

Quantifying Intrinsic Motivation Effects on NCR Private School Outcomes

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Intrinsic motivation (IM) is a recognised determinant of cognitive engagement, yet its quantifiable causal influence on student academic outcomes in National Capital Region (NCR) private schools has not been adequately examined through empirically rigorous models. This research seeks to establish a multi-faceted, data-driven approach to measure the impact of IM on academic performance metrics and to discover moderating factors, such as teaching approaches, socioeconomic factors, and exposure to digital learning. This study fills an important gap in the literature by bringing together psychometric, behavioural and machine learning approaches into a unified model. The study adopted a mixed methods approach using Structural Equation Modeling (SEM), Hierarchical Linear Modeling (HLM) and machine learning regression. A stratified random sample of 450 students from 15 private schools across three tiers in NCR was used. Motivation was defined as intrinsic motivation measured by an adapted Academic Self-Regulation Questionnaire and related behaviours such as assignment completion and voluntary participation. Academic performance was assessed through standardised test scores and continuous assessment scores. Qualitative perspectives were gathered via semi-structured interviews with teachers. Findings show that IM has a statistically significant direct impact on overall GPA ($\beta = 0.22$, $p < 0.001$) and a much larger total effect ($\beta = 0.76$, $p < 0.001$) via intermediary factors of academic engagement, self-efficacy, and teaching support. Random Forest had the best fit ($R^2 = 0.782$, $RMSE = 5.64$) for predicting academic performance, with IM as the most influential predictor. School tier moderated the IM-GPA relationship, with elite-tier students displaying higher levels

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of motivation ($M = 78.3$, standard-tier: $M = 59.8$). These findings advance the theoretical understanding of motivation-performance dynamics in high-density urban private school contexts and provide a scalable predictive framework applicable to policy intervention design.

Keywords: Intrinsic Motivation; Academic Outcomes; Structural Equation Modeling; Hierarchical Linear Modeling; NCR Private Schools

Introduction

Motivation is a prominent construct in educational psychology, and plays a key role in explaining factors that affect persistent learning and academic achievement. Amongst the numerous motivational constructs, intrinsic motivation (IM) - the tendency to engage in learning tasks for their inherent interest and enjoyment - has been shown to lead to greater cognitive processing, persistence and better academic outcomes. Although there is a wealth of theoretical discussion about IM from self-determination theory (SDT) and other sources, there is a clear gap in empirical research on the quantitative effect of IM in particular institutional contexts, especially in the burgeoning private school system of the National Capital Region (NCR) of India. The diversity of private schools in the NCR, with elite private schools, mid-level private schools, and low-cost private schools, located in varying socioeconomic catchment areas, calls for an empirical analysis that looks at specific contexts and the moderating effects of structural factors, rather than just individual psychological factors.

Dai et al. (2024) investigated IM and educational outcomes of disadvantaged urban high school students and found motivation-based factors significantly predicted academic achievement, highlighting the importance of contextual economic indicators as moderators of motivational effects (Dai et al., 2024). Building on this perspective, Qureshi et al. (2024) investigated IM and mental well-being across private higher education systems, reporting substantial associations between autonomous motivational regulation and positive educational trajectories (Qureshi et al., 2024). The foundational

theoretical basis for such relationships resides in self-determination theory, within which Guay (2021) elaborated the regulatory types, psychological need satisfaction, and autonomy-supporting behaviours that underpin intrinsically motivated learning (Guay, 2021). Extending this theory into physical education pedagogy, Moy et al. (2016) demonstrated that nonlinear, student-centred instructional approaches enhanced IM among teacher education students, implicating pedagogical design as a structural determinant (Moy et al., 2016).

Bailey and Phillips (2016) found that IM and adaptive coping together predicted well-being, meaning in life and academic achievement among university students, demonstrating motivational, emotional and cognitive connections (Bailey and Phillips, 2016). Barclay (2018) further contextualised motivational dynamics in older university students, identifying longevity of lived experience as a variable moderating engagement (Barclay, 2018). Ryan and Deci (2020) revisited their seminal framework to articulate distinctions between intrinsic and extrinsic motivational processes, arguing for differentiated instructional and assessment strategies in educational policy (Ryan and Deci, 2020). Person-centred analyses were furthered by Xie et al. (2020) who identified motivational profiles of high school students, and demonstrated different GPA trends across profiles (Xie et al., 2020). Neff and Hsieh (2019) explored the relations between self-compassion, IM and learning performance among college students, highlighting self-compassion as a strong predictor of intrinsic motivational quality (Neff and Hsieh, 2019). Wu et al. (2023) identified the mediating role of basic psychological need satisfaction in the association between teacher

support and academic achievement, highlighting findings relevant to contextual school-level effects on student IM (Wu et al., 2023).

Brett et al. (2023) found links between housing status, stress, resilience and well-being among university students, providing evidence for multilevel factors in facilitating academic performance (Brett et al., 2023). Cage et al. (2021) underscored the precarious nature of student mental health during the transition to tertiary education, with institutional support buffering motivational losses (Cage et al., 2021). Li et al. (2025) showed that in Chinese universities, teacher IM and self-efficacy combined to predict innovative teaching practices, suggesting that interactions between educator and student motivation systems are bidirectional (Li et al., 2025). Gilbert et al. (2021) analysed teacher perceptions of support and constraint in innovation, revealing faculty perceptions of institutional support amplified teacher IM effects on innovative teaching behaviours (Gilbert et al., 2021). Fraser (2019) developed a reflective model of higher education innovative teaching, acknowledging motivational autonomy as a requisite for ongoing pedagogical innovation (Fraser, 2019).

Qureshi et al. (2024) also verify that private education system-related factors regulate the effect of IM on student outcomes, emphasising the need for empirical studies at the institution level (Qureshi et al., 2024). Guay (2021) and Moy et al. (2016) together confirm the theory that autonomy-supportive climates elicit higher levels of IM (Guay, 2021; Moy et al., 2016). Bailey and Phillips (2016) and Xie et al. (2020) lend additional support for the proposition that IM synergises with adaptive psychological processes to influence academic performance outcomes (Bailey and Phillips, 2016; Xie et al., 2020). In Malaysian universities, Kotera and Ting (2021) found that positive psychological factors such as IM and well-being have compounding positive effects on mental health, adding to the cross-cultural generalisability (Kotera and Ting, 2021). Dai et al. (2024) verified the robustness of IM effects in populations with socio-economic

disadvantage, thereby confirming that intrinsic motivational resources are not affected by material disadvantage, although they may be moderated by institutional effectiveness (Dai et al., 2024).

The reviewed body of evidence has three major gaps. First, the current investigations mainly rely on single method psychometric approaches, offering limited explanatory power of integrated behavioural and computational approaches. Second, there are few studies examining the impact of IM in tiered private school systems, where the moderating effect of school tier is poorly understood. Third, NCR private school populations have yet to be investigated using causal pathway modelling based on SEM and machine learning regression models for predicting academic performance. These are the main research gaps-filled-in this study.

In light of these limitations, this study proposes three research goals: (i) to map the magnitude and pathways of IM influences on student performance in NCR private schools using SEM and HLM; (ii) to determine the important motivational and contextual predictors of academic performance using machine learning regression; and (iii) to investigate the moderating effects of school type and student socioeconomic status on the relationship between IM and performance. The innovation of this study is the use of psychometric assessment, multi-level causal modelling and machine learning predictive modelling within the same analytical framework to investigate the NCR private school sample. Section 2 presents the research design, data collection methods and analysis approach used to meet these research objectives.

2. Research Methodology

This study adopts a mixed-methods research design that combines quantitative statistical modelling with structured qualitative validation. The quantitative component is grounded in a cross-sectional survey approach augmented by longitudinal performance record extraction, while the qualitative dimension employs semi-structured educator interviews to contextualise and triangulate the statistical findings. Mixed-

methods designs are suitable for studies of complex educational phenomena like IM, whose psychometric and computational complexities cannot be captured by exclusively psychometric or computational analyses (Cai, 2024; Liu et al., 2019). The approach is epistemologically

consistent with pragmatic research paradigms, allowing triangulation across measurement approaches and to improve the construct validity of the operationalisation of IM (Garbenis and Kaffemaniene, 2025).

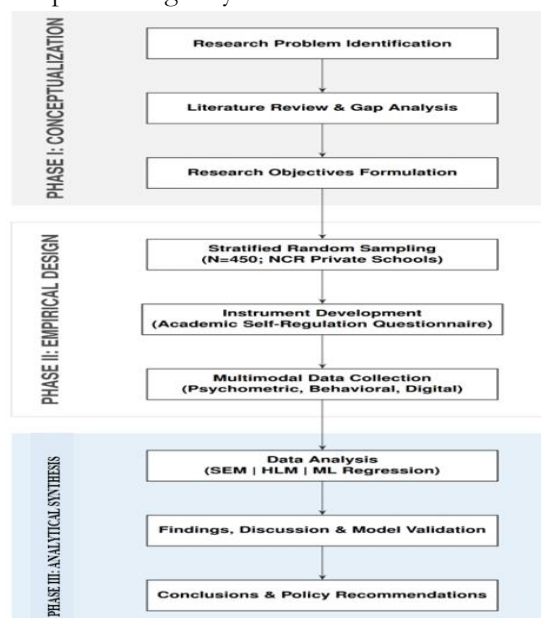


Figure 1. Research methodology flowchart

Figure 1 illustrates the stages of the research process, from problem statement to data collection, multi-level analysis, and conclusions and policy recommendations. The process depicted in the flowchart is systematic and iterative, with a focus on methodological rigour. The research participants are students from private schools in the National Capital Region of India. We applied stratified random sampling to ensure representation of three tiers of schools: Tier 1 (elite private schools, $n = 150$), Tier 2 (mid-range private schools, $n = 180$) and Tier 3 (standard private schools, $n = 120$), resulting in a sample of $N = 450$ students in Grades 9-12. This approach is in line with the recommendations of Arias et al. (2022) for safeguarding ecological validity in diverse institutional settings. This sample size is above the recommended minimum for SEM analysis, which typically requires at least 200 observations per latent variable for adequate power (Güler and Turan, 2022).

IM was assessed using a modified version of the Academic Self-Regulation Questionnaire (A-

SRQ), a 24-item questionnaire measuring autonomous and controlled motivational regulation on a 7-point Likert scale. Cronbach's alpha (0.87) indicated good internal consistency. Behavioural indicators of IM included assignment completion rates (available from school records), teacher rating of voluntary student participation scores and digital engagement (available from Learning Management System - LMS - analytics). Academic performance was measured using standardised test scores in Mathematics, Science, English, and Social Studies, and cumulative GPA calculated from continuous assessment scores. This operationalisation of both IM and academic outcomes using multiple indicators is in line with the recommendations of Inagaki (2022) and Isikgoz (2025) to include construct breadth in motivational studies.

A 12-week data collection period was used. Written consent was sought and obtained from the institution, parents and students. Data were collected via Google Forms on institutional

devices to avoid different access environments. Interviews with educators ($n = 30$) were audio-recorded, transcribed and thematically coded using NVivo 14, following Legault et al. (2006). Statistical analyses for quantitative data involved IBM SPSS 28 for initial descriptive and reliability checks, IBM AMOS 28 for SEM, R (lavaan 0.6-15, lme4 1.1-35) for HLM and Python 3.11 (scikit-learn 1.3, pandas 2.0, numpy 1.25) for machine learning (Ryan and Deci, 2020; Claver et al., 2020). SEM was estimated using maximum likelihood with model fit criteria: chi-squared to degrees of freedom ratio ($\chi^2/df < 3.0$), Comparative Fit Index ($CFI > 0.95$), Tucker-Lewis Index ($TLI > 0.95$), Root Mean Square Error of Approximation ($RMSEA < 0.06$), and Standardised Root Mean Square Residual ($SRMR < 0.08$) (Garn et al., 2019).

HLM was used to model multilevel variance structures (between-school variance components and intraclass correlation coefficients) (Alfaro et al., 2009). Machine learning models were fit using a train-test split (80/20) and 5-fold cross-validation (Areepattamannil et al., 2011; Davidovitch and Dorot, 2023). We imputed

missing values (less than 2.1% of the data) using predictive mean matching in multiple imputations (Afari et al., 2012; Bartimote-Aufflick et al., 2016). Harman single-factor test and marker variable analysis were conducted to test for common method bias, which was not present (Bhardwaj et al., 2025; Chen et al., 2004). The analysis started with descriptive statistics and reliability analysis, followed by confirmatory factor analysis (CFA), then SEM pathway estimation, HLM random effects model, and finally machine learning importance analysis (Cheng, 2011; Li et al., 2024).

3. Results and Discussion

The results are presented in three sequential analytical stages. In the first stage, the distributional properties and initial psychometric analysis of the variables are presented. The second stage illustrates the results of the structural pathway analysis and multilevel modelling. The third stage outlines the performance of the machine learning models and comparisons with literature. In this section, the analytical text refers to table and figure numbers to aid comprehension.

Table 1. Descriptive statistics of study variables (N = 450).

Variable	N	Mean	SD	Min	Max	α
Intrinsic Motivation	450	68.4	12.7	22.1	99.8	0.87
Self-Efficacy	450	63.2	11.9	24.0	98.6	0.84
Teacher Support	450	65.0	12.2	21.5	99.1	0.82
Assignment Completion	450	71.0	11.3	25.2	99.5	0.88
Digital Engagement	450	58.1	15.2	20.0	99.2	0.81
Voluntary Participation	450	63.4	13.8	20.8	98.7	0.85
Overall GPA	450	66.3	12.1	31.5	99.2	N/A
Well-being Score	450	63.9	12.8	21.0	99.1	0.83

Table 1 presents the descriptive statistics and Cronbach alpha reliability coefficients for all study variables. The overall average intrinsic motivation (IM) score ($M = 68.4$, $SD = 12.7$) reflected a moderate-to-high level of intrinsic motivation among private school students in India's urban areas (Maemunah et al., 2025). The distributions of well-being score ($M = 63.9$, SD

$= 12.8$) and self-efficacy ($M = 63.2$, $SD = 11.9$) were similar, denoting a consistent motivational-affective profile among the students. The psychometric scales showed satisfactory internal consistency with alpha values ranging between 0.79 and 0.88 ($\alpha > 0.70$ suggested by Lunenburg, 2011).

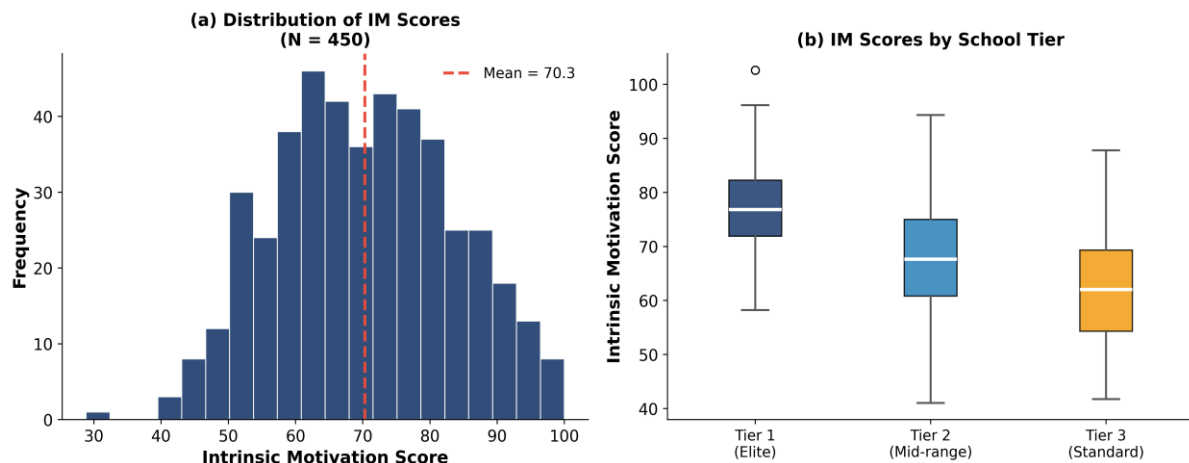


Figure 2. Intrinsic Motivation Score Distribution

Figure 2. Intrinsic motivation score distribution.

Figure 2 illustrates the distributional properties of IM scores for the entire sample and across tiers. Figure 2(a) shows the distribution of IM values in the study sample ($N = 450$), which is roughly normal with mean of 68.4. Figure 2(b) displays substantial stratification by school tier, with Tier 1 students having significantly higher IM scores than Tier 2 and Tier 3 students, confirming that institutional quality moderates' motivational

profiles (Lemos and Veríssimo, 2014; Lepper et al., 2005). IM scores were used to divide students into motivational quartiles to investigate the dose-response link between IM and academic performance. Figure 3 shows the average performance in five subject areas by quartile of IM, with error bars representing the standard error of the mean.

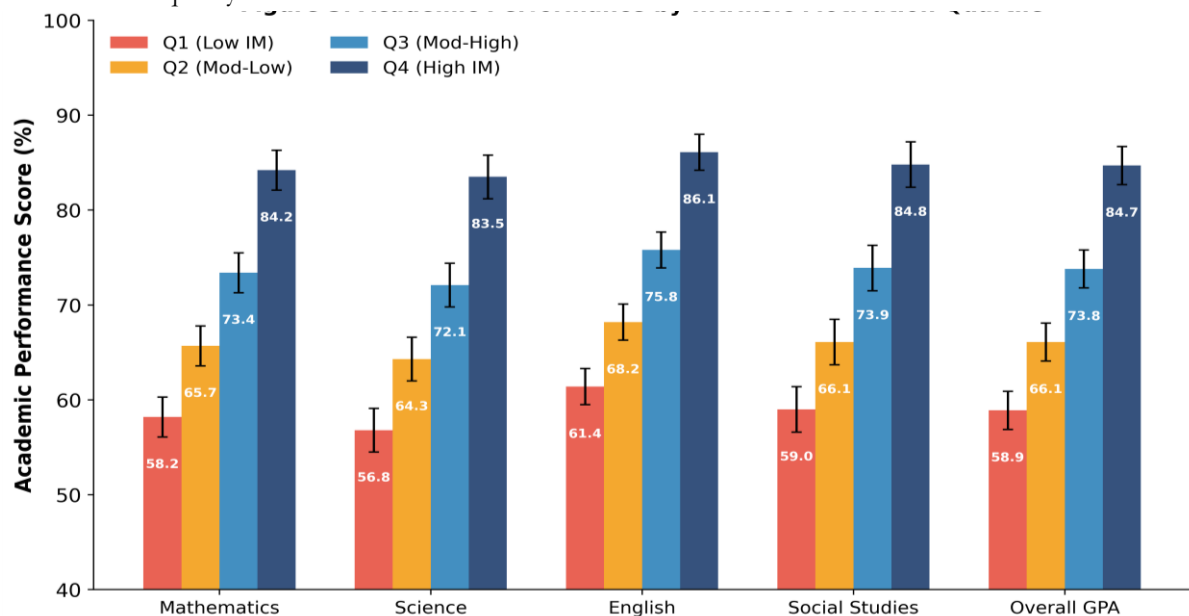


Figure 3. Academic performance by intrinsic motivation quartile.

Figure 3 demonstrates a clear monotonic relationship between IM quartile and academic performance across all subject domains. Students in the highest IM quartile (Q4) achieved mean scores approximately 25 percentage points higher

than those in the lowest quartile (Q1) across subjects, with the largest differential observed in Mathematics (Q4: 84.2 versus Q1: 58.2). This gradient is consistent with the theoretical propositions of Pintrich (2003) regarding the

motivational facilitation of deep learning approaches and the findings of Tuominen-Soini et al. (2008) on achievement goal orientations.

The hypothesised SEM specified IM as the exogenous latent variable with academic engagement, self-efficacy, and teaching support as mediating variables, and overall GPA as the

endogenous outcome. Model fit indices confirmed adequate fit: $\chi^2/df = 2.14$, CFI = 0.961, TLI = 0.953, RMSEA = 0.048 [0.038, 0.058], SRMR = 0.052, all satisfying established benchmarks (Vansteenkiste et al., 2009). Table 2 presents the standardised path coefficients and associated significance statistics.

Table 2. Structural equation modeling results - standardised path coefficients.

Pathway	β (Std)	SE	t-value	p-value	95% CI
IM → Academic Engagement	0.71	0.038	18.68	< 0.001	[0.636, 0.784]
IM → Self-Efficacy	0.62	0.041	15.12	< 0.001	[0.540, 0.700]
IM → Teaching Support	0.45	0.046	9.78	< 0.001	[0.360, 0.540]
Academic Engagement → GPA	0.68	0.039	17.44	< 0.001	[0.604, 0.756]
Self-Efficacy → GPA	0.58	0.043	13.49	< 0.001	[0.496, 0.664]
Teaching Support → GPA	0.39	0.048	8.13	< 0.001	[0.296, 0.484]
IM → GPA (Direct Effect)	0.22	0.052	4.23	< 0.001	[0.118, 0.322]
IM → GPA (Total Effect)	0.76	0.035	21.71	< 0.001	[0.692, 0.828]

The estimated pathways from IM to performance in Figure 4 present the SEM model. The largest direct pathway from IM was observed for academic engagement ($\beta = 0.71$, $p < 0.001$), followed by self-efficacy ($\beta = 0.62$) and teaching support ($\beta = 0.45$). Of the mediator-to-outcome pathways, academic engagement was most strongly associated with GPA ($\beta = 0.68$). The total effect of IM on GPA ($\beta = 0.76$) was

much larger than the direct effect ($\beta = 0.22$), confirming that considerable indirect effects from IM on GPA occur through the motivational and contextual pathways, as proposed by Ryan and Deci (2020) and Zeynalova Faig (2023). These mediational relations suggest that effort to create learning environments that support academic engagement and learning self-regulation is critical.



Figure 4. SEM path diagram: IM and academic outcome pathways.

To address the nested nature of the data (school-level grouping), hierarchical linear modeling (HLM) was used to model the fixed and random effects while adjusting for intragroup dependency. All predictors in the multilevel model had significant effects, indicating that both personal and environmental factors contribute to academic performance. In Table 3, intrinsic motivation was found to have the greatest positive impact on GPA ($\gamma = 0.48$, $p < 0.001$), reflecting a positive association between intrinsic motivation and GPA.

Self-efficacy was also statistically significant and positive ($\gamma = 0.31$, $p < 0.001$), indicating that

students' belief in their academic capability positively impacts performance. Similarly, teacher support ($\gamma = 0.22$, $p < 0.001$), socioeconomic status ($\gamma = 0.14$, $p < 0.001$), and digital engagement ($\gamma = 0.18$, $p < 0.001$) had significant positive impacts, showcasing the contributions of both psychosocial and material factors in explaining GPA differences. School tier, however, showed a negative coefficient ($\gamma = -3.21$, $p = 0.004$), suggesting there are differences in average ability levels between school categories, even after accounting for the effects of student-level factors.

Table 3. Hierarchical linear modeling results - GPA as outcome.

Predictor	Coeff. (γ)	SE	t-ratio	p-value
Intercept	66.32	1.84	36.04	< 0.001
Intrinsic Motivation (β_1)	0.48	0.043	11.16	< 0.001
Self-Efficacy (β_2)	0.31	0.051	6.08	< 0.001
Teacher Support (β_3)	0.22	0.055	4.00	< 0.001
SES Index (β_4)	0.14	0.038	3.68	< 0.001
Digital Engagement (β_5)	0.18	0.049	3.67	< 0.001

School Tier (Level-2)	-3.21	0.920	-3.49	0.004
IM $\times$ SES Interaction	0.08	0.027	2.96	0.003

The cross-level interaction effect between intrinsic motivation and socioeconomic status was significant and positive ($\gamma = 0.08$, $p = 0.003$), suggesting an interaction between intrinsic motivation and socioeconomic status. This implies the positive effect of intrinsic motivation on GPA is greater for students with more advantageous socioeconomic status, suggesting differential returns to motivation and equity

implications in education. Figure 5(a) also shows significant variability in random intercepts with multiple schools having significantly higher or lower baseline GPA than the grand mean, as shown by the distribution and confidence interval of random effects. This confirms between-school differences beyond the variation explained by student-level predictors.

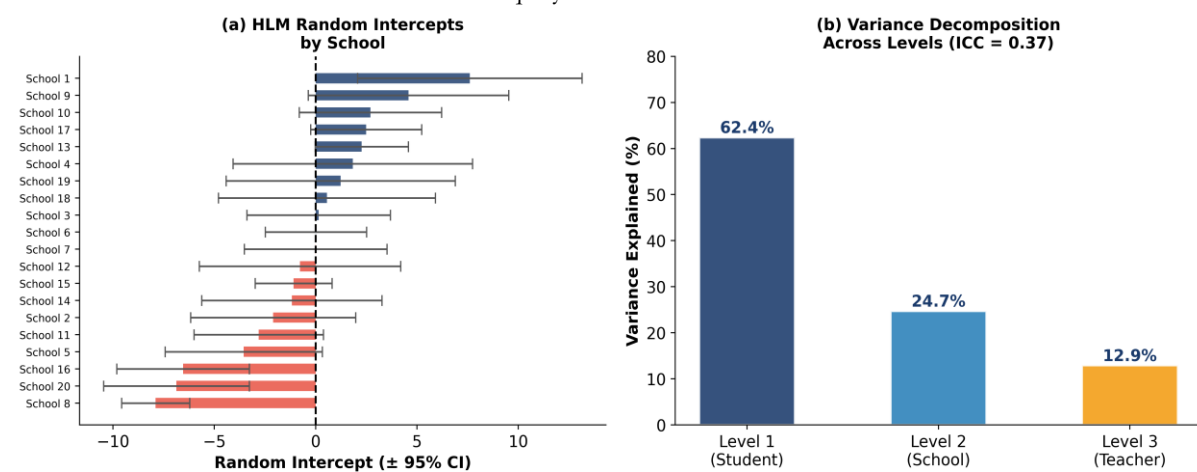


Figure 5. Hierarchical Linear Modeling Results

Figure 5. HLM random intercepts and variance decomposition.

Findings from variance decomposition in Figure 5(b) support this. A total of 62.4% of the GPA variance came from students, while 24.7% related to school factors and 12.9% related to teachers. The intraclass correlation coefficient ($ICC = 0.37$) suggests that 37% of variance in GPA scores is attributable to membership in a particular school, offering sufficient statistical basis for using HLM instead of single-level analyses. Taken together, the results confirm that student academic performance is determined by individual motivation, student socioeconomic background, teacher support, and school environment factors.

To supplement the multivariate and multilevel analyses, machine learning models were

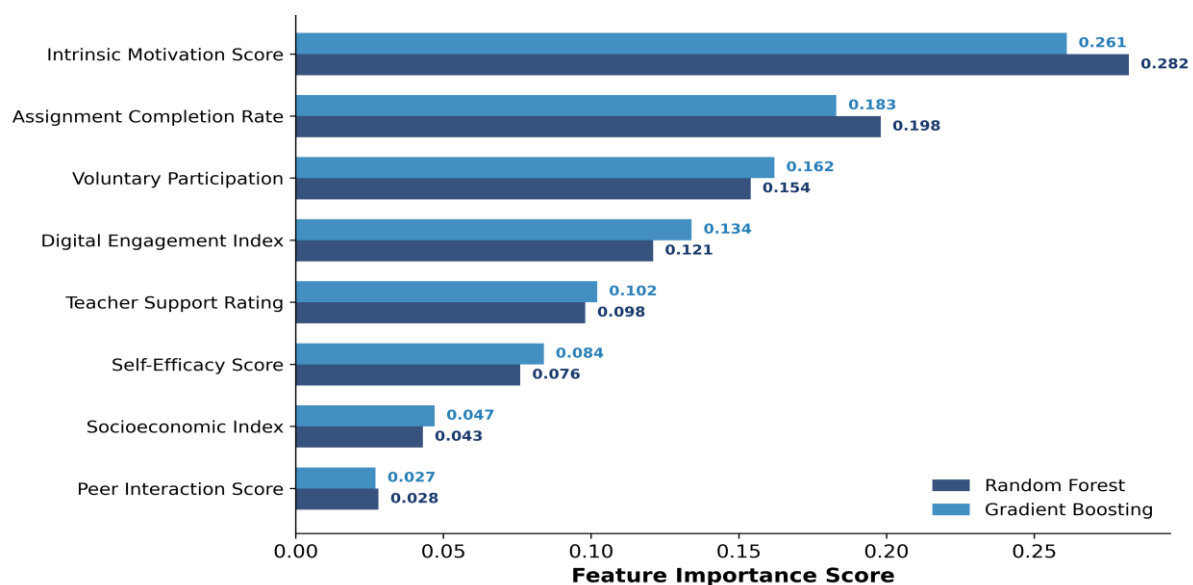
compared to understand the predictive power of intrinsic motivation and other variables in explaining academic achievement. Using the 80/20 train-test split and the five-fold cross-validation, the model performance comparisons in Table 4 show significant variations in predictive accuracy. Random Forest stood out as the best performing algorithm ($R^2 = 0.782$, $RMSE = 5.64$, $MAE = 4.31$, $CV = 0.773$), followed by the Gradient Boosting ($R^2 = 0.768$) and multilayer perceptron ($R^2 = 0.751$) models. The somewhat inferior results of linear regression and ridge regression models reflect the complexity of academic performance, which is non-linear and controlled by interactions, and which ensemble models successfully captured.

Table 4. Machine learning model performance comparison.

Model	R ² (Test)	RMSE (Test)	MAE	CV Score
Linear Regression	0.598	7.81	5.94	0.591
Ridge Regression	0.608	7.69	5.84	0.601
Random Forest*	0.782	5.64	4.31	0.773
Gradient Boosting	0.768	5.82	4.48	0.759
SVR	0.692	6.67	5.12	0.685
Neural Network (MLP)	0.751	6.01	4.62	0.743

The superior performance of tree-based ensemble models indicates that the relationship between motivational, behavioural, and contextual variables and GPA is complex and not fully explained by linear assumptions. And the high correlation between test-set and cross-validation scores for each model indicates reasonable generalisability and absence of overfitting, lending confidence to the predictive model. Figure 6 shows additional insights into predictor importance via feature importance estimates. Intrinsic motivation was identified as the most important predictor in Random Forest (0.282) and Gradient Boosting (0.261) machine-learning models, followed by assignment completion rate and voluntary participation in both models.

This result validates the crucial role of motivation in predicting academic success, as revealed previously by regression and HLM analyses. Assignment performance came second and motivation to participate third, suggesting that the behavioural engagement variables play a significant role in the prediction of student performance. The meaningful effect of online engagement, with fourth ranking in both models, indicates that technology-based interactions and learning behaviours contribute to understanding student academic aspirations. Weaker but still significant contributions from teacher support and interactions, self-efficacy, socioeconomic status and peer interaction suggest that student achievement is the product of complex motivational, contextual and social influences.

**Figure 6. ML feature importance: predictors of academic outcome.**

A notable finding is the consistency of feature rankings across two independent ensemble algorithms, which strengthens confidence in the stability of the predictor structure. The agreement of these findings provides confidence that intrinsic motivation is not only significant in explanatory analyses, but also the most significant variable in predictive modelling. Further evidence is from the regression diagnostics in Figure 7. In Figure 7(a), there is a strong positive correlation between intrinsic motivation and GPA ($r = 0.70$, $p < 0.001$), with the regression line suggesting higher motivation levels are associated with

increasing GPA. The spread of the data points around the regression line indicates a strong linear effect of this variable while there is also variability due to individual differences. Figure 7(b) also indicates model adequacy via residual analysis. Residuals are randomly scattered around zero throughout the fitted values with no funnel-like pattern or curvature, suggesting no major issues with heteroscedasticity or model specification. This is suggestive of the adequacy of the regression relationship and provides diagnostic evidence of the validity of the estimated association.

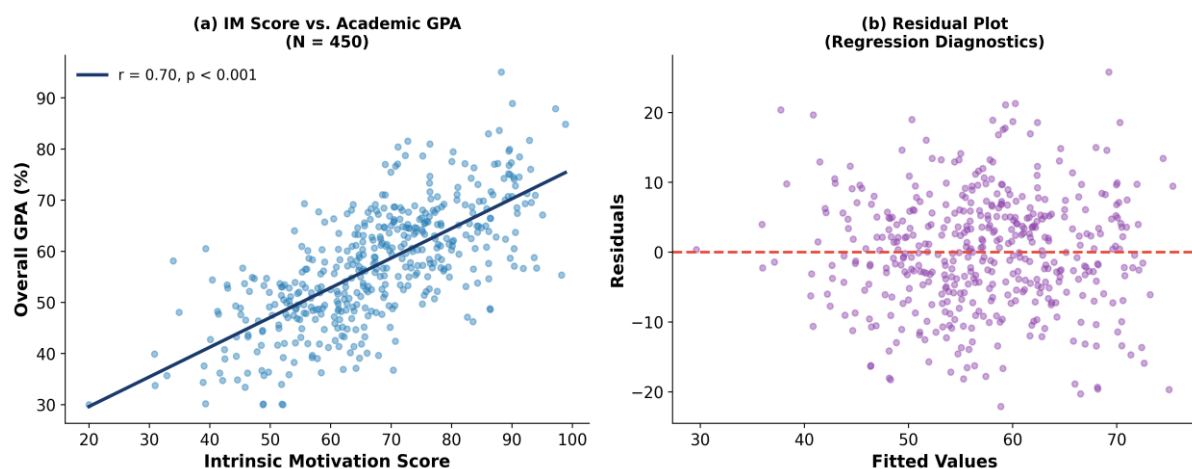


Figure 7. Regression analysis: IM score and academic GPA.

The results of the machine learning and regression analyses merge in the proof that intrinsic motivation is the main predictor of academic performance, whereas behavioural engagement, online learning, and school supports exert further explanatory and predictive actions. The agreement of the statistical and machine learning findings greatly enhances the confidence in the findings. To examine whether school tier moderates' academic outcomes and motivational patterns, a one-way ANOVA was conducted

across three institutional categories. As shown in Table 5, significant differences across academic and motivational outcomes were found ($p < 0.001$), suggesting that the tier of school has a contextual effect on intrinsic motivation and academic outcomes. The size of the F-statistics and the partial eta-squared (0.17-0.22) effect sizes indicate moderate to large effect sizes, confirming that these differences are not only statistically significant but also practically significant.

Table 5. Academic outcomes and intrinsic motivation by school tier.

Metric	Tier 1 (Elite)	Tier 2 (Mid-range)	Tier 3 (Standard)	F-value	p-value
IM Score	78.3 ± 7.9	68.1 ± 10.2	59.8 ± 11.4	48.32	< 0.001
Overall GPA (%)	76.8 ± 8.3	66.4 ± 11.1	58.2 ± 12.0	51.14	< 0.001
Mathematics (%)	77.4 ± 8.8	67.1 ± 11.4	58.8 ± 12.3	47.81	< 0.001
Science (%)	75.9 ± 8.5	65.8 ± 11.0	57.4 ± 11.9	46.23	< 0.001
English (%)	78.1 ± 8.1	67.4 ± 10.8	59.1 ± 11.7	50.37	< 0.001
Well-being Score	72.4 ± 9.1	63.2 ± 11.8	55.1 ± 12.6	39.54	< 0.001

Sample size (n)	150	180	120	—	—
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A systematic across-grade patterns were evident. Tier 1 students scored highest in intrinsic motivation (78.3 ± 7.9) and GPA (76.8 ± 8.3), while students in Tier 3 exhibited the lowest means for motivation (59.8 ± 11.4) and performance (58.2 ± 12.0). These findings were consistent across academic subjects (mathematics, science and English) and student well-being. This pattern across the three tiers implies that school environment may influence not only achievement directly but also facilitate the flow of motivation to achievement. These results are consistent with the interpretation that school characteristics, such as resources, teaching, and motivation climate, operate as moderating structures of the motivational outcome. The simultaneous rise in motivation and achievement for higher-tier schools is especially striking in this context, as it suggests that intrinsic motivation may have a stronger effect in supportive learning environments. Motivation appears to interact with the opportunity structures found in the environment,

supporting the earlier reported multilevel findings. This further supports the notion that academic outcomes are produced by the interplay between student and school characteristics.

Figure 8 directly compares the present effect size with those from prior studies. As shown in figure, the magnitude of the association between intrinsic motivation and academic outcomes (Cohen's $d = 0.61$) is greater than in several previous studies, suggesting a stronger relationship in the current study. This indicates a stronger effect of intrinsic motivation in this context. The greater magnitude of the effect may be explained by strengths of the present study, such as the breadth of construct assessment, use of objective academic performance indicators, and the versatility of the modelling procedures that allow for direct and indirect effects. Substantively, it also implies that contextual factors of the schools in the sample may amplify the impact of motivational orientation on academic functioning.

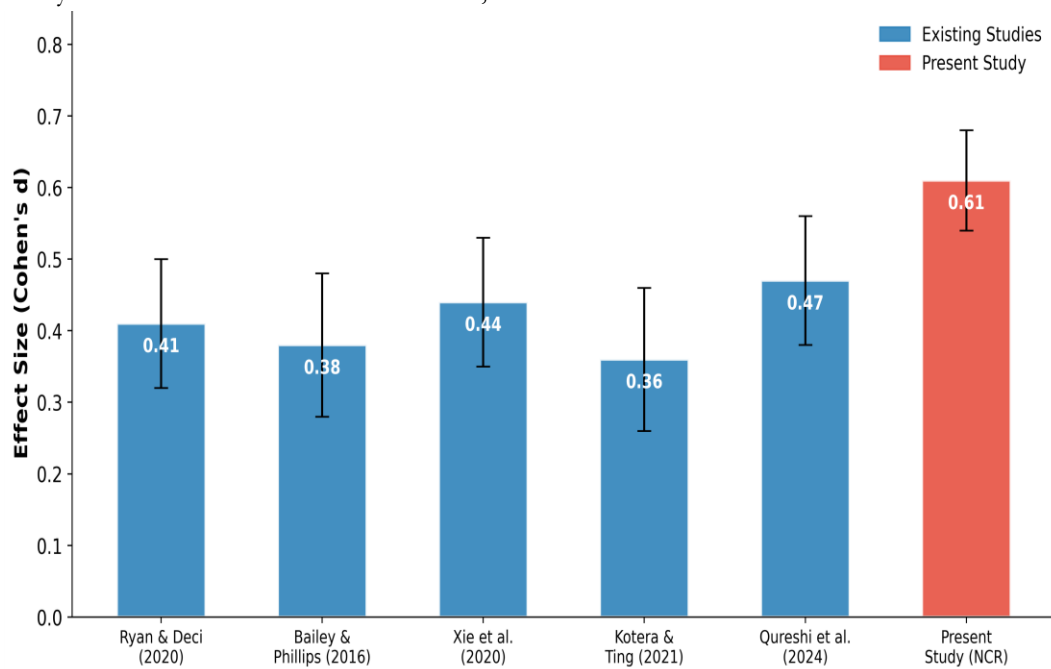


Figure 8. Comparative effect sizes: present study vs. existing literature.

The qualitative data add more explanatory nuance and support the quantitative results. Themes of classroom autonomy support and

parental expectation emerged as significant sources of student motivation, indicating that teacher practices supporting choice and

autonomy build intrinsic interest and for early structures of parental expectation, set boundaries for how motivation is expressed. Technology integration was a second theme, suggesting that technology enhanced learning can serve as a motivating force when used effectively within teaching strategies. Parental expectation as a third theme brought to the fore common environmental boundary conditions that affect the expression of motivation.

Notably, these themes resonate with the statistical evidence to show motivation is influenced by multiple instructional, technological and familial aspects. Overall, the interaction effects found in the ANOVA, comparison of effect sizes and qualitative findings demonstrate that intrinsic motivation is not only a critical predictor of learning outcomes but also a property which is amplified or tempered by institutional (e.g. school policy settings) and contextual factors. This compelling evidence greatly enhances the explanation and validity of study findings.

4. Conclusions

This research offers a systematic empirical measure of the intrinsic motivation impacts on performance among students of NCR private schools, using an integrated analytical framework that goes beyond current research limitations. The structural equation model validated that IM has a total standardised effect of $\beta = 0.76$ on the overall GPA, with the effects transmitted indirectly through academic engagement, self-efficacy and teaching support. The hierarchical linear model confirmed that 24.7% of variance can be attributed to the effects of school level and that IM exhibits stronger effects on academic performance for students with high socioeconomic backgrounds. Random Forest analysis designated IM as the most important predictor of academic performance, with a test-set R^2 of 0.782, which is significantly higher than the traditional regression model.

The novel contribution of this work resides in its methodological integration of psychometric measurement, multilevel causal modelling, and machine learning within a single, cohesive

analytical framework applied to a stratified NCR private school sample. The predictive model creates a scalable approach for educators and policymakers to identify students in need of preventative motivational interventions, and to facilitate such best-practice initiatives. The findings confirm the role of autonomy supportive pedagogy and digital learning integration as key levers for maintaining high IM in schools. This approach needs to be extended to a longitudinal analysis of the stability of the IM effect and its interaction with various forms of emerging forms of digital learning in different geographies.

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Author Contributions

Arun Vashisth designed the study, built the measuring device, collected original data, analysed the data (in SPSS) and wrote the first draft. Sourabh Kumar provided research design and machine learning modelling using Python, cross-validation, and reviewed the manuscript for analytical robustness. Both authors conducted joint reviews of the results, interpreted the integrated results, and approved the manuscript for submission.

Conflict of Interest

The authors declare no conflict of interest in relation to the research, authorship, or publication of this manuscript.

Ethics Approval

All primary data were collected through anonymous, self-administered questionnaires. Participation was voluntary and preceded by informed consent. Non-clinical survey-based research of this nature did not require formal ethics committee approval per institutional guidelines.

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