Global Scientific JOURNALS

GSJ: Volume 7, Issue 12, December 2019, Online: ISSN 2320-9186
www.globalscientificjournal.com

MATHEMATICS ANXIETY AS A PREDICTOR ON STATISTICS ANXIETY

A PARADOX IN THE PUBLIC DISCOURSE

Siluzile Martin Toboti

Department of Educational Foundations

University of Botswana

siluziletoboti@gmail.com

Abstract

Botswana has shortage of manpower especially in the science and technical fields, therefore more emphasis should be geared towards this. It is therefore necessary that as Botswana moves from a resourced knowledge based economy it is there advisable the curriculum should promote more of the sciences and researchers for statistical in conducting research, Hierarchical regression was conducted with Mathematics anxiety being a predictor over and computer incompetence and friends' influence on the anxiety of statistics anxiety. It is therefore very important to know and understand the pre-requisites for students not to have anxiety in Statistics. Students must be allowed to acquire skills and be assertive in statistics by not be helpless. A survey questionnaire was administered and completed by (N=2571) students on their perceptions on their association and learning of different discipline, and this was used to predict their perceptions of different and how to learn about them

Keywords: Anxiety, Exploratory factor analysis, Hierarchical regression, predictor

Introduction

The knowledge of Mathematics has played significant role in the performance of students in the Statistics subject and hence bad performance in Statistics has caused anxiety. Several researchers examined the relationship between attitudes toward mathematics and achievement in statistics and found conflicting results. It is such the dilemma that is in the public discourse whether performance of one in Mathematics has any bearing on Statistics, hence the anxiety. The contention is that while some hold the view that it is the Mathematics knowledge some argue that it is the attitude, feelings and perceptions that students has of Mathematics and its applications to Statistics. According to Adams and Holcomb (1986) “no significant relationship between attitudes toward mathematics and achievement in statistics while Feinberg and Halprin (1978) did find a relationship between the two”. On the other hand, Wisenbaker, Scott, and Nasser (2000) stated that this relationship appears to be fairly consistent regardless of the instrument used, the time of administration of either the attitudes or performance measure, or the level of the students. “Statistics anxiety is a pervasive problem in the context of university studies, especially in social science degrees, such as psychology, education, or sociology.” (Onwuegbuzie and Wilson, 2003;; Ruggeri et al., 2008).

Furthermore, situation-related antecedents, for instance, experiences and attitudes that result from statistics courses or courses in related knowledge domains, such as mathematics (Baloglu, 2003), are assumed to be related to statistics anxiety.

According to Galagedera, Woodward, and Degamboda (2000), “Perceived Mathematics Ability (PMA) itself is not a good predictor of Elementary Statistics (ES) performance, rather its effect may be channeled through interest, expected grade and motivation to do well in ES”. It is evident that low perception in mathematics ability impedes effort put forth when learning ES than the issue of being endowed with computational skills.

Studies in recent years, discovered that statistics anxiety as being conceptually different from mathematics anxiety (Cruise et al., 1985; Baloglu, 2003). It is evident that statistics uses basic mathematical concepts and calculations but its learning contents differ from mathematics in various aspects (Aksentijevic, 2015). Statistic tasks in majors, such as education, psychology, or sociology are more closely related to verbal reasoning (Buck, 1987), they require probabilistic reasoning processes, such as making inferences or drawing conclusions from data (Baloglu, 1999, 2003), and are often embedded into an applied context. The influence of PMA on ES performance is likely to be the consequence of the belief that mathematics is essential to learn ES. Students were assessed on a number of pretest and posttest cognitive and non-cognitive variables, including the Statistic Attitude Survey (SAS). SAS scores were found to be significantly related to such cognitive variables as basic mathematics skills, statistics pre-knowledge, and course grades

In view of the above diametrically opposed views, it is necessary to investigate whether mathematics predict the performance of students in Statistics. On account of the fact that mathematics anxiety remains a concern for students, for the school, for parents and for education in particular, this study makes an attempt to investigate the prediction capacity of mathematics anxiety in statistics performance..

Statement of the problem

There is ample evidence stemming from students' performance in mathematics and mathematics related modules that there is great apathy when it comes to solving problems in these subjects.

According to Mogotsi, Garegae and Kesianye (2018);

> Through the learning of geometry concepts students develop problem solving skills and become critical thinkers. Unfortunately, performance on geometry questions by Botswana students is not good as shown by their performance in Trends in International Mathematics and Science Study 2003, 2007 and 2011. Good performance in geometry is very crucial because it is linked to other mathematical content and is a foundation of many science

based careers. Mathematics teachers need to have the appropriate content and pedagogy in teaching geometry concepts (p. 55)

There is dilemma as to whether students who have poor background of Mathematics perform badly in Statistics which may cause anxiety. According to many teachers of statistics are likely to focus on transmitting knowledge, many students are likely to have trouble with statistics due to non-cognitive factors, such as negative attitudes or beliefs towards statistics. Such factors can disturb learning of statistics, or hinder the extent to which students will develop useful statistical intuitions and apply what they have learned outside the classroom. Cognitive factors (such as mathematical ability, mathematical background, and cognitive dimensions of attitudes towards mathematics and statistics) and affective factors (such as mathematics and statistics anxiety, motivation, and affective dimensions of attitudes toward mathematics and statistics) are some of the variables thought of as related to performance in statistics (Feinberg and Halprin 1978; Nasser 1999).

Many students experience anxiety when they are required to take statistics courses. Cruise, Cash, and Bolton (1985) argued that anxious students' image of statistics is generally not a very positive one. Furthermore, students often enter their first statistics class with negative attitudes about learning quantitative subjects. These students experience mathematics anxiety (McLeod 1992), apprehension about taking tests (Hunsley 1987), and/or negative attitudes with respect to the relevance of statistics for their future (Galagedera et al., 2000)careers (Roberts and Saxe 1982).

Purpose of the study

The purpose of the study is to investigate whether statistics anxiety is a genuine form of anxiety that contributes to students' achievements or whether learners mainly transfer previous experiences in mathematics and their anxiety in mathematics to statistics. (1) to extract the underlying factors of anxiety, 2). to determine the whether the performance of one in mathematics predicts the outcome performance in Statistics.

Study Hypotheses

The hypothesis (H) tested. H_0 was that mathematics anxiety is a predictor to Statistics anxiety. The expectation was that anxiety of Mathematics predicts the performance of students. This is based on the argument raised by (Aiken, 1971) who stated that when students engage in questions that involve geometry concepts it develops their spatial ability. Also hypothesized does performance of one's knowledge in Mathematics predicts the performance of students in Statistics. This is agreement with the assertion that cognitive factors (such as mathematical ability, mathematical background, and cognitive dimensions of attitudes towards mathematics and statistics) and affective factors (such as mathematics and statistics anxiety, motivation, and affective dimensions of attitudes toward mathematics and statistics) are some of the variables thought of as related to performance in statistics (Feinberg and Halprin 1978; Nasser 1999).The knowledge and the anxiety in Mathematics as a subject has a predictive capacity of students in Statistics.

To the researchers' dismay, such an assumption of that Mathematics skill serve as a predictor in the performance of students in Statistics needs investigation and attention should be paid in addressing .

Factor analysis

Exploratory Factor Analysis (EFA) was used as a data reduction technique and to extract the latent or unobserved factors from the respondent's perspective. . More specifically, the goal of factor analysis is to reduce "the dimensionality of the origin(Habing 2003: 2) Thus, factor space and to give an interpretation to the new space, spanned by a reduced number of new dimensions which are supposed to underlie the old ones" (Rietveld & Van Hout 1993: 254), or to explain the variance in the observed variables in terms of underlying latent factors" analysis offers not only the possibility of gaining a clear view of the data, but also the possibility of using the output in subsequent analyses (Field 2000; Rietveld & Van Hout 1993) . Data was therefore factor-analyzed with principal component analysis (PCA) to maximize variance extracted by orthogonal factors because the factors were uncorrelated, a view echoed by Koloi Keakitse (2012). According to McDonald (1985) rotation as “performing arithmetic to obtain a new set of factor loadings (v-f regression weights) from a given set,” while Bryant and Yarnold (1995) defines it as “a procedure in which the eigenvectors (factors) are rotated in an attempt to achieve simple structure.

Assumptions of Exploratory factor analysis (EFA)

Sample size, is one of the assumptions of EFA, as the technique is sensitive to this as to how much is the sample size, some say 100 or in some cases 200, level of measurement (e.g., the measurement/data scenarios above), normality, linearity, outliers (factor analysis is sensitive to outliers) and factorability

Table 1

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.930
Bartlett's Test of Sphericity	Approx. Chi-Square	19334.492
	df	253
	Sig.	.000

Prior to the extraction of the factors, several tests were conducted to assess the suitability of the respondent data for factor analysis. These tests include Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The KMO index was .93 particular, is recommended when the cases to variable ratio are less than 1:5 which indicates that the sample is suitable for EFA. The KMO index ranges from 0 to 1, with 0.60 considered suitable for factor analysis. Exploratory Factor Analysis is too sensitive to sample size and hence this size of 2571 subjects is suitable to run this technique. The Bartlett's Test of Sphericity was statistically significant ($p<.05$) =000 for factor analysis to be suitable. (see table 1)

Table 2
Component Correlation Matrix

Component	1	2	3	4
1	1.000	-.153	.360	-.277
2	-.153	1.000	-.193	.093
3	.360	-.193	1.000	-.464
4	-.277	.093	-.464	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

It is evident from that the independent variables are uncorrelated because most of the coefficients are close to 0, this then required the rotation orthogonal because of this uncorrelation. Multicollinearity is a phenomenon in which two or more independent variables are highly correlated with each other. Grewal et al. (2004) suggested that the main sources of multicollinearity are low measurement reliability, small sample sizes and low explained variance in endogenous constructs. (see Table 2) There is also no linear relationship between the factors which then tell us that this assumption is met and they may be need to use Varimax (Orthogonal) rotation.

Table 3 *Total Variance Explained*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.290	31.696	31.696	7.290	31.696	31.696	3.730	16.219	16.219
2	1.739	7.560	39.256	1.739	7.560	39.256	3.340	14.523	30.742
3	1.317	5.725	44.981	1.317	5.725	44.981	2.553	11.099	41.841
4	1.227	5.336	50.317	1.227	5.336	50.317	1.950	8.476	50.317

There were 23 items factor-analyzed relying on the scree plot and (eigenvalues >1), and a cut-off of 0.40, the 23 items converged into four factors that explained 50. 32% total variance, see Table 2. The four factors that were extracted are Anxiety in Statistics (α =.80), Computer incompetence (α =.82), friends performing better in Statistics (α =.57), and Mathematics anxiety (α = .82), see Table 3 The researcher decided to retain four all the factors. The extraction sums of squared loadings the % variance of each component 1, 2,3 and 4 is 31.69%, 7.56%, 5.73% and 5.34% respectively. (see Table 3)

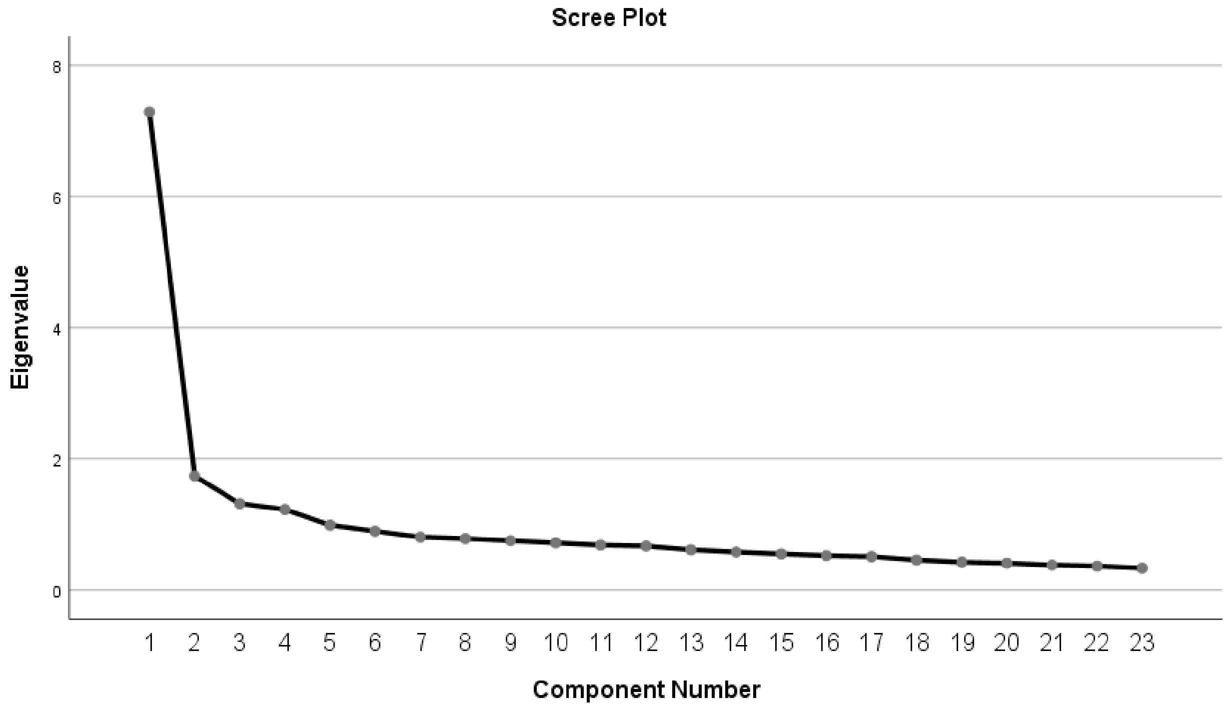

Figure 1

There are several methods in factor analysis and rotation is more dependent upon whether the factors are believed to be correlated (oblique) or uncorrelated (orthogonal) for which orthogonal was used as the factors were correlated," (Yaremko, Harari, Harrison, and Lynn, 1986). Both the Scree plot and Eigenvalues are used to decide how many factors to extract. and for this study is four factors, see figure 1. Retain only those factors with an eigenvalue larger than (Guttman-Kaiser rule), usually we keep the factors which, in total, account for about 70-80% of the variance and make a scree-plot keeping all factors before the breaking point or elbow, (see figure 1)

GSJ: Volume 7, Issue 12, December 2019
ISSN 2320-9186

Table 4

Rotated Component Matrix[a]

	Component			
	1	2	3	4
Statiscs makes me cry		.496		
My friends will think I'm stupid for not being able to cope with SPSS				.543
Standard deviations excite me		-.567		
I dream that Pearson is attacking me with correlation coefficients		.516		
I don't understand statistics		.429		
I have little experience of computers	.800			
All computers hate me	.638			
I have never been good at mathematics			.833	
My friends are better at statistics than me				.648
Computers are useful only for playing games	.550			
I did badly at mathematics at school			.747	
People try to tell you that SPSS makes statistics easier to understand but it doesn't	.473	.523		
I worry that I will cause irreparable damage because of my incompetence with computers	.647			
Computers have minds of their own and deliberately go wrong whenever I use them	.579			
Computers are out to get me	.459			
I weep openly at the mention of central tendency		.514		
I slip into a coma whenever I see an equation			.747	
SPSS always crashes when I try to use it	.684			
Everybody looks at me when I use SPSS				.428
I can't sleep for thoughts of Eigen vectors		.677		
I wake up under my duvet thinking that I am trapped under a normal distribution		.661		
My friends are better at SPSS than I am				.645
If I'm good at statistics my friends will think I'm a nerd				.586

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 8 iterations.

The rotated component matrix, sometimes referred to as the loadings, is the key output of principal components analysis. It contains estimates of the correlations between each of the variables and the estimated components. It shows and make for us easier to pick the items under the component they are loading hence making the interpretation easier. (see table 4)

Hierarchical regression analysis

One model that researchers use to serve as predictors of outcome variable is hierarchical regression. This statistical technique involves where variables that are controlled for are put first in the model and the primary or variable of interest is entered into the model to determine its predictive capacity of the dependent variable. Researchers are often interested in testing theoretical assumptions and examining the influence of several predictor variables in a sequential way, such that the relative importance of a predictor may be judged on the basis of how much it adds to the prediction of a criterion, over and above that which can be accounted for by other important predictors.

This statistical technique is theory based and Hierarchical regression, on the other hand, deals with how predictor (independent) variables are selected and entered into the model. Specifically, hierarchical regression refers to the process of adding or removing predictor variables from the regression model in steps (https://www.statisticssolutions.com/hierarchical-linear-modeling-vs-hierarchical-regression). Therefore, hierarchical regression analysis was used to predict students' anxiety in Statistics using anxiety in mathematics over and beyond friends' influence and computer incompetence on the performance of students in statistics. The purpose of this was to examine the predictive capacity of poor performance(anxiety in mathematics) (Computer incompetence and friends' better performance) were therefore entered first as a block in the regression model; students' model (anxiety in Mathematics) was entered last to determine its predictive capacity.

Table 5

Collinearity Diagnostics	
Tolerance	VIF
.883	1.133
.883	1.133
.656	1.525
.883	1.133
.715	1.399

Tests for multicollinearity indicated that a low level of multicollinearity was present and ranges from .715 and .883 and VIF is far from 10. When the tolerance is not approaching 0 and the VIF is far from 10 like in this case it means there is no multicollinearity, hence the predictor variables are not correlated. (see table 5)

Results

Hierarchical regression analysis was run in order to determine the predictive capacity of Mathematics anxiety of students on the students' anxiety in Statistics subjects over and above friends' influence and computer incompetence of students. First and foremost, analyses were done to ascertain that there is no violation of assumptions of multiple regressions. The correlation coefficients of predictor variables were computed to determine the size of linear relationship and to check any presence of multicollinearity, that is to say correlations between independent variables. There were weak inter-correlations between predictor variables and the dependent variable (see Table 5). Tolerance values were close to 1 and VIF way below 10, meaning that there was no multicollinearity between the predictor variables (Mansfield &Helms, 1982). Linearity between variables was checked using a matrix-scatter plot. There was some linear relationship between the outcome variable (Mathematics anxiety) and predictor's variables except for friends' influence, meaning that there is no multi-collinearity between the predictor variables. All variables, three predictor variables including the predicted variable were continuous. Multiple regression assumptions normality, homoscedasticity and independence of errors were assessed by using residual plot. All the assumptions were tenable and allowed for conducting of Hierarchical regression. To compute Hierarchical regression analysis, friends' influence (friends performing better) and Computer incompetence were entered first as a block (Model 1) in the regression model and students' anxiety in Mathematics (not good in Mathematics) was entered last (block 2). It is evident that in Model 1, with Friends better than me in Statistics and not good with statistics, explains 39.6%, R_2 is .396 towards the outcome variable while Model 2 with not good in mathematics (Mathematics anxiety), R_2 is .441 predicts or explains 4.6% towards the outcome variable (see table 9)

Table 6*: Model Summary*

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.629[a]	.396	.395	3.08399	.396	840.272	2	2568	.000
2	.664[b]	.441	.441	2.96561	.046	210.099	1	2567	.000

a. Predictors: (Constant), Friends better than me in Statistics , Not good with computers
b. Predictors: (Constant), Friends better than me in Statistics , Not good with computers, Not good with Mathematics
c. Dependent Variable: Poor performance in Statistics

Next we are going to look at our model summary, which compares each of the two models. Note that for model 1, with two predictors, computer incompetence and friends better than me as predictors, *r* is the same as the zero-order correlation between mathematics anxiety and friends better than me in Statistic. But the associated R square is significant (i.e., the regression equation is better than using the mean of Y as a predictor) at *F* (2, 2568) = 840.272, p < .001. Model 2, with all the three predictors, is even better, with an *r* of .664 and an R square of .441 of the variance accounted for. This change in R square is significant (F (1, 2567) = 210, 079, p<.001), indicating that the second and last predictor, mathematics anxiety added significantly to the regression equation after the first predictor had done its work.

Table 7 *ANOVA*

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	15983.608	2	7991.804	840.272	.000[b]
	Residual	24424.174	2568	9.511		
	Total	40407.781	2570			
2	Regression	17831.400	3	5943.800	675.827	.000[c]
	Residual	22576.381	2567	8.795		
	Total	40407.781	2570			

a. Dependent Variable: Poor performance in Statistics

GSJ: Volume 7, Issue 12, December 2019
ISSN 2320-9186

b. Predictors: (Constant), Friends better than me in Statistics, Not good with computers
c. Predictors: (Constant), Friends better than me in Statistics, Not good with computers, Not good with Mathematics

Our ANOVA table gives us the significance of each of the three models (one predictor, two predictors, three predictors) and we see that the *F* is largest for the two-predictor model). (These *F*s are for the overall predictive effect and are different than the *F* for the amount of change we get when adding in an additional variable as on the previous slide.) The *F* for the three-variable equation (840.272) is also equal to the final *F* we got in the standard (simultaneous) method when we entered all of the variables at once. So we have all the evidence we need to toss out that mathematics anxiety of students predicts the anxiety of students in Statistics (see Table 7)

Table 8: *Correlations*

		Poor performance in Statistics	Not good with Computers	Friends better than me in Stats	Not good with Mathematics
Pearson Correlation	Poor performance in Statistics	-			
	Not good with Computers	.627**	-		
	Friends better than me in Stats	-.263**	-342**	-	
	Not good with Mathematics	.516**	.534**	-.193**	-

Note: ***p* < .05; Not good in Mathematics = Mathematics anxiety

It is evident from the results that not being good with computers is a good predictor of the dependent variable, poor performance is statistics and was the strongest and also statistically significant. In Model 1 (β = .608, *p*=.000), it has the strongest beta value, followed by not being good in mathematics.

Table 9: Summary of the Hierarchical regression analysis (N= 2571)

Predictors	R^2	R^2_{change}	*B(SE)*	*β*
1. Computer incompetence	39.6**	.396**	.485(.013)	.608**
Friends better			.064(.019)	-.055(ns)
2. Maths anxiety	44.1**	.046**	.444 (.031)	.253**

Note ** p < .05, n's = not significant; Dependent variable of not good in Statistics

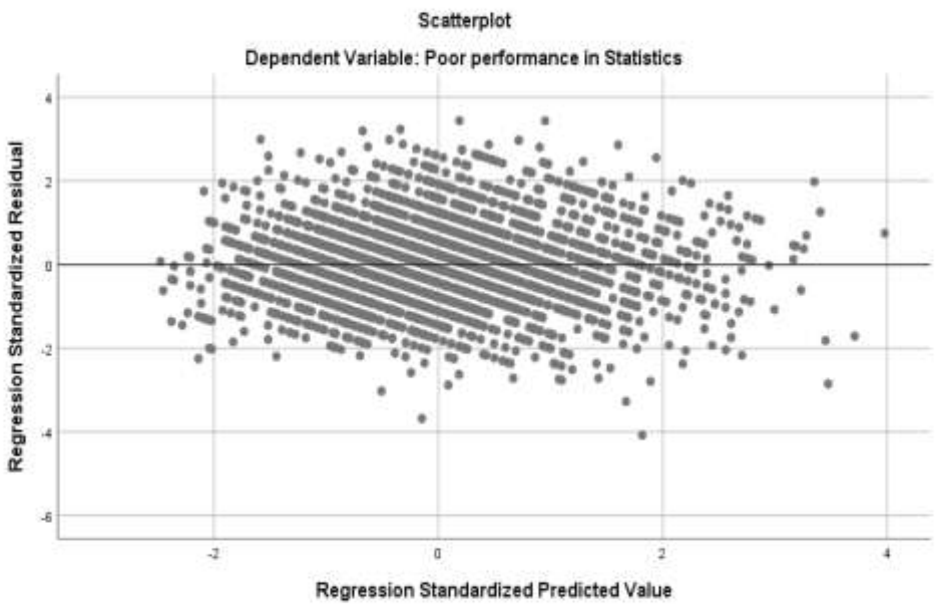

Figure 2: Residual plot

Assumptions of normality, homoscedasticity and independence of errors were assessed by using residual plot, all the assumptions were met satisfactorily making it possible to run a regression analysis, (see figure 2)

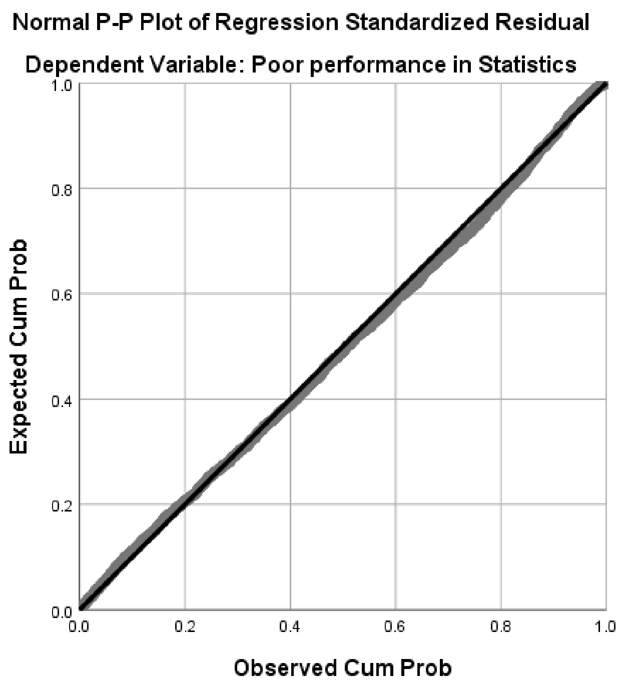

Figure 3: Normality

Discussion

It is evident from the results that not being good in Mathematics is a good predictor of how one will perform in the Statistics subject. So the anxiety of students in Mathematics can lead to students having not to perform well in the Statistics subject. This is not necessarily that mathematics is abstract but the worry, helplessness of students of having to imagine dealing the numbers. This view is shared by Galagedera, (2000), " who stated that perceived Mathematics Ability (PMA) itself is not a good predictor of Elementary Statistics (ES) performance, rather its effect may be channeled through interest, expected grade and motivation to do well in ES". It is evident that low perception in mathematics ability impedes effort put forth when learning ES than the issue of being endowed with computational skills. However, Mogotsi, Garegae and Kesianye (2018);

Through the learning of geometry concepts students develop problem solving skills and become critical thinkers. Unfortunately, performance on geometry questions by Botswana students is not good as shown by their performance in Trends in International Mathematics and Science Study 2003, 2007 and 2011. Good performance in geometry is very crucial because it is linked to other mathematical content and is a foundation of many science based careers.

Mathematics teachers need to have the appropriate content and pedagogy in teaching geometry concepts numbers. The emphases should be only policy developers and implementers so as to give more attention to geometrical computational skills so to reduce the anxiety of students in Mathematics. Students should know that Mathematical concepts are helpful and can aid students to have good mastery in statistics. The implications are that if this not addressed the human resource competence in science will always be in the shortfall. It can also be realized that knowledge in computer is good predictor of performance in Statistics. The shortage of human capital in the area of Statistics precipitate the unemployment rate. This will force the government to offset the shortage by getting non-citizens, albeit at a higher cost.

It is then safe to state that these findings agree with the stated hypothesis that mathematics anxiety is a good predictor of anxiety, of students in Statistics, hence likely to cause poor performance.

Reference

Adams, N. A., & Holcomb, W. R. (1986). Analysis of the relationship between anxiety about mathematics and performance. *Psychological Reports, 59*(2), 943-948.

Aiken Jr, L. R. (1971). Intellective variables and mathematics achievement: Directions for research. *Journal of School Psychology, 9*(2), 201-212.

Blackman, E. G., & Field, G. B. (2000). Coronal activity from dynamos in astrophysical rotators. *Monthly Notices of the Royal Astronomical Society, 318*(3), 724-732.

Bryant, F. B., & Yarnold, P. R. (1995). Principal-components analysis and exploratory and confirmatory factor analysis.

Cruise, J. L., & Michalopoulos, G. (1985). Norepinephrine and epidermal growth factor: dynamics of their interaction in the stimulation of hepatocyte DNA synthesis. *Journal of cellular physiology, 125*(1), 45-50.

Cruise, R. J., Cash, R. W., & Bolton, D. L. (1985). *Development and validation of an instrument to measure statistical anxiety*. Paper presented at the American Statistical Association Proceedings of the Section on Statistical Education.

Cucchiarini, C. (1993). *Phonetic transcription: a methodological and empirical study*: [Sl: sn].

Daller, H., Van Hout, R., & Treffers- Daller, J. (2003). Lexical richness in the spontaneous speech of bilinguals. *Applied linguistics, 24*(2), 197-222.

Dukhan, N. R., Mohamad, N., & Ali, A. B. (2017). TESTING A CONSTRUCT VALIDITY AND RELIABILITY OF THE FACTORS AFFECTING ON THE EMPLOYEES'PERFORMANCE USING (EXPLORATORY & CONFIRMATORY). *Asian journal of management sciences & education, 6*(1), 53-61.

Feinberg, L. B., & Halperin, S. (1978). Affective and cognitive correlates of course performance in introductory statistics. *The Journal of Experimental Education, 46*(4), 11-18.

Galagedera, D., Woodward, G., & Degamboda, S. (2000). An investigation of how perceptions of mathematics ability can affect elementary statistics performance. *International Journal of Mathematical Education in Science and Technology, 31*(5), 679-689.

Grewal, R., Cote, J. A., & Baumgartner, H. (2004). Multicollinearity and measurement error in structural equation models: Implications for theory testing. *Marketing science, 23*(4), 519-529.

Habing, B. (2003). Exploratory factor analysis theory and application.

Hunsley, J. (1987). Cognitive processes in mathematics anxiety and test anxiety: The role of appraisals, internal dialogue, and attributions. *Journal of Educational Psychology, 79*(4), 388.

Koloi-Keaikitse, S. (2012). Classroom assessment practices: A survey of Botswana primary and secondary school teachers.

Ma, X. (1999). A meta-analysis of the relationship between anxiety toward mathematics and achievement in mathematics. *Journal for research in mathematics education, 30*(5), 520.

Macher, D., Paechter, M., Papousek, I., & Ruggeri, K. (2012). Statistics anxiety, trait anxiety, learning behavior, and academic performance. *European journal of psychology of education, 27*(4), 483-498.

McDonald, R. P. (1985). *Comments on DJ Bartholomew," Foundations of factor analysis: Some practical implications."*.

McLeod, D. B. (1992). Research on affect in mathematics education: A reconceptualization. *Handbook of research on mathematics teaching and learning, 1*, 575-596.

Mogotsi, S. M., Garegae, K. G., & Kesianye, S. K. TEACHERS AND STUDENTS VIEWS PERTAINING TO THE TEACHING AND LEARNING OF SCHOOL GEOMETRY IN BOTSWANA JUNIOR SECONDARY SCHOOLS.

Mosothwane, M. (2012). The role of senior secondary school mathematics teachers in the development of mathematics curriculum in Botswana.

Nemat-Nasser, S., Guo, W., & Cheng, J. (1999). Mechanical properties and deformation mechanisms of a commercially pure titanium. *Acta materialia, 47*(13), 3705-3720.

Nyakudya, M. N., Ngwenya, M., Khumalo, B., Kontle, T., Mothupi, T., Mokgware, O., . . . Munjoma, M. An Investigation oif the Levels of Mathematics Anxiety n BA ISAGO Foundation Students.

Onwuegbuzie, A. J. (1998). Statistics anxiety: A function of learning style? *Research in the Schools*.

Onwuegbuzie, A. J., & Wilson, V. A. (2003). Statistics Anxiety: Nature, etiology, antecedents, effects, and treatments--a comprehensive review of the literature. *Teaching in Higher Education, 8*(2), 195-209.

Paechter, M., Macher, D., Martskvishvili, K., Wimmer, S., & Papousek, I. (2017). Mathematics anxiety and statistics anxiety. Shared but also unshared components and antagonistic contributions to performance in statistics. *Frontiers in psychology, 8*, 1196.

Roberts, D. M., & Saxe, J. E. (1982). Validity of a statistics attitude survey: A follow-up study. *Educational and psychological measurement, 42*(3), 907-912.

Ruggeri, K., Díaz, C., Kelley, K., Papousek, I., Dempster, M., & Hanna, D. (2008). International Issues in Education. *Psychology Teaching Review, 14*(2), 65-74.

Wampold, B. E., & Freund, R. D. (1987). Use of multiple regression in counseling psychology research: A flexible data-analytic strategy. *Journal of Counseling Psychology, 34*(4), 372.

Wisenbaker, J. M., Scott, J. S., & Nasser, F. (2000). *Structural equation models relating attitudes about and achievement in introductory statistics courses: A comparison of results from the US and Israel.* Paper presented at the 9th International Congress on Mathematics Education, Tokyo, Japan.

Yaremko, R. M., Harari, H., Harrison, R. C., & Lynn, E. (2013). *Handbook of research and quantitative methods in psychology: For students and professionals*: Psychology Press.

Yeomans, K. A., & Golder, P. A. (1982). The Guttman-Kaiser criterion as a predictor of the number of common factors. *The Statistician*, 221-229.