International Journal of Learning, Teaching and Educational Research
Vol. 25, No. 5, pp. 252-282, May 2026
https://doi.org/10.26803/ijlter.25.5.12
Received Feb 22, 2026; Revised Apr 20, 2026; Accepted Apr 21, 2026

Distributional Inequality in Mathematics Achievement: Quantile Regression Evidence from Low-Performing Secondary Schools in Ghana

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Abstract. This study examines how demographic, family, motivational and contextual factors are associated with mathematics achievement across the achievement distribution among students in low-performing public Senior High Schools in Ghana. Using a cross-sectional survey of 725 final-year students, of whom 418 listwise-complete cases were retained for the main ordinary least squares and quantile models, the study estimates quantile regression at the 25th, 50th, and 75th conditional quantiles and interprets the findings through family capital theory and expectancy-value theory. Results show clear heterogeneity across achievement levels. Mathematics self-confidence is a strong positive correlate at the median and upper quantiles, classroom engagement is negatively associated with achievement at the lower and median quantiles, and regional disadvantage is most evident among lower-achieving students in the Middle Belt. The findings show that mean-based estimates can mask important differences across achievement levels and support a distribution-sensitive understanding of mathematics achievement inequality in under-resourced school settings.

Keywords: mathematics achievement; quantile regression; expectancy–value theory; motivation

Citation:
Armah, P. H. (2026). Distributional Inequality in Mathematics Achievement: Quantile Regression Evidence from Low-Performing Secondary Schools in Ghana. *International Journal of Learning, Teaching and Educational Research*, *25*(5), 252–282. https://doi.org/10.26803/ijlter.25.5.12

1. Introduction

Mathematics achievement, commonly assessed through standardised examinations and curriculum-based tests, is a key indicator of educational quality and of how learning opportunities are distributed within an education system (OECD, 2023). In Ghana, provisional results from the 2025 West African Senior School Certificate Examination for School Candidates show that fewer than half of candidates attained grades A1 to C6 in Core Mathematics, where A1 denotes the highest grade and C6 the minimum credit pass often used in tertiary

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admission screening (WAEC, 2025). Weak attainment in mathematics, therefore, matters not only because it constrains further study, but also because it can signal unequal access to effective learning conditions (Hanushek & Woessmann, 2015; UNESCO, 2022; World Bank et al., 2022).

Prior research in Ghana and elsewhere identifies demographic, family, motivational and school-related predictors of mathematics achievement, yet most studies estimate average effects and therefore assume that these relationships operate uniformly across learners (Appiah et al., 2023; Mensah & Koomson, 2020). That assumption can obscure distributional differences, especially in under-resourced settings where students unevenly convert family support, motivation and school conditions into achievement. Quantile regression is useful because it reveals whether predictors differ across the lower, middle nd upper portions of the achievement distribution rather than only at the mean (Hajovsky et al., 2020). Evidence from a recent systematic review of PISA studies and from Australia suggests that contextual effects can indeed vary across the distribution (Perry et al., 2022; Wang et al., 2023).

To interpret such heterogeneity, this study draws on family capital theory and expectancy-value theory. Family capital theory explains how parental education and parental support shape access to learning resources and academic expectations, while expectancy-value theory explains how confidence, value and engagement shape effort and persistence (Coleman, 1988; Eccles & Wigfield, 2020). The study uses these frameworks as complementary analytical lenses to organise the predictor set and interpret quantile-specific associations. It does not test mediation or causal pathways between them.

Ghanaian student-level research has rarely examined whether correlates of mathematics achievement vary across the achievement distribution. Existing inequality-sensitive work has focused more on district disparities or infrastructural inequality than on subject-specific student mathematics outcomes (Agyei et al., 2024; Boadi, 2023). This study, therefore, examines how demographic, family, motivational and contextual factors relate to mathematics achievement at the 25th, 50th, and 75th conditional quantiles among students in low-performing public secondary schools in Ghana. These quantiles were selected to represent lower-, median-, and higher-achieving students while capturing distributional heterogeneity without relying on unstable tail estimates (Hajovsky et al., 2020; Perry et al., 2022).

The study makes two contributions. First, it extends Ghanaian evidence beyond mean-based models, and second, it contributes to the wider literature on distributional inequality in under-resourced school settings. Three questions guide the analysis: (1) which correlates are associated with achievement at each quantile; (2) which correlates are more salient at lower, median, and higher points of the distribution; and (3) what these patterns imply for a distribution-sensitive interpretation of mathematics achievement inequality in low-performing school contexts.

2. Literature Review and Theoretical Framework

This section reviews relevant empirical literature on mathematics achievement and then outlines the theoretical framework guiding the analysis.

2.1 Family Capital Theory and Empirical Support

Family capital theory holds that parental education, aspirations and involvement shape achievement through the transmission of human, social, and cultural resources (Coleman, 1988). Empirical studies generally show that supportive home environments, parental education and academically oriented routines are associated with stronger achievement, although the magnitude and direction of these associations vary across contexts and forms of involvement (Bofah & Hannula, 2017; Castro et al., 2020; Fan & Chen, 2001; Hanushek & Woessmann, 2011).

Two cautions are important, however. First, family capital is often measured using coarse proxies, such as parental education or general involvement, which may obscure differences among autonomy-supportive guidance, monitoring and reactive supervision (Harris & Robinson, 2016; Hill & Tyson, 2009; Pomerantz et al., 2007). Second, the conversion of family resources into achievement depends partly on school conditions. Where school routines, teaching quality, or student support are weak, the academic return to family resources may be reduced (Berkowitz et al., 2017; Larson et al., 2020; Wang & Degol, 2016).

Accordingly, the present study treats parental education and parental support as distinct constructs and includes school climate and regional location as contextual conditions. This specification allows the analysis to assess whether family-related predictors operate differently across the achievement distribution, rather than assuming that home resources yield uniform returns for all learners. Recent PISA 2022 analyses across Singapore, Korea, Finland and Denmark likewise show that student- and school-level mathematics correlates vary across systems (Niu et al., 2025). Research also suggests that family capital shapes motivational beliefs.

Students from more advantaged homes often report stronger self-concept, value, and enjoyment of mathematics, whereas parental involvement in adolescent samples may intensify after underperformance becomes visible (Davis-Kean, 2005; Erdem & Kaya, 2020; Marsh et al., 2019; Yang et al., 2024). Distributional studies further show that socioeconomic and contextual disadvantage often weigh more heavily on lower achievers than on their higher-achieving peers (Costanzo & Desimoni, 2017; Flannery et al., 2023; Molina-Muñoz et al., 2025; Wu & Tian, 2008). The same concern is reflected in PISA 2022, which foregrounds learning and equity together in the analysis of achievement differences across education systems (OECD, 2023).

2.2 Expectancy-Value Theory and Empirical Support

Expectancy-value theory complements this structural perspective by explaining why students invest effort in mathematics. It proposes that achievement behaviour is shaped by beliefs about expected success and by the value students attach to the task (Eccles & Wigfield, 2020). Empirical studies consistently identify confidence, value, and enjoyment as correlates of mathematics achievement, although their effects often depend on context and on how closely they are linked to performance (Marsh et al., 2019; Peixoto et al., 2024). This interpretation aligns with the classic synthesis of expectancy-value theory and its later situated extension (Eccles & Wigfield, 2002, 2020).

Two cautions also apply to expectancy-value theory in this study. Because the design is cross-sectional, motivational variables are treated as correlates rather than as directional causes, and reciprocal relationships remain plausible. In addition, motivational beliefs are not assumed to operate independently of context. Their academic returns may be constrained in settings characterised by weak instructional support or broader school disadvantage (Eccles & Wigfield, 2020; Wang & Degol, 2016). From this standpoint, confidence, value, enjoyment and engagement are treated as context-sensitive motivational dispositions rather than as universally effective predictors. A distributional approach is therefore appropriate because it allows the study to assess whether these motivational correlates are weaker among lower achievers and stronger once basic competencies are more secure.

2.3 Towards a Conceptual Framework Integrating Structural and Motivational Explanations

Taken together, family capital theory and expectancy-value theory provide a coherent framework for examining mathematics achievement as the outcome of structural resources, motivational dispositions, and school context. The integration is analytical rather than causal. The study does not test mediation between family capital and motivation. Instead, it uses both frameworks to organise the predictor set and to assess whether associations vary across the achievement distribution. The model, therefore, groups related predictors; it does not test mediation or directional pathways between family capital and motivation.

Figure 1 offers a concise summary of this analytical framework. It places achievement at the intersection of demographic and family background, motivational dispositions and contextual conditions, and it supports the use of quantile regression to compare associations across the lower, median and upper parts of the distribution. The following section explains how these relationships were examined empirically. In this study, lower, middle and higher achievers correspond to the 25th, 50th, and 75th conditional quantiles, respectively.

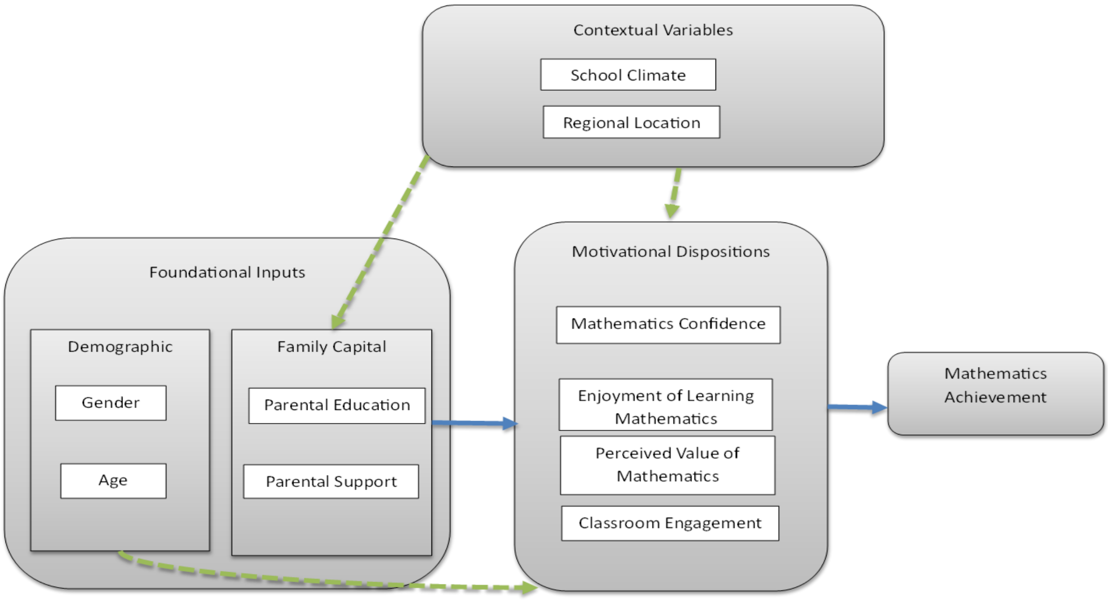


Figure 1: Conceptual framework for study

Note. The framework shows how structural variables (demographic and family capital factors) influence motivational dispositions (expectancy–value factors) within contextual settings, together determining students' mathematics achievement.

3. Methodology

3.1 Research Design and Sample

This study used a cross-sectional survey of final-year Senior High School students in Ghana. Data were collected from 725 students in purposively selected public schools in the Southern Zone, Middle Belt and Northern Zone. These schools had been identified within a national education improvement programme as persistently weak-performing in Core Mathematics and related learning outcomes. The focus on these schools was deliberate, as the study sought to examine distributional patterns of achievement in contexts where learning difficulties were already pronounced. Mathematics achievement scores were available for 712 students.

After screening and removing two implausible age values, and applying listwise deletion across the full predictor set, the main OLS and quantile models were estimated on 418 students. Because students were nested within schools, the estimates should be interpreted with caution. The findings are most applicable to similar low-performing public-school contexts rather than to all secondary schools in Ghana. The design captured achievement and correlates at a single point near completion of SHS, after students had experienced most of the Core Mathematics curriculum and shortly before the WASSCE. Purposive selection was used to focus the analysis on low-performing public-school contexts, where distributional inequality is substantively and policy-relevant.

3.2 Instrument Development and Validation

Items were adapted from established measures of mathematics motivation and school climate, with minor wording adjustments for Ghanaian Senior High School students. Three experts in mathematics education and educational measurement reviewed the instrument for construct alignment and contextual appropriateness, and a pilot with 50 students was used to refine wording. The questionnaire employed a four-point forced-choice Likert-type scale ranging from 1 (Strongly Disagree) to 4 (Strongly Agree), with no neutral option. Negatively worded items were reverse-coded, and composite indices were computed as mean scores for each construct. The analysis retained this original coding and treated the composite indices as approximately continuous, consistent with common practice for aggregated Likert measures (Carifio & Perla, 2008; Norman, 2010; Rhemtulla et al., 2012).

Construct validity was assessed using confirmatory factor analysis of the item-level indicators. A six-factor model was specified for parental support, school climate, enjoyment, value, mathematics self-confidence and classroom engagement, with correlated latent factors. Indicators with negative loadings or loadings below 0.40 were removed where construct coverage was preserved. Six items were excluded, namely Q7b, Q8b, Q8g, Q9e, Q9g and Q9h, because they did not function as intended, reflecting reverse-wording artefacts, distraction or instructional provision, and anxiety or comparative difficulty rather than expectancy for success. The refined model was estimated on complete cases for the retained indicators (N = 533) and showed acceptable fit, $\chi 2(260) = 554.804$, CFI = 0.924, TLI = 0.912, RMSEA = 0.046. Standardised loadings in the refined model ranged from 0.408 to 0.825 across constructs. Reliability of the refined composite scales is reported using Cronbach's alpha and McDonald's omega in Table 1.

3.3 Outcome Measure – Mathematics Achievement

The dependent variable was achievement in a standardised mathematics mock examination administered across participating schools prior to the 2024 West African Senior School Certificate Examination (WASSCE). The test covered the Senior High School (SHS) Core Mathematics curriculum, including algebra, geometry, trigonometry and statistics, and was scored out of 100. Scores ranged from 10 to 90 (M = 44.5, SD = 15.9), indicating generally low achievement. The distribution was approximately symmetric (skewness = 0.17, kurtosis = 0.42), supporting the use of quantile regression.

3.4 Predictors and Measures

Predictors were grouped into demographic, family, motivational and contextual domains. Parental education and parental support represented family capital, enjoyment, value, confidence and classroom engagement represented motivational dispositions, and school climate and geographic zone captured contextual conditions. Table 1 reports the reliability of the composite scales. Because the school climate index is brief and has low internal consistency ($\alpha = .50$; $\omega = .50$), its coefficients are treated cautiously and should not be over-interpreted. In this study, classroom engagement refers to students' reported attention, interest, participation and perceived responsiveness to classroom tasks and teacher expectations. It is therefore broader than behavioural effort alone.

Table 1: Variables, descriptions and reliability of composite scales

Domain	Variable	Description / Example Item	Scale Range / Coding	Cronbach's α	McDonald's ω
Family Capital	Parental Education	Index of highest parental education (0 = none/primary to 4 = university)	Ordinal index	Not applicable	Not applicable
	Parental Support	4 items (e.g., "My parents check if I have done my homework") covering homework supervision, lesson discussion, and encouragement	1–4 Likert	0.76	0.77
Motivational Factors (EVT)	Enjoyment of math	3 items (e.g., "I enjoy learning mathematics") capturing enjoyment of mathematics	1–4 Likert	0.79	0.80
	Value of Mathematics	5 items (e.g., "I need mathematics to get the job I want") measuring perceived importance and utility	1–4 Likert	0.70	0.77
	Mathematics Self-Confidence	6 items (e.g., "I usually do well in mathematics") assessing expectancy for success	1–4 Likert	0.79	0.80
	Classroom Engagement	4 items (e.g., "I am interested in what my mathematics teacher says") capturing effort, attention, and participation	1–4 Likert	0.67	0.70
Contextual Variable	School Climate index	3 items (e.g., "I feel safe when I am in school") assessing perceived safety and teacher–student relations	1–4 Likert	0.50	0.50

Note. Items were coded so that higher scores indicate greater levels of the construct, and reverse-coded items were recoded before scale construction. Internal consistency is reported using Cronbach's alpha and McDonald's omega.

School climate is a brief three-item index assessing perceived school safety, belonging and general school enjoyment, so reliability coefficients should be interpreted cautiously given the limited item coverage.

3.5 Procedure and Data Collection

Data were collected with the cooperation of school administrators. The mock mathematics examination was administered in June 2024 under standardised conditions and scored out of 100 using a common marking scheme. Scripts were graded by subject teachers. Within one week of the examination, students completed the questionnaire during a class period. Participation was voluntary and anonymous. Coded identifiers were used to link examination scores to questionnaire responses without recording names. Of 800 targeted students, 725 provided matched examination and questionnaire records after excluding non-respondents and cases missing either component, yielding a usable response rate of 90.6 per cent. These 725 cases formed the initial dataset for subsequent screening.

3.6 Data Screening and Diagnostics

Item-level missingness ranged from 0.1 per cent to 21.4 per cent. Missingness was highest for mathematics self-confidence and parental education. Missing data patterns were examined using Little's MCAR test, and the main analyses were based on complete cases. This choice reduced the analytic sample substantially. No formal sensitivity analysis was undertaken. The smallest variable-specific N was 570 for mathematics self-confidence, but the main OLS and quantile models used 418 listwise-complete cases across all model variables. Listwise deletion was retained to preserve one common analytic sample across the OLS and full quantile models, although descriptive statistics continued to use all available cases per variable. The estimates should therefore be interpreted with caution, as non-trivial missingness may still have affected precision and inference (Enders, 2010; Schafer & Graham, 2002).

The CFA sample differed because it required complete responses on the retained indicators. The supplementary moderation models reported in Appendices 3 and 4 used a larger case base (N = 568) because they required non-missing values for the interaction terms and associated covariates, rather than complete data for all predictors in the full main model. The moderation estimates should therefore be read as supplementary analyses based on a different admissible-case sample, not as a contradiction of the 418-case analytic base used for the main OLS and quantile models. To assess multicollinearity, an ordinary least squares model including all predictors was estimated. Variance inflation factors ranged from 1.08 to 1.82, and tolerance values exceeded 0.54, indicating no multicollinearity concerns (Field, 2018). The condition index was 27.7, below the conventional threshold of 30 (Tabachnick & Fidell, 2019). Outlier screening indicated no achievement scores more than three standard deviations from the mean.

3.7 Analytical Approach

Analyses began with descriptive statistics and bivariate correlations, followed by an ordinary least squares model as a mean-based baseline. The main analysis then estimated quantile regression models at the 25th, 50th, and 75th percentiles to assess whether the effects of the predictors differed across lower-, median-, and higher-achieving groups. Quantile regression was appropriate because heterogeneity across the achievement distribution was central to the study's research aim. Models were estimated using the simplex algorithm with 1,000 bootstrap replications to obtain robust standard errors and 95 per cent confidence intervals. Model performance was summarised using pseudo R-squared and mean absolute error for each quantile. The analysis did not implement multilevel quantile models or cluster-adjusted standard errors, so school-level clustering remains a limitation when interpreting statistical precision. All analyses were conducted in IBM SPSS Statistics Version 28 using two-tailed tests with α = 0.05. A single-level specification was retained because the analysis was designed as an exploratory quantile model within the study's estimation framework.

3.7.1 Quantile Regression Specification
For student i, the conditional τth quantile of mathematics achievement was modelled as:

$$Q_\tau(Y_i \mid X_i) = \beta_{0,\tau} + \beta_{1,\tau}\,\text{Male}_i + \beta_{2,\tau}\,\text{Age}_i + \beta_{3,\tau}\,\text{ParSup}_i + \beta_{4,\tau}\,\text{ParEdu}_i \\ + \beta_{5,\tau}\,\text{Conf}_i + \beta_{6,\tau}\,\text{Enjoy}_i + \beta_{7,\tau}\,\text{Value}_i + \beta_{8,\tau}\,\text{Engage}_i \\ + \beta_{9,\tau}\,\text{Climate}_i + \beta_{10,\tau}\,\text{MiddleBelt}_i + \beta_{11,\tau}\,\text{North}_i.$$

Here, Qτ(Yi | Xi) denotes the τth conditional quantile of the mathematics score for student i given covariates Xi. Male is a gender dummy, Age is measured in years, ParSup and ParEdu capture family capital, Conf, Enjoy, Value, and Engage represent motivational dispositions, Climate captures perceived school climate, and Middle Belt and Northern Zone are regional dummies, with Southern Zone as the reference category. Coefficients were estimated separately for τ = 0.25, 0.50, and 0.75.

3.7.2 Supplementary Moderation Analysis
To deepen contextual interpretation of the motivational predictors, supplementary quantile regression models were estimated that included interaction terms between mathematics self-confidence and school climate and between classroom engagement and school climate at the 25th, 50th, and 75th quantiles. Predictors were mean-centred prior to computing product terms to improve the interpretability of main effects. Interaction coefficients were examined to assess whether the conditional association between the motivational predictor and achievement varies with perceived school climate at a given point in the distribution (Koenker & Hallock, 2001). These supplementary tests were used to assess the potential context sensitivity of motivational associations rather than to extend the primary research questions.

4. Results

4.1 Descriptive Statistics and Preliminary Analysis

Descriptive statistics are reported using all available cases per variable. The N = 570 shown for mathematics self-confidence in Table 2 is therefore a variable-specific count, not the listwise sample for the main OLS and quantile models. The main OLS and quantile models use the listwise-complete analytic sample (N = 418) after screening. Table 2 reports descriptive statistics for the study variables and Figure 2 shows the distribution of mathematics mock examination scores. Scores ranged from 10 to 90, with a mean of 44.5 (SD = 15.9), indicating generally low achievement in the sampled low-performing schools. The 25th and 75th percentiles were approximately 33 and 55, indicating that even higher-achieving students typically scored in the mid-50s. Approximately 18 per cent of students scored above 60, while about 25 per cent scored below 33. This dispersion supports a distributional approach that examines whether predictors operate differently across lower, middle and higher achievers, rather than relying solely on mean effects.

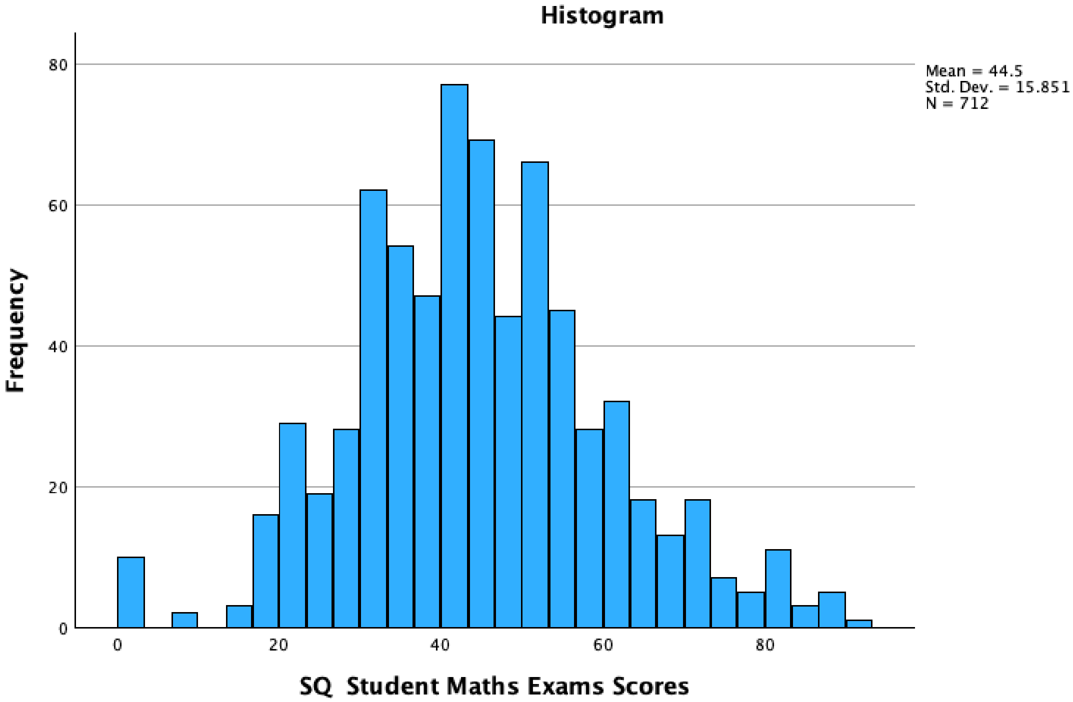


Figure 2: Distribution of students' mathematics mock examination scores

Note. The histogram displays the distribution of mathematics scores (N = 712). Vertical markers at the 25th, 50th, and 75th percentiles illustrate the spread of achievement, supporting the use of quantile regression.

Students reported moderate levels of motivational dispositions, including confidence (M = 2.7), enjoyment (M = 2.8), and perceived value (M = 3.1) on 1 to 4 scales, alongside comparatively high reported engagement (M = 3.3). Family capital indicators showed moderate parental support (M = 2.5) and low-average parental education (M = 1.0 on a 0-4 scale). Approximately 52 per cent of students were male, and the mean age was 18.5 years. Zero order correlations, not tabled, showed that achievement was positively associated with confidence ($r \approx .45$) and gender ($r \approx .15$) and negatively associated with age ($r \approx -.20$).

Engagement was weakly negative ($r \approx -.12$, $p < .01$), and parental support was close to zero ($r \approx -.05$, not significant), while parental education was weakly positive ($r \approx .10$). These patterns suggest that expectancy-related beliefs are more strongly aligned with achievement than family indicators in bivariate terms, while the negative association for engagement warrants careful interpretation given that the engagement measure partly reflects classroom processes that may intensify in response to underachievement.

Table 2: Descriptive statistics for model constructs

Construct	Variable	N	Mean	SD	Min	Max
Mathematics Achievement	Exam score (0–100; analytic 10–90)	712	44.50	15.90	10	90
Demographic Variables	Age (years)	713	18.50	1.10	16	21
	Gender (0 = female, 1 = male)	717	0.52	0.50	0	1
Family Capital	Parental support (1–4)	657	2.50	0.80	1.00	4.00
	Parental education (0–4)	610	1.00	0.90	0.00	4.00
Motivational Dispositions	Mathematics confidence (1–4)	570	2.70	0.65	1.00	4.00
	Enjoyment of mathematics (1–4)	626	2.80	0.63	1.00	4.00
	Perceived value of mathematics (1–4)	656	3.10	0.55	1.00	4.00
	Classroom engagement (1–4)	619	3.30	0.70	1.00	4.00
Contextual Factors	School climate (1–4)	664	2.80	0.75	1.00	4.00
	Middle Belt Zone (0–1)	724	0.40	0.49	0	1
	Northern Zone (0–1)	724	0.20	0.40	0	1

4.2 Model Fit and Overview

Table 3 reports model diagnostics for the quantile regression models estimated on the listwise-complete full-model sample (N = 418). Pseudo R-squared values increased from .070 at the 25th quantile to .106 at the 75th quantile, while MAE was lowest at the median quantile. These results indicate that the predictor set provides greater explanatory leverage among higher-achieving students than among lower-achieving students, although pseudo-R-squared values should be interpreted as descriptive measures of model fit rather than as directly comparable measures of variance explained across quantiles.

Table 3: Model diagnostics for quantile regression models

Quantile (τ)	Pseudo R^2	MAE
0.25	0.070	14.28
0.50	0.084	11.59
0.75	0.106	14.14

4.2.1 Baseline Ordinary Least Squares (OLS) Regression

Table 4 presents the baseline OLS model estimated on the same listwise-complete full-model sample (N = 418). Mathematics confidence was the strongest positive predictor. Parental support, classroom engagement and Middle Belt location were negatively associated with achievement. Parental education, enjoyment of mathematics, and perceived value of mathematics were not statistically significant. Gender and age were also not statistically significant in the aligned OLS model. School climate and Northern Zone were positive but only marginal.

These mean-based estimates provide a benchmark for interpreting the quantile-specific coefficients.

Table 4: Ordinary least squares regression (OLS) predicting mathematics achievement

Predictor	B	SE	t	P
Demographic Variables				
Gender (male = 1)	1.90	1.56	1.22	.223
Age (years)	−0.74	0.50	−1.48	.141
Family Capital				
Parental Support	−2.07	1.01	−2.04	.042
Parental Education	0.24	0.92	0.26	.793
Motivational Dispositions				
Mathematics Confidence	6.28	1.44	4.38	< .001
Enjoyment of Mathematics	1.81	1.63	1.11	.267
Perceived Value of Mathematics	−2.23	1.56	−1.43	.153
Classroom Engagement	−4.49	1.53	−2.93	.004
Contextual Factors				
School Climate	2.90	1.53	1.89	.059
Middle Belt Zone	−6.87	2.38	−2.89	.004
Northern Zone	3.50	1.86	1.88	.060
Model Statistics				
R^2	.148			
Adjusted R^2	.125			
F(11, 406)	6.429		< .001	
N	418			

4.3 Quantile Regression Results

Quantile regression estimates associations between each predictor and specific points in the conditional achievement distribution. Coefficients represent the expected difference in the τth conditional quantile of mathematics scores associated with a one-unit change in a predictor, holding other variables constant. The results therefore describe distributional heterogeneity in conditional associations rather than causal effects.

4.3.1 Demographic Variables

Gender and age effects were most evident at the median quantile. At $\tau = 0.50$, males scored 4.83 points higher than females ($p = .005$), and each additional year of age was associated with a 1.49-point lower median score ($p = .007$). At $\tau = 0.25$ and $\tau = 0.75$, these coefficients were smaller and not statistically significant, indicating that demographic differences were concentrated around the centre of the achievement distribution rather than among the lowest- or highest-achieving students.

4.3.2 Family Capital

Family capital variables showed limited direct association with achievement once motivational variables and context were included. Parental support displayed a negative coefficient at all quantiles and was statistically significant only at $\tau = 0.50$

(B = −2.66, $p = .017$). This pattern is consistent with reactive monitoring, where higher reported supervision co-occurs with lower achievement, but it should be interpreted cautiously because cross-sectional data cannot distinguish reactive involvement from ineffective or misaligned involvement. Parental education was not statistically significant at any quantile. Given the purposive sample of low-performing schools, restricted variation in family resources, and measurement coarseness may have limited detectable associations. The results therefore suggest that any family background influence in this dataset is more likely to operate indirectly through proximal dispositions and classroom processes than through large conditional direct effects. This does not, however, imply that parental support is inherently detrimental. Rather, the negative coefficient may reflect the timing or form of involvement, a point taken up more fully in the Discussion section.

4.3.3 Motivational Dispositions

Motivational variables exhibited the most pronounced heterogeneity across quantiles. Mathematics confidence was strongly positive at $\tau = 0.50$ (B = 7.53, $p < .001$) and $\tau = 0.75$ (B = 6.06, $p = .006$), but not statistically significant at $\tau = 0.25$. This pattern suggests that confidence differentiates median and higher achievers more clearly than lower achievers, which is consistent with the possibility that expectancy beliefs become more consequential once a basic level of competence has been secured. Classroom engagement showed a significant negative association at $\tau = 0.25$ (B = −4.05, $p = .026$) and $\tau = 0.50$ (B = −5.23, $p = .002$), with attenuation and non-significance at $\tau = 0.75$.

The coefficient should be interpreted cautiously. It may reflect compensatory classroom effort among struggling students, but it may also reflect measurement overlap between student behaviour and perceived instructional processes. Because the design is cross-sectional, reverse causality cannot be ruled out. Enjoyment and perceived value were not statistically significant at any quantile once confidence and engagement were included. Their conditional associations are therefore not distinguishable from zero in the presence of the other predictors in this model.

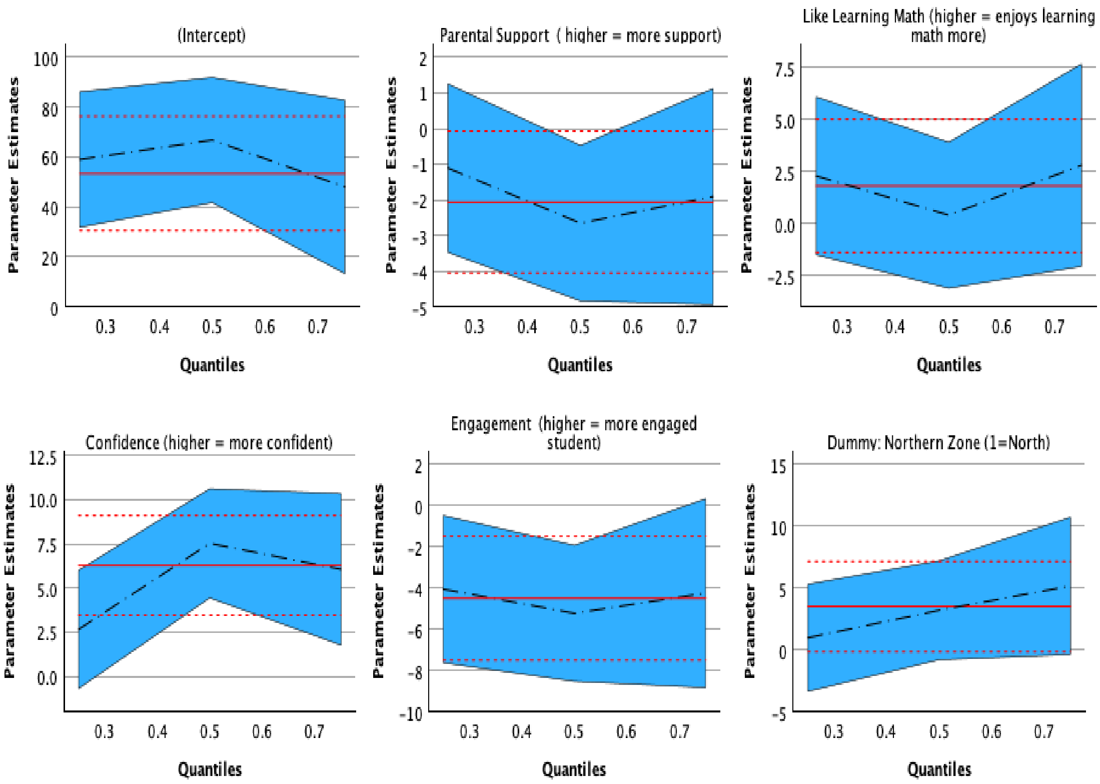
4.3.4 Contextual Factors

Contextual influences operated as expected in the model. School climate had positive but statistically non-significant coefficients across quantiles. Given the brevity and modest reliability of the climate index, along with the likelihood of limited variation within the sampled schools, the estimates may be imprecise, and the absence of statistical significance should be interpreted with caution. Regional location showed clearer distributional patterning. The Middle Belt coefficient was large and negative at $\tau = 0.25$ (B = −9.87, $p < .001$) and remained negative at $\tau = 0.50$ (B = −5.17, $p = .048$) but was not statistically significant at $\tau = 0.75$. This implies that regional disadvantage was concentrated among lower-achieving students, while higher achievers were less differentiated by zone. The Northern Zone was not statistically significant at any quantile, though the $\tau = 0.75$ estimate was positive and marginal (B = 5.18, $p = .068$), indicating a suggestive but imprecise pattern rather than a reliable advantage.

Table 5: Summary of quantile patterns

Construct	τ = 0.25	τ = 0.50	τ = 0.75
Demographic Variables	Gender ns; Age −1.10 (ns)	Gender 4.83**; Age −1.49**	Gender ns; Age ns
Family Capital	Support −1.10 (ns); Education ns	Support −2.66*; Education ns	Support ns; Education ns
Motivational Dispositions	Confidence ns; Engagement −4.05*; Value ns	Confidence 7.53***; Engagement −5.23**; Value ns	Confidence 6.06**; Engagement −3.51 (ns); Value ns
Contextual Factors	Middle Belt −9.87***; North ns	Middle Belt −5.17*; North ns	Middle Belt ns; North 5.18 (p = .068)

*Note. Values are unstandardised coefficients (B). ns = non-significant. *p < .05. **p < .01. ***p < .001.*



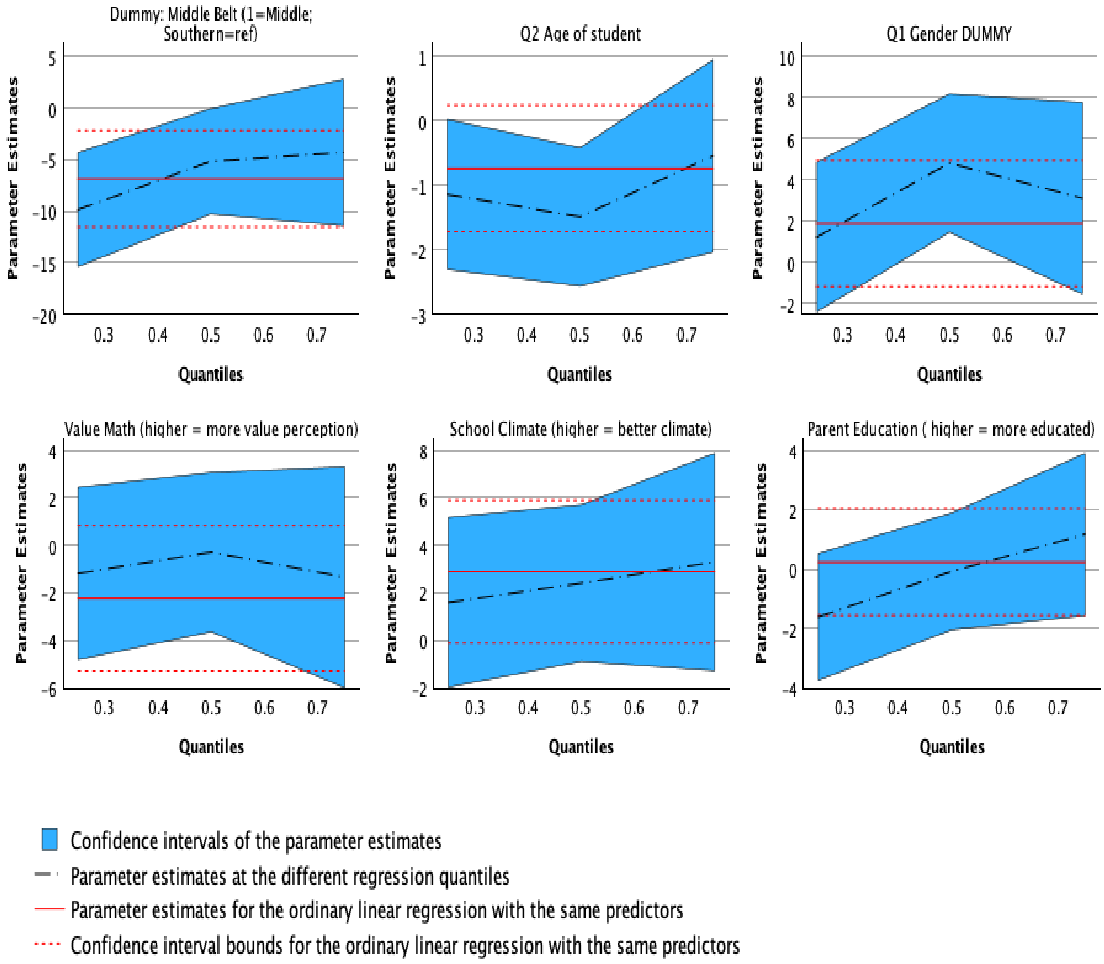


Figure 3: Quantile regression coefficients for predictors of mathematics achievement (τ = .25, .50, .75)

Note. The figure shows quantile regression coefficients and bootstrapped 95 per cent confidence intervals at τ = 0.25, 0.50, and 0.75, alongside the ordinary least squares coefficient for comparison. The coefficients indicate conditional associations that vary across the achievement distribution. Mathematics confidence increases in magnitude and precision toward the median and upper quantiles, whereas the Middle Belt disadvantage is concentrated at the lower quantiles. Engagement is negative at the lower and median quantiles, consistent with compensatory dynamics and the measure's content in low-performing settings.

Table 6: Comparison of ordinary least squares and quantile regression estimates across the achievement distribution

Predictor	**OLS (mean)**	**τ = 0.25**	**τ = 0.50**	**τ = 0.75**
Gender (male = 1)	1.90 (ns)	ns	4.83**	ns
Age (years)	−0.74 (ns)	−1.10 (ns)	−1.49**	ns
Parental support	−2.07*	−1.10 (ns)	−2.66*	ns
Parental education	0.24 (ns)	ns	ns	ns
Mathematics confidence	6.28***	ns	7.53***	6.06**
Enjoyment of mathematics	1.81 (ns)	ns	ns	ns
Perceived value of mathematics	−2.23 (ns)	ns	ns	ns
Classroom engagement	−4.49**	−4.05*	−5.23**	−3.51 (ns)
School climate	2.90 (p = .059)	ns	ns	ns
Middle Belt Zone	−6.87**	−9.87***	−5.17*	ns
Northern Zone	3.50 (p = .060)	ns	ns	5.18 (p = .068)

*Note. Values are unstandardised coefficients (B). OLS coefficients represent mean associations. Quantile regression coefficients represent conditional associations at the 25th, 50th, and 75th percentiles. ns = non-significant. *p < .05. **p < .01. ***p < .001.*

Table 6 provides a compact comparison of the OLS and quantile estimates. Appendix 5 reports the full quantile coefficients, standard errors, p values, and 95 per cent confidence intervals for τ = 0.25, 0.50, and 0.75.

4.3.5 Supplementary Moderation Analysis

Supplementary interaction models provide no robust evidence that perceived school climate moderates the associations between self-confidence or engagement and achievement across quantiles; therefore, the moderation results are reported in Appendices 3 and 4.

5. Discussion

5.1 Key Findings in the Theoretical Context

Taken together, the results show that key predictors do not exert uniform effects across the achievement distribution, thereby advancing Ghanaian research on mathematics achievement. The quantile estimates indicate a systematic shift in explanatory importance: structural and contextual constraints are more pronounced at the lower end of the distribution, whereas mathematics self-confidence emerges as the primary positive correlate at the median and upper quantiles. This pattern is consistent with the combined use of family capital theory and expectancy-value theory. The theoretical contribution lies in showing that structural and motivational correlates vary in salience across achievement levels rather than operating with constant effects at the mean. More broadly, the study contributes to international work on educational inequality in under-resourced systems by showing why mean-based estimates can miss distributional differences, although the evidence remains associational. The pattern is also consistent with work on learning barriers in under-resourced systems, where weak foundational skills, uneven instructional quality, and constrained academic support can intensify underperformance among already vulnerable learners (Ayebale et al., 2020; Bashir et al., 2018).

5.2 Demographic Characteristics

Gender and age effects are most evident around the centre of the distribution rather than at the extremes. A median advantage for males is consistent with evidence that gender gaps in mathematics can be mediated by differences in self-concept, confidence, and exposure to performance-affirming cues, even when average achievement gaps are modest or inconsistent across contexts (Else-Quest et al., 2010). The concentration of the gender effect at the median suggests that gendered differences may be most consequential for students who are neither persistently struggling nor already outperforming peers. For high achievers, selection processes and stronger academic supports may compress gender differences, while for low achievers, structural barriers may dominate the variance in performance.

The negative association between age and achievement at the median is consistent with the interpretation that over age status may proxy delayed entry, repetition, interrupted progression, or cumulative disengagement, all of which can weaken academic momentum, reflecting broader evidence on age for grade heterogeneity and grade repetition dynamics in sub-Saharan Africa (Carew et al., 2024; Sunny et al., 2017). However, because age is not randomly assigned and the design is cross-sectional, the coefficient should be interpreted as a conditional association rather than a developmental effect. In low-performing school contexts, age can also capture hidden heterogeneity in prior learning opportunities and school histories, not simply maturational differences.

5.3 Family Background and Parental Involvement

The absence of a direct parental education effect across quantiles may reflect limited variability in socioeconomic resources within a purposive sample of under-resourced schools and the fact that parental education is a coarse proxy that does not distinguish the mechanisms through which families shape achievement. Meta-analytic and recent empirical evidence indicates that parental involvement is multidimensional and that its association with achievement depends on the form it takes and learners' developmental stage (Amponsah et al., 2018; Castro et al., 2020; Hidayatullah & Csíkos, 2023; Hill & Tyson, 2009).

This helps explain why parental support shows a negative association at the median quantile in the present study. In low-achievement contexts, parental monitoring may intensify after underperformance becomes visible, making involvement appear negatively related to scores because it is reactive rather than preventive. The negative coefficient for parental support is not without precedent in the literature. Prior studies suggest that parental involvement may show weak or negative associations with achievement when it is reactive to prior underperformance, heavily homework-focused, or experienced as controlling rather than autonomy-supportive (Li & Hamlin, 2019; McNeal, 2012; Pomerantz et al., 2007; Xu et al., 2024). This interpretation is plausible, but the data do not test it directly. Coarse measurement and unobserved household strain may also contribute to the pattern. The practical implication is therefore not simply to increase parental monitoring, but to promote forms of support that are academically structured, autonomy-supportive and better aligned with students' actual learning needs.

A further implication concerns measurement. When parental support is operationalised mainly as checking, supervision, or homework monitoring, it may capture surveillance rather than academically productive support, which aligns with recent meta-analytic and empirical evidence showing that homework-related parental involvement can vary in direction and strength depending on whether it is autonomy-supportive, controlling, or reactive to difficulty (Benckwitz et al., 2024). Reviews of homework-related involvement indicate that some common forms of parental help, particularly direct assistance, are weakly or negatively associated with achievement when they substitute for learner sense-making or occur mainly in response to difficulty (Patall et al., 2008). These interpretations fit the present findings and reinforce the value of disaggregating family capital into autonomy-supportive guidance, academic socialisation, and monitoring, rather than treating involvement as a single uniform construct.

5.4 Motivational Dispositions

Mathematics self-confidence emerges as the strongest positive predictor at the median and upper quantiles, consistent with expectancy-value arguments that the expectation of success is a proximate driver of persistence and achievement in cognitively demanding subjects. The distributional pattern matters. Confidence does not significantly differentiate the lowest achievers in the model, suggesting either a floor effect in skills that constrains the returns to confidence, or that confidence in this group is less well calibrated to competence. For mid- and high-achieving students, confidence likely reflects accumulated mastery experiences and feedback loops that strengthen both effort and strategic engagement, a pattern consistent with evidence that academic self-concept predicts achievement across the distribution (Susperreguy et al., 2018).

Classroom engagement is negatively associated with achievement at the lower and median quantiles. This result should be interpreted cautiously. Engagement is a multidimensional construct, and self-reported behavioural engagement can reflect compliance, effortful coping, or compensatory persistence rather than effective strategy use (Fredricks et al., 2004). In low-performing school settings, students with weaker prior knowledge may report higher effort because they are trying to keep up, yet that effort may not translate into achievement without aligned instruction, feedback and scaffolding. The negative coefficient is therefore compatible with a compensatory account, but it may also reflect measurement limits or reverse causality. Greater reported engagement in this sample should not automatically be read as more productive learning. This interpretation is also consistent with the present results. Engagement is negative at the 25th and 50th quantiles, but not significant at the 75th quantile, while confidence is positive at the median and upper quantiles. Taken together, this pattern suggests that reported engagement may be concentrated among students who are exerting effort while still struggling to convert that effort into higher scores.

Enjoyment and perceived value are not significant when controlling for confidence and engagement. This pattern is theoretically plausible. Value and enjoyment often operate indirectly through persistent choices and long-run course-taking rather than immediate test performance, and their effects can be attenuated in cross-sectional achievement models when expectancy beliefs capture the most proximal performance mechanism. It also suggests that in low-performing contexts, affective affinity for mathematics may be insufficient to overcome gaps in foundational knowledge and instructional support.

5.5 Contextual Influences and Regional Disparities

Regional location shows a clear distributional signature. The Middle Belt disadvantage is concentrated among lower- and median-achieving students and disappears at the upper quantile. This pattern is consistent with an inequality mechanism in which contextual constraints weigh most heavily on students with weaker skills, while high achievers are better placed to compensate through personal resources, peer effects, or informal learning supports. The non-significant Northern Zone coefficients should be interpreted with caution.

In purposive samples, regional patterns can be shaped by the selection of districts and schools, as well as by unmeasured differences in school leadership, staffing stability and programme intensity. School climate is positive but not statistically significant across quantiles. Given that the climate measure is a brief index, the result may reflect limited construct coverage and higher measurement error. Reliability for short scales is sensitive to item count and item heterogeneity, so null effects should not be taken as evidence that climate is irrelevant. Rather, the finding indicates that, as measured here, perceived climate does not add explanatory power beyond the other covariates, possibly because climate varies more meaningfully at the school level than at the student level, or because limited between-school variance is available in the analytic sample (Cortina, 1993; Sijtsma, 2009).

6. Conclusion

Guided by family capital theory and expectancy-value theory, this study shows that mathematics achievement inequality in low-performing public Senior High School contexts in Ghana is distributional rather than uniform. Contextual disadvantage is most visible at the lower end of the distribution, while mathematics self-confidence is the strongest positive correlate at the median and upper quantiles. Parental education shows limited direct association, and the negative coefficient for parental support is more consistent with reactive involvement than with proactive academic socialisation, though this interpretation remains tentative. Overall, the study's theoretical contribution lies in showing that structural, motivational and contextual correlates do not operate with constant salience across achievement levels, an insight that is relevant to similar low-performing contexts beyond Ghana.

6.1 Implications for Research, Policy and Practice

The study suggests a differentiated logic for low-performing SHS settings. For lower-achieving students, priority should be given to diagnosis of prerequisite gaps, corrective support and low-stakes feedback in Core Mathematics. For students around the median and upper quantiles, repeated mastery experiences and criterion-referenced feedback may be better than messages. These implications are provisional and should not be read as causal prescriptions.

Family engagement strategies should also move beyond monitoring alone. The results suggest greater value in academically oriented and autonomy-supportive routines, such as regular study time, revision planning and brief conversations about learning progress, than in reactive supervision that follows poor performance. The objective is therefore to improve the quality of parental support, not merely its frequency. For research, the main implication is that programme evaluations should report distributional outcomes rather than mean effects alone. Future studies should examine whether interventions shift the lower tail of the distribution, support movement into the middle range, or increase the proportion reaching a proficiency threshold.

6.2 Limitations and Future Research

Three limitations frame inference. First, purposive sampling of low-performing schools strengthens contextual relevance but limits generalisability to the full Ghanaian secondary-school population. The findings are better understood as applicable to similar under-resourced, low-performing settings within Ghana and potentially to comparable contexts in other systems. Second, the cross-sectional design supports associational rather than causal interpretation, and reciprocal relationships remain plausible, particularly for parental support and engagement. Third, measurement and estimation constraints may have attenuated some effects, especially given the brevity and low reliability of the school climate index, the non-trivial missingness that required complete-case modelling, and the absence of cluster-adjusted or multilevel estimation. Future research could strengthen inference through richer measures, sensitivity checks for missing data, school-identified data that permit cluster-aware modelling and longitudinal or quasi-experimental designs.

7. Acknowledgements

The author acknowledges the cooperation and support provided by the students, mathematics teachers, and heads of department in the participating schools. Their commitment enabled the successful execution of the study. The author also appreciates the assistance of school administrators who facilitated access and ensured a smooth data collection process.

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Appendix 1
CFA fit indices for initial and refined measurement models

Model	N	χ²	df	p	CFI	TLI	RMSEA	SRMR
Full measurement model	500	1063.747	419	< .001	0.841	0.824	0.056	0.074
Refined measurement model	533	554.804	260	< .001	0.924	0.912	0.046	0.067

Note. The refined model corresponds to the retained indicators reported in Appendix 2 (standardised factor loadings).

Appendix 2

Standardised factor loadings for the refined measurement model

S/NO	Construct	Item code	Item wording	Standardised loading
1	Parental support	Q5a	My parents check if I have done my homework	0.792
2	Parental support	Q5b	I talk about my schoolwork with my parents or guardian	0.496
3	Parental support	Q5c	My parents make sure I set aside time for homework	0.670
4	Parental support	Q5d	My parents ask what I am learning in school	0.716
5	School climate	Q6a	I like being in school	0.587
6	School climate	Q6b	I feel safe when I am in school	0.550
7	School climate	Q6c	I feel I belong in this school	0.408
8	Enjoyment of mathematics	Q7a	I enjoy learning mathematics	0.774
9	Enjoyment of mathematics	Q7c	I learn many interesting things in mathematics	0.695
10	Enjoyment of mathematics	Q7d	I like mathematics	0.825
11	Value of mathematics	Q10a	I would like to do a job that involves mathematics	0.478
12	Value of mathematics	Q10b	I need mathematics to get the job I want	0.715
13	Value of mathematics	Q10c	I need to do well in mathematics to achieve my goals	0.632
14	Value of mathematics	Q10d	I need mathematics to learn other subjects	0.644
15	Value of mathematics	Q10e	I think learning mathematics will help me in the future	0.699
16	Mathematics self-confidence	Q9a	Mathematics is harder for me than any other subject	0.498
17	Mathematics self-confidence	Q9b	My teacher tells me I am good at mathematics	0.731
18	Mathematics self-confidence	Q9c	My teacher thinks I can do well with difficult materials	0.446
19	Mathematics self-confidence	Q9d	I am good at working out difficult mathematics problems	0.678
20	Mathematics self-confidence	Q9f	I learn things quickly in mathematics	0.656
21	Mathematics self-confidence	Q9i	I usually do well in mathematics	0.802
22	Classroom engagement	Q8a	I know what my teacher expects me to do	0.426
23	Classroom engagement	Q8c	My mathematics teacher is easy to understand	0.628
24	Classroom engagement	Q8d	I am interested in what my mathematics teacher says	0.679
25	Classroom engagement	Q8f	My mathematics teacher gives me interesting things to do	0.643

Note. Loadings are standardised. Items were coded so higher values indicate more of the construct, with reverse coding applied where relevant.

Appendix 3
Moderation of mathematics self-confidence by school climate on mathematics achievement

Variable	τ = 0.25 B (SE)	95% CI	p	τ = 0.50 B (SE)	95% CI	p	τ = 0.75 B (SE)	95% CI	p
Mathematics self-confidence (centred)	1.61 (2.31)	[−2.64, 6.07]	.489	8.08 (1.80)	[4.60, 11.88]	.018	8.37 (2.06)	[4.76, 12.61]	.016
School climate (centred)	0.76 (2.38)	[−4.39, 4.61]	.765	2.13 (2.00)	[−1.73, 6.20]	.319	2.34 (3.22)	[−4.17, 7.07]	.473
Self-confidence × school climate	−3.75 (1.47)	[−6.09, 0.23]	.058	−1.77 (1.27)	[−4.55, 0.37]	.146	−0.05 (1.78)	[−3.32, 3.95]	.982

Note. N = 568. 1,000 bootstrap replications. Predictors are mean-centred and coefficients are unstandardised.

Appendix 4

Moderation of classroom engagement by school climate on mathematics achievement

Variable	τ = 0.25 B (SE)	95% CI	p	τ = 0.50 B (SE)	95% CI	p	τ = 0.75 B (SE)	95% CI	p
Classroom engagement (centred)	−4.57 (2.49)	[−9.19, 0.72]	.064	−7.19 (3.02)	[−13.81, 0.19]	.050	−2.34 (4.21)	[−11.29, 5.21]	.536
School climate (centred)	4.34 (2.32)	[0.03, 9.36]	.052	1.52 (2.68)	[−3.37, 7.19]	.567	1.91 (4.89)	[−8.36, 9.71]	.700
Engagement × school climate	−1.34 (1.46)	[−4.72, 1.31]	.264	0.51 (1.71)	[−3.07, 3.90]	.740	−0.19 (2.45)	[−5.70, 3.36]	.902

Note. N = 568. 1,000 bootstrap replications. Predictors are mean-centred and coefficients are unstandardised.

Appendix 5
Full quantile coefficient table for the main model

Predictor	τ = 0.25	τ = 0.50	τ = 0.75
(Intercept)	B = 58.991 SE = 13.8030 p < .001 95% CI [31.857, 86.126]	B = 66.835 SE = 12.7479 p < .001 95% CI [41.775, 91.895]	B = 47.991 SE = 17.6923 p = .007 95% CI [13.211, 82.771]
Parental Support	B = -1.110 SE = 1.2028 p = .357 95% CI [-3.475, 1.254]	B = -2.658 SE = 1.1108 p = .017 95% CI [-4.841, -.474]	B = -1.909 SE = 1.5417 p = .216 95% CI [-4.940, 1.122]
Enjoyment of Mathematics	B = 2.294 SE = 1.9335 p = .236 95% CI [-1.507, 6.095]	B = .401 SE = 1.7857 p = .823 95% CI [-3.110, 3.911]	B = 2.805 SE = 2.4784 p = .258 95% CI [-2.067, 7.677]
Confidence	B = 2.652 SE = 1.7022 p = .120 95% CI [-.694, 5.998]	B = 7.532 SE = 1.5721 p < .001 95% CI [4.442, 10.623]	B = 6.062 SE = 2.1818 p = .006 95% CI [1.773, 10.352]
Engagement	B = -4.053 SE = 1.8185 p = .026 95% CI [-7.628, -.478]	B = -5.226 SE = 1.6795 p = .002 95% CI [-8.528, -1.925]	B = -4.245 SE = 2.3309 p = .069 95% CI [-8.827, .337]
Northern Zone	B = .973 SE = 2.2048 p = .659 95% CI [-3.362, 5.307]	B = 3.198 SE = 2.0363 p = .117 95% CI [-.805, 7.201]	B = 5.175 SE = 2.8261 p = .068 95% CI [-.380, 10.731]
Middle Belt Zone	B = -9.866 SE = 2.8181 p < .001 95% CI [-15.406, -4.326]	B = -5.170 SE = 2.6027 p = .048 95% CI [-10.287, -.054]	B = -4.303 SE = 3.6122 p = .234 95% CI [-11.404, 2.798]
Age	B = -1.139 SE = .5918 p = .055 95% CI [-2.302, .025]	B = -1.490 SE = .5465 p = .007 95% CI [-2.564, -.415]	B = -.542 SE = .7585 p = .475 95% CI [-2.033, .949]
Gender (male = 1)	B = 1.234 SE = 1.8469 p = .504 95% CI [-2.397, 4.864]	B = 4.831 SE = 1.7057 p = .005 95% CI [1.478, 8.184]	B = 3.130 SE = 2.3673 p = .187 95% CI [-1.524, 7.783]
Perceived Value of Mathematics	B = -1.185 SE = 1.8477	B = -.284 SE = 1.7064	B = -1.342 SE = 2.3683

Predictor	τ = 0.25	τ = 0.50	τ = 0.75
	p = .522 95% CI [-4.817, 2.447]	p = .868 95% CI [-3.638, 3.071]	p = .571 95% CI [-5.998, 3.313]
School Climate	B = 1.598 SE = 1.8176 p = .380 95% CI [-1.975, 5.171]	B = 2.410 SE = 1.6787 p = .152 95% CI [-.890, 5.710]	B = 3.304 SE = 2.3298 p = .157 95% CI [-1.276, 7.884]
Parental Education	B = -1.608 SE = 1.0849 p = .139 95% CI [-3.741, .525]	B = -.081 SE = 1.0020 p = .936 95% CI [-2.050, 1.889]	B = 1.170 SE = 1.3906 p = .401 95% CI [-1.563, 3.904]