High School Mathematics Teachers' Knowledge About Stem Education: The Ordinal Logistic Regression Model

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Abstract: - **This study analyses high school mathematics teachers' knowledge about STEM education. Three hundred and fifty (350) Senior High School teachers, comprising one hundred and eighty-one (181) males and one hundred and sixty-nine (169) females, selected from schools in the central region of Ghana, participated in the study. The proportional odds model of the ordinal logistic regression comprising a five-point Likert scale (i.e., highly not aware, not aware, neutral, aware, highly aware) dependent variable, and continuous and nominal predictor variables were used for the study. The results indicated that the significant predictors were math attitude, teacher competency in math, motivation, Asanti, Fanti, Ewe, Ashanti, Bono, Northern, Savannah, and Volta, *P* < *.05*. These variables either significantly decreased or increased the predicted log odds of falling at a higher level of the outcome variable while holding the other variables constant. The Exp(β) provides the odds ratio associated with each predictor, with a 95 % *C. I*. The adjusted odds ratio for Math attitude was 2.56, with a *C.I* of -.34-.32. The adjusted odds ratio for Teacher competency in Math was 1.08, with a *C. I* of -.17-.33, the adjusted odds ratio for Motivation was 2.25, with a *C. I* of -.56--.02, the adjusted odds ratio for Fanti was 2.23, with a *C. I* of .08-1.31 and the adjusted odds ratio for Islam was 1.10, with a *C.I* of -1.41-1.22. The implication of the study is that the government could enact laws that would make it mandatory for all science and mathematics teachers to use a comprehensive integrative STEM curriculum for instruction. This integrative curriculum must have science, technology, engineering, and mathematics components appropriately selected. The study concludes that teachers should reorient their perspectives and understanding of their self-efficacy beliefs about STEM education. The government, municipal, and district education offices could organise periodic professional development programmes on STEM education for teachers to possess specific personal and professional characteristics.**

Keywords: **STEM, Odds ratio, self-efficacy, Likert scale, proportional odds model.**

I. INTRODUCTION

Over the past two decades, considerable attention has attracted STEM education worldwide (Honey, Pearson, & Schweingruber, 2014). STEM education includes inquiry and project-based teaching approaches, other than the traditional lecture-based teaching strategies. Some mathematics teachers propound that STEM education integrates science, technology, engineering, and mathematics curricula to enable scientists, engineers, and mathematicians to solve real-life problems. Others believe that STEM education creates opportunities for many students to graduate in the science, technology, engineering, and mathematics fields (Breiner, Harkness, Johnson, & Koehler, 2012). This global concern to improve STEM education is necessary because a STEM-skilled workforce is critical to meeting economic challenges and sustaining development in the 21st Century (Partnership for 21st Century Skills, 2017; Rockland et al., 2010). As STEM fields expand and the demand for skilled workers increases, researchers are overwhelmed with the necessary skills and knowledge people must acquire to remain competitive (Caprile, Palmen, Sanz, & Dente, 2015; English, 2017). Although there is a global demand for STEM expertise, students' enthusiasm toward STEM learning has declined in many countries because some teachers lack confidence in STEM teaching, thus limiting students' exposure to a full breadth of STEM knowledge (Thomas & Watters, 2015).

II. LITERATURE REVIEW

Teachers' role in the classroom and community significantly impacts student learning and interest in STEM pathways and careers (Autenrieth, Lewis, & Butler-Perry, 2017; Brophy, Klein, Portsmore, & Roger, 2008). Teacher self-efficacy is a significant factor that impacts student learning (Nadelson, Seifert, Moll, & Coats, 2012; Yoon, Evans, & Strobel, 2012, 2014). According to Bandura (1994), self-efficacy is "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events to affect their lives. Self-efficacy beliefs determine how people feel, think, motivate themselves, and behave." (p. 71). Therefore, teachers become less knowledgeable and comfortable teaching subjects they have not been trained to teach. It affects their self-efficacy and confidence in following any integrated STEM curriculum (Stohlmann, Moore, & Roehrig, 2012). Teacher self-efficacy influences teacher behaviour and student outcomes. Therefore, teacher professional development should be organised periodically and well-targeted to improve teacher skills and self-efficacy (Bray-Clark & Bates, 2003).

Student academic achievement could be influenced by teachers' self-efficacy, motivation, attitude, and aptitude in the classroom (Witt-Rose, 2003). Among the list, teacher self-efficacy influences their preparation, teaching strategies, pedagogical approaches, and students' academic achievement (Bray-Clark & Bates, 2003; Yoon et al., 2012, 2014). It influences students' cognitive achievement and sense of efficacy (Caprara, Barbaranelli, Steca, & Malone, 2006).

Despite the importance of STEM education, inequalities in higher education still exist. Classroom instruction should be more inclusive and equity-minded for all students to have the opportunity to succeed academically. For this to occur, teachers must not demonstrate biases in the classroom. They must show commitment to adopt culturally responsive pedagogy, affirm positive attitudes about students, and embrace a mindset of inclusive education. An inclusive approach to teaching builds a positive classroom climate (Cabrera, Nora, Terenzini, Pascarella, & Hagedorn, 1999). It improves the achievement gap between males and females (Canning, Muenks, Green, & Murphy, 2019) and leads to equitable student outcomes (Bauman, Bustillos, Bensimon, Christopher Brown II, & Bartee, 2005).

However, teachers' roles and responsibilities in cultivating a learning environment for all students to have the opportunity to succeed academically, are often neglected (Whittaker & Montgomery, 2014). Teachers, therefore, should be encouraged and motivated to play an active role in supporting the academic success of these students (Bauman et al., 2005; Fairweather, 2008; Killpack & Melon, 2016). To this end, teachers could continually implement curricular strategies to improve student performance. For example, teachers could introduce active learning into STEM courses, thus considerably reducing student failure rates and improving their performance (Freeman et al., 2014; Haak, HilleRisLambers, Pitre, & Freeman, 2011).

Teachers must embrace multicultural teaching for this to succeed. Research indicates that a diverse student body enhances the educational outcomes of all students since these students have distinct experiences and come from unique backgrounds (Gurin, Dey, Hurtado, & Gurin, 2002; Milem, Chang, & Antonio, 2005). Further, professional development programmes that support teachers in embracing diversity would be an asset to enable them to become more culturally responsive in their teaching (Barrington, 2004; Powell, Cantrell, Malo-Juvera, & Correll, 2016; Prater & Devereaux, 2009; Villegas & Lucas, 2002). Inclusive pedagogy interventions, such as workshops, enable teachers to select the appropriate content and incorporate relevant instructional strategies that leverage the educational benefits of diverse classrooms (Booker, Merriweather, & Campbell Whatley, 2016).

There are two schools of thought about how effective STEM instruction should be. One school of thought asserts that if teachers teach any of the individual disciplines of mathematics, science, engineering, or technology, they are not teaching STEM (Larson, 2017). There is a strong commitment in this vision for teachers to teach mathematics and science using methods that emphasize the relevance of the disciplines and engage students in developing thinking, reasoning, and problem-solving skills. The other school of thought suggests that teaching the individual disciplines (i.e., math and science) is vital for STEM. But the real STEM is integrative (Dugger, 2010; New York City Department of Education 2015, 2018; Pelesko, 2015).

For STEM teaching to be appealing and fun to students, teachers must select activities that address how much of each STEM field they require in those activities. When teachers implement a comprehensive integrative programme, they should pay attention to individual component disciplines (Stevens, 2012). For any carefully planned programme, mathematics and science play a role different from technology and engineering. Mathematics and science are school subjects taught as both a comprehensive education and a foundation for any STEM initiative. When teachers incorporate mathematics as part of any STEM activity, they must ensure that the mathematics is consistent with the standards for the targeted grade level(s) (Larson, 2017). A well-designed and effective STEM programme should have strong mathematics and science component and many opportunities to use mathematical and scientific thinking, reasoning, and modelling across disciplines. Thus, mathematics and science disciplines should be integral be part of any comprehensive STEM programme.

The purpose of this study was to determine the predictor variables (i.e., Math attitude, Motivation, Teacher competency in math, Gender, Ethnicity, and Religion), which influenced SHS teachers' knowledge (i.e., highly not aware, not aware, neutral, aware, highly aware) about STEM education. This study was guided by the following research questions:

1. What is the nature of teachers' level of awareness about STEM education?
2. Which predictor variables contributed significantly to the ordinal logistic regression model?
3. Which predictor variables did not contribute significantly to the ordinal logistic regression model?
4. What is the nature of odds ratios associated with a unit increase in each predictor variable?
5. What are the predicted probabilities of a teacher falling in the *jth* category, given the set of predictor variables?

III. METHOD

Ordinal Logistic Regression Model

The ordinal logistic regression model is a statistical analysis method used to model the relationship between an ordinal response variable and one or more predictor or explanatory variables. The explanatory variables could either be continuous or categorical. An assumption normally considered when applying the ordinal regression model is the assumption of proportional, or parallel odds. It implies that the effect of the explanatory variables remains constant for each increase in the level of the response (i.e., the explanatory variables have the same effect on the odds, regardless of different consecutive splits to the data, for each category as shown in Table 1

Table 1 Category comparisons associated with two different ordinal regression approaches, based on a 5-Level ordinal outcome ($j = 1, 2, 3, 4, 5$)

Cumulative Odds (ascending) $P(Y \leq j)$	*Cumulative Odds* $P(Y \geq j)$
Category 1 versus all above	Category 5 versus all below
Categories 1 and 2 combined versus all above	Categories 5 and 4 combined versus all below
Categories 1, 2, and 3 combined versus all above	Categories 5, 4, and 3 combined versus all below
Categories 1, 2, 3, and 4 combined versus Category 5	Categories 5, 4, 3, and 2 combined versus 1

(Adapted from O'Connell, 2006).

The cumulative logit parameterization of ordinal logistic regression

The cumulative odds model is often used to predict the odds of being at or below a particular category. If *j* possible outcomes are presented, then the model would have *J-1* predictions, each corresponding to the accumulation of probability across successive categories. Table 2 shows the common parametrizations for the cumulative logit model, where *j* represents the number of levels in the categorical response variable, and *k* represents the number of explanatory variables. The most common parametrizations are models 1 and 2, where the outcome of interest is observing "*Y l*ess than or equal to *j",* where *j* is one of the ordered categories of the response variable. For model 3, the cumulative logit parametrization specifies that the outcome of interest is observing *"Y* is greater than *j*". Regardless of the parametrization, the model would have *J-1* cutoffs also referred to as intercepts or threshold values, denoted by α_j in the parametrizations, and one parameter for each explanatory variable. This allows for the intercepts to vary for each cumulative logit. However, the model assumes that each explanatory variable exerts the same effect on each cumulative logit. This is why the ordinal logistics regression model is also known as the proportional-odds model. Model 1 incorporates a negative sign, so that there is a direct correspondence between the slope and ranking. Thus, a positive coefficient indicates that as the value of the explanatory variable increases, the likelihood of a higher-ranking increases. This is also the case for the parametrization of model 3, but notice that the intercepts will differ between model 1 and model 3.

Table 2 Three parameterizations of the ordinal logistic regression model

Model 1	$log\left(\frac{P(Y\leq j)}{1-P(Y\leq j)}\right) = \alpha_j - (\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k), j = 1, \dots, j-1$
Model 2	$log\left(\frac{P(Y\leq j)}{1-P(Y\leq j)}\right) = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k, j = 1, \dots, j-1$
Model 3	$log\left(\frac{P(Y>j)}{1-P(Y>j)}\right) = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k, j = 2, \dots, j-1, j$

A latent Variable Model

The ordinal logistic regression model can be expressed as a latent variable model (Agresti, 2002; Greene, 2003; Long, 1997; Long & Freese, 2006; Powers & Xie, 2000; Wooldridge & Jeffrey, 2001).

Assuming a latent variable, $Y^* = X\beta + \varepsilon$, where X a row vector $(1 * k)$ containing no constant, β is a column vector $(k * 1)$ of structural coefficients, and ε is random error with standard normal distribution; $\varepsilon \sim N(0,1)$. Let Y^* be divided by some cut points (thresholds): $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_j$. Regarding the extent of in-service teachers' knowledge of STEM education in the ordinal outcome, Y^* ranging from 1 to 5 where 1 = highly not aware, 2 = not aware, 3 = neutral, 4 = Aware, 5 = highly aware is defined by:

$$Y = \begin{cases} 1\ if\ Y^* \leq \alpha_1 \\ 2\ if\ \alpha_1 < Y^* \leq \alpha_2 \\ 3\ if\ \alpha_2 < Y^* \leq \alpha_3 \\ 4\ if \alpha_3 < Y^* \leq \alpha_4 \\ 5\ if\ \alpha_4 < Y^* \leq \infty \end{cases}$$

Therefore, the probability of in-service mathematics teachers' knowledge about STEM can be computed as follows:

$$p(y=1) = p(Y^* \leq \alpha_1)$$
$$= p(x\beta + \varepsilon \leq \alpha_1)$$
$$= F(\alpha_1 - x\beta)$$
$$p(y=2) = p(\alpha_1 < Y^* \leq \alpha_2)$$
$$= F(\alpha_2 - x\beta) - F(\alpha_1 - x\beta)$$
$$p(y=3) = p(\alpha_2 < y^* \leq \alpha_3)$$
$$= F(\alpha_3 - x\beta) - F(\alpha_2 - x\beta)$$
$$p(y=4) = p(\alpha_3 < Y^* \leq \alpha_4)$$
$$= F(\alpha_4 - x\beta) - F(\alpha_3 - x\beta)$$
$$p(y=5) = p(\alpha_4 < Y^* \leq \infty)$$
$$= 1 - F(\alpha_4 - x\beta);$$

The cumulative probabilities can also be computed using the form:

$p(Y \leq j) = F(\alpha_j - x\beta)$, where j = 1, 2, 3…, J-1 (1)

General Logistic Regression Model

In a binary logistic regression model, the response variable has two levels, with 1 = success of the event, and 0 = failure of the event. The probability of success is predicted over a set of predictors. The logistic regression model can be expressed as:

$$ln(Y) = logit[\pi(x)]$$

$$= ln\left[\frac{\pi(x)}{1-\pi(x)}\right]$$

$$= \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad (2)$$

SPSS Plum (Polychotomous Universal Model) is an extension of the generalized linear model for ordinal response data. It takes the following form:

$$logit[\pi(Y \leq j|x_1, x_2, \dots x_k)] = ln\left[\frac{\pi(Y \leq j|x_1, x_2, \dots x_k)}{\pi(Y > j|x_1, x_1, \dots x_k)}\right]$$

$$= \alpha_j + (-\beta_1 X_1 - \beta_2 X_2 + \cdots - \beta_k X_k) \quad (3)$$

Where α_{js} are the thresholds, and $\beta_1, \beta_2, \dots, \beta_k$, are the logit coefficients; $j = 1,2, \dots j-1$

Participants and Setting

Three hundred and fifty (350) Senior High School (SHS) mathematics teachers, made up of one hundred and eighty-one (181) males and one hundred and sixty-nine (169) females selected from Senior High Schools in the central region of Ghana, participated in the study. The region has six (6) category A schools (3 males and 3 females), twenty-one (21) category B schools, and forty (40) category C schools (39 day/boarding and 1 day). First, one male and one female school were randomly selected from category A, seven (7) schools were randomly from category B schools, and fourteen schools were randomly selected from category C schools. Second, seventeen (17) teachers were randomly selected from the first nineteen (19) schools, whilst, ten (10) teachers, were randomly selected from the last school. The teachers' religion was (Christianity = 205; Islam = 112; African Traditional Religion = 24; Other Religion = 9), ethnicity was (Asanti = 79; Fanti = 74; Ga = 61; Ewe = 62; and other ethnicity = 74), region of birth was (Ahafo = 16; Ashanti = 50; Bono = 20; Bono East = 15; Central = 37; Eastern = 30; Greater Accra = 36; North East = 13; Northern = 42; Oti = 12; Savannah = 14; Upper East = 12; Upper West = 11; Volta = 17; Western = 15; and Western North = 10). Additionally, the ordinal Likert scale items of teachers' responses (highly not aware = 1; not aware = 2; neutral = 3; aware = 4; and highly aware = 5) of their knowledge about STEM education were collected using a questionnaire. The average age of the teachers was 36 years. Table 3 indicates the teachers' demographic characteristics.

Table 3 Teachers' Demographic Characteristics

Demographic Characteristic	Category	Number of teachers	Percentage
Religion	Christianity	205	58.6
	Islam	112	32.0
	African Traditional Religion	24	6.9
	Others	9	2.6
	Total	350	100.0
Gender	Male	181	51.7
	Female	169	48.3
	Total	350	100.0
Ethnicity	Asanti	79	22.6
	Fanti	74	21.1
	Ga	61	17.4
	Ewe	62	17.7
	Others	74	21.1
	Total	350	100.0
Region of Birth	Ahafo	16	4.6
	Ashanti	50	14.3
	Bono	20	5.7
	Bono East	15	4.3
	Central	37	10.6
	Eastern	30	8.6
	Greater Accra	36	10.3
	North East	13	3.7
	Northern	42	12.0
	Oti	12	3.4

Demographic Characteristic	Category	Number of teachers	Percentage
	Savannah	14	4.0
	Upper East	12	3.4
	Upper West	11	3.1
	Volta	17	4.9
	Western	15	4.3
	Western North	10	2.9
	Total	350	100.0

Instrumentation and data collection procedure

This study analysed questionnaire responses of 350 mathematics teachers, to determine the predictor variables contributing to their responses on their knowledge about STEM education. The questionnaire consisted of six (6) subscales, with each scale having between five (5) and eight (8) five-point Likert scale items. The teachers were assured of anonymity and confidentiality. Therefore, their names were not written on the questionnaires. The teachers answered the questionnaires in their schools. The teachers took between 10 and 15 minutes to complete the questionnaires.

Validity and Reliability

Validity is the extent to which researchers really measure a concept in a quantitative study (Field, 2005). A type of validity, known as content validity, looks at the extent to which a research instrument accurately measures all aspects of a construct. Content validity is assessed by checking how well the results correspond to established theories and other measures of the same concept. so, a survey designed to measure depression but actually measures anxiety, is not valid.

Reliability is the extent to which a measurement of a phenomenon provides a stable and consistent result (Carmines & Zeller, 1979). Thus, a scale or test is said to be reliable if repeated measurement under constant conditions gives the same result (Moser & Kalton, 1989). Testing for reliability is important since it refers to the consistency across the parts of a measuring instrument (Huck, 2007). A scale is said to have high internal consistency reliability if the items of a scale "hang together" and measure the same construct (Huck, 2007, Robinson, 2009). The most commonly used internal consistency measure is the Cronbach's Alpha coefficient. Cronbach's alpha is calculated using the formula $\alpha = \frac{nc}{[v+(n-1)]c}$, where n = number of test items; c = average inter-item covariance among items; and v = average variance. It is viewed as the most appropriate measure of reliability when making use of Likert scales (Whitley, 2002; Robinson, 2009). No absolute rules exist for internal consistencies, however most agree on a minimum internal consistency coefficient of .70 (Whitley, 2002; Robinson, 2009). Hinton et al. (2004) have suggested four cut-off points for reliability, which includes excellent reliability (0.90 and above), high reliability (0.70-0.90), moderate reliability (0.50-0.70) and low reliability (0.50 and below). For a test or scale to be reliable, it should first be valid (Wilson, 2010). If a questionnaire or test has a strong internal consistency, most measurements should show only moderate correlation among items (.70 to 0.90). The reliability of the Likert scale items of teachers' responses (highly not aware = 1; not aware = 2; neutral = 3; aware = 4; and highly aware = 5) of their knowledge about STEM education was 0.82. Table 4 shows the number of teachers who responded under each categorical variable.

IV. RESULTS

Table 4: Number of teachers who responded under each categorical variable

Categorical Variables		Highly not aware	Not aware	Neutral	Aware	Highly aware	Total
Ethnicity	Asanti	11	19	24	14	11	79
	Fanti	20	11	21	7	15	74
	Ga	13	20	17	8	3	61
	Ewe	18	11	11	14	8	62
	Others	25	22	16	5	6	74
Total		87	83	89	48	43	350
Gender	Female	31	45	44	26	23	169
	Male	56	38	45	22	20	181
Total		87	83	89	48	43	350
Religion	Christianity	50	52	50	28	25	205
	Islam	30	26	22	19	15	112

Categorical Variables		Highly not aware	Not aware	Neutral	Aware	Highly aware	Total
	African Traditional Religion	6	5	11	0	2	24
	Others	1	0	6	1	1	9
Total		87	83	89	48	43	350
Region of Birth	Ahafo	3	5	5	2	1	16
	Ashanti	12	10	19	3	6	50
	Bono	2	5	1	5	7	20
	Bono East	6	1	4	2	2	15
	Central	12	8	8	4	5	37
	Eastern	9	7	7	4	3	30
	Greater Accra	12	4	8	8	4	36
	North East	2	7	1	0	3	13
	Northern	5	10	13	8	6	42
	Oti	4	5	3	0	0	12
	Savannah	3	2	2	5	2	14
	Upper East	5	1	1	4	1	12
	Upper West	3	5	3	0	0	11
	Volta	2	5	5	3	2	17
	Western	2	6	6	0	1	15
	Western North	5	2	3	0	0	10
Total		87	83	89	48	43	350

Table 4 categorises the teacher responses in each of the four categorical variables: Ethnicity, gender, religion and region of birth. Ethnicity consist of 5 categories, gender consists of 2 categories, religion consists of 6 categories, and region of birth consists of 16 categories. Table 5 shows the model fitting information.

Table 5: Model Fitting Information

Model	-2Log Likelihood	Chi-Square	df	Sig.
Intercept only	1058.79			
Final	1011.99	46.79	26	.01

Table 5 compares the model without any explanatory variables (the baseline or" intercept only" model) to the model with all the explanatory variables (the final model). The two models are compared to see whether the final model is a good fit to the data. From the table, ${\chi^2}_{26} = 46.79 < .05$ indicates that the final model gives significant improvement over the baseline intercept-only model. Thus, the model gives better predictions than what one would have guessed based on the marginal probabilities for the outcome categories. Table shows the goodness-of-fit table.

Table 6: Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	1230.38	1194	.23
Deviance	977.68	1194	1.00

Table 6 presents the Pearson and Deviance statistics. They test whether the observed data are consistent with the fitted model. The null hypothesis states that the model fits the data, while the alternative hypothesis states that the model does not fit the data. The null hypothesis is not rejected if P > .05. The conclusion to draw is that the data and the model predictions are similar and that the model is good. However, if the assumption of good fit is rejected, i.e., p < .05, then the model does not fit the data well. Since ${\chi^2}_{1194} = 1230, p > .05$, the model does fit the data well. Table shows the Pseudo R-Square table.

Table 7 Pseudo R-Square 8

Cox and Snell	.23
Nagelkerke	.44
McFadden	.14

In Table 7, the Pseudo R-square statistics value (i.e., Nagelkerke = 44%) indicates that the explanatory variables in the model explain 44% of the variance in the cumulative log odds, while 54% of the variance in the cumulative log odds are unexplained by the model. Overall, it is a good model. Table 8 shows the parameter estimates.

Table 8: Parameter Estimates

Parameter		β	Std. Error	Wald	df	Sig.	Exp(β)	95% C. I Lower Bound	95% C. I Upper Bound
Threshold/Intercept	Outcome 1	-1.51	1.32	7.02	1	.1	.03	.92	6.11
	Outcome 2	1.72	1.32	3.64	1	.06	.08	-.07	5.11
	Outcome 3	2.31	1.32	.97	1	.32	.27	-1.27	3.88
	Outcome 4	4.16	1.31	.02	1	.90	.85	-2.41	27.4
Location	Math Attitude	.94	.17	.00	1	.04	2.56	-.34	.32
	Teacher Competency in Math	.08	.13	.41	1	.03	1.08	-.17	.33
	Motivation	.81	.14	4.92	1	.03	2.25	-.56	-.02
	Asanti	-1.00	.32	9.77	1	.00	.37	.37	1.63
	Fanti	.80	.31	4.92	1	.03	2.23	.08	1.31
	Ga	-.46	.33	1.90	1	.17	.64	-.19	1.10
	Ewe	-.83	.34	6.09	1	.01	.44	.17	1.49
	Others	0	-	-	0	-	-	-	-
	Female	-.35	.21	2.75	1	.10	.70	-.07	.77
	Male	0	-	-	0	-	-	-	-
	Christianity	-.14	.66	.05	1	.83	.87	-1.15	1.43
	Islam	.10	.67	.02	1	.89	1.10	-1.41	1.22
	African Traditional Religion	-.21	.77	.07	1	.79	.81	-1.31	1.72
	Others	0	-	-	0	-	-	-	-
	Ahafo	-.80	.77	.77	1	.30	.45	-.70	2.31
	Ashanti	-1.34	.67	.67	1	.04	.26	.03	2.64
	Bono	-2.30	.77	.77	1	.00	.10	.79	3.81
	Bono East	-.89	.79	.79	1	.26	.41	-.66	2.43
	Central	-.96	.67	.68	1	.16	.39	-.37	2.82
	Eastern	-1.13	.70	.70	1	.10	.32	-.23	2.50
	Greater Accra	-1.34	.69	.69	1	.05	.26	-.00	2.69
	North East	-1.16	.82	.82	1	.16	.31	-.44	2.76
	Northern	-1.88	.67	.67	1	.00	.15	.56	3.20
	Oti	-.22	.81	.07	1	.79	.80	-1.36	1.80
	Savannah	1.52	.79	3.74	1	.03	.21	-.02	3.07
	Upper East	-.75	.81	.86	1	.35	.47	-.83	2.33
	Upper West	-.72	.85	.71	1	.40	.49	-.95	2.38
	Volta	-1.47	.75	3.82	1	.04	.23	-.00	2.95

Parameter		β	Std. Error	Wald	df	Sig.	Exp(β)	95% C. I Lower Bound	95% C. I Upper Bound
	Western	-1.20	.77	2.47	1	.12	.30	-.30	2.71
	Western North	0	-	-	0	-	-	-	-

Table 8 shows the parameter estimates. An ordinal logistic regression model was used to investigate whether SHS mathematics teachers' mathematics attitude, competency in mathematics, motivation, ethnicity, gender, religion, and region of birth, predict their knowledge (highly not aware, not aware, neutral, aware, highly aware) of STEM education in the central region. The significant predictors were Math attitude, Teacher competency in math, Motivation, Asanti, Fanti, Ewe, Ashanti, Bono, Northern, Savannah, and Volta ($P < .05$). These variables either significantly decreased or increased the predicted log odds of falling at a higher level of the outcome variable while holding the other variables constant.

For a unit increase in the Math Attitude measure, there was a predicted increase of .94 in the log odds of falling at a higher level of the outcome variable. Thus, as Math attitude scores increased, there was an increase in the probability of falling at a higher level on the outcome variable. For a unit increase in Teacher competency in mathematics measure, there was a predicted increase of .08 in the log odds of falling at a higher level of the outcome variable. Thus, as Teacher competency in math scores increased, there was an increase in the probability of falling at a higher level on the outcome variable. Similarly, for a unit increase in motivation, there was a predicted increase of .81 in the log odds of falling at a higher level of the outcome variable. Thus, as motivation scores increased, there was an increase in the probability of falling at a higher level on the outcome variable. As ethnicity changes from others to Fanti, there was a predicted increase of .80 in the log odds of falling at a higher level of the outcome variable. Thus, as ethnicity changes by one unit from others to Fanti, there was an increase in the probability of falling at a higher level on the outcome variable. As ethnicity changes from others to Asanti, there was a predicted decrease of -1.00 in the log odds of falling at a higher level of the outcome variable. Thus, as ethnicity changed by one unit from others to Asanti, there was a decrease in the probability of falling at a higher level on the outcome variable. As ethnicity changes from others to Ewe, there was a predicted decrease of -.83 in the log odds of falling at a higher level of the outcome variable. This means that as ethnicity changed by one unit from others to Ewe, there was a decrease in the probability of falling at a higher level on the outcome variable.

As the region of birth changes by one unit from Western North to Ashanti, there was a predicted decrease of -1.34 in the log odds of falling at a higher level of the outcome variable. Thus, as the region of birth changes by one unit from Western North to Ashanti, there was a decrease in the probability of falling at a higher level on the outcome variable. As the region of birth changes by one unit from Western North to Northern, there was a predicted decrease of -1.88 in the log odds of falling at a higher level of the outcome variable. Thus, as the region of birth changes by one unit from Western North to Northern, there was a decrease in the probability of falling at a higher level on the outcome variable. As the region of birth changes by one unit from Western North to Bono, there was a predicted decrease of -2.30 in the log odds of falling at a higher level of the outcome variable. Thus, as the region of birth changes by one unit from Western North to Bono, there was a decrease in the probability of falling at a higher level on the outcome variable. Similarly, as the region of birth changes by one unit from Western North to Volta, there was a predicted decrease of -1.47 in the log odds of falling at a higher level of the outcome variable. This means that as the region of birth changes by one unit from Western North to Volta, there was a decrease in the probability of falling at a higher level on the outcome variable.

The Exp(β) provides the odds ratio associated with each predictor (adjusting for the other predictors), with a 95 % C. I associated with each provided in the final two columns. The adjusted odds ratio for Math attitude was 2.56, with a C.I of -.34-.32. The odds ratio indicates that for a unit increase in Math attitude, a teacher was 2.56 more likely to fall in a higher level of the outcome variable than the lower. The adjusted odds ratio for Teacher competency in Math was 1.08, with a C.I of -.17-.33. The odds ratio indicates that for a unit increase in Teacher competency in Math, a teacher was 1.08 more likely to fall in the higher level of the outcome variable than the lower. The adjusted odds ratio for Motivation was 2.25, with a C.I of -.56--.02. The odds ratio indicates that for a unit increase in Motivation, a teacher was 2.25 more likely to fall in the higher level of the outcome variable than the lower. The adjusted odds ratio for Fanti was 2.23, with a C.I of .08-1.31. The odds ratio indicates that as ethnicity changes from others to Fanti, a teacher was 2.23 more likely to fall in the higher level of the outcome variable than the lower. The adjusted odds ratio for Islam was 1.10, with a C.I of -1.41-1.22. The odds ratio indicates that as religion changes from others to Islam, a teacher was 1.10 more likely to fall in the higher level of the outcome variable than the lower.

By using model 1 of the parameterization of the ordinal logistic regression model:

$$log\left(\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right) = \alpha_j - \beta_1 x_1 - \beta_2 x_2 - \cdots - \beta_k x_k, j = 1, \ldots, j - 1$$

The predicted probabilities are: $p(Y \leq j) = \frac{EXP(\alpha_j - \beta_1 x_1 - \beta_2 x_2 - \ldots - x_k)}{1 + EXP(\alpha_j - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}$, For $j = 1, 2, 3, 4$; $\alpha_4 = 4.16$; $\alpha_3 = 2.31$; $\alpha_2 = 1.72$; $\alpha_1 = -1.51$; Math attitude = .94; Motivation = .81; Teacher competency = .08; Gender (Female) = -.35; Religion (Christianity) = -.14; Region of birth (Ashanti) = -1.34; Ethnicity (Fanti) = .80; $x_1 = 4$; $x_2 = 5$; $x_3 = 5$; $x_4 = 1$; $x_5 = 1$; $x_6 = 1$; $x_7 = 1$

$$p(Y \le 1) = \frac{EXP(\alpha_1 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}{1 + EXP(\alpha_1 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}$$

$$= \frac{EXP(-1.51-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))}{1+EXP(-1.51-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))} = \frac{EXP(-1.51-7.18)}{1+EXP(-1.51-7.18)}$$

$$= \frac{EXP(-8.69)}{1+EXP(-8.69)} = \frac{.000168}{1.000168} = .0002$$

$$p(Y \le 2) = \frac{EXP(\alpha_2 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}{1 + EXP(\alpha_2 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}$$

$$= \frac{EXP(1.72-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))}{1+EXP(1.72-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))} = \frac{EXP(1.72-7.18)}{1+EXP(1.72-7.18)}$$

$$= \frac{EXP(-5.46)}{1+EXP(-5.46)} = \frac{.00425}{1.00425} = .004$$

$$p(Y = 2) = p(Y \le 2) - p(Y \le 1) = .004 - .0002 = .0038$$

$$p(Y \le 3) = \frac{EXP(\alpha_3 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}{1 + EXP(\alpha_3 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}$$

$$= \frac{EXP(2.31-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))}{1+EXP(2.31-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))} = \frac{EXP(2.31-7.18)}{1+EXP(2.31-7.18)}$$

$$= \frac{EXP(-4.87)}{1+EXP(-4.87)} = \frac{.00767}{1.00767} = .0076$$

$$p(Y = 3) = p(Y \le 3) - p(Y \le 2) = .0076 - .004 = .0036$$

$$p(Y \le 4) = \frac{EXP(\alpha_2 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}{1 + EXP(\alpha_2 - \beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_k x_k)}$$

$$= \frac{EXP(4.16-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))}{1+EXP(4.16-(.94)(4)-(.81)(5)-(.08)(5)-.80(1)+.35(1)+.14(1)+1.34(1))} = \frac{EXP(4.16-7.18)}{1+EXP(4.16-7.18)}$$

$$= \frac{EXP(-3.02)}{1+EXP(-3.02)} = \frac{.04880}{1.04880} = .0465$$

$$p(Y = 4) = p(Y \le 4) - p(Y \le 3) = .0465 - .0076 = .0389$$

Table 9: Test of Parallel Lines

Model	-2Log Likelihood	Chi-Square	df	Sig
Null Hypothesis	1011.99			
General	870.14	90.86	78	.17

The assumption of proportional odds means that each independent variable has an identical effect at each cumulative split of the ordinal dependent variable (O'Connell, 2006). For the ordinal logistic model, the odds ratio at each threshold is equal for a unit increase in each explanatory variable. It is because the model constrains it to have this unique characteristic through the proportional odds assumption. It evaluates the appropriateness of this assumption through the test of parallel lines as indicated in Table 9. This test compares the ordinal model which has a set of coefficients for all thresholds (labelled Null hypothesis), to a model with a separate set of coefficients for each threshold (labelled General). If the general mode gives a significantly better fit to the data than the ordinal (proportional odds) model ($p < .05$), then the proportional odds assumption is rejected. In Table 8, the proportional odds assumption is upheld for the data because ${\chi^2}_{78} = 90.86, p > .05$. It can be concluded that the effect of *ethnicity* is not statistically different across the four cumulative splits for the data. This means that if four separate binary logistics were fitted, the slopes (and odds ratios) for ethnicity in each of these models would be similar.

V. DISCUSSIONS

Mathematics teachers' knowledge about STEM education was generally low (see table 4). The low levels of probabilities in the four-level categorical responses, strongly corroborated this observation. To improve their knowledge about STEM, they need to reorient their perspectives and understanding about their self-efficacy beliefs. Such beliefs could include how they think, feel, motivate themselves and behave (Bandura, 1994). In fact, teacher self-efficacy influences teacher behaviour and student learning outcomes (Nadelson, Seifert, Moll, & Coats, 2012; Yoon, Evans, & Strobel, 2012, 2014). The extent to which mathematics teachers are knowledgeable, would determine how they teach using the STEM curriculum (Autenrieth, Lewis, & Butler-Perry, 2017; Brophy, Klein, Portsmore, & Roger, 2008).

The government, municipal and district education offices could organise periodic teacher professional development programmes for mathematics teachers to possess specific personal and professional characteristics on STEM education (El Nagdi, Leammukda, Roehrig, 2018). Such programmes should be well-targeted to improve their skills and self-efficacy (Bray-Clark & Bates, 2003). These programmes must enable them understand variuos topics by using effective instructional practices (Bush et al., 2020; Ong et al., 2020). Mathematics teachers could contribute to cognitive, metacognitive, and motivational affective learning outcomes by selecting and executing curricular content that provides students' adequate learning and socio-emotional support. It is worthy to note that teachers' professional knowledge lies at the core of teacher competency. It includes general educational concepts, practices and information specific to the discipline (Depaepe, Verschaffel, & Star, 2020). Professional development programmes that enhance knowledge and practice should include support for transfering information or techniques (Luft, Diamond, Zhang, & White, 2020). Professional development programmes are series of training events that occur when teachers work in schools after they graduate from teacher education institutions (Niemi, 2015). They are the cornerstone of all educational reform (Fore et al., 2015). Effective professional development programmes are vital to equip teachers with the necessary knowledge and skills to improve the quality of their instruction (Gencturk, & Thacker, 2021; Tan & Ang, 2016). Professional development programmes potentially provide opportunities for teachers to grow professionally. Research shows that students whose teachers participate in professional development reach higher levels than students whose teachers do not (Wojnowski & Pea, 2013).

STEM professional development programmes are essential for teachers to adopt an integrated STEM curriculum. Learning about numerous disciplines and their link to each other is undoubtedly more complex than learning the content of a single discipline (Luft, Diamond, Zhang, & White, 2020). Mohamad Hasim et al. (2022) recognise nine subthemes consisting of activities under STEM professional development. The activities are engineering-based, computational thinking, inquiry-based, problem-based, project-based learning, modelling, interdisciplinary subjects, integrated STEM and technology-based activities. These activities could impact mathematics teachers' self-efficacy, designing ability, conceptual understanding, pedagogical content knowledge related to engineering fields, inquiry skills, computational thinking and an interdisciplinary teaching approach.

As teachers' math attitude, competency in math, and motivation scores increased, their knowledge about STEM education, correspondingly increased. Thus, mathematics teachers should always exhibit good attitude and competency in mathematics and demonstrate high motivation for mathematics teaching and learning. For this to happen, teacher education programmes must review their mathematics curriculum to include relevant skills training to improve teachers' attitude, competency and motivation. Asanti and Ewe teachers' knowledge about STEM education was lower than the other ethnicities. As a solution, all stakeholders, including teachers, regional and district education directors, and professional development experts, must ensure that they give these teachers the needed training to perform. STEM education knowledge of teachers born in the Northern, Bono and Volta regions was lower than those born elsewhere. Stakeholders of education should ensure that all teachers are motivated to teach effectively.

As the scores for math attitude, teacher competency in math, and motivation, increased by a unit, the odds of a teacher falling at a higher level of the outcome variable was more than the odds of a teacher falling at the lower level. Thus, these variables largely influence teachers' knowledge about STEM education. The more teachers' ratings on these variables increase, the more their knowledge about STEM education. As ethnicity changed from others to Fanti, the odds of a teacher falling at a higher level of the outcome variable was more than the odds of a teacher falling at the lower level. Also, as religion changed from others to Islam, the odds of a teacher falling at a higher level of the outcome variable was more than the odds of a teacher falling at the lower level. Thus, Fanti and Islamic teachers should be motivated to embrace STEM education.

VI. IMPLICATION FOR THE STUDY

Undoubtedly, STEM education equips people with the skills they need to be employable and to meet the current labour demand. The government could enact laws that would make it mandatory for all science and mathematics teachers to use a comprehensive integrative STEM curriculum for instruction. This integrative curriculum must have science, technology, engineering and mathematics components appropriately selected. In fact, science could help students to conduct research and think critically. Technology prepares young people to work in an environment full of high-tech innovations. Engineering allows students to enhance problem-solving skills and apply knowledge in new projects. Mathematics enables people to analyze information, eliminate errors, and make conscious decisions when designing solutions. STEM education links these disciplines into a cohesive system.

STEM education is based on teamwork and collaboration of professionals from different disciplines. Teachers need not become experts in all STEM disciplines in order to work effectively. Instead, they require a mindset that would enable them become a part of the highly qualified workforce. All stakeholders of education, including the government, policy makers and school administrators should inculcate collaboration and teamwork in the school curriculum, especially at the colleges of education and universities.

STEM education changes society by offering teachers skills that are valued in any profession. STEM teachers always flexible in their thinking, looking for patterns, finding connections, and evaluating information. They provide opportunities for students to explore their creativity and communicate their confidently. They are responsible for having a solid intellectual foundation for their students.

VII. CONCLUSION

Mathematics teachers' knowledge about STEM education in the central region was generally low. Teachers need to reorient their perspectives and understanding about their self-efficacy beliefs about STEM education. The government, municipal and district education offices could organise periodic professional development programmes on STEM education for teachers to possess specific personal and professional characteristics.

Activities that could improve teachers' STEM knowledge include but not limited to engineering-based, computational thinking, inquiry-based learning, problem-based learning, project-based learning, modelling, interdisciplinary subjects, integrated STEM and technology-based activities. By practicing these activities could impact mathematics teachers' self-efficacy, designing ability, conceptual understanding, pedagogical content knowledge related to engineering fields, inquiry skills, computational thinking and an interdisciplinary teaching approach.

Mathematics teachers should always exhibit good attitude and competency in mathematics and demonstrate high motivation for mathematics teaching and learning. To realise this, teacher education programmes must review their mathematics curriculum to include relevant skills training that would improve teachers' attitude, competency and motivation in mathematics.

Teachers from all ethnic backgrounds should improve their knowledge about STEM education. For this to happen, the government should assist all stakeholders, including teachers, regional and district education directors, and professional development experts to ensure that these teachers are given the needed training to live up to expectation in the teaching profession. STEM education knowledge of teachers born in the Northern, Bono and Volta regions was lower than those born elsewhere. Again, all stakeholders must ensure that all teachers are motivated to teach effectively. As the scores for Math attitude, Teacher competency in Math, and Motivation, increased by a unit, the odds of a teacher falling at a higher level of the outcome variable was more than the odds of a teacher falling at the lower level. Similarly, as ethnicity changed from others to Fanti, the odds of a teacher falling at a higher level of the outcome variable was more than the odds of a teacher falling at the lower level. Again, as religion changed from others to Islam, the odds of a teacher falling at a higher level of the outcome variable was more than the odds of a teacher falling at the lower level.

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