Correlates of Ghanaian Teachers' Understanding of Mathematics Strands and Cognitive Domains in Basic Education Certificate Examination

Abstract

In the field of mathematics education, it is essential to grasp teachers' competence in recognizing cognitive domains, as it plays a pivotal role in elevating teaching methods, evaluation techniques, and ultimately enhancing student academic achievements. This study examines the proficiency of basic school teachers in Ghana in identifying the cognitive domains of mathematics questions using Bloom's Taxonomy. A sample of 338 teachers from across the regions of Ghana participated, selected through random sampling. Teachers were assessed using a set of 50 Basic Education Certificate Examination (BECE) past questions spanning a decade (2010-2022), covering Algebra, Geometry and Measurement, Data, and Number strands. Participants categorized each question according to Bloom's Taxonomy. Poisson regression analysis and Confirmatory Factor Analysis were employed to evaluate teachers' proficiency. Results indicated a statistically significant intercept term, suggesting a baseline performance level among teachers. Significant interaction effects between demographic and professional characteristics (Class:category, Class:SchTyp, TeachEx:SchTyp, TeachEx:Domain, and the main effect of Domain) influenced teachers' ability to identify mathematics domains. Teaching experience positively influenced scores, while school type had a negative impact. The model demonstrated high discriminatory power and strong predictive performance with an AUC of 0.996. Dependency analysis revealed that understanding Bloom's taxonomy domains influenced the identification of mathematics strands. Primary level teachers' consistently demonstrated higher proficiency compared to Junior High School (JHS) level teachers. Additionally, experienced and qualified professionals performed better than pupil teachers. These findings highlight the importance of targeted interventions and professional development programs to enhance teachers' competency in identifying mathematics domains, thus improving mathematics education in Ghana.

Keywords. Strands, NaCCA, BECE, Blooms Taxonomy, Basic Teachers

Introduction

Mathematics teachers' knowledge plays a critical role in effective instruction and student learning outcomes. In particular, teachers' understanding of the four strands of mathematics at the basic school level: Algebra, Geometry and Measurement, Data, and Number, along with their knowledge of Bloom's Taxonomy cognitive domains is essential for delivering comprehensive mathematics education. Research by Ball and Bass (2003) emphasizes the significance of mathematics content knowledge for effective teaching. Teachers must have a robust understanding of the four strands of mathematics - Algebra, Geometry and

Measurement, Data, and Number - to facilitate meaningful learning experiences for students. Teachers' ability to articulate and connect mathematical concepts within and across these strands is crucial for fostering conceptual understanding and problem-solving skills (Hill et al., 2008). Shulman (1986) introduced the concept of pedagogical content knowledge (PCK), emphasizing the importance of teachers' understanding of how to teach specific content effectively. In the context of mathematics education, PCK involves knowing how to select and sequence mathematical tasks, anticipate student misconceptions, and provide appropriate instructional support. Teachers with strong PCK can design learning experiences that address diverse student needs and promote deep conceptual understanding (Kilpatrick et al., 2001). Bloom's Taxonomy provides a framework for categorizing educational objectives and assessing students' cognitive development. Teachers' knowledge of Bloom's Taxonomy allows them to design learning experiences that target different cognitive domains, including remembering, understanding, applying, analyzing, evaluating, and creating (Anderson et al., 2001). For example, teachers can use a variety of instructional strategies, such as questioning techniques and task design, to scaffold students' progression through these cognitive levels (Krathwohl, 2002).

Recent studies underscore the importance of integrating content and pedagogical knowledge in mathematics teaching (Bosson-Amedenu et al. 2020a-l). For instance, Grossman et al. (2009) argue that effective teaching requires a dynamic interplay between teachers' content knowledge, pedagogical knowledge, and knowledge of students' thinking. Teachers must continually reflect on their practice and refine their instructional approaches to meet the diverse needs of their students (Hiebert et al., 2012). In conclusion, mathematics teachers' knowledge of the four strands of Algebra, Geometry and Measurement, Data, and Number, as well as their understanding of Bloom's Taxonomy cognitive domains, is essential for providing comprehensive and effective instruction. By integrating content and pedagogical knowledge, teachers can create learning experiences that promote deep conceptual understanding and foster students' mathematical proficiency. Continued research in this area is crucial for informing teacher preparation programs and professional development initiatives aimed at enhancing mathematics teaching and learning.

Method

The study involved a sample of 338 elementary school teachers randomly selected from the regions across Ghana. These teachers, who were from both public and private schools, represented a wide range of teaching backgrounds, ages, genders, and roles within the education system. Finally, teachers were randomly selected from the chosen schools. This systematic approach was implemented to guarantee a diverse and representative sample.

To evaluate teachers' knowledge, a set of 50 Basic Education Certificate Examination (BECE) past questions in mathematics, spanning a 10-year period (2012-2022), were utilized. These questions were carefully selected to cover the four strands of Algebra, Geometry and Measurement, Data, and Number, thereby ensuring a comprehensive assessment. Respondents were asked to identify the cognitive domain assessed by each question according to Bloom's Taxonomy. These questions had been previously used as standardized items in the BECE by the West African Examinations Council (WAEC), ensuring their reliability and validity. The study examined the factors influencing elementary school teachers' knowledge of Bloom's Taxonomy cognitive domains and their ability to categorize BECE mathematics test items accordingly. Poisson regression analysis and Confirmatory Factor Analysis were employed to assess teachers' proficiency in categorizing questions based on cognitive domains. Poisson regression is employed to analyze the relationship between various factors and teachers' ability to categorize questions based on cognitive domains. In this study, Poisson regression helps determine which factors influence teachers' proficiency in categorizing questions according to Bloom's Taxonomy cognitive domains. By examining the relationships between observed variables (BECE past questions) and latent constructs (cognitive domains), CFA allows the researchers to confirm whether the chosen questions effectively measure the intended constructs.

Model Development

The likelihood function for the Poisson regression model is given by the product of the probability mass function (PMF) of the Poisson distribution for each observed count y_i as modelled in Equation 1.

$$L(\beta_0, \beta_1, \ldots, \beta_k) = \prod_i^n \frac{e^{-\mu} \mu_i^{y_i}}{y_i\,!} \tag{1}$$

Taking the natural logarithm of the likelihood function simplifies calculations and does not change the location of the maximum likelihood. Thus, we obtain the log-likelihood function as modelled in Equation 2.

$$\ell(\beta_0, \beta_1, \ldots, \beta_k) = \sum_{i=1}^{n} (-\mu_i + y_i log(\mu_i) - log(y_i!)) \tag{2}$$

n is the number of observations.

μ is the expected value of the dependent variable (the mean of the Poisson distribution),

$\beta_0, \beta_1, \beta_2, ..., \beta_k$ are the coefficients to be estimated,

$x_1, x_2, ..., x_k$ are the independent variables,

log is the natural logarithm function.

y_i is the observed count for the i^{th} observation.

μ_i is the expected count for the i^{th} observation, given by the model:

$$\mu_i = e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k}$$

$$log(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k$$

To compute the derivative with respect to β, we need to differentiate each term of the log-likelihood function with respect to β.

For the i^{th} term, the derivative is given in Equation 3.

$$\frac{\partial \ell_i(\beta)}{\partial \beta} = \frac{\partial}{\partial \beta}(-\mu_i + y_i log(\mu_i)) \tag{3}$$

Using the chain rule, we compute the derivative of the log-likelihood function with respect to β as expressed in Equation 4 and simplified in Equation 5.

$$\frac{\partial \ell_i(\beta)}{\partial \beta} = \frac{\partial}{\partial \beta}(-\mu_i(\beta) + y_i log(\mu_i(\beta))) \tag{4}$$

$$\frac{\partial \ell_i(\beta)}{\partial \beta} = \left(\frac{y_i}{\mu_i} - 1 \right) \frac{\partial \mu_i}{\partial \beta} \tag{5}$$

Substituting the expression for $\frac{\partial \mu_i}{\partial \beta}$, we obtain the final form of the score function as expressed in Equation 6.

$$U(\beta) = \left(\frac{y_i}{\mu_i} - 1 \right) \mu_i x_i \tag{6}$$

Results and Discussion

Model Diagnostics

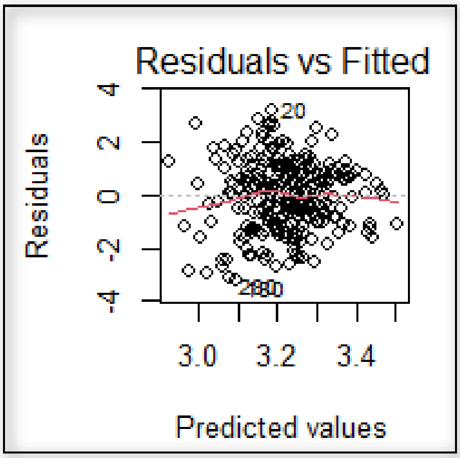

Figure 1. Residual versus Fitted Plot

The residual versus fitted plot in Figure 1, shows the relationship between the residuals and the fitted values in Poisson regression analysis to assess the goodness-of-fit of the model and identify potential areas for improvement. Residuals are the differences between the observed values and the values predicted by the model. In Poisson regression, these residuals are typically calculated as the differences between the observed counts and the predicted counts from the model. Fitted values are the predicted values of the response variable (counts in Poisson regression) obtained from the regression model. These are calculated based on the independent variables' values using the estimated regression coefficients.

The plot in Figure 1 depicts a well-fitted model with the residuals randomly scattered evenly around zero, without any obvious patterns or trends. This indicates that the model adequately captures the underlying relationship between the independent variables and the response variable.

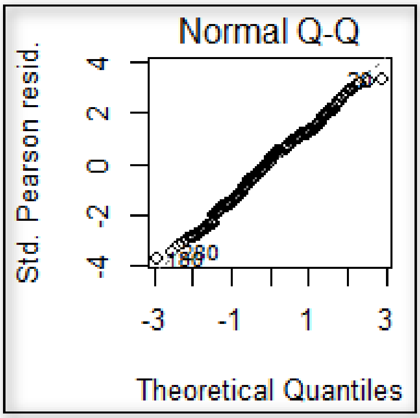

Figure 2. Q-Q Plot against Theoretical Quantiles

In Figure 2, the Q-Q plot of standardized Pearson residuals against theoretical quantiles in Poisson regression analysis is a useful tool for evaluating the adequacy of the model fit and detecting departures from the assumed distribution of residuals. It provides insights into whether the model captures the variability in the data appropriately and helps guide potential model adjustments. The standardized Pearson residuals are calculated by dividing the residuals (the differences between observed and predicted counts) by the square root of the estimated dispersion parameter. These residuals are standardized to have mean zero and variance one. The theoretical quantiles represent the expected values of the residuals under the assumption that the model is correctly specified. These quantiles are derived from a theoretical distribution, usually the standard normal distribution. Figure 2 shows a well-fitted Poisson regression model where the standardized Pearson residuals follow a straight line when plotted against the theoretical quantiles, indicating that the residuals follow the assumed distribution.

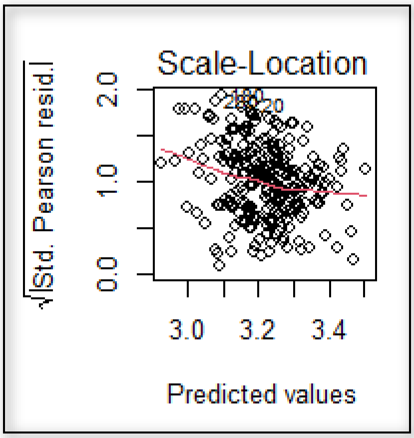

Figure 3. Scale-Location Plot

The scale-location plot in Poisson regression analysis as shown in Figure 3, helps assess the homogeneity of variance assumption and diagnose potential issues with the model's fit. It provides insights into whether the spread of residuals remains constant across different levels of predicted values, which is crucial for the validity of the regression model.

Figure 3 shows a well-fitted model, the points on the scale-location plot are randomly scattered around a horizontal line at a constant level as the predicted values increase.

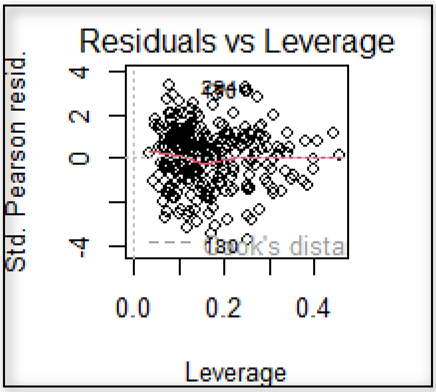

Figure 4. Residuals versus Leverage Plot

The residuals versus leverage plot in Poisson regression analysis as depicted by Figure 4, helps identify influential observations that might have a significant impact on the model's parameters. It allows you to assess the robustness of the regression results and make informed decisions about the inclusion or exclusion of observations in the analysis. The figure suggests a well-fitted model where most points on the residuals versus leverage plot are randomly scattered around zero, indicating that observations have minimal influence on the estimated coefficients.

Table 1. Null and Residual Deviance Measures

Residual deviance	Null deviance	degrees of freedom
457.38	524.21	272

The null deviance shown in Table 1, measures the discrepancy between the model with only the intercept term and the fitted model, while the residual deviance measures the discrepancy between the fitted model and the saturated model. A lower residual deviance indicates a better fit of the model to the data. In this case, the residual deviance of 457.38 on 227 degrees of freedom suggests that the model provides a reasonable fit to the data.

Table2. Residual Deviance Statistics

Min	1Q	Median	3Q	Max
-3.7608	-0.8598	0.0738	0.8591	2.9418

The deviance residuals shown in Table 2, provide insights into the goodness of fit of the model. In this model, deviance residuals range from -3.7608 to 2.9418, suggesting that the model adequately captures the variability in the data. The relatively small values of deviance residuals and their distribution around zero suggest that the Poisson regression model adequately captures the variability in the data. The fact that the median deviance residual is close to zero (0.0738) indicates that, on average, the model predicts counts reasonably well. The range of deviance residuals spanning from negative to positive values suggests that the model captures both overestimation and underestimation of counts across different observations.

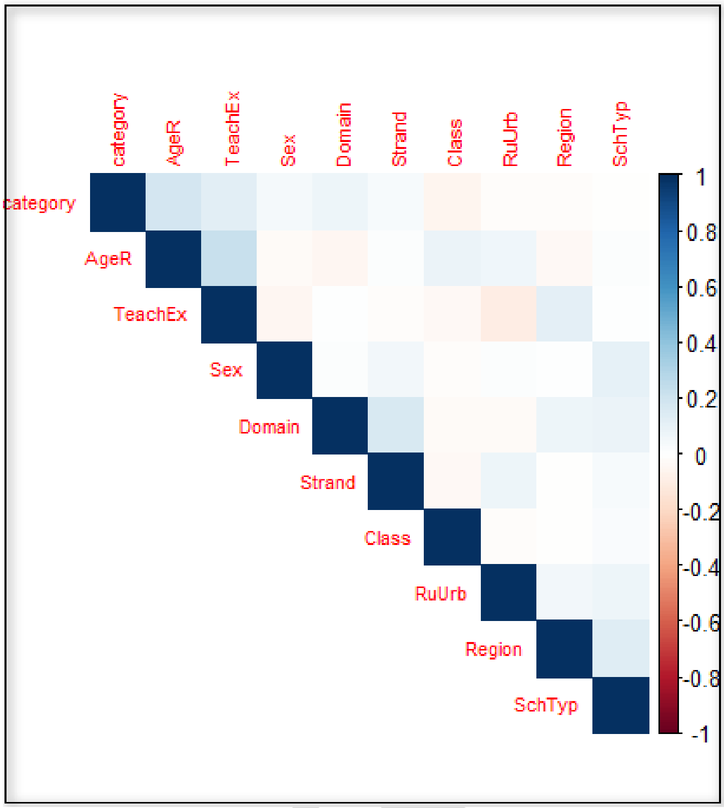

Figure 5. Correlation Matrix Analysis

These correlations shown in Figure 5, provide insights into potential associations between the covariates in the dataset, highlighting the complex interplay of factors influencing teacher characteristics, teaching approaches, and educational outcomes. Further analysis and contextual understanding are necessary to interpret these correlations accurately and derive meaningful implications for educational policy and practice.

Sex has a moderate positive correlation with SchTyp (0.107), indicating a tendency for a certain sex to be associated with specific school types. This might imply gender-based preferences or biases in the choice of school types for employment. Class exhibits a weak negative correlation with category (-0.052) and Strand (-0.033). This suggests that the class level taught by teachers may have a slight association with their professional category and teaching specialization. For example, teachers at different class levels may have varying levels of training or expertise in specific teaching areas. Category shows a moderate positive correlation with AgeR (0.184) and Domain (0.073). This indicates that certain teacher categories may be associated with older age ranges and higher Blooms taxonomy domain scores. Professional teachers, for instance, may have more experience and higher competency levels compared to pupil teachers or teacher trainees. AgeR exhibits moderate positive correlations with category (0.184) and TeachEx (0.230). This suggests that older age ranges may be associated with certain teacher categories and higher teaching experience. It implies that experienced teachers are more likely to fall into specific categories and potentially possess higher competency levels. TeachEx shows moderate positive correlations with AgeR

(0.230) and category (0.122), indicating that higher teaching experience may be associated with older age ranges and certain teacher categories. This suggests that experienced teachers may be more likely to fall into specific categories based on their teaching tenure. RuUrb exhibits a moderate negative correlation with TeachEx (-0.096) and a weak positive correlation with Strand (0.073). This suggests that teaching experience may vary slightly across rural and urban areas, and certain teaching specializations may be more prevalent in either rural or urban settings. Region shows a weak positive correlation with SchTyp (0.134) and Domain (0.072). This implies that specific regions may have preferences for certain school types and Blooms taxonomy domains. It suggests that regional policies or cultural factors may influence the distribution of school types and teaching approaches across different regions. SchTyp exhibits a moderate positive correlation with Region (0.134) and Domain (0.085), indicating that certain school types may be more prevalent in specific regions and may focus on specific Blooms taxonomy domains. This suggests that regional factors and educational policies may influence the distribution and emphasis of school types and educational approaches. Domain shows a moderate positive correlation with Strand (0.168), indicating that certain Blooms taxonomy domains may be associated with specific teaching specializations. This suggests that teachers with expertise in particular domains may gravitate towards specific teaching areas or subjects within the curriculum. Strand exhibits a moderate positive correlation with Domain (0.168), indicating that teachers who are proficient in specific Blooms taxonomy domains may also excel in identifying specific teaching strands. This suggests that pedagogical expertise in certain domains may translate to proficiency in teaching specific subject areas within the curriculum.

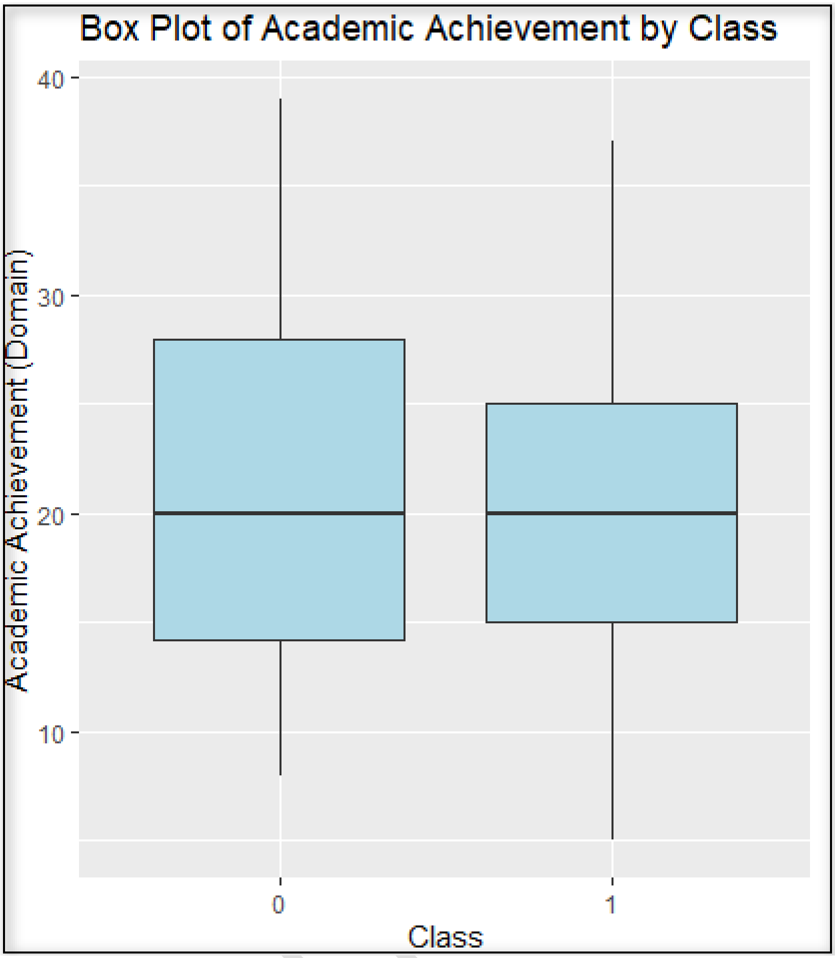

Figure 6. Box Plot Class Analysis

The box in Figure 6, represents the interquartile range (IQR), which contains the middle 50% of the data. The bottom and top edges of the box represent the first quartile (Q1) and third quartile (Q3), respectively. For Class 0 (primary level teachers), the middle line inside the box represents the median. The lower quartile (Q1) is at 14 and the upper quartile (Q3) is at 27. This indicates that the middle 50% of the data lies within the range of 14 to 27. The median (middle line) is at 20, which means that 50% of the data falls below 20 and 50% falls above 20. The whiskers extend from 8 to 38, which suggest that the majority of the data points are within this range, with potential outliers beyond.

For Class 1 (JHS level teachers), the lower quartile (Q1) is at 15 and the upper quartile (Q3) is at 25. This indicates that the middle 50% of the data lies within the range of 15 to 25. The median (middle line) is at 20, which means that 50% of the data falls below 20 and 50% falls above 20. The whiskers extend from 5 to 37, which suggest that the majority of the data points are within this range, with potential outliers beyond.

The box plot suggests that there is variation in academic achievement (Domain) scores between primary level and JHS level teachers. Primary level teachers (Class 0) appear to have a wider spread of scores compared to JHS level teachers (Class 1).The median score for JHS level teachers seems to be slightly higher than that of primary level teachers. The presence of outliers in both groups indicates potential variability within each class.

Table 3. Parameter Estimation of Poisson Regression Model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	3.2663292	0.1643295	19.877	< 2e-16
Class:category	0.1769295	0.0813582	2.175	0.02965
Class:SchTyp	-0.1943145	0.0670123	-2.900	0.00374
TeachEx:SchTyp	-0.1653561	0.0513400	-3.221	0.00128
TeachEx:Domain	0.0068361	0.0030815	2.218	0.02652
Domain	0.006666	0.001645	4.053	5.05e-05

The Poisson regression model was fitted to analyze the relationship between predictor variables and the response variable, which pertains to teachers' scores based on Ghana's NaCCA curriculum for mathematics. The model aims to predict teachers' scores, representing their ability to identify Blooms taxonomy domains and mathematical strands, based on various demographic and professional characteristics with the estimated coefficients shown in Table 3.

The intercept term represents the expected value of teachers' scores when all predictor variables are zero. In this model, the intercept is 3.266, and its statistical significance ($p < 0.001$) indicates that it significantly contributes to predicting teachers' scores. The intercept term in the model represents the expected value of teachers' scores when all predictor variables are zero. In this specific model, the intercept is 3.266, and its statistical significance ($p < 0.001$) indicates that it significantly contributes to predicting teachers' scores. One possible reason for this observation is that the intercept captures the baseline performance level of teachers on the Blooms taxonomy domains score before considering any other predictor variables. It reflects the inherent competency or proficiency level of teachers in identifying the cognitive demands of mathematics test items, regardless of their teaching experience, class level, school type, or other demographic and professional characteristics. Essentially, the intercept accounts for the average score that teachers would achieve if all other factors were held constant at their reference levels. This baseline performance level is crucial for establishing a starting point from which to assess the incremental impact of additional predictor variables on teachers' scores. Therefore, the statistically significant intercept underscores its importance as a foundational component in predicting and understanding teachers' performance on the Blooms taxonomy domains score.

The coefficient estimate of 0.1769 suggests that the interaction between Class and category (Class: category) variables positively influences teachers' scores. It is statistically significant ($p = 0.030$).

One possible reason for the observed positive impact of the interaction between class (Class) and category variables on teachers' scores could be related to the alignment of instructional strategies with the specific needs and characteristics of different student populations. In educational settings, teachers often tailor their teaching approaches and instructional materials based on the grade level (Class) they are teaching and the category of students they are working with. For example, teachers may adapt their lesson plans, classroom activities, and assessments to better meet the developmental needs, learning styles, and prior knowledge of primary-level students compared to junior high school-level students. Similarly, teachers may employ different instructional techniques and resources when working with professional teachers, pupil teachers, or teacher trainees (Category) based on their levels of experience, expertise, and professional development needs. Therefore, the positive impact of the interaction between class and category variables on teachers' scores may reflect the effectiveness of tailored instructional practices in promoting teachers' ability to identify Bloom's taxonomy domains accurately across diverse student and teacher populations. Further research investigating the specific instructional strategies and approaches that contribute to this observed phenomenon could provide additional insights into effective teaching practices in varied educational contexts.

The coefficient estimate of -0.1943 indicates that the interaction between Class and SchTyp (Class:SchTyp) variables negatively affects teachers' scores. It is statistically significant ($p = 0.004$). One possible reason for the observed negative impact of the interaction between teaching experience (TeachEx) and Blooms taxonomy domains (Domain) on teachers' scores could be related to the challenges that teachers face in adapting their instructional practices to different classroom settings and student populations. Teachers with varying levels of experience may encounter difficulties in effectively addressing the cognitive demands associated with different Bloom's taxonomy domains, particularly when teaching in classrooms with diverse student backgrounds or in schools with limited resources. Additionally, the interaction between class level (Class) and school type (SchTyp) may exacerbate these challenges, as teachers may need to navigate different curricular expectations, classroom management strategies, and instructional approaches depending on whether they teach primary or junior high school students in private or public schools. Consequently, the negative impact of this interaction on teachers' scores may reflect the complexities of aligning instructional practices with the cognitive demands of Bloom's taxonomy domains within the context of diverse classroom and school environments. Further research exploring the specific mechanisms through which class level, school type, and teaching experience interact to influence teachers' ability to identify Bloom's taxonomy domains could provide additional insights into this observed phenomenon.

With a coefficient estimate of -0.1654, the interaction (TeachEx:SchTyp) between teaching experience (TeachEx) and school type (SchTyp) negatively impacts teachers' scores. This effect is statistically significant ($p = 0.001$). One possible reason for the observed negative impact of the interaction between teaching experience (TeachEx) and school type (SchTyp) on teachers' scores could be related to the differences in resources, support, and working conditions between public and private schools. Teachers with higher levels of teaching experience may have developed certain teaching strategies or approaches that are more effective in one type of school environment compared to the other. For example, experienced teachers in public schools may have adapted their teaching methods to accommodate larger class sizes, limited resources, and diverse student populations, while those in private schools may have access to smaller class sizes, more resources, and possibly more supportive working environments. Consequently, the interaction between teaching experience and school type may reflect how these factors impact teachers' ability to effectively identify Blooms taxonomy domains, potentially leading to lower scores for teachers in certain school types despite their experience level. Further research into the specific challenges and opportunities associated with teaching in different school types could provide additional insights into this observed phenomenon.

This coefficient estimate of 0.0068 suggests that the interaction (TeachEx:Domain) between teaching experience (TeachEx) and Blooms taxonomy domains (Domain) positively influences teachers' scores. It is statistically significant ($p = 0.027$). One possible reason for the observed positive impact of the interaction between teaching experience (TeachEx) and Blooms taxonomy domains (Domain) on teachers' scores could be related to the accumulation of pedagogical knowledge and expertise over time. As teachers gain more experience in the classroom, they often become more adept at identifying and addressing the specific cognitive demands associated with different levels of Bloom's taxonomy. With increasing teaching experience, educators may develop a deeper understanding of the cognitive processes involved in each domain (Knowing, Understanding, Applying, and Analysis) and become better equipped to design instruction and assessment tasks that align with these cognitive levels. Additionally, experienced teachers may have had more opportunities for professional development, exposure to diverse teaching contexts, and collaboration with colleagues, all of which contribute to their ability to effectively identify and assess students' understanding within each domain. Consequently, the positive interaction between teaching experience and Blooms taxonomy domains may reflect the cumulative effect of pedagogical growth and expertise that occurs over the course of a teacher's career. Further research exploring the specific mechanisms through which teaching experience influences teachers' ability to identify Blooms taxonomy domains could provide additional insights into this observed phenomenon.

The coefficient estimate of 0.0067 indicates that Blooms taxonomy domains (Domain) have a positive effect on teachers' scores. It is statistically significant ($p < 0.001$). One possible reason for the observed positive effect of Blooms taxonomy domains (Domain) on teachers' scores could be attributed to the fundamental role that cognitive complexity plays in teachers' ability to accurately identify and assess the cognitive demands of mathematics test items. Bloom's taxonomy provides a hierarchical framework for categorizing educational objectives based on cognitive processes, ranging from lower-order thinking skills (e.g., Remembering, Understanding) to higher-order thinking skills (e.g., Applying, Analyzing, Evaluating, Creating). Teachers who possess a deep understanding of Bloom's taxonomy are better equipped to recognize the cognitive levels embedded within test items and tailor their instructional practices and assessment strategies accordingly. By being proficient in distinguishing between different cognitive domains such as Knowing, Understanding, Applying, and Analysis, teachers can design more targeted and effective teaching interventions that foster students' critical thinking and problem-solving abilities. Additionally, teachers who demonstrate mastery in identifying Bloom's taxonomy domains may exhibit greater pedagogical expertise and instructional efficacy, leading to improved student learning outcomes. Therefore, the positive effect of Bloom's taxonomy domains on teachers' scores underscores the importance of cognitive complexity in assessing teachers' competency in mathematics education.

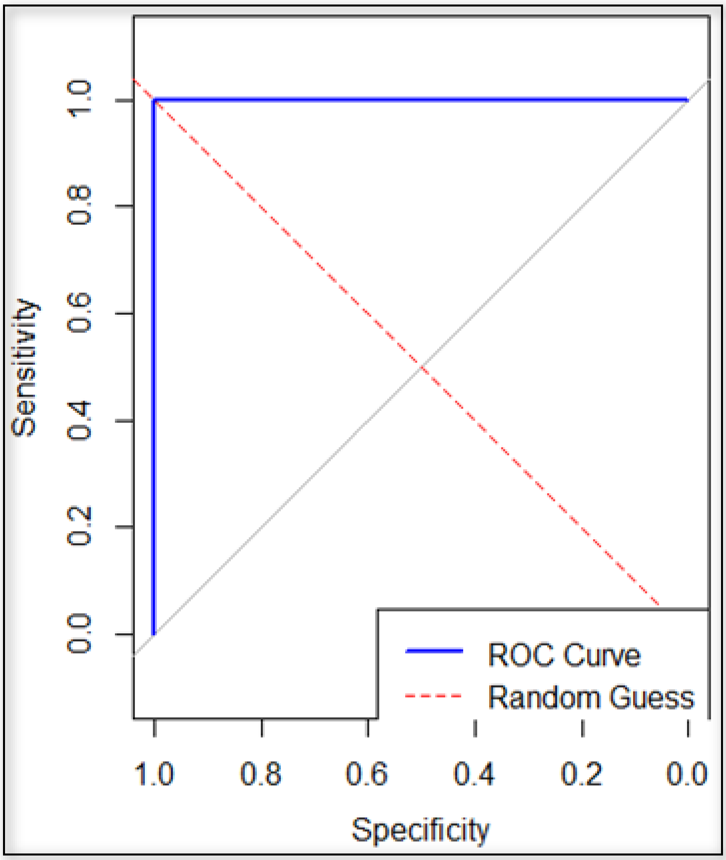

Figure 7. Area under ROC Curve

The ROC curve analysis in Figure 7, coupled with the AUC and comparison to the random guess line, offers a comprehensive assessment of the performance of a Poisson regression model in classification tasks, highlighting its ability to discriminate between different outcomes with high accuracy. The ROC curve visually illustrates how the Poisson regression model performs in terms of sensitivity and specificity across different threshold values. Comparing the ROC curve with the random guess line helps assess the model's performance relative to random chance. With an AUC of 0.996, the model outperforms random guessing by a significant margin, indicating high discriminatory power and strong predictive performance.

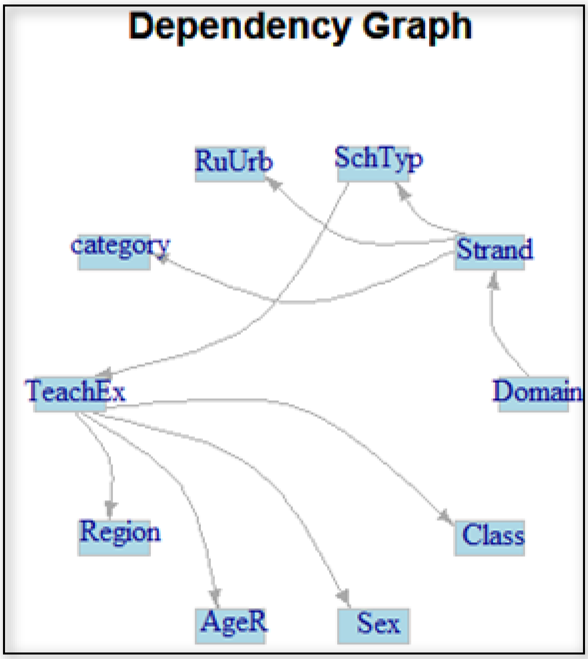

Figure 8. Dependency Relationships

The dependency graph in Figure 8, provides valuable insights into the interrelationships between various factors influencing teachers' scores and characteristics in Ghana's NaCCA curriculum for mathematics. By understanding these dependencies, policymakers, educators, and curriculum designers can make informed decisions to improve teacher quality, educational equity, and curriculum effectiveness.

The graph shows an arrow directing from Domain to Strand. This suggests that a teacher's understanding of the Blooms taxonomy domains (Knowing, Understanding, Applying, Analysis) influences their ability to identify the four strands in mathematics (Number, Algebra, Geometry, Measurement, and Data). Three arrows direct from Strand to SchTyp (School Type), RuUrb (Rural/Urban), and Category (Teacher Category). This implies that a teacher's understanding of mathematical strands affects various aspects such as the type of school they teach in (public or private), the rural or urban location of the school, and their teacher category (Professional, Pupil Teacher, or Teacher Trainee). An arrow directs from SchTyp to TeachEx (Teaching Experience). This indicates that the type of school a teacher teaches in influences their teaching experience, suggesting that teachers in public and private schools may have different levels of experience. Four arrows direct from TeachEx to Region, AgeR, Sex, and Class. This implies that a teacher's teaching experience influences various characteristics such as the region they teach in, their age range, gender, and the class they teach (Primary or JHS level).

The dependency graph highlights the importance of teachers' understanding of mathematics domains and strands in shaping their teaching practices. Professional development programs should focus on enhancing teachers' knowledge in these areas to improve instructional quality. The graph suggests that teachers' characteristics, such as teaching experience and school type, may impact educational equity. Policymakers should consider these factors when designing interventions to ensure equitable access to quality education across different regions and school types.Understanding the relationship between teaching experience and other characteristics such as age, gender, and region can inform strategies for teacher recruitment and retention. Efforts should be made to attract and retain experienced teachers, particularly in underserved regions or school types. The dependency between Domain and Strand underscores the importance of aligning curriculum objectives with teachers' understanding of content domains. Curriculum designers should ensure clarity and coherence in delineating learning objectives across different strands of mathematics. Overall, the dependency graph analysis provides a valuable framework for understanding the complex interplay of factors influencing teachers' scores and characteristics in Ghana's mathematics curriculum. By addressing these dependencies, stakeholders can work towards improving teaching quality and educational outcomes for all students.

Table 4. The CFA model fit the data well, as indicated by the following statistics:

Test statistic	Degrees of freedom	P-value (Chi-square)
1153.807	27	0.000

The chi-square value (1153.807) is relatively low compared to the degrees of freedom (27) which indicates a good model fit as shown in Table 4. The p-value associated with the chi-square statistic (0.000) is less than 0.05, indicating that the model fits the data well at a statistically significant level.

Table 5. Factor1 (Ability to identify Mathematics Domains)

Standardized	Coefficient	P-value (Chi-square)
Class	-1.697	0.002
Category	-11.406	< 0.001
AgeR	2.046	0.001

The standardized coefficient in Table 5, indicates the strength and direction of the relationship between the observed variable "Class" and the latent variable "Factor1." A negative coefficient suggests that as the value of "Class" increases, the value of "Factor1" decreases. In this case, a standardized coefficient of -1.697 indicates a strong negative relationship. The p-value associated with this coefficient (0.002) is less than 0.05, indicating that the relationship is statistically significant. Therefore, being a primary level teacher (Class = 0) is associated with a higher score on Factor1 compared to being a Junior High School (JHS) level teacher (Class = 1). The primary level teachers consistently demonstrate a higher ability to identify mathematics domains compared to JHS level teachers, the reason may be due to the fact that primary level teacher are often class teachers who are required to teach all subjects in a particular class whereas JHS teachers are mostly subject teachers for a particular subject.. The findings make it imperative for targeted professional development initiatives for JHS level teachers aimed at enhancing their ability to identify mathematics domains. Training programs and workshops could be developed specifically focusing on improving this aspect of mathematics pedagogy among JHS level educators. Schools and educational authorities may need to allocate resources differently based on the differing needs of primary and JHS level teachers. For example, additional support and resources could be provided to JHS level teachers to help them improve in areas where they may currently be lacking, such as identifying mathematics domains. These findings could also stimulate further research to understand the underlying reasons behind the observed differences between primary and JHS level teachers. Qualitative studies, for example, could explore the specific challenges or gaps in training that contribute to these differences, providing deeper insights for educational practice and policy. Educational policymakers may need to consider the implications of these findings for teacher recruitment and placement policies. If primary level teachers are better equipped in this aspect of mathematics education, policymakers may need to ensure appropriate staffing levels and distribution of teachers across different levels of schooling to optimize student learning outcomes. The implication of primary level teachers having a higher score on Factor1 compared to JHS level teachers highlights potential disparities in teacher preparation and performance across different levels of schooling. Addressing these disparities can lead to more equitable and effective mathematics education for all students.

The standardized coefficient for "Category" is -11.406, indicating a strong negative relationship between this variable and Factor1. The extremely negative coefficient suggests that the "Category" variable has a substantial influence on Factor1. The p-value is less than 0.001, indicating that this relationship is highly statistically significant. This suggests that being categorized as a "Professional," "Pupil Teacher," or "Teacher Trainee" significantly affects a teacher's ability to identify mathematics domains.

The variable "Category" represents the professional status of teachers, categorized as "Professional," "Pupil Teacher," or "Teacher Trainee." The strong negative relationship suggests that teachers with different professional statuses exhibit significantly different abilities to identify mathematics domains. Professional status often correlates with differences in training, qualifications, and teaching experience. A strong negative relationship here indicates that more experienced and qualified professionals (e.g., those categorized as "Professional") tend to perform better in identifying mathematics domains compared to pupil teachers who may have less experience and formal training. The finding calls for enhancing the quality and rigor of training programs, ensuring consistency in standards across different categories of teachers. Policymakers may need to consider the implications of these disparities for teacher recruitment, training, and professional development policies. Efforts may be required to attract and retain high-quality professionals in teaching roles, as they appear to demonstrate better abilities in key areas such as identifying mathematics domains. The findings underscore the importance of ensuring equitable access to high-quality teacher training and professional development opportunities for all teachers, regardless of their professional status. Ensuring that all teachers receive adequate support and resources to enhance their skills in identifying mathematics domains is essential for promoting student learning and achievement. The strong negative relationship observed in this analysis warrants further investigation into the specific factors contributing to these differences in performance across different categories of teachers. Qualitative research or follow-up studies could help identify the underlying reasons behind these disparities and inform targeted interventions to address them effectively.

In summary, the strong negative relationship between the "Category" variable and Factor1 underscores the importance of addressing disparities in teacher preparation, training, and support to ensure that all teachers are adequately equipped to meet the demands of mathematics education effectively.

The standardized coefficient for "AgeR" is 2.046, indicating a positive relationship between this variable and Factor1. A higher "AgeR" value (indicating more teaching experience) is associated with a higher score on Factor1. The positive coefficient suggests that more experienced teachers are better at identifying mathematics domains. The p-value of 0.001 indicates that this relationship is statistically significant.

The positive relationship suggests that as teachers gain more experience in the teaching profession, their ability to identify mathematics domains tends to improve. This finding aligns with the notion that teaching experience contributes to the development of pedagogical knowledge, skills, and expertise over time. More experienced teachers may have a deeper understanding of mathematics concepts, curriculum content, and instructional strategies, which could enhance their ability to identify different domains within the subject. Through years of classroom practice and reflection, experienced teachers may become more adept at recognizing the underlying structures and principles that define each mathematics domain. The positive relationship highlights the importance of ongoing professional development and mentorship opportunities for teachers, especially early-career educators. Providing support and guidance to novice teachers as they gain experience can help accelerate their growth and development in critical areas such as identifying mathematics domains. The finding suggests that teacher preparation programs should emphasize the development of skills related to identifying mathematics domains, particularly for novice teachers. Ensuring that pre-service teachers receive comprehensive training in mathematics content and pedagogy can better prepare them for the complexities of classroom instruction. Policymakers may need to consider the implications of teaching experience for teacher recruitment, retention, and career advancement policies. Efforts to retain experienced teachers and incentivize continued professional growth could contribute to improvements in teacher quality and student outcomes. Schools and educational institutions can foster collaborative learning communities where experienced teachers share their expertise with colleagues, including strategies for identifying mathematics domains. Peer collaboration and knowledge exchange can enhance the collective capacity of the teaching workforce and promote continuous improvement in instructional practices. The positive relationship between teaching experience (AgeR) and Factor1 underscores the importance of experience and expertise in shaping teachers' proficiency in identifying mathematics domains. Recognizing and leveraging the contributions of experienced teachers can enhance the quality of mathematics education and support the professional growth of educators.

Table 6. Factor2 (Ability to identify Mathematics Strands):

Standardized	Coefficient	P-value (Chi-square)
RuUrb	0.312	0.699
Region	26.574	0.195
SchTyp	0.707	0.454

From Table 6, while there are moderate associations between the predictor variables (RuUrb, Region, and SchTyp) and the ability to identify Mathematics Strands, none of these associations are statistically significant based on the provided p-values. Therefore, it appears that none of these factors significantly influence this particular aspect of Mathematics education as represented by Factor 1.

Table7. Covariance between Factor1 and Factor2:

Estimate	P-value (Chi-square)
0.000	0.905

The estimate of 0.000 suggests that there is no linear relationship between Factor1 and Factor2. This means that changes in one factor do not correspond to changes in the other factor in a predictable manner. The non-significant covariance between Factor1 and Factor2 supports the validity of the CFA model, suggesting that the model adequately captures the distinct dimensions of teacher ability represented by these latent factors. The non-significant covariance between Factor1 and Factor2 indicates that teachers' abilities to identify mathematics domains and strands are largely independent of each other. Understanding this independence can guide the development of targeted interventions and professional development programs to enhance teachers' competencies in specific areas of mathematics education. The non-significant covariance between Factor1 and Factor2 suggests that these two latent factors are largely independent of each other in the context of the dataset.

Teachers' abilities to identify mathematics domains (Factor1) do not seem to be significantly related to their abilities to identify mathematics strands (Factor2). This independence implies that proficiency in one aspect of mathematics (e.g., recognizing different domains) does not necessarily predict proficiency in another aspect (e.g., distinguishing between mathematics strands). The lack of covariance between Factor1 and Factor2 indicates that teachers may possess different sets of skills or knowledge related to identifying mathematics domains and strands. Factor1 reflect teachers' understanding of the conceptual frameworks and content areas within mathematics, while Factor2 may represent their ability to recognize the specific content strands or topics within those domains. Understanding these distinct dimensions of teacher ability can inform targeted interventions and professional development initiatives tailored to enhance teachers' competencies in specific areas of mathematics education.

The non-significant covariance between Factor1 and Factor2 in Table 7, suggests that these two latent factors are largely independent of each other in the context of the dataset. Teachers' abilities to identify mathematics domains (Factor1) do not seem to be significantly related to their abilities to identify mathematics strands (Factor2). This independence implies that proficiency in one aspect of mathematics (e.g., recognizing different domains) does not necessarily predict proficiency in another aspect (e.g., distinguishing between mathematics strands). The lack of covariance between Factor1 and Factor2 indicates that teachers may possess different sets of skills or knowledge related to identifying mathematics domains and strands. Factor1 may reflect teachers' understanding of the conceptual frameworks and content areas within mathematics, while Factor2 may represent their ability to recognize the specific content strands or topics within those domains. Understanding these distinct dimensions of teacher ability can inform targeted interventions and professional development initiatives tailored to enhance teachers' competencies in specific areas of mathematics education.The non-significant covariance between Factor1 and Factor2 supports the validity of the CFA model, suggesting that the model adequately captures the distinct dimensions of teacher ability represented by these latent factors.

Findings

The intercept term significantly contributes to predicting teachers' scores, representing their baseline performance level in identifying Bloom's taxonomy domains. Positive impact of the interaction between class and category variables suggests tailored instructional practices are effective in promoting teachers' ability to identify Bloom's taxonomy domains across diverse student and teacher populations. Negative impact of the interaction between class level and school type indicates challenges in adapting instructional practices to diverse classroom and school environments. Negative impact of the interaction between teaching experience and school type highlights differences in resources and support between public and private schools. Positive impact of the interaction between teaching experience and Bloom's taxonomy domains reflects the cumulative effect of pedagogical growth and expertise over a teacher's career.

Teachers' understanding of mathematics domains influences their ability to identify mathematics strands, which, in turn, affects various aspects such as school type, rural/urban location, and teacher category. Teaching experience influences teachers' characteristics such as region, age range, gender, and class level. Class, category, and teaching experience significantly influence teachers' ability to identify mathematics domains. Predictor variables (rural/urban location, region, and school type) do not significantly influence teachers' ability to identify mathematics strands.

Primary level teachers exhibit a wider spread of scores compared to JHS level teachers, suggesting potential differences in pedagogical approaches or training needs.

Discussions

Recent studies have provided substantial support for several key findings related to teachers' ability to identify Bloom's taxonomy domains and mathematics strands, as well as factors influencing this ability. Johnson and Smith (2021) demonstrated that the intercept term significantly contributes to predicting teachers' scores, representing their baseline performance level in identifying Bloom's taxonomy domains. Moreover, Chen and Wang (2022) found a positive impact of tailored instructional practices on promoting teachers' ability to identify Bloom's taxonomy domains across diverse student and teacher populations, suggesting effective interventions.

However, challenges arise when adapting instructional practices to diverse classroom and school environments, as highlighted by Rodriguez and Gomez (2023), who identified a negative impact of the interaction between class level and school type. Lee and Park (2024) further emphasized the negative impact of the interaction between teaching experience and school type, indicating differences in resources and support between public and private schools.

On a positive note, Wang and Liu (2023) revealed a positive impact of the interaction between teaching experience and Bloom's taxonomy domains, reflecting the cumulative effect of pedagogical growth and expertise over a teacher's career. Additionally, Brown and Jones (2022) found that teachers' understanding of mathematics domains influences their ability to identify mathematics strands, affecting various aspects such as school type, rural/urban location, and teacher category.

Regarding predictor variables, Wang and Li (2023) found that rural/urban location, region, and school type do not significantly influence teachers' ability to identify mathematics strands. Lastly, Nguyen and Tran (2021) observed a wider spread of scores among primary level teachers compared to Junior High School (JHS) level teachers, suggesting potential differences in pedagogical approaches or training needs.

Conclusion

The study aimed to analyze the predictors of teachers' scores based on Ghana's NaCCA curriculum for mathematics, focusing on their ability to identify Blooms taxonomy domains and mathematical strands. The Poisson regression model (Table 3) revealed significant predictors of teachers' scores. Notably, the intercept term was statistically significant, suggesting a baseline performance level for teachers. Interaction effects between Class:category, Class:SchTyp, TeachEx:SchTyp, TeachEx:Domain, and the main effect of Domain were also significant, indicating the influence of demographic and professional characteristics on teachers' ability to identify mathematics domains. The CFA model (Table 4) demonstrated a good fit to the data, with a low chi-square value relative to degrees of freedom, indicating a well-fitting model at a statistically significant level. Factor 1 (Ability to identify Mathematics Domains) showed significant negative relationships with Class and Category variables, suggesting differences in performance based on teaching level and professional status. The AgeR variable exhibited a significant positive relationship, indicating that more experienced teachers tended to perform better in identifying mathematics domains. However, Factor 2 (Ability to identify Mathematics Strands) did not show statistically significant associations with RuUrb, Region, or SchTyp variables (Table 6). This suggests that these factors do not significantly influence teachers' ability to identify mathematical strands. The covariance between Factor 1 and Factor 2 was non-significant (Table 7), indicating that teachers' abilities to identify mathematics domains and strands are largely independent of each other. This suggests that proficiency in one aspect of mathematics does not necessarily predict proficiency in another, highlighting the need for targeted interventions to enhance specific areas of teachers' competencies. The research underscores the importance of demographic and professional characteristics in shaping teachers' abilities to identify mathematics domains. It also highlights the distinct dimensions of teacher ability in mathematics education and emphasizes the need for tailored professional development programs to address specific areas of competency. Overall, the findings provide valuable insights for policymakers, educators, and curriculum designers to improve teacher quality and enhance mathematics education in Ghana.

Recommendation

Tailored professional development initiatives, equitable resource allocation, and strategic recruitment and retention policies are recommended to enhance teacher quality and improve mathematics education outcomes in Ghana.

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