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The Multinomial Logistic Regression Model's Utility to Assess Parameters in Predicting Junior High School Students' Preference for Selected Mathematics Topics

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Abstract: This study predicts the preference for three mathematics topics among Junior High School students. Four hundred (400) Junior High School (JHS) students, comprising two hundred and eighteen (218) males and one hundred and eighty-two (182) females selected from Junior High Schools in a school district in Ghana, participated in the study. The multinomial logistic regression model, consisting of three unordered outcome categories (i.e., Relations and Functions, Algebraic expressions, and Linear equations), with predictor variables comprising continuous, nominal, and ordinal variables were used for the study. For Relations and Functions, the results indicated that Math self-concept, Arithmetic ability, Motivation, Instructional strategies and methods, Asanti, Fanti, Ga, and Ewe, were statistically significant ($p < .05$). Hence, for a unit increase in the Math self-concept measure, a student is 5.82 times more likely to be in the Relations and Functions topic category than in the Linear equations topic category, controlling for the other variables. Again, a female student is 1.15 times more likely than a male student to be in the Relations and Functions topic category than in the Linear equations topic category, controlling for other variables. Similarly, for Algebraic expressions, the results indicated that Math self-concept, Math attitude, Motivation, Instructional strategies and methods, female, Asanti, Fanti, Ga, and Ewe, were statistically significant ($p < .05$). Thus, for a unit increase in the Math self-concept measure, a student is 2.63 times more likely to be in the Algebraic expressions topic category than in the Linear equations topic category, controlling for the other variables. Again, a female student is 3.75 times more likely than a male student to be in the Algebraic expressions topic category than in the Linear equations topic category, controlling for other variables. These significant predictor variables influencing students' preference for mathematics topics, add to the body of literature on the factors affecting decision-making in mathematics teaching and learning.

Keywords: Relations and Functions, Algebraic Expressions, Linear Equations, Categories, Multinomial Logistic Regression Model

1. Introduction

People make constant decisions from childhood till they die. They make these decisions or choices to satisfy a need, solve a problem, or meet an expectation. Choice making, also known as the decision-making process, plays a substantial role in an individual's life. The main difference between choice and decision is that choice is defined as the right, power, or ability to choose whereas decision is defined as a conclusion or resolution reached after consideration [15]. When people make their own choices about the things they do, it gives them meaning in life. Therefore, the ability to make choices is fundamental in developing an individual's life's responsibility [9]. Throughout life, people make various choices such as what to wear, what to eat, which television programme to watch, and what plans to adopt for the future [9].

Many factors influencing the decision-making process, enable individuals to make choices based on their experiences and are often guided by a set of values [22]. It is always difficult for individuals to make informed decisions in this process. Despite this challenge, the decisions individuals make are the facts of their lives and should be taken into account [5]. Sometimes, people's decisions can influence others. Since individual values have an impact on the decision-making process, social values are also effective [4]. In the decision-making process, what motivates an individual to demonstrate certain characteristics or traits is the creation of a difficulty causing the need for such decision-making. The individual has the freedom to select one among many alternatives to handle such a difficulty [24]. In an individual's life, some situations may require him/her to make choices among desirable ones. Such choices are interpersonal and social, in nature. In terms of values, they are referred to as the sense of responsibility. The decision-making process comes about as a result of a need or difficulty. The individual battles with two or more alternatives before making a decision [2]. During this process, there are choices for the formation of options, understanding these options, and determining these options [6]. The individual making the decision thinks of an ideal option among several options before he/she makes the preference [2].

Several factors influence decision-making. They include experience [21], cognitive biases [28], individual differences [7], belief in personal relevance [1], escalation of commitment [21], age, socioeconomic status (SES), and cognitive abilities [7, 17]. In a quest to attain solutions to a problem, an individual resorts to mental evaluation [32]. Through this process, the individual's preferences are affected by the meaning he/she assigns to a stimulus. He/She is confronted with the ability to choose between two preferred stimuli. The descriptive approach includes the effective factors of the individual's decisions, the source of the decisions, and the environmental impacts of such decisions [26]. Through lateral thinking, effective decisions are made quickly and easily [27]. It is the general decision-making strategy people choose from available information and is very accurate. It acts as a mental shortcut by reducing the cognitive burden associated with decision-making [27]. It enables individuals to work because it reduces the tension associated with making decisions. It offers them a guide in reducing the effort they expend. Together, lateral thinking and factors influencing decision-making are significant ingredients of critical thinking [31].

Self-determination refers to an individual's ability to make his/her own decisions without any external pressure, by exercising autonomy [13]. It is indeed individuals taking responsibility for their own lives, and experiencing the feeling of selection in initiating and organizing their behaviours [11]. Self-determination means desiring, selecting an action completely, and requesting personal approval [26]. Mental autonomy allows an individual to make choices for himself/herself, and be knowledgeable about how to decide. Affective autonomy, which arises from the relationship of mutual respect, is first established with peers and then with adults. It takes its source from children's social activities and is based on cooperation without any coercion. The concept of autonomy, emphasizes cooperation with others, the relationship of mutual respect, and shared values [30]. Empirical research shows that autonomy does not only affect the academic performance of children but also affects the job satisfaction and professional job performance of adults [13, 12, 18].

Decision-making is an important life skill. Timely, accurate, and appropriate decisions yield positive changes in an individual's life, while wrong decisions negatively affect an individual's life [29]. To become successful, an individual should be made aware of the alternatives and select appropriate ones(s), leading to better outcomes. In this case, there is a link between the ability to decide and personal accomplishment [8]. This selection process depends on the characteristics of the environment in which the individual lives [13]. What is important is the degree of autonomy that the environment provides. The support of autonomy an individual receives from the environment increases the levels of self-determination because he/she can make decisions willingly and voluntarily, not controlled, does not feel pressure and coercion, and is self-determined.

The purpose of this study was to determine the predictor variables (i.e., Math self-concept, Math attitude, Arithmetic ability, Motivation, Instructional strategies and methods, Teacher competency in math, Gender, and Ethnicity), which influenced JHS students to select their preference for a mathematics topic (i.e., Relations and Functions, Algebraic expressions, and Linear equations). This study was guided by the following research questions:

a) Which predictor variables contributed significantly to the multinomial logistic regression model if *linear equations* were taken as the reference category?
b) Which predictor variables did not contribute significantly to the multinomial logistic regression model if *linear equations* were taken as the reference category?
c) What was the nature of odds ratios associated with a unit increase in each predictor variable if *linear equations* were taken as the reference category?
d) What was the probability of a student falling in the jth topic category, given the set of predictor variables?
e) What was the probability of a student falling in the J (reference category), given the set of predictor variables?

2. Method

2.1. Multinomial Logistic Regression Model

The multinomial logistic regression model extends the binary logistic regression of two outcome categories to three or more unordered outcome categories [20]. Predictor variables could be any combination of continuous, nominal, or ordinal variables. Despite having three or more unordered outcome categories, multinomial logistic regression still deals with a binary prediction of group membership (researchers predict target group membership with respect to a reference group). This is accommodated within the multinomial analysis by designating one of the groups (in the analysis setup) as the reference group. Each of the other groups serves as a target group and is compared to this reference group. Thus, with three outcome categories, two separate (binary logistic regression) sets of parameter estimates (the raw score coefficients and the odds ratios) are generated, one contrasting one of the outcomes to the reference category and another contrasting the other of the outcomes to the reference category. However, in the classification portion of the analysis, all outcome categories are considered together in that classification coefficients are generated for and applied to all groups, with the group achieving the highest score for each case determining the group to which that case is predicted to belong. Multinomial logistic regression is also known as the polytomous or multiclass regression method.

Let $X_1, X_2, X_3, ..., X_K$ be a set of k predictors, which may be continuous, nominal, or ordinal, and an outcome variable Y with J nominal category. Then, the multinomial logistic regression model may be presented as:

$$logit(Y_j) = In\left(\frac{p(Y=j|X)}{P(Y=J|X)}\right) = \beta_{j0} + \beta_{j1}X_1 + \beta_{j2}X_2 + \ldots + \beta_{jk}X_k$$

Where j = 1, 2, 3,..., J – 1. In such a situation, we have J – 1 logit equations. Each of them is a linear function that models the logarithm of probability as having response j to baseline J [3]. All logits are defined relative to such a predetermined baseline category. It is worthy to note that, they are unordered, where any of the J categories can act as the reference outcome [16]. Logit coefficients (β_{jk}) provide information on how great a change in the logit is made by a unit increase in the value of the *kth* predictor, controlling for the effect of the other predictors. The relative risk ratio (RRR) is used commonly for the interpretation of the model:

$$\frac{P(Y=j|X)}{P(Y=J|X)} = \exp\left(\beta_{j0} + \sum_{k=1}^{K} \beta_{jk}X_k\right)$$

RRR is an exponential function of regression coefficients. RRR greater than 1 means that the probability of occurrence of the *jth* category is greater than the probability of obtaining the reference category J. Since the sum of all probabilities $P(Y = j|X) = 1$, where j = 1, 2, 3,..., J. It can be established that:

$$P(Y = j|X) = \frac{\exp(\beta_{j0}+\beta_{j1}X_1+\beta_{j2}X_2+\ldots+\beta_{jK}X_K)}{1+\sum_{j=1}^{J-1}\exp(\beta_{jo}+\beta_{j1}X_1+\beta_{j2}X_2+\ldots+\beta_{jK}X_K)} \quad (1)$$

$$P(Y = J|X) = \frac{1}{1+\sum_{j=1}^{J-1}\exp(\beta_{jo}+\beta_{j1}X_1+\beta_{j2}X_2+\ldots+\beta_{jK}X_K)} \quad (2)$$

Parameters β_{jk} (j = 1, 2, 3,..., J; k = 1, 2, 3,..., K) are estimated using the maximum likelihood method [22, 31]. The likelihood function dependent observations can be written as:

$$L(\beta) = \prod_{i=1}^{n}\prod_{j=1}^{J} P(Y = j)^{d_{ij}}, \text{ where } d_{ij} = \begin{cases} 1 \; if \; Y_i = j \\ 0 \; if \; Y_i \neq j \end{cases}$$

So $d_{ij} = 1$ if *ith* case belongs to *jth* category. The parameters of a multinomial regression model were determined in several ways. It is possible to take the logarithm of the function $L(\beta)$ and then calculate the first partial derivatives of $InL(\beta)$ with respect to each of the estimated β_{jk} coefficients. These equations should be equated to zero and solved. Testing for statistical significance of individual regression coefficients was performed with the statistics based on the Wald coefficient: $Wald\ (Z) = \frac{\beta_k}{SE(\beta)}$.

To confirm the appropriateness of the model using the multinomial logistic regression model, the likelihood ratio chi-square test was performed. Test statistics was based on the difference of logarithms of the likelihood function of the reduced model with intercept only (L_0) and the fitted model (L_1), in which $p = K * (J - 1)$ parameters were considered: $LR = -2(InL_0 - InL_1) \sim \chi^2{}_p$.

2.2. Participants and Setting

Four hundred (400) Junior High School (JHS) students, comprising two hundred and eighteen (218) males and one hundred and eighty-two (182) females from selected Junior High Schools in a school district in Ghana, participated in the study. First, ten (10) JHSs were randomly selected from twenty-five (25) public JHSs in the school district. Second, from each JHS, forty (40) students were randomly selected. The cohort of students were final year JHS students, who had completed their mock Basic Education Certificate Examination (BECE) and were in the process of writing their final examination. By using a questionnaire, demographic data on students' ethnicity, students' preferred topic, parental educational level, parental socioeconomic status, were obtained. Additionally, the following quantitative variables were collected: Math self-concept, Math attitude, Arithmetic ability, Motivation, Instructional strategies and methods, and Teacher competency in math, with responses between 1 and 7, where 1 = least response and 7 = greatest response. The average age of the students was fifteen years, four (4) months. Table 1 indicates the demographic characteristics of the students.

Table 1. *Demographic Characteristic of Students.*

Demographic Characteristics	Category	Number of Students	Percentage
Gender	Male	218	54.5
	Female	182	45.5
	Total	400	100
Ethnicity	Asanti	55	13.8
	Fanti	220	55.0
	Ga	35	8.8
	Ewe	41	10.3
	Others	49	12.3
	Total	400	100

Demographic Characteristics	Category	Number of Students	Percentage
Socio Economic Status	High	83	20.8
	Middle	164	41.0
	Low	153	38.3
	Total	400	100
Parents' Educational Level	None	22	5.5
	Junior High School (JHS)	56	14.0
	Senior High School (SHS)	64	16.0
	Diploma	56	14.0
	Higher National Diploma (HND)	62	15.5
	Bachelors	97	24.3
	Masters	34	8.5
	Doctorate	9	2.3
	Total	400	100
Public JHS	JHS A	40	10
	JHS B	40	10
	JHS C	40	10
	JHS D	40	10
	JHS E	40	10
	JHS F	40	10
	JHS G	40	10
	JHS H	40	10
	JHS I	40	10
	JHS J	40	10
	Total	400	100

Instrumentation and data collection procedure

The questionnaire responses of 400 JHS students were analysed to determine the predictor variables contributing to the probabilities of students falling in the respective topic categories (Relations and functions, Algebraic expressions, Linear equations) and predict their preference topic categories. The questionnaire consisted of six (6) subscales, where the students apart from the categorical variables, responded to each quantitative construct with a value between 1 and 7. The questionnaire was initially explained to the students, who were assured of anonymity and confidentiality. Therefore, their names were not written on the questionnaires. Each JHS was visited, and the questionnaires were administered to the respective students after consent has been given by the headmasters. The students completed the questionnaires between 10 and 15 minutes.

2.3. Validity and Reliability

Validity refers to the degree to which an assessment measures what it is supposed to measure [23]. According to [10], one form of validity is content validity which seeks to verify if the items measure the content they were intended to measure. To address this, the instrument, which had six (6) subscales in addition to biographical data, was sent to four lecturers with extensive knowledge in regression analyses and their application. The lecturers' feedback was considered in constructing the final version of the questionnaire. The lecturers' feedback addressed the wording and clarity of the items.

Reliability is the extent to which an experiment, test, questionnaire, or any measuring procedure yields the same result on repeated trials [19]. Reliability is usually calculated using a statistic called Cronbach's alpha, a coefficient (a number between 0 and 1), which is used to rate the internal consistency or the correlation of the items in a test. 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. If a questionnaire or test has a strong internal consistency, most measurements should show only a moderate correlation among items (.70 to 0.90). After computing the internal consistencies of the items under each subscale, the following were obtained: Math self-concept = .70; Math attitude = .75; Arithmetic ability = .81, Motivation = .79; Instructional strategies and methods = .76; and, Teacher competency in math = .78. In this study, Cronbach's alpha coefficients for the items were at least .70, indicating that the internal consistencies and reliabilities of the survey instrument under their respective subscales were very good.

3. Results

Table 2. *Model Fitting Information.*

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-square	df	Sig.
Intercept only	790.64			
Final	513.31	277.34	22	.00

Table 2 shows the model fit information. The final model has a -2 Log likelihood value of 513.31, which is statistically significant ($p < .05$). This implies that an individual can predict at a better than chance level using the set of predictors. Table 3 shows the Pseudo R-square.

Table 3. *Pseudo R-square.*

Cox and Snell	.50
Nagelkerke	.57
McFadden	.33

Table 3 shows the Nagelkerke Pseudo R-Square value of .57. It indicates that approximately 57% of the variance associated with student preference for each of the three subjects. Table 4 shows the likelihood ratio tests.

Table 4. *Likelihood Ratio Tests.*

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-square	df	Sig.
Intercept	513.31	.00	0	-
Math self-concept	582.90	69.59	2	.00
Math attitude	537.49	24.18	2	.00
Arithmetic ability	522.43	9.13	2	.01
Motivation	539.21	25.90	2	.00
Instructional strategies and methods	524.06	10.75	2	.01
Teacher Competency in math	513.74	9.59	2	.01
Gender	539.92	26.61	2	.00
Ethnicity	531.54	18.24	8	.02

Table 4 shows the Likelihood Ratio Tests. It presents the consequences of removing one of the predictors from the model. It results when an effect is removed, and the reduced model is tested for statistical significance with a chi-square procedure. Each of the rows, except the intercept, considers removing the particular predictor named in the Effect column. Hence, apart from "ethnicity" which has 8 degrees of freedom, the other predictors have 2 degrees of freedom each. For example, removing "teacher competency in math" yields a -2 Log-likelihood value of 513.74 and a corresponding chi-square value of 9.59, resulting in a statistically significant predictive model based on the other predictors (p = .01). The model remains statistically significant when each of the predictors is removed in turn. Table 5 shows the parameter estimates.

Table 5. *Parameter estimates.*

Outcome		β	Std. Error	Wald	df	Sig.	Exp(β)	95% C. I for Exp(β)	
								Lower Bound	Upper Bound
Relations and functions	Intercept	-9.01	2.22	16.43	1	.00			
	Math self-concept	1.76	.27	44.08	1	.00	5.82	3.46	9.78
	Math attitude	-.54	.32	2.75	1	.10	.58	.31	1.10
	Arithmetic ability	-.82	.29	7.92	1	.01	.44	.25	.78
	Motivation	1.26	.32	15.10	1	.00	3.52	1.86	6.63
	Instructional strategies and methods	.80	.31	6.67	1	.01	2.23	1.21	4.09
	Teacher competency in math	.05	.29	.03	1	.86	1.05	.60	1.86
	Female	.14	.43	.11	1	.74	1.15	.50	2.69
	Male	0	-	-	0	-	-	-	-
	Asanti	-1.98	.73	7.35	1	.01	.14	.03	.58
	Fanti	-2.36	.72	10.64	1	.00	.09	.02	.39
	Ga	-2.39	.74	10.38	1	.00	.09	.02	.39
	Ewe	-2.29	.77	8.92	1	.00	.10	.02	.46
	Others	0	-	-	0	-	-	-	-
Algebraic expressions	Intercept	-.54	1.45	.14	1	.71			
	Math self-concept	.97	.17	31.19	1	.00	2.63	1.87	3.68
	Math attitude	-1.01	.22	20.39	1	.00	.37	.24	.57
	Arithmetic ability	-2.2	.20	1.20	1	.27	.80	.54	1.19
	Motivation	.95	.22	19.14	1	.00	2.58	1.69	3.95
	Instructional strategies and methods	-.00	.22	.00	1	.20	.20	.65	1.54
	Teacher competency in math	-.09	.20	.18	1	.68	.92	.62	1.37
	Female	1.32	.34	15.23	1	.00	3.75	1.93	7.29
	Male	-	-	-	-	-	-	-	-
	Asanti	-1.47	.62	5.61	1	.02	.23	.07	.78
	Fanti	-1.67	.64	6.85	1	.01	.19	.05	.66
	Ga	-2.00	.66	9.14	1	.00	.14	.04	.50
	Ewe	-1.36	.65	4.42	1	.04	.26	.07	.91
	Others	0	-	-	0	-	-	-	-

Table 5 shows the parameter estimates, which use the model to predict student preferred topic category. It needs emphasizing that the reference topic category was linear equations. Each of the major rows reports the results of contrast between one of the other topic categories and the linear equations preference category. The column β provides the raw score coefficients (adjusted for the presence of the other predictors in the model) associated with each of the predictors, and the standard error (Std. Error) of these statistics is shown next to the coefficients. These partial regression coefficients are tested for statistical significance using the Wald test, and the outcome of these tests is shown in the Sig. column. The odds ratio, which is the primary part of the output is shown as Exp (β).

The first major row labelled Relations and Functions contrasts with Linear equations. The raw score coefficients associated with Math self-concept, Motivation, and Instructional strategies and methods were positive and significant, while those associated with Arithmetic ability, Asanti, Fanti, Ga, and Ewe, were negative and significant. However, those associated with Math attitude and Teacher competency in math and gender for females were positive, but not significant. The odds ratio, adjusted for the other predictor variables in the model, yielded an interpretation of the dynamics of the predictor variables. For example, the math self-concept measure was associated with an adjusted odds ratio of 5.82.

This means that a unit increase in the math self-concept measure increased the odds of a student being in the Relations and functions topic category by 5.82 versus the odds of being in the Linear equations topic category, controlling for the other predictors. In the same vein, math attitude was associated with an adjusted odds ratio of .58. This means that a unit increase in the math attitude measure decreased the odds of a student being in the Relations and functions topic category by .58 versus the odds of being in the Linear equations topic category, controlling for the other predictors. For the categorical predictor gender (coded 0 = female; 1 = male), the odds ratio for female is .74. This means that the odds of a female student being in the Relations and functions topic category, as compared to a male, reduced by .74 the odds of being in the Linear equations topic category, controlling for the other predictors. Similarly, for the categorical predictor ethnicity (coded 1 = Asanti; 2 = Fanti; 3 = Ga; 4 = Ewe; 5 = others), the odds of a student being an Asanti is .14. This means that the odds of an Asanti student being in the Relations and functions topic category, as compared to the other tribes, reduced by .14 the odds of being in the Linear equations topic category, controlling for the other predictors.

The second major row labelled Algebraic expressions contrasts with Linear equations. The raw score coefficients associated with Math self-concept and Motivation were also positive and significant, while those associated with Math attitude, Asanti, Fanti, Ga, Ewe, were negative and significant. However, those associated with Arithmetic ability, Teacher competency in math, and gender for females were positive, but not significant. Math self-concept is associated with an adjusted odds ratio of 2.63. This means a unit increase in the math self-concept measure increased the odds of a student being in the Algebraic expressions topic category by 2.63 versus the odds of being in the Linear equations topic category, controlling for the other predictors.

In the same vein, math attitude was associated with an adjusted odds ratio of .37. This means that a unit increase in the math attitude measure decreased the odds of a student being in the Algebraic expressions topic category by .37 versus the odds of being in the Linear equations topic category, controlling for the other predictors. For the categorical predictor gender (coded 0 = female; 1 = male), the odds ratio for female is 3.75. This means that the odds of a female student being in the Algebraic expressions topic category, as compared to a male, increased by 3.75 the odds of being in the Linear equations topic membership, controlling for the other predictors. Similarly, for the categorical predictor ethnicity (coded 1 = Asanti; 2 = Fanti; 3 = Ga; 4 = Ewe; 5 = others), the odds of a student being, for example, an Asanti is .23. This means that the odds of an Asanti student being in the Algebraic expressions topic category, as compared to the other tribes, reduced by .23 the odds of being in the Linear equations topic category, controlling for the other predictors. Table 6 shows the classifications.

Table 6. *Classifications.*

Observed	Predicted			
	Relations and functions	Algebraic expressions	Linear equations	Percent correct
Relations and functions	55	44	0	55.6%
Algebraic expressions	33	147	21	73.1%
Linear equations	2	34	64	64.0%
Overall percentage	22.5%	56.3%	21.3%	66.5%

Table 6 indicates the classifications. It displays how well the model classifies cases into the three categories of the outcome variable. Overall, the predictive accuracy is 66.5%. Those students falling in the Algebraic subject group were most accurately predicted (73.1%), then those falling in the Linear equations subject group were the next most accurately predicted (64.0%), while those in the Relations and functions subject group were the least accurately predicted.

Let $j = 1 =$ Relations and functions, and $j = 2 =$ Algebraic expressions, J = 3= Linear equations. In particular, assume, $X_1 = 4, X_2 = 3, X_3 = 4, X_4 = 5, X_5 = 4, X_6 = 3, X_7 = 1, X_8 = 1, X_9 = 0, X_{10} = 0, X_{11} = 0$.

Equations (1) & (2) become:

$$P(Y = 1|X) = \frac{exp(\beta_{10}+\beta_{11}X_1+\ldots+\beta_{1K}X_K)}{1+exp(\beta_{10}+\beta_{11}X_1+\ldots+\beta_{1K}K_K)+\exp(\beta_{20}+\beta_{20}X_1+\ldots+\beta_{2K}X_K)}$$

$$= \frac{\exp(-9.01+1.76X_1+\ldots-2.29X_{11})}{1+exp(-9.01+1.76X_1+\ldots-2.29X_{11})+\exp(-.54+.97X_1+\ldots-1.36X_{11})}$$

$$= 0.716$$

$$P(Y = 2|X) = \frac{exp(\beta_{20}+\beta_{21}X_1+\ldots+\beta_{2K}X_K)}{1+exp(\beta_{10}+\beta_{11}X_1+\ldots+\beta_{1K}K_K)+\exp(\beta_{20}+\beta_{20}X_1+\ldots+\beta_{2K}X_K)}$$

$$= \frac{\exp(-.54+.97X_1+\ldots-1.36X_{11})}{1+exp(-9.01+1.76X_1+\ldots-2.29X_{11})+\exp(-.54+.97X_1+\ldots-1.36X_{11})}$$

$$= 0.004$$

$$P(Y=3|X) = \frac{1}{1+exp(\beta_{10}+\beta_{11}X_1+\ldots+\beta_{1K}K_K)+\exp(\beta_{20}+\beta_{20}X_1+\ldots+\beta_{2K}X_K)}$$

$$= \frac{1}{1+exp(-9.01+1.76X_1+\ldots-2.29X_{11})+\exp(-.54+.97X_1+\ldots-1.36X_{11})}$$

$$= 0.280$$

4. Discussions

Factors affecting decision-making are numerous and varied. According to [21], people's experiences influence the decisions they make. When people's decisions resulted in positive outcomes, they are likely to make those decisions today and, in the future, because they believe they could experience similar outcomes. On the other hand, people would avoid past mistakes if those decisions resulted in negative outcomes [25]. People's cognitive biases influence them to cause them to heavily rely on or give more credence to expected observations and previous knowledge, but it dismisses information perceived as uncertain. It enables people to make efficient decisions [28, 29].

Again, [26], asserts that people make decisions based on an irrational escalation of commitment. Thus, people put effort and time to make a decision that they feel so much committed to. Further, people make risky decisions when they feel responsible for the effort and time spent. Research shows that age, socioeconomic status (SES), and cognitive abilities influence decision-making [7, 17]. The research shows a significant difference in decision-making across ages. As cognitive functions decline due to age, decision-making ability declines correspondingly. Additionally, older people become more confident in their ability to make decisions, which inhibits their ability to apply strategies [7]. Finally, there is evidence to support the notion that older adults prefer fewer choices than younger adults [17].

For Relations and functions, the study has demonstrated that Math self-concept, Motivation, and Instructional strategies and methods significantly influenced the students' preference for the topics. In fact, with positive coefficients for the predictor variables and odd ratios greater than one, the probability of a student falling in this category increased. Similarly, Arithmetic ability, Asanti, Fanti, Ga, Ewe, significantly influenced the students' preference for the topics. With negative coefficients for the predictor variables and odds ratios less than one, the probability of students falling in this category decreased.

For Algebraic expressions, the study has shown that Math self-concept and Motivation significantly influenced the students' preference for the topics. In fact, with positive coefficients for the predictor variables and odd ratios greater than one, the probability of a student falling in this category increased. Similarly, Math attitude, Asanti, Fanti, Ga, Ewe, significantly influenced the students' preference for the topics. all with odds ratios less than one. The probability of students falling in this category correspondingly decreased with negative coefficients for the predictor variables and odds ratios less than one.

The findings of this study should be disseminated widely among researchers, policy-makers, and mathematics teacher educators, and draw their attention to the importance of those predictor variables (Math self-concept, Math attitude, Arithmetic ability, Motivation, Instructional strategies and methods, Teacher competency in math, Gender, and Ethnicity), in teaching and learning of mathematics, which could influence students' preference for mathematics topics.

5. Conclusions

In addition to variables that influence decision-making in research, this study has highlighted those that determine students' preferences for mathematics topics. The onus, therefore, lies in the ability of mathematics teachers and researchers to continually look for ways to improve students' abilities in respect of these variables.

The probability for relations and functions was the highest among the three topic categories. This indicated that the mathematics teachers may have employed variety of teaching methods and skills that enabled the students to gain preference for the topic. It needs to emphasize that students' preference for a mathematics topic increases when they easily understand the topic and can solve problems related to their everyday experiences.

References

[1] Acevedo, M., & Krueger, J. I. (2004). Two egocentric sources of the decision to vote: The voter's illusion and the belief in personal relevance. *Political Psychology, 25* (1), 115–134. https://doi.org/10.1111/j.1467-9221.2004.00359.x.

[2] Adair. J., (1986). *Effective teambuilding*. Gower.

[3] Agresti, A. (2002*). Categorical data analysis* (2nd ed.). John Wiley & Sons, Inc. http://dx.doi.org/10.1002/0471249688.

[4] Allison, S. T., Jordan, A. M. R., & Yeatts, C. E. (1992). A cluster-analytic approach toward identifying the structure and content of human decision-making. *Human Relations*, *45* (1), 49-72.

[5] Barker, A. (1998). How to be a better decision maker, Instanbul. Retrieved on 18th April 2022, from https://dergipark.org.tr/en/pub/comuybd/issue/43601/533909

[6] Blunden, R. (1994). The concept of choice in health and social services: An overview. In creating opportunities for choice for people with learning difficulties. *Proceedings of a conference held in Southampton, 10-11 November*. Southampton: University of Southampton Institute for Health Policy Studies.

[7] Bruine de Bruin, W., Parker, A. M., & Fischhoff, B. (2007). Individual differences in adult decision-making competence. *Journal of Personality and Social Psychology*, 92 (5), 938–956. https://doi.org/10.1037/0022-3514.92.5.938.

[8] Byrnes, J., P. (2002). The Development of Decision-Making. *Journal of Adolescent Health*, *31* (6), 208-215.

[9] Cote Sparks, S. & Cote, D. L. (2012). Teaching choice-making to elementary students with mild to moderate disabilities. *Intervention in School and Clinic, 47* (5), 290–296.

[10] Creswell, J. W. (2003). *Research design: Qualitative, quantitative, and mixed methods approach*. Sage Publications.

[11] Deci, E. L., Connell, J. P., & Ryan, R. M. (1989). Self-determination in a work organization. *Journal of Applied Psychology, 74* (4), 580–590. https://doi.org/10.1037/0021-9010.74.4.580

[12] Deci, E. L. & Flaste, R. (1996). *Why we do what we do: Understanding self-motivation.* Penguin Books.

[13] Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior.* Springer Science & Business Media. https://doi.org/10.1007/978-1-4899-2271-7.

[14] Deci, E. L., Ryan, R. M. & Williams, G. C. (1996). Need satisfaction and the self-regulation of learning. *Learning and Individual Differences,* 8, 165-183.

[15] Difference Between Choice and Decision. Retrieved on 11th March 2022 from https://pediaa.com/difference-between-choice-and-decision.

[16] El-Habil, A. M. (2012). An application of the multinomial logistic regression model. *Pakistan Journal of Statistics and Operation Research*, 8 (2), 271-291.

[17] Finucane, M. L., Mertz, C. K., Slovic, P. & Schmidt, E. S. (2005). Task complexity and older adults' decision-making competence. *Psychology and Aging*, *20* (1).

[18] Garcia, T. & Pintrich, P. R. (1996). The effects of autonomy motivation and performance in the college classroom. *Contemporary Educational Psychology*, 21, 477-486.

[19] Gay, L. R., & Airasian, P. (2003). *Education research. Competencies for analysis and applications*. McGraw-Hills.

[20] Hosmer, D. W. & Lemeshow, S. (2000). *Applied logistic regression* (2nd ed.). John Wiley & Sons, Inc. doi: 10.1002/0471722146.

[21] Jullisson, E. A., Karlsson, N., & Garling, T. (2005). Weighing the past and the future in decision-making. *European Journal of Cognitive Psychology*, 17 (4), 561-575. doi: 10.1080/09541440440000159.

[22] Kaltsounis, T. (1987). *Teaching social studies in elementary school*. Prentice Hall.

[23] Kaplan, R. M., & Saccuzzo, D. P. (2012). *Psychological testing: Principles, applications, and issues*. Cengage Learning.

[24] Kuzgun, Y. (1992): Decision strategy scale: Development and standardization. VII. Scientific studies of the National Congress of Psychology. Retrieved on 18th April, 2022 from https://www.caves.res.in/journal/articles/Amb_Sci_07(Sp1)_Oa29.pdf.

[25] Sagi, A., & Friedland, N. (2007). The cost of richness: The effect of the size and diversity of decision sets on post-decision regret. *Journal of Personality and Social Psychology, 93* (4), 515–524. https://doi.org/10.1037/0022-3514.93.4.515

[26] Schiefele, U. (2001). The role of interest in motivation and learning, In J. M. Collis and S. Messick (Eds.). Intelligence and personality: Bridging the gap in theory and measurement. Mahwah, NJ: Erlbaum, 163–193.

[27] Shah, A. K., & Oppenheimer, D. M. (2011). Grouping information for judgments. *Journal of Experimental Psychology: General, 140* (1), 1–13. https://doi.org/10.1037/a0021946

[28] Stanovich, K. E., & West, R. F. (2008). On the relative independence of thinking biases and cognitive ability. *Journal of Personality and Social Psychology*, *94* (4), 672-695. doi: 10.1037/0022-3514.94.4.672.

[29] Tatlılıoğlu, K. (2014). A research subscales of undergraduates' personality traits according to five factor personality theory in terms of some variants. *Journal of History School* (JOHS), 7 (XVII), 939-971.

[30] Wadsworth, B. J. (2015). *Piaget's theory of cognitive development: An introduction for students of psychology and education.* Mckay.

[31] West R. F., Toplak M. E., Stanovich K. E. (2008). Heuristics and biases as measures of critical thinking: associations with cognitive ability and thinking dispositions. *Journal of Educational Psychology*, 100, 930–941.

[32] Zeleny, M. (1982). *Multi-criteria decision-making*. McGraw-Hills.