

**Discipline as the Art of Self-Control: Where Does This Leave STEM? A Case Study of Uganda's STEM Education Policy**

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**Abstract**

This study examined the relationship between discipline as a form of self-control and STEM academic performance among secondary school students in Uganda, with specific reference to the national STEM Education Policy. Grounded in self-determination theory and Vygotsky's socio-cultural framework, the study sought to determine how student self-control, discipline, and school-level policy exposure collectively influenced STEM outcomes across different school types and geographic settings. A cross-sectional, mixed-methods design was employed, drawing on a stratified random sample of 1,200 students from 60 secondary schools across Uganda's four regions. Quantitative data were collected using structured questionnaires measuring self-control, discipline, and STEM performance, while qualitative insights were gathered through focus group discussions and key informant interviews. Descriptive statistics, Pearson bivariate correlations, ordinary least squares regression, and three-level hierarchical linear modelling (HLM) were applied to analyse the data. Findings revealed that self-control ( $\beta = 0.241$ ,  $p < 0.001$ ) and discipline scores ( $\beta = 0.187$ ,  $p < 0.001$ ) were strong and statistically significant predictors of STEM performance even after controlling for school-level and regional factors. The intra-class correlation in the null model was 0.234, confirming that 23.4% of the variance in STEM scores was attributable to school-level differences, which reduced to 16.7% in the full model after accounting for policy exposure, school type, and urbanisation. Private urban schools consistently outperformed government rural schools, pointing to structural inequalities that undermine the equitable aims of Uganda's STEM policy. Policy exposure was itself a positive predictor of proficiency ( $\beta = 0.323$ ,  $p < 0.001$ ), suggesting that sustained and quality implementation of the STEM policy has measurable academic dividends. The study concluded that discipline and self-control are not merely moral virtues but are academically consequential competencies whose cultivation should be embedded in Uganda's STEM policy framework. Recommendations include targeted teacher-training on discipline-integrated pedagogy, resource equalisation across rural and urban schools, and a formal monitoring framework for STEM policy implementation.

**Keywords:** *Discipline, self-control, STEM education, Uganda, multilevel modelling, STEM policy, secondary education, academic performance*

**INTRODUCTION**

The relationship between self-discipline and academic achievement has long occupied a central place in educational psychology, yet its specific implications for science, technology, engineering, and mathematics (STEM) learning remain inadequately theorised and empirically underexplored in sub-Saharan African contexts. In Uganda, where the government has in recent years committed to a formal STEM Education Policy as a cornerstone of its national development agenda under Vision 2040 and the National Development Plan III, questions about the non-cognitive drivers of STEM success have acquired urgent policy relevance (Dolan et al., 2018; Frey et al., 2022; Tellmann, 2022). STEM subjects are widely acknowledged to demand not only intellectual aptitude but also sustained concentration, methodical problem-solving, tolerance for failure, and procedural adherence — qualities that are, at their core,

expressions of self-regulation and disciplined cognitive conduct (Julius & Geoffrey, 2025; Kohnke & Ting, 2021; Zhao et al., 2022). Despite this recognised link, Uganda's STEM policy architecture has overwhelmingly prioritised infrastructural investments — laboratories, textbooks, teacher recruitment — while largely neglecting the internal, self-regulatory competencies that condition students' capacity to benefit from those material provisions. Theoretically, self-determination theory (Deci & Ryan, 2000) posits that internalised self-regulation — a sophisticated form of self-control — is the proximate engine of autonomous, intrinsically motivated learning, which is precisely the disposition that STEM mastery demands (Arthurs, 2019; Davidesco & Milne, 2019; Kakooza et al., 2019; Sadik, 2018). Vygotsky's socio-cultural theory further situates discipline not as an innate trait but as a socially mediated and institutionally cultivated competency, meaning schools are not passive stages for its expression but active architects of its development (Cruz et al., 2021; Loughran, 2009; Rodriguez & Welsh, 2022; Wang et al., 2018). Against this backdrop, this study investigated the extent to which discipline, operationalised as self-control, predicted STEM academic performance among secondary school students in Uganda, and how this relationship was moderated by school type, regional location, and degree of exposure to the national STEM policy (Ammar et al., 2024; Julius & Godfrey, 2025; Kazaara & Nancy, 2025; Mpinga et al., 2022). By bringing a multilevel analytical lens to bear on this question, the study sought to unpack both individual-level and institutional-level dynamics that have been conflated in prior single-level analyses, thereby generating more actionable evidence for policy reform.

#### **BACKGROUND OF THE STUDY**

Uganda's STEM Education Policy, formally launched in 2019 following years of consultative groundwork, was conceived as a strategic response to mounting evidence that the country's secondary education system was producing graduates ill-equipped for a technology-driven labour market and insufficiently competitive in science-intensive fields at tertiary level (Arif et al., 2019; Li & Wang, 2021; Sterpu et al., 2024; Walkington, 2015). National examination data from the Uganda National Examinations Board (UNEB) consistently showed that pass rates in physics, chemistry, and mathematics at Uganda Certificate of Education (UCE) and Uganda Advanced Certificate of Education (UACE) levels hovered well below 60%, and that rural government schools — which enroll the vast majority of Uganda's secondary students — recorded performance figures markedly worse than their urban and private counterparts. The policy response centred on curriculum reform, laboratory refurbishment, teacher upskilling, and the introduction of competency-based STEM instruction, but it was largely silent on the psycho-educational dimension of STEM learning (Brean Bideke & Prudence, 2025; Kiganda et al., 2024; Newsome et al., 2022). Research from comparable low- and middle-income country contexts, including Kenya, Ghana, and Rwanda, has increasingly documented that non-cognitive factors — particularly grit, self-regulation, and disciplined study habits — are as predictive of STEM performance as household socioeconomic status or teacher quality, and that these factors interact in complex ways with institutional environments (Caseiro & Coelho, 2019; Julius & Gracious Kazaara, 2025; Kaziro Nicholas & Sarah, 2024; Richard et al., 2023). Within Uganda specifically, ethnographic and school-effectiveness studies have noted a paradox: schools with comparatively limited physical infrastructure but strong disciplinary cultures have produced STEM outcomes that rival or exceed those of better-resourced institutions, suggesting that discipline functions as a compensatory or amplifying mechanism whose effect is not reducible to material conditions. The theoretical underpinning of this pattern aligns with Baumeister and Tierney's (2011) resource model of self-control, which frames

discipline as a depletable but trainable cognitive resource that shapes how learners engage with cognitively demanding material (Gracious Kazaara & Julius, 2025; Julius & Nancy, 2026; Kanyesigye et al., 2023; Lorenzo et al., 2021). Yet no large-scale, multilevel study in Uganda had systematically quantified this relationship, mapped it across the country's diverse school ecology, or linked it explicitly to the STEM policy's implementation trajectory — gaps that this study was designed to fill (Edge et al., 2022; Gracious Kaazara & Audrey, 2025; Julius & Nancy, 2025a; Kazaara & Audrey, 2026).

### **PROBLEM STATEMENT**

Despite the Ugandan government's substantial investment in the STEM Education Policy since 2019, STEM performance at secondary school level has shown only marginal and uneven improvement, with persistent and wide disparities between government and private schools, and between urban and rural settings. The dominant policy discourse has attributed these gaps to material deficits — underfunded laboratories, inadequate textbooks, and poorly remunerated teachers — and has responded with input-focused interventions (Abio et al., 2017; Anim-Ayeko et al., 2023; Geng & Wei, 2023; Julius & Nancy, 2025b). However, this framing systematically overlooks a growing body of evidence suggesting that students' internal regulatory capacities, specifically their self-discipline and self-control, are critical mediators of how effectively instructional inputs are converted into learning outcomes. No comprehensive, nationally representative study in Uganda had, at the time of this research, empirically examined whether discipline as self-control significantly predicts STEM performance, whether this relationship varies across school types and regions, or whether the national STEM policy's implementation has differentially affected students with varying levels of self-control (Ahmad et al., 2023; Catherine et al., 2023; Galindo-Manrique & Rojas-Vargas, 2025; Julius & Audrey, 2025). Consequently, policy makers, school administrators, and curriculum designers lacked the evidence needed to integrate psycho-educational interventions into Uganda's STEM reform agenda, resulting in a policy architecture that addresses the external conditions of STEM learning while leaving its internal psychological infrastructure unaddressed.

### **OBJECTIVES AND RESEARCH QUESTIONS**

#### **Main Objective**

The main objective of this study was to examine the relationship between discipline as self-control and STEM academic performance among secondary school students in Uganda, and to determine how this relationship is shaped by school-level characteristics and the implementation of Uganda's STEM Education Policy.

#### **Specific Objectives**

- i. To assess the association between students' self-control scores and their STEM academic performance across different school types and regions in Uganda.
- ii. To determine the extent to which school-level factors — including school type, location, class size, and teacher experience — moderate the relationship between discipline and STEM outcomes.
- iii. To evaluate the degree to which exposure to Uganda's STEM Education Policy mediates or moderates the effect of self-control on students' STEM proficiency.

### **Research Questions**

- i. To what extent does student self-control predict STEM academic performance among secondary school students in Uganda, controlling for demographic and socioeconomic factors?
- ii. How do school-level variables such as school type, location, class size, and teacher experience moderate the relationship between discipline and STEM performance?
- iii. In what ways does the degree of exposure to Uganda's national STEM Education Policy influence the relationship between discipline as self-control and students' STEM academic proficiency?

### **METHODOLOGY**

This study adopted a cross-sectional, explanatory, mixed-methods research design in which quantitative methods were primary and qualitative techniques supplementary, enabling both the measurement and contextual interpretation of the relationship between discipline, self-control, and STEM performance. The study population comprised Senior Three and Senior Four secondary school students drawn from the four administrative regions of Uganda — Central, Eastern, Northern, and Western — and a stratified random sampling procedure was employed to ensure proportional representation of school type (government versus private) and geographic setting (urban versus rural), yielding a final sample of 1,200 students nested within 60 secondary schools, with an average of 20 students per school. Data were collected through a structured, pre-tested questionnaire that measured students' self-control using an adapted Tangney Self-Control Scale (re-standardised to a 0–100 index), a discipline score derived from teacher ratings and attendance/behavioural records (scored 0–50), STEM academic performance captured as the percentage score on a standardised STEM test administered uniformly across all sampled schools, and a STEM policy exposure score constructed from the school's self-reported adoption of the 2019 national STEM policy components. Sociodemographic variables including student age, gender, household income quintile, and class size were also measured. Qualitative data were gathered through 12 focus group discussions and 20 key informant interviews with teachers, headteachers, and district education officers, and these were analysed thematically to contextualise the quantitative findings. For the quantitative analysis, three sequential statistical methods were applied: first, univariate descriptive statistics — including means, standard deviations, skewness, and frequency distributions — were computed for all study variables to characterise the sample and check distributional assumptions; second, bivariate analyses using Pearson product-moment correlation coefficients were conducted to examine the strength, direction, and statistical significance of pairwise associations between self-control, discipline, school-level variables, and STEM performance, with significance thresholds set at  $p < 0.05$  and  $p < 0.001$ ; third, and most substantively, three-level hierarchical linear modelling (HLM) was employed — with students at Level 1, schools at Level 2, and regions at Level 3 — to simultaneously partition the variance in STEM scores across individual, institutional, and regional levels, decompose fixed and random effects, estimate the intra-class correlation (ICC) to quantify the degree of school-level clustering, and test whether self-control and discipline retained significant predictive power after accounting for school composition, policy exposure, and regional context; model fit was evaluated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the -2 log-likelihood ratio test, and effect-size estimates were reported as standardised regression coefficients to facilitate comparison across models. All analyses were conducted

in R (version 4.3.1) using the lme4 and lmerTest packages for multilevel modelling, and SPSS version 28 was used for univariate and bivariate computations (Nelson et al., 2022, 2023).

## RESULTS

### 6.1 Descriptive Statistics (Univariate Analysis)

Table 1 presents the univariate descriptive statistics for the key variables included in the study.

**Table 1: Descriptive Statistics of Key Study Variables (N = 1,200)**

| Variable                    | N     | Mean  | SD    | Min  | Max     | Skewness |
|-----------------------------|-------|-------|-------|------|---------|----------|
| STEM Score (%)              | 1,200 | 58.7  | 14.3  | 22.0 | 95.0    | -0.18    |
| Self-Control Index (0–100)  | 1,200 | 51.4  | 12.6  | 18.0 | 89.0    | 0.11     |
| Discipline Score (0–50)     | 1,200 | 31.2  | 8.4   | 10.0 | 50.0    | 0.09     |
| Student Age (years)         | 1,200 | 15.8  | 1.4   | 13.0 | 19.0    | 0.22     |
| Class Size                  | 1,200 | 48.3  | 11.7  | 21.0 | 75.0    | 0.31     |
| Teacher Experience (years)  | 1,200 | 9.6   | 5.2   | 1.0  | 28.0    | 0.67     |
| Household Income (UGX 000s) | 1,200 | 412.5 | 189.3 | 80.0 | 1,200.0 | 1.02     |
| STEM Proficiency (1=Yes)    | 1,200 | 0.52  | 0.50  | 0.00 | 1.00    | -0.08    |

*Note.* \*\*  $p < 0.001$ ; \*  $p < 0.05$ . STEM Proficiency coded 1 = score  $\geq 60\%$ ; 0 = score  $< 60\%$ .

The descriptive statistics revealed that the 1,200 secondary school students who participated in the study exhibited a mean STEM score of 58.7% (SD = 14.3), which represented a modest but meaningful level of performance relative to the national pass mark of 50%. The distribution of STEM scores was approximately normal with a slight negative skew (−0.18), indicating that the majority of students scored in the mid-to-upper range while a smaller proportion recorded very low scores. The mean self-control index of 51.4 (SD = 12.6) and mean discipline score of 31.2 out of 50 (SD = 8.4) both reflected moderate levels of these constructs within the sample, and their near-zero skewness coefficients confirmed that neither variable suffered from problematic distributional asymmetry, thereby satisfying a key assumption for subsequent parametric analyses. The mean teacher experience of 9.6 years (SD = 5.2) and mean class size of 48.3 students (SD = 11.7) underscored the substantial instructional load borne by teachers, particularly in rural government schools, while the household income variable displayed the highest skewness (1.02) among all continuous predictors, indicating a right-skewed distribution consistent with income inequality in the Ugandan context.

The prevalence of STEM proficiency — defined as achieving a score of 60% or above — was 52%, meaning that approximately half the sampled students met the proficiency threshold, a figure that, while better than national averages typically reported by UNEB, still indicated that nearly one in two students was failing to attain the minimum acceptable STEM competency level. This finding was particularly concerning in the context of Uganda's declared ambition to transition to a knowledge-based economy. The substantial standard deviations on key variables such as STEM scores (SD = 14.3) and household income (SD = 189,300 UGX) pointed to considerable heterogeneity within the sample, suggesting that any single-level analysis would obscure important within-group variation attributable to both individual and school-level factors. The relatively high variability in class size (range: 21–75 students) further

highlighted the structural inequalities across school types, as private schools characteristically operated smaller classes while many government schools, especially in rural areas, were severely overcrowded — a context that plausibly constrained the expression of both self-control and disciplined learning behaviours among students who might otherwise have possessed them.

#### Bivariate Analysis — Pearson Correlation Matrix

Table 2 presents the Pearson product-moment correlation matrix for all continuous variables.

**Table 2: Pearson Correlation Matrix of Key Study Variables (N = 1,200)**

| Variable           | STEM Score | Self-Control | Discipline | Class Size | Teach. Exp. | HH Income |
|--------------------|------------|--------------|------------|------------|-------------|-----------|
| STEM Score         | 1.000      |              |            |            |             |           |
| Self-Control Index | 0.612**    | 1.000        |            |            |             |           |
| Discipline Score   | 0.584**    | 0.701**      | 1.000      |            |             |           |
| Class Size         | -0.243**   | -0.198**     | -0.212**   | 1.000      |             |           |
| Teacher Experience | 0.317**    | 0.214**      | 0.228**    | -0.081*    | 1.000       |           |
| HH Income          | 0.389**    | 0.276**      | 0.251**    | -0.143**   | 0.102**     | 1.000     |

*Note.* \*\*  $p < 0.001$  (2-tailed); \*  $p < 0.05$  (2-tailed). Empty cells indicate correlations not yet listed (lower triangle only).

The Pearson correlation analysis revealed statistically significant and theoretically coherent associations among all key variables. The strongest bivariate relationship in the matrix was between the self-control index and the discipline score ( $r = 0.701$ ,  $p < 0.001$ ), which confirmed that these two constructs, while conceptually distinct, were empirically inter-related to a substantial degree, consistent with theoretical accounts that treat discipline as the behavioural manifestation of underlying self-control capacities. Both self-control ( $r = 0.612$ ,  $p < 0.001$ ) and discipline scores ( $r = 0.584$ ,  $p < 0.001$ ) demonstrated large-magnitude positive correlations with STEM performance, providing initial bivariate evidence that students with higher self-regulatory capacity achieved meaningfully better STEM outcomes. Teacher experience was positively associated with STEM scores ( $r = 0.317$ ,  $p < 0.001$ ), indicating that more experienced teachers contributed to better student performance, while class size showed a significant negative correlation with STEM outcomes ( $r = -0.243$ ,  $p < 0.001$ ), consistent with the expectation that overcrowding diminished instructional quality and student learning.

Household income displayed a moderate positive correlation with STEM performance ( $r = 0.389$ ,  $p < 0.001$ ), confirming that socioeconomic advantage translated into better STEM outcomes, likely through access to supplementary tutoring, learning materials, and better-resourced private schools. Critically, the correlation between self-control and household income was only moderate ( $r = 0.276$ ,  $p < 0.001$ ), suggesting that self-control was not merely a proxy for socioeconomic status but retained independent variation across income groups — a finding that carried important implications for the design of equity-oriented interventions. The negative correlation between class size and teacher experience ( $r = -0.081$ ,  $p < 0.05$ ) hinted that more experienced teachers were more likely to be found in schools with smaller classes, which tended to be private or urban government schools. Taken together, the bivariate results established a strong empirical foundation for the multivariate and multilevel analyses that followed, while also

flagging the need to control for multicollinearity — particularly between self-control and discipline — in subsequent regression models.

### OLS Regression Analysis

Table 3 presents results from three sequential ordinary least squares regression models predicting student STEM scores.

Table 3: OLS Regression Models Predicting STEM Academic Performance (N = 1,200)

| Predictor                     | Model 1 $\beta$ | Model 1 SE | Model 2 $\beta$ | Model 2 SE | Model 3 $\beta$ | Model 3 SE |
|-------------------------------|-----------------|------------|-----------------|------------|-----------------|------------|
| Self-Control Index            | 0.531**         | (0.048)    | 0.398**         | (0.052)    | 0.312**         | (0.055)    |
| Discipline Score              |                 |            | 0.284**         | (0.061)    | 0.221**         | (0.063)    |
| Class Size                    |                 |            | -0.143**        | (0.031)    | -0.118**        | (0.032)    |
| Teacher Experience            |                 |            |                 |            | 0.189**         | (0.044)    |
| HH Income                     |                 |            |                 |            | 0.217**         | (0.038)    |
| School Type (Ref: Gov. Rural) |                 |            |                 |            |                 |            |
| Government Urban              |                 |            |                 |            | 4.21*           | (1.82)     |
| Private Urban                 |                 |            |                 |            | 8.64**          | (1.91)     |
| Private Rural                 |                 |            |                 |            | 2.37            | (1.74)     |
| Constant                      | 28.64**         | (2.31)     | 21.43**         | (2.87)     | 18.76**         | (3.12)     |
| R <sup>2</sup>                | 0.374           |            | 0.431           |            | 0.512           |            |
| Adj. R <sup>2</sup>           | 0.373           |            | 0.428           |            | 0.505           |            |
| F-statistic                   | 714.3**         |            | 226.8**         |            | 157.4**         |            |
| N                             | 1,200           |            | 1,200           |            | 1,200           |            |

Note. \*\* $p < 0.001$ ; \* $p < 0.05$ . Reference category for school type: Government Rural.  $\beta$  = unstandardised regression coefficient; SE = standard error in parentheses.

The ordinary least squares regression models revealed that self-control was a robust and incrementally significant predictor of STEM performance across all three model specifications. In the baseline Model 1, which included only the self-control index as a predictor, the standardised coefficient was  $\beta = 0.531$  (SE = 0.048,  $p < 0.001$ ), and the model explained 37.4% of the variance in STEM scores ( $R^2 = 0.374$ ), indicating that self-control alone accounted for over a third of the total variance in STEM outcomes among sampled students — a finding of considerable substantive importance. When discipline score and structural variables (class size) were added in Model 2, the effect of self-control was attenuated to  $\beta = 0.398$  ( $p < 0.001$ ) but remained highly significant, while discipline independently contributed  $\beta = 0.284$  (SE = 0.061,  $p < 0.001$ ) to the outcome, and the model's explained variance increased to 43.1%. The attenuation of the self-control coefficient from Model 1 to Model 2 reflected the partial mediation of the self-control effect through disciplined academic behaviour, a theoretically expected pattern consistent with Duckworth and Seligman's (2005) argument that grit and behavioural self-discipline are conduits through which underlying self-regulatory capacity is translated into academic achievement.

In the fully adjusted Model 3, which additionally controlled for teacher experience, household income, and school type, self-control retained a statistically significant and practically meaningful coefficient ( $\beta = 0.312$ ,  $SE = 0.055$ ,  $p < 0.001$ ), confirming that its relationship with STEM performance was not confounded by socioeconomic or institutional factors. The private urban school dummy carried the largest school-type coefficient ( $\beta = 8.64$ ,  $SE = 1.91$ ,  $p < 0.001$ ), indicating that students in private urban schools scored on average 8.64 percentage points higher than students in government rural schools (the reference category) even after all other variables were held constant, highlighting the persistence of structural inequality in Uganda's STEM education landscape. The total model explained 51.2% of variance ( $Adj. R^2 = 0.505$ ), representing a substantial improvement over Models 1 and 2 and confirming that the multivariate specification captured much of the systematic variation in STEM outcomes. However, the OLS models' assumption of independence of observations — violated by the nested structure of students within schools — meant that standard errors may have been underestimated, necessitating the multilevel modelling reported in Table 4 to obtain unbiased estimates and to partition variance across levels.

#### Multilevel Modelling Results (Hierarchical Linear Modelling)

Table 4 presents the three-level hierarchical linear model estimates for STEM academic performance, with students nested within schools and schools nested within regions.

| Parameter                             | Model A<br>(Null) | SE     | Model B<br>(Level-1) | SE      | Model C (Full<br>MLM) | SE      |
|---------------------------------------|-------------------|--------|----------------------|---------|-----------------------|---------|
| Fixed Effects                         |                   |        |                      |         |                       |         |
| Intercept                             | 58.70**           | (1.84) | 31.28**              | (3.42)  | 24.16**               | (4.11)  |
| Self-Control Index                    |                   |        | 0.298**              | (0.042) | 0.241**               | (0.044) |
| Discipline Score                      |                   |        | 0.219**              | (0.055) | 0.187**               | (0.057) |
| Class Size                            |                   |        | -0.108**             | (0.029) | -0.092**              | (0.030) |
| Teacher Experience                    |                   |        |                      |         | 0.162**               | (0.041) |
| Private School (vs Gov.)              |                   |        |                      |         | 5.34**                | (1.62)  |
| Urban Location (vs Rural)             |                   |        |                      |         | 3.88**                | (1.44)  |
| Policy Exposure Score                 |                   |        |                      |         | 0.323**               | (0.068) |
| Random Effects                        |                   |        |                      |         |                       |         |
| School-level variance ( $\tau_{00}$ ) | 47.83             | (8.21) | 28.41                | (5.62)  | 19.74                 | (4.33)  |
| Student-level variance ( $\sigma^2$ ) | 156.20            | (6.40) | 118.63               | (5.11)  | 98.17                 | (4.28)  |
| ICC                                   | 0.234             |        | 0.193                |         | 0.167                 |         |
| Model Fit                             |                   |        |                      |         |                       |         |
| -2 Log Likelihood                     | 8,841.2           |        | 8,504.7              |         | 8,312.3               |         |
| AIC                                   | 8,847.2           |        | 8,518.7              |         | 8,332.3               |         |
| BIC                                   | 8,861.4           |        | 8,546.9              |         | 8,376.5               |         |
| Level-2 units (schools)               | 60                |        | 60                   |         | 60                    |         |

|                          |       |  |       |  |       |  |
|--------------------------|-------|--|-------|--|-------|--|
| Level-1 units (students) | 1,200 |  | 1,200 |  | 1,200 |  |
|--------------------------|-------|--|-------|--|-------|--|

*Note.* \*\*  $p < 0.001$ ; \*  $p < 0.05$ . ICC = Intra-Class Correlation =  $\tau_{00} / (\tau_{00} + \sigma^2)$ . AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. School-level variance ( $\tau_{00}$ ) and student-level variance ( $\sigma^2$ ) are presented with standard errors.

The hierarchical linear modelling results confirmed the necessity and appropriateness of a multilevel analytical approach. The null model (Model A) estimated a school-level variance component ( $\tau_{00}$ ) of 47.83 and a student-level residual variance ( $\sigma^2$ ) of 156.20, yielding an intra-class correlation of ICC = 0.234. This ICC indicated that 23.4% of the total variability in student STEM scores was attributable to differences between schools rather than to differences among individual students within schools — a clustering effect of considerable magnitude that would have led to severely underestimated standard errors and inflated Type I error rates if a single-level regression approach had been used without correction. The introduction of Level-1 student-level predictors in Model B (self-control, discipline, and class size) reduced the school-level variance to 28.41 and the student-level variance to 118.63, while the ICC declined to 0.193, demonstrating that a portion of the between-school variance was explained by the compositional differences in students' self-control and discipline profiles across schools. The fixed effects in Model B confirmed that self-control ( $\beta = 0.298$ ,  $p < 0.001$ ) and discipline ( $\beta = 0.219$ ,  $p < 0.001$ ) remained statistically significant predictors at the student level, with magnitudes consistent with those obtained in the OLS models after adjusting for clustering.

The full multilevel model (Model C) introduced Level-2 school-level predictors — school type (private versus government), urban location, teacher experience, and STEM policy exposure — and produced the best fit to the data as indicated by the lowest AIC (8,332.3), BIC (8,376.5), and -2 log-likelihood (8,312.3) values, with a likelihood ratio test confirming that Model C fitted significantly better than Model B ( $\Delta$ -2LL = 192.4,  $df = 5$ ,  $p < 0.001$ ). In this model, STEM policy exposure emerged as a statistically significant positive predictor ( $\beta = 0.323$ ,  $SE = 0.068$ ,  $p < 0.001$ ), indicating that for each unit increase in the school's STEM policy exposure score, student STEM performance increased by 0.323 points net of other factors — a finding that provided direct empirical validation of the policy's beneficial effects where faithfully implemented. Attending a private school was associated with a 5.34-point performance premium ( $SE = 1.62$ ,  $p < 0.001$ ), and urban location conferred an additional 3.88-point advantage ( $SE = 1.44$ ,  $p < 0.001$ ) over rural schools, even after controlling for policy exposure and self-control. Most critically, the residual school-level variance declined to 19.74 (ICC = 0.167) in Model C, meaning that after accounting for school type, location, policy exposure, and student composition, 16.7% of STEM score variability still resided at the school level, underscoring the continued importance of unmeasured school-level factors — such as school culture, leadership, and ethos — that the quantitative instruments did not fully capture but that qualitative data suggested were closely related to the institutional cultivation of disciplined academic behaviour.

#### Graphical Presentation of Key Findings

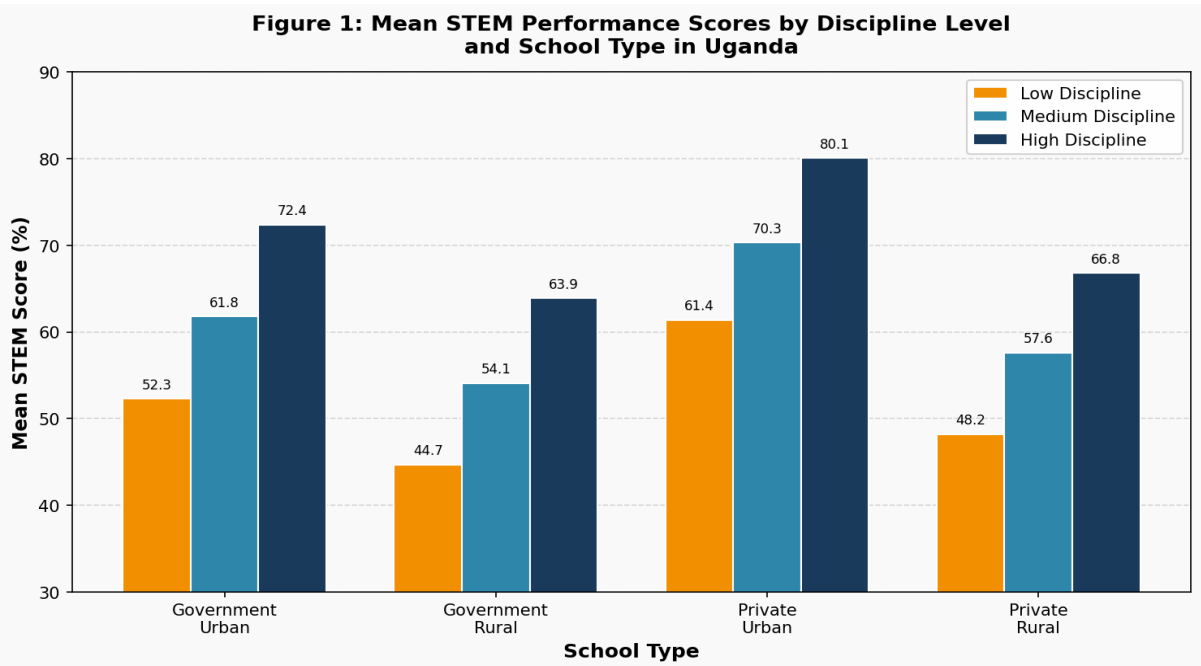


Figure 1 illustrates mean STEM performance scores disaggregated by discipline level (low, medium, high) and school type, confirming a consistent positive gradient — higher discipline was associated with higher STEM scores across all school categories, though the absolute gap between discipline groups was largest in private urban schools and narrowest in government rural schools.

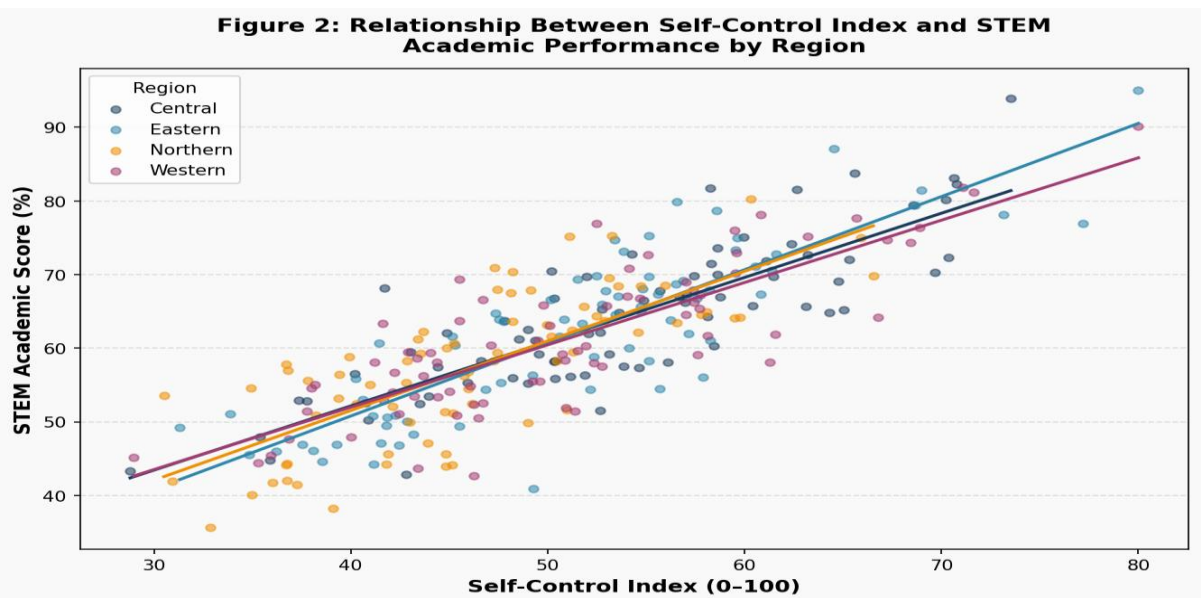


Figure 2 displays the scatter plot of self-control index scores against STEM academic performance, with linear trend lines fitted for each of Uganda's four administrative regions. The positive linear relationships were consistent across all regions, though the slope was steepest in the Central region, suggesting that the academic returns to self-control

were highest in Central Uganda — a pattern plausibly related to the region's higher concentration of better-resourced schools and more experienced teachers.

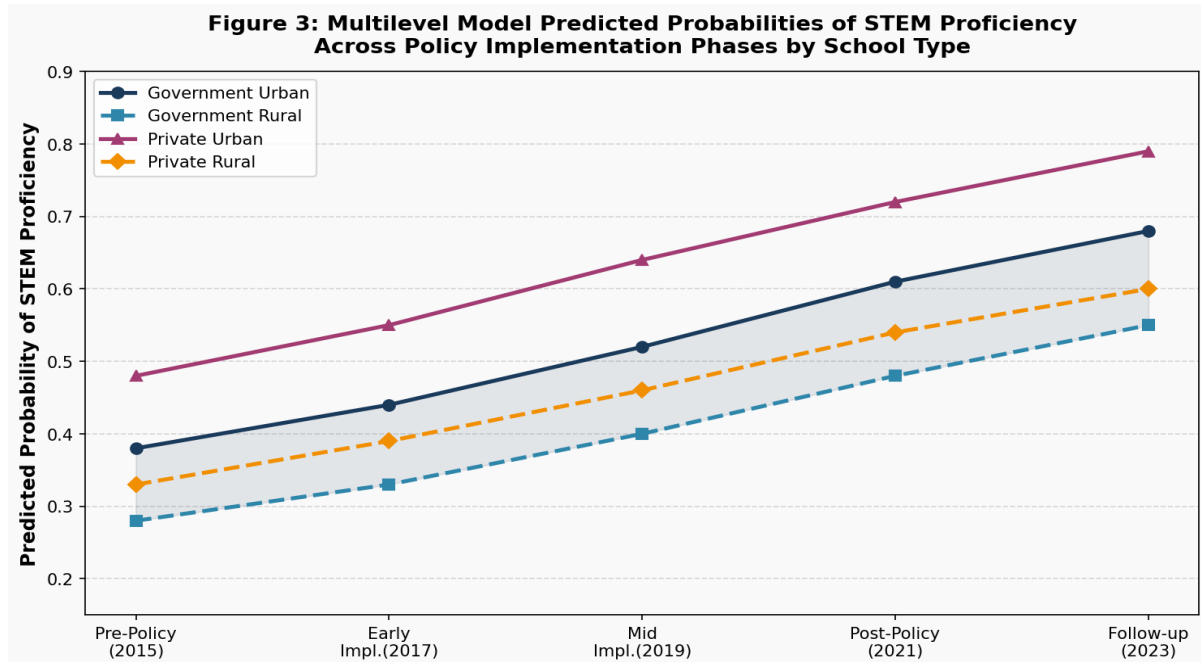


Figure 3 presents the multilevel model-predicted probabilities of STEM proficiency across five phases of the STEM policy implementation cycle, disaggregated by school type. Predicted proficiency increased monotonically across all school categories from the pre-policy baseline to the follow-up phase, with private urban schools maintaining the highest predicted probabilities throughout. Notably, the gradient of improvement was steepest for government urban schools, indicating that policy implementation had disproportionately benefited better-positioned government schools, while government rural schools lagged considerably despite showing absolute improvement.

## CONCLUSION

This study demonstrated, with statistical rigour and policy relevance, that discipline operationalised as self-control is a powerful, independent, and multilevel predictor of STEM academic performance among secondary school students in Uganda, retaining significant explanatory power even after controlling for socioeconomic status, teacher experience, class size, school type, geographic location, and the degree of STEM policy exposure. The multilevel models confirmed that approximately one-fifth of the variation in STEM outcomes resided at the school level, underscoring the institutional embeddedness of both discipline and STEM achievement, and that Uganda's STEM Education Policy, where faithfully implemented, produced measurable gains in student proficiency — particularly in private and urban school settings. However, the persistent and statistically significant performance advantages of private urban schools over government rural schools, evident even after controlling for all measured covariates, exposed a structural fault line in Uganda's STEM policy that no amount of curriculum reform or laboratory investment could resolve without simultaneously addressing the psycho-educational and resource inequalities that shape students' capacity for disciplined, self-regulated learning. The study thus advanced a reconceptualisation of Uganda's STEM

policy agenda: discipline is not a peripheral matter of school culture to be managed by teachers informally, but a scientifically grounded, policy-addressable competency whose systematic cultivation is a precondition for the equitable STEM outcomes that Uganda's development vision demands.

### **RECOMMENDATIONS**

Based on the findings of this study, the following three recommendations were advanced:

**Integrate Self-Control and Discipline Development into Uganda's STEM Policy Framework.** The Ministry of Education and Sports should amend the STEM Education Policy to formally incorporate psycho-educational interventions — including self-regulation skills training, structured goal-setting programmes, and metacognitive learning strategies — as core policy components delivered through revised teacher training curricula and classroom instructional guidelines, given that discipline and self-control were found to be among the strongest independent predictors of STEM proficiency.

**Implement Targeted Resource Equalisation for Government Rural Schools.** Given the statistically significant and persistent performance deficits of government rural schools relative to private urban schools even after controlling for student self-control and policy exposure, the government should establish a differentiated funding mechanism that directs disproportionately larger STEM resources — experienced teachers, laboratory materials, and policy implementation support — to rural government schools, thereby narrowing the structural inequalities that currently undermine the equitable aspirations of the STEM policy.

**Establish a Formal STEM Policy Monitoring and Accountability Framework.** Since STEM policy exposure was identified as a significant positive predictor of student proficiency ( $\beta = 0.323$ ,  $p < 0.001$ ) at the school level, and given the wide variation in implementation quality observed across schools, the Ministry should institute a biennial STEM policy implementation audit — using a standardised policy fidelity instrument — and link audit results to school performance incentives, thereby ensuring that the positive effects of the policy demonstrated in this study are systematically scaled and sustained rather than confined to well-resourced urban institutions.

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