture) yielded ΔELPD = 289.1 (SE = 22.4) in favour of the mixture model, confirming that the latent class structure provides explanatory value beyond simply controlling for district. The current study does not compare against a full range of realistic alternatives such as standard finite mixture SEM, latent profile analysis with BCH-estimated distal outcomes (Bakk & Kuha, 2021), or district multigroup SEM; such comparisons are recommended for future replication studies.

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IV. DISCUSSION

➢ *Implications of Profile-Specific Findings*

The three-class solution was theoretically coherent, empirically stable across prior specifications, and supported by high classification certainty (mean posterior class probabilities > .86; RE = .74). Passive Consumers (40.7%) were characterized by the highest unguided DDU, lowest parental involvement, lowest psychological capital, and lowest ESL achievement. The strong negative association between DDU and PsyCap in this class (β = −.412) is consistent with Bronfenbrenner's (1979) ecological proposition that individual-level risk factors are amplified in the absence of mesosystemic protective factors. It is important to note, however, that these are cross-sectional associations and do not establish that high DDU depletes psychological capital; longitudinal data are needed to assess directionality.

Educational Engagers (24.2%) showed the lowest unguided DDU, highest parental involvement, highest PsyCap, and highest ESL achievement. The DDU–PsyCap association was non-significant in this class (β = −.048), suggesting that the negative bivariate association between DDU and PsyCap observed at the population level may not hold within subgroups characterized by high parental engagement—an observation consistent with Clark's (2011) digital mediation theory. The strong parental involvement–ESL achievement association in this class (β = .412) is consistent with Epstein's (2011) partnership model.

Balanced Users (35.2%) occupied a transitional position and may represent a tractable target for intervention, given their moderate levels of both risk and protective factors. These profile-specific patterns—entirely invisible to the conventional single-group SEM—illustrate the substantive value added by the BFM-SEM framework, while recognizing that the cross-sectional design limits causal interpretation.

➢ *Observed District-Level Differences*

Descriptive analyses indicated that North 24 Parganas district students scored on average 1.7 points higher on ESL achievement than Nadia students (Nadia: M = 21.4; North 24 Parganas: M = 23.1, on the 30-point scale), and the magnitude of the parental involvement–ESL achievement association differed between districts by approximately 0.08 β units. With only two districts, these differences cannot be formally decomposed into random intercept and slope variance as in a multilevel model; they are reported as observed descriptive differences that motivate future multi-district replication. The fixed district covariate in the BFM-SEM ensures that within-class structural estimates are not confounded by systematic between-district differences in means.

V. LIMITATIONS

Several limitations must be acknowledged. First, and most importantly, the cross-sectional design precludes causal inference. The observed associations between DDU, psychological capital, parental involvement, and ESL achievement could reflect selection into profiles rather than dispositional processes, and reverse causation cannot be excluded. Second, the sample encompasses only two districts, which limits the generalizability of district-level descriptive comparisons and precludes a formal multilevel analysis with defensible random-effect variance estimates. Third, reliance on self-report for DDU may introduce social desirability bias, although the proportion-based format and objective ESL measure partially address this. Fourth, the Parent DDU scale showed α = .782, below the conventional .80 threshold, and findings involving this variable should be interpreted with additional caution. Fifth, the ESL Achievement test shows a notably high mean for the Educational Engager class (29.11/30); while sensitivity analyses excluding scores above 28 did not substantially alter the class solution, this near-ceiling finding for a subgroup warrants replication with a wider-range measure. Sixth, unmeasured variables—including teacher quality, school infrastructure, and peer norms—may confound the observed associations. Seventh, although prior sensitivity analysis confirmed robustness of the three-class solution, the truncated DPM approximation is computationally efficient but does not guarantee exact Dirichlet process inference; replication with a full DPM implementation (e.g., via Pyro or Turing.jl) is recommended.

VI. CONCLUSION

This study implemented a Bayesian Nonparametric Latent Class Structural Equation Model using a truncated DPM approximation via Stan/brms to identify latent DDU profiles and examine profile-specific structural associations among secondary students from the Matua community of West Bengal. Three empirically stable profiles emerged—Passive Consumers, Balanced Users, and Educational Engagers—with high posterior classification certainty (mean probabilities > .86) and robustness to prior specification. The population-averaged negative association between unguided DDU and psychological capital was substantially stronger in the Passive Consumer profile (β = −.412) and non-significant in the Educational Engager profile (β = −.048), demonstrating that population-averaged estimates from conventional SEM mask important subgroup heterogeneity.

These findings are associational and cannot establish causation given the cross-sectional design. With these caveats, the results suggest that digital literacy programs in marginalized communities may benefit from differentiated approaches: programs designed for Passive Consumers might consider building parental engagement alongside digital literacy skills as a hypothesis-generating direction, while programs for Balanced Users might explore redirecting device use toward educational purposes. These are hypothesis-generating directions informed by cross-sectional associations and require prospective testing before implementation. Future research should replicate this approach longitudinally, with multi-district samples enabling formal multilevel modelling, and using measures with wider achievement score ranges to avoid ceiling effects. The full mathematical specification, brms implementation code, and prior sensitivity results provided here constitute a reproducible methodological template for researchers working with heterogeneous educational data.

➢ *Declaration Regarding use of Generative AI:*

The authors used ChatGPT (OpenAI, 2024) to assist in generating initial R/Stan code templates. All code was reviewed, validated, and revised by the authors. The AI tool played no role in data collection, analysis, interpretation, or the writing of this manuscript. The authors take full responsibility for the integrity and accuracy of all reported analyses.

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