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CHECKING THE ASSUMPTIONS FOR USING PARAMETRIC TESTS IN RELATION TO LOW SOCIO-ECONOMIC DISTRICTS EARLY ADOLESCENTS MOTIVATION AND ENGAGEMENT LEVELS IN LEARNING

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ABSTRACT
Low participation in learning of secondary students is a matter affirms examination, mostly in low socio-economic districts in Sri Lanka. One of the main factors contributing to this situation may be students' motivation and engagement in learning. Therefore, this study tried to find out the levels of motivation and engagement among early adolescents. Motivation and Engagement Scale-Junior School was employed to collect data from Monaragala and Nuwara Eliya districts in Sri Lanka. Hundred male and 100 female students were chosen using stratified random sampling method. Confirmatory factor analysis did not provide a robust factor solution and it was decided to conduct exploratory factor analysis. Accordingly, four factors were identified: Positive Motivation (PM), Positive Engagement (PE), Failure Avoidance and Anxiety (FAA), and Uncertain Control (UC). It was decided to identify their motivation and engagement levels in relation to these factors using parametric tests. Therefore, the assumptions of using parametric tests were checked; normality, homogeneity of variance, data type, and independently distributed errors. In relation to the assumption of normality, the results of the normality tests using skewness and kurtosis were checked; all the scales showed substantial normality. This is further evident from the histograms and box-plots for all the scales. The PM, PE, and FAA scales show results from tests of homogeneity of variance based on gender. Only PM and FAA scales variances demonstrated homogeneity of variance for ethnicity. The test based upon grouping by school indicated that only the PM scale possessed homogeneity of variance. Of the four basic assumptions, normality, data type, and independently distributed errors were fulfilled; the assumption of homogeneity of variances was not. Therefore, it was decided to conduct both parametric tests and non-parametric tests.

Key Words: Engagement, Low socio-economic d.stricts, Motivation, Assumptions of parametric tests.

1. INTRODUCTION
Low participation in learning of secondary students is a matter affirms examination, mostly in low socio-economic districts in Sri Lanka. One of the main factors contributing to this situation may be students' motivation and engagement in learning. Therefore, this study tried to find out the levels of motivation and engagement among early adolescents. Motivation and Engagement Scale-Junior School was employed to collect data. Confirmatory factor analysis did not provide a robust factor solution and it was decided to conduct exploratory factor analysis. Accordingly, four factors were identified: Positive Motivation (PM), Positive Engagement (PE), Failure Avoidance and Anxiety (FAA), and Uncertain Control (UC). It was decided to identify their motivation and

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engagement levels in relation to these factors using parametric tests. Therefore, the main objective of this study is to check the assumptions of using parametric tests; normality, homogeneity of variance, data type, and independently distributed errors.

2. LITERATURE REVIEW

In inferential statistics, calculations of the study sample and parameters are calculations of the population; and conclusions are drawn about the parameters from the figures (Wiersma & Jurs, 2009). There are two categories of inferential statistics: parametric and non-parametric (Blaikie, 2003).

Parametric methods are a numerical method describing the probability distribution variables and draws conclusions about the parameters of the distribution (Kim, 2015). Parametric measures are strong and need fewer data to make a powerful inference (Neideen & Brasel, 2007). Though, to employ a parametric test, parameters of the data need to be exact. The data must be distributed normally. This means all data points must have a bell-shaped curve and there should be no skewed data above or below the mean. The data also needs to have equal variance and equal standard deviation.

In addition, the data must be continuous (Neideen & Brasel, 2007). Robson (1994) notes the conditions that must be included: the observations are to be made from normally distributed populations, these populations must have equal variances and variables engaged must have been calculated at least at interval scale, in addition the observations must be independent. These requirements are supported by Cooksey (2014) who described it as “assumption of independently distributed errors”. The measure selected to analyse the data is based on the kind of data gathered and the main characteristics of those data (Neideen & Brasel, 2007).

Cohen, Manion, and Morrison (2011) stated that parametric tests assist the researcher in data processing and in drawing conclusions. Parametric tests are stronger and usually require fewer data to draw a robust inference than nonparametric tests. Abdulazeez (2014) explained that, though the nonparametric tests need fewer assumptions and could be employed on a broad span of data types, parametric tests are favoured because nonparametric tests are likely to be less responsive to perceiving differences among samples or an impact of the independent variable on the dependent variable. The power effectiveness of the nonparametric tests is less than the parametric tests. A larger sample size is essential for the nonparametric tests to discover any certain effect at a particular significance level than for the parametric tests (Robson, 1994).

However, if the data veer significantly from the assumptions of parametric tests, using those tests can result in invalid inferences. Therefore, researchers have to be aware of the assumptions connected with parametric tests and should study techniques to assess the validity of those assumptions (Abdulazeez, 2014).

In this study with the new four scales identified (PM, PE, FAA and UC), the parametric tests used were t-tests, two-way MANOVA, two-way ANOVA, and one-way ANOVA; t-tests were used to identify the significant differences between gender and ethnic groups in four motivation and engagement dimensions; two-way MANOVA and two-way ANOVA tests were used to evaluate the interaction effect between gender and ethnic groups; and one-way ANOVA tests were employed to identify the significant differences between schools based on ethnicity.

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3. METHODS

The survey research design was employed in this study. Motivation and Engagement Scale-Junior School (Martin,2014) was employed to identify the levels of motivation and engagement levels of junior secondary students in Monaragala and Nuwara Eliya districts in Sri Lanka. Hundred male and 100 female students were chosen using stratified sampling method (Table 1).

Table 1: Study Sample

District	No. of schools	No. of students	
		Male	Female
Monaragala (Sinhala-medium)	7	50	50
Nuwara Eliya (Tamil-medium)	5	50	50
Total	12	100	100

Confirmatory factor analysis did not provide a robust factor solution and it was decided to conduct exploratory factor analysis. Accordingly, four factors were identified: Positive Motivation (PM), Positive Engagement (PE), Failure Avoidance and Anxiety (FAA), and Uncertain Control (UC). It was decided to identify their motivation and engagement levels in relation to these factors using parametric tests. Therefore, the assumptions of using parametric tests were checked; normality, homogeneity of variance, data type, and independently distributed errors.

4. RESULTS AND DISCUSSION

Checking the Assumption of Normality

Kim (2013) explains that the formal normality tests consisting of the Shapiro-Wilk test and the Kolmogorov-Smirnov test might be employed for small to medium sized samples but might be unreliable for larger samples. Moreover, their use might be difficult since the “eyeball test” and formal normality tests might demonstrate inappropriate outcomes for the same data. For solving the issue, a different way of assessing normality by skewness and kurtosis of the distribution might be employed, which might be more suitable for any sample size. One method (Kim, 2013) to assess normality for medium-sized samples ($50 < n < 300$) engages measurement of the Z-score for both skewness and kurtosis. This is measured by dividing the value of the skewness/kurtosis statistic by the standard error. If the absolute value of the Z-score is greater than 3.29, the distribution is regarded as being beyond the satisfactory limits for normality.

Visual examination of the distribution might be employed for evaluating normality (Field, 2009; Oztuna, Elhan, & Tuccar, 2006). While data are offered visually, distribution assessment could be made by the readers themselves (Elliott & Woodward, 2007). For visual inspection of normality, the frequency distribution (histogram) is employed (Ghasemi & Zahediasl, 2012). In this study, the normal distribution assumption was checked in relation to the four scales that resulted from the EFA using two methods. Those were: assessing normality by skewness and kurtosis of the distribution and visual examination of the distribution. All the scales showed substantial normality in this study, as discussed below.

Descriptive Statistics of PM

In this section descriptive statistics of PM is examined (see Table 2).

Table 2: Descriptive Statistics of PM

PM		Statistic	Std. Error
	N	198	
	Mean	17.0859	.14101
	Std. Deviation	1.98413	
	Minimum	12.00	
	Maximum	20.00	
	Range	8.00	
	Skewness	-.144	.173
	Kurtosis	-.541	.344

As shown in Table 2, students responded positively for PM. The skewness/kurtosis ratio indicates that the test for deviation from normality has not been violated (Kim, 2013) and the scale is able to be analysed using parametric analysis. This is further evident from the histogram (Figure 1) and box-plot for PM (Figure 2).

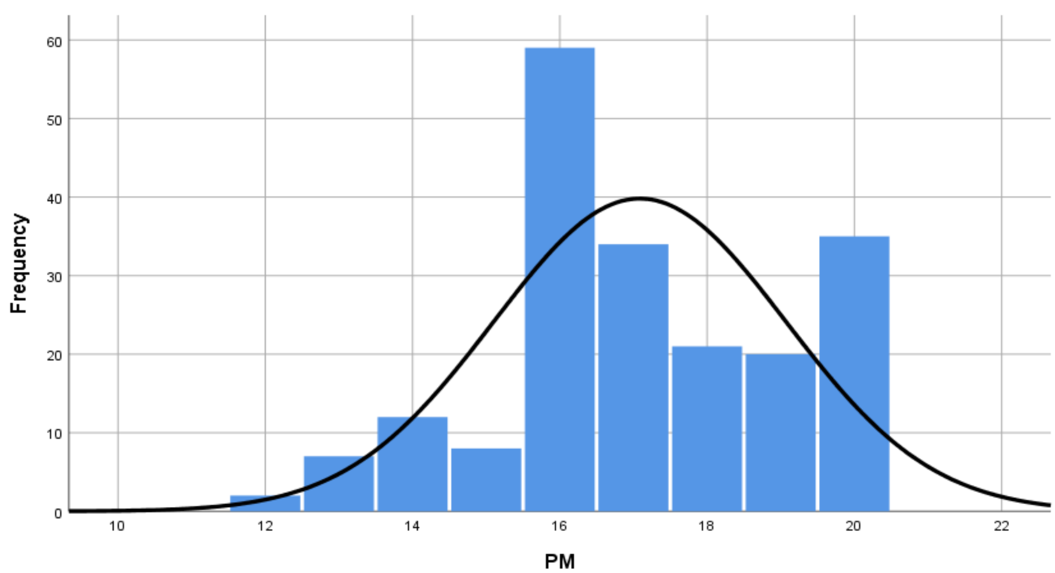

Figure 1: Histogram for PM

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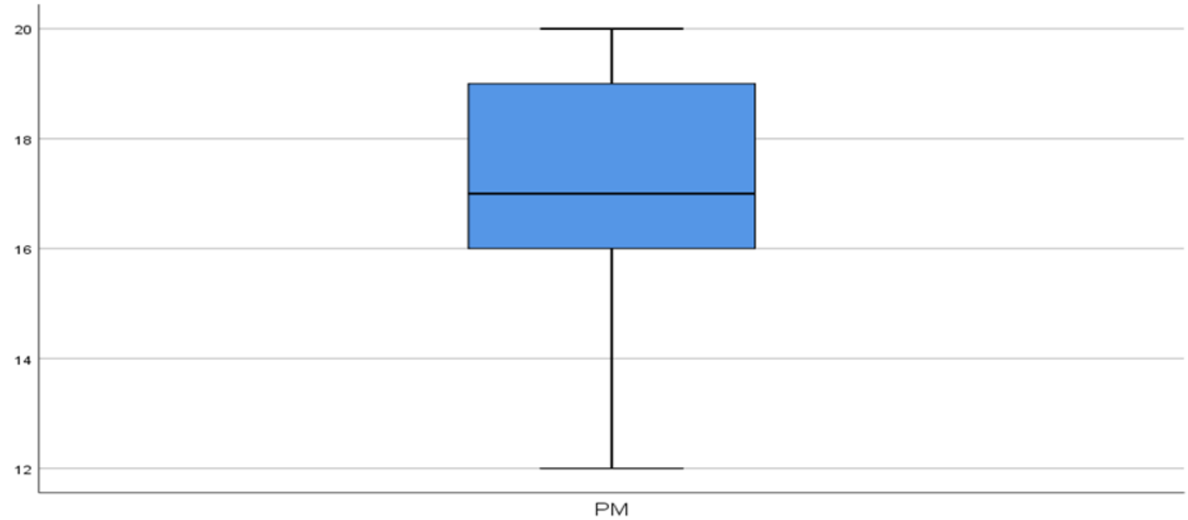

Figure 2: Box-plot for PM

Descriptive Statistics of PE

In this section descriptive statistics of PE is examined (see Table 3).

Table 3: Descriptive Statistic of PE

PE		Statistic	Std. Error
	N	198	
	Mean	16.3434	.13441
	Std. Deviation	1.89127	
	Minimum	11.00	
	Maximum	20.00	
	Range	9.00	
	Skewness	-.218	.173
	Kurtosis	.148	.344

As shown in Table 3, students have responded positively for PE. The skewness/kurtosis ratio indicates that the test for deviation from normality has not been violated (Kim, 2013) and the scale is able to be analysed using parametric analysis. This is evident from the histogram (Figure 3) and box-plot for PE (Figure 4).

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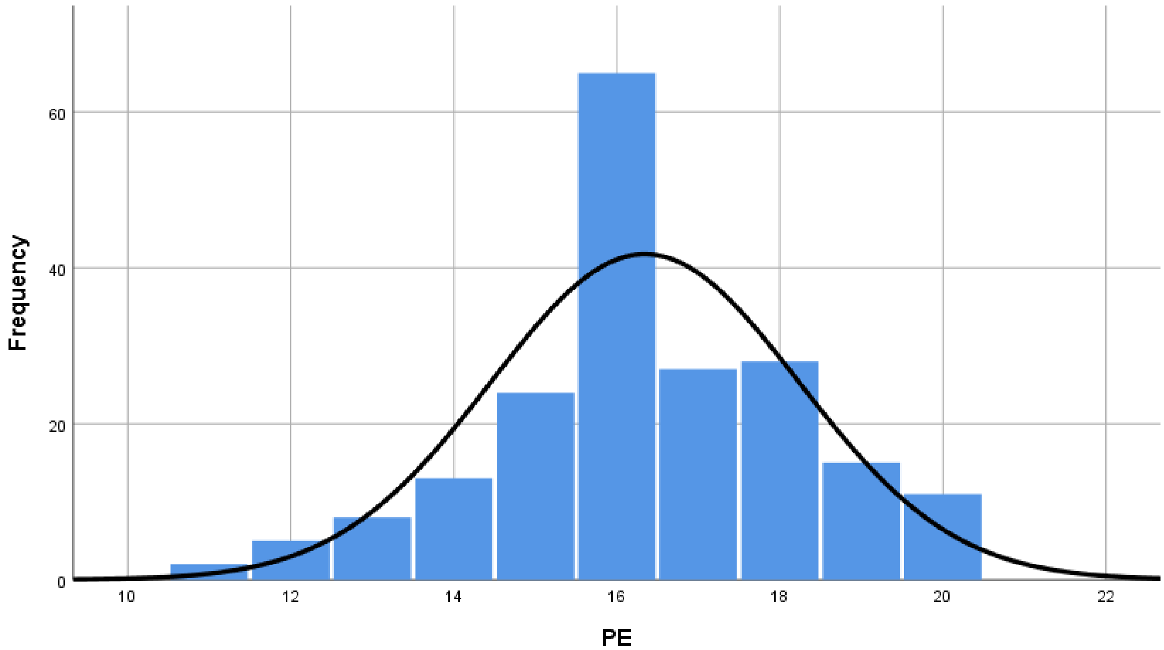

Figure 3: Histogram for PE

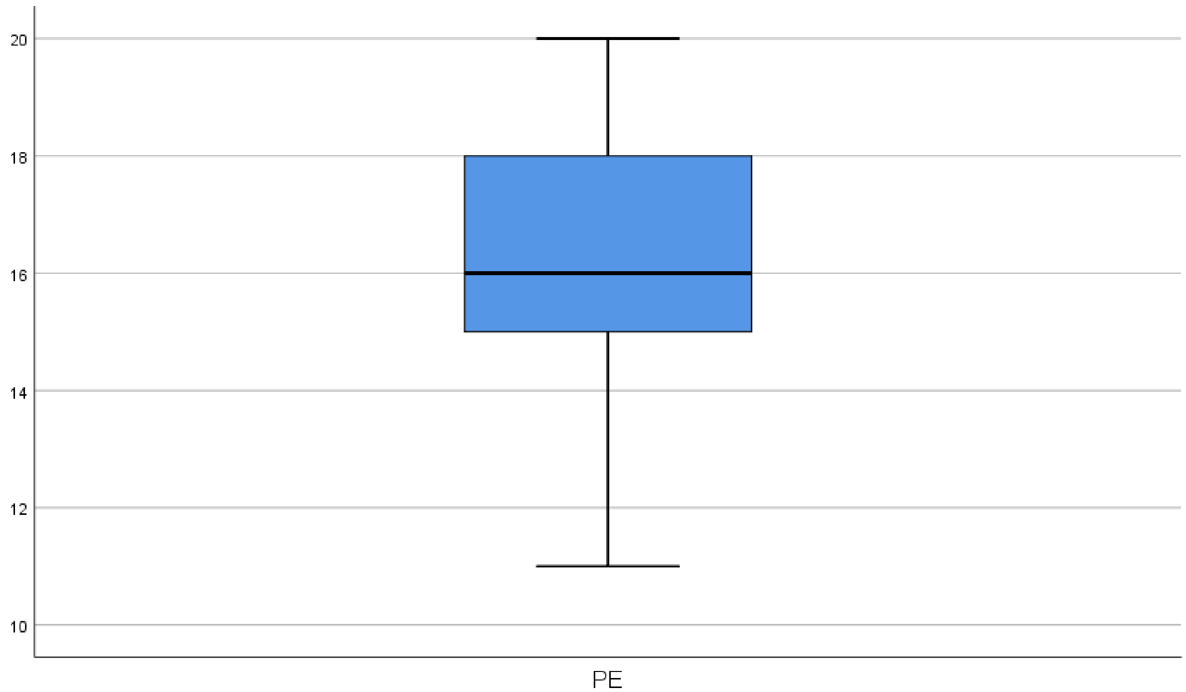

Figure 4: Box-plot for PE

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Descriptive Statistics of FAA

In this section descriptive statistics of FAA is examined (see Table 4).

Table 4: Descriptive Statistics of FAA

FAA		Statistic	Std. Error
	N	198	
	Mean	13.6061	.27785
	Std. Deviation	3.90969	
	Minimum	4.00	
	Maximum	20.00	
	Range	16.00	
	Skewness	-.325	.173
	Kurtosis	-.638	.344

As shown in Table 4, students have responded negatively for FAA. The skewness/kurtosis ratio indicates that the test for deviation from normality has not been violated (Kim, 2013) and the scale is able to be analysed using parametric analysis. This is evident from the histogram (Figure 5) and box-plot for FAA (Figure 6).

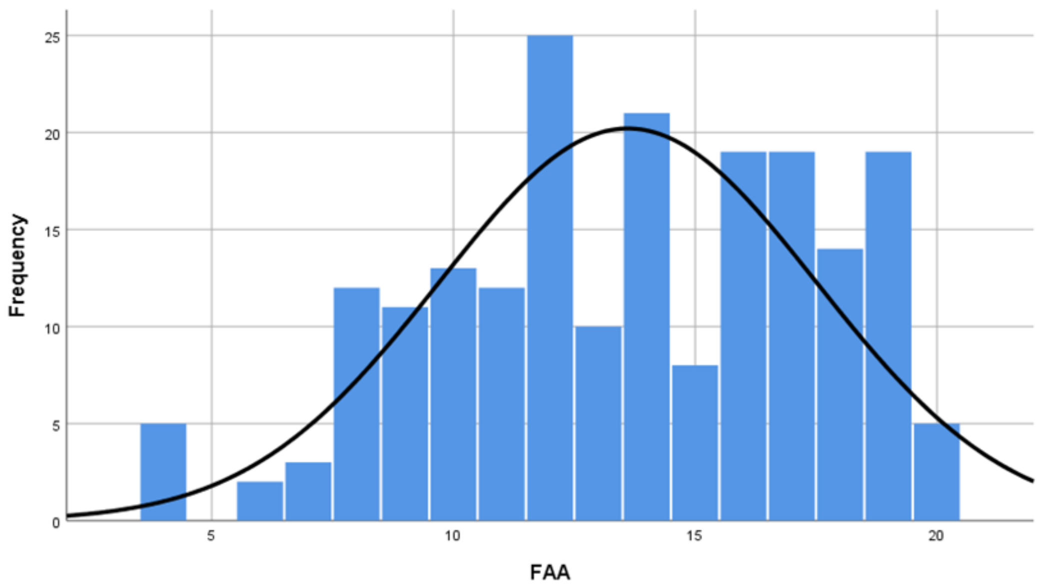

Figure 5: Histogram for FAA

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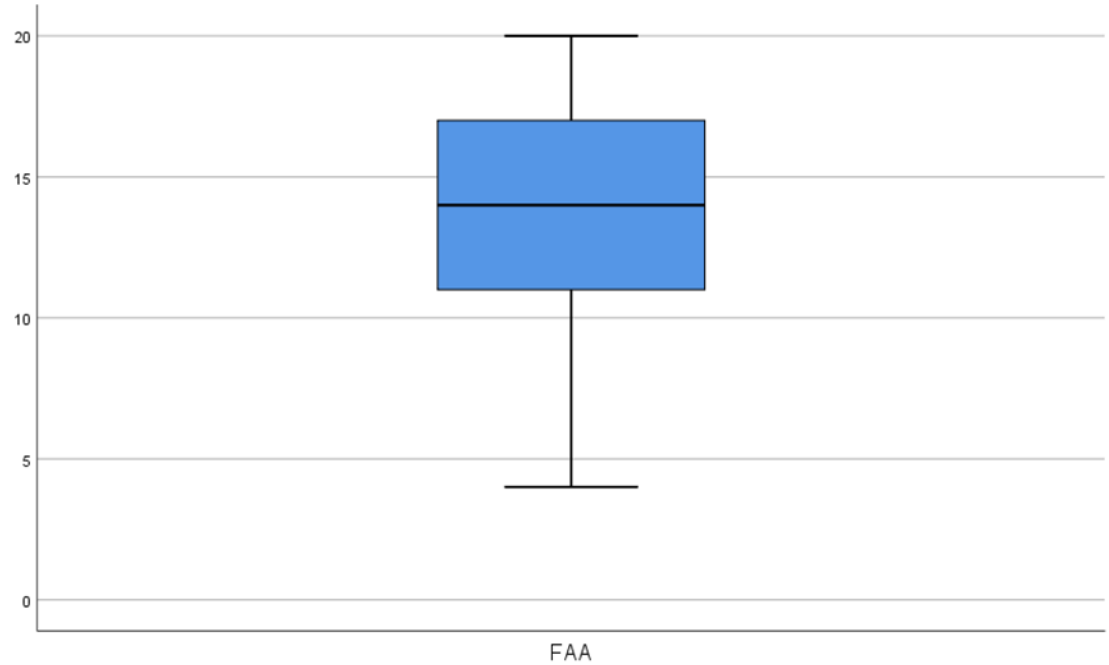

Figure 6: Box-plot for FAA

Descriptive Statistics of UC

In this section descriptive statistics of UC is examined (see Table 5).

Table 5: Descriptive Statistics of UC

UC		Statistic	Std. Error
	N	198	
	Mean	8.7778	.20368
	Std. Deviation	2.86606	
	Minimum	3.00	
	Maximum	15.00	
	Range	12.00	
	Skewness	.253	.173
	Kurtosis	-.897	.344

As shown in Table 5, students have responded negatively for UC. The skewness/kurtosis ratio indicates that the test for deviation from normality has not been violated (Kim, 2013) and the scale is able to be analysed using parametric analysis. This is evident from the histogram (Figure 7) and the box-plot for UC (Figure 8).

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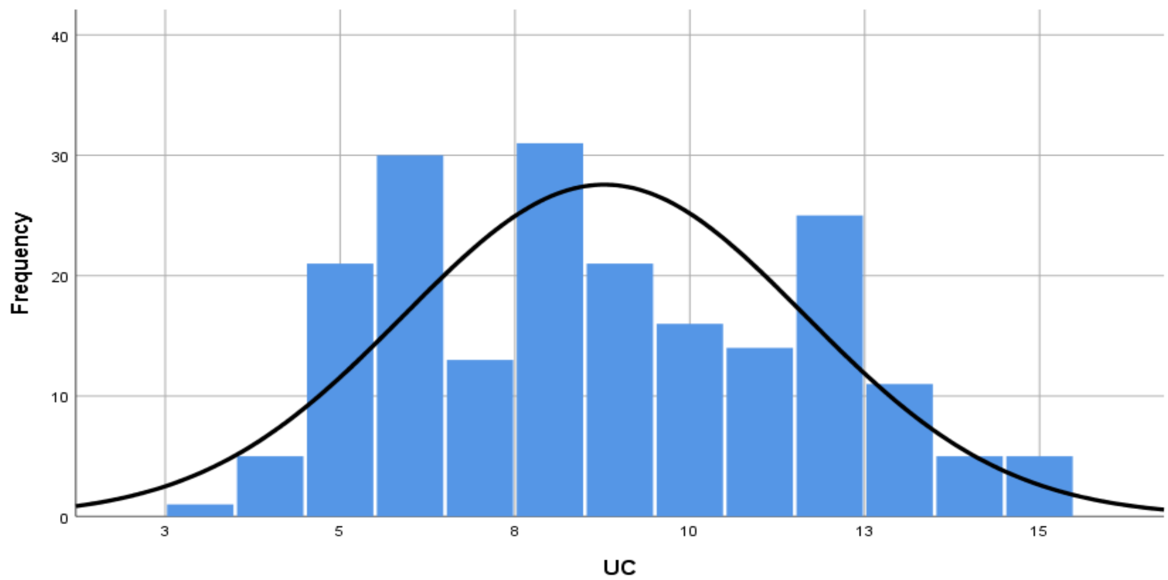

Figure 7: Histogram for UC

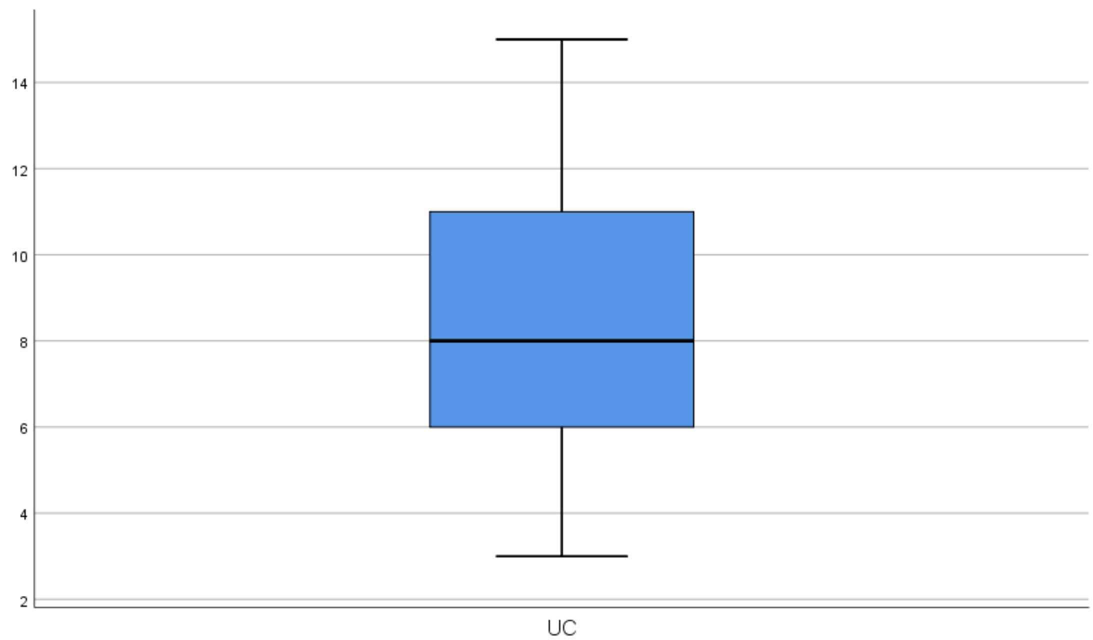

Figure 8: Box-plot for UC

Overall, in relation to the assumption of normality, Table 6 shows the results of the normality test using skewness and kurtosis; all the scales showed substantial normality.

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Table 6: Normality Test Using Skewness and Kurtosis Based on Four Scales

Factor	Skewness	SE skewness	Z skewness	Kurtosis	SE kurtosis	Z kurtosis
PM	-.144	.173	-0.83	-.541	.344	-1.57
PE	-.218	.173	-1.26	.148	.344	0.43
FAA	-.325	.173	-1.87	-.638	.344	-1.85
UC	.253	.173	1.46	-.897	.344	-2.60

Overall, histograms for all the scales (Figures 1, 3, 5, and 7) and box-plots for all the scales (Figures 2,4,6, and 8) were confirmed the normal distribution.

Checking the assumption of homogeneity of variance

Williamson and Johanson (2013) explained that the assumption of homogeneity of variance assumes there is no difference between the variance in the distributions. Osborne (2008) explained that the assumption of homogeneity of variances requires the error variances to be equal among the populations under examination. In this study, the homogeneity of variances was measured for all the scales in relation to gender groups, ethnic groups and schools. The PM, PE, and FAA scales demonstrated homogeneity of variance based on gender but only the PM and FAA scales variances demonstrated homogeneity of variance for ethnicity. The test based upon grouping by school indicated that only the PM scale demonstrated homogeneity of variance.

The PM, PE, and FAA scales show results from tests of homogeneity of variance based on gender (Table 7): only PM and FAA scale variances demonstrated homogeneity of variance for ethnicity (Table 8). The test based upon grouping by school indicated that only the PM scale possessed homogeneity of variance (Table 9).

Table 7: Test of Homogeneity of Variances for Scales Based on Gender

		Levene Statistic	df1	df2	Sig.
PM	Based on Mean	.018	1	196	**.894**
PE	Based on Mean	.009	1	196	**.925**
FAA	Based on Mean	3.886	1	196	**.050**
UC	Based on Mean	6.249	1	196	.013

Table 8: Test of Homogeneityof Variances for Scales Based on Ethnicity

		Levene Statistic	df1	df2	Sig.
PM	Based on Mean	1.612	1	196	**.206**
PE	Based on Mean	26.646	1	196	.000
FAA	Based on Mean	2.715	1	196	**.101**
UC	Based on Mean	6.847	1	196	.010

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Table 9: Test of Homogeneity of Variances for Scales Based on Schools

		Levene Statistic	df1	df2	Sig.
PM	Based on Mean	1.440	13	184	**.145**
PE	Based on Mean	5.104	13	184	.000
FAA	Based on Mean	4.949	13	184	.000
UC	Based on Mean	2.304	13	184	.008

Assumption of data type

Neideen and Brasel (2007) state that to employ parametric tests, data should be continuous. Robson (1994) emphasised that variables must have been calculated at least at an interval scale. In an ordinal scale, responses could be rated or ranked but the distance between those is not calculable. In interval data, the difference between responses can be measured (Sullivan & Artino, 2013). Jamieson (2004) noted that specialists disagreed on whether the median should be employed as the calculation of central tendency for Likert scale data. Likewise, they have questioned whether frequencies, contingency tables, tests, the Spearman rho assessment, or the Mann-Whitney U test should be employed for analysis as an alternative to parametric tests, which need interval data (e.g., t-tests, analysis of variance, Pearson correlations, and regression). However other experts have argued that if there is a sufficient sample size (at least 5-10 observations per group) and if the data are normally distributed (or nearly normal), parametric tests can be employed with Likert scale ordinal data. Therefore, parametric tests are able to produce satisfactory unbiased answers that are adequately close to “the truth” when analysing Likert scale responses (Norman, 2010).

Checking the assumption of independently distributed errors

Best and Khan (2006) described how choosing one case is independent of choosing any other case. This assumption can be managed via research design and samplings’ structure (Osborne, 2008). If this assumption is violated, it directs to dependent or correlated observations. According to Osborne (2008), in most research conditions, the need for independence is characteristically realised by randomisation. In instances of nonindependence, the scores/observations of the subject are impacted by other subjects or prior scores. In this study, the observations were independent and thus this assumption was fulfilled. As a whole, of the four basic assumptions of normality, three were fulfilled: data type and independently distributed errors. The assumption of homogeneity of variances was not fulfilled.

Non-parametric statistics Nahm (2016) explained that parametric statistical analyses are undertaken when assumptions are met. If these assumptions are not satisfied, if the distribution of the sample is skewed, or the distribution is unidentified because of small sample size, parametric tests cannot be employed. In that situation, nonparametric tests are an attractive option. There are two considered applications in nonparametric tests. First, as easy methods to analyse ordinal data and, second, as alternatives to parametric tests, frequently employed when there is proof of non-normality (Fagerland, 2012). Nonparametric tests decrease the danger of making incorrect inferences since these tests do not make any assumptions about the population. Therefore, nonparametric methods are always valid but not always systematic, whereas parametric methods

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are always systematic, but not always valid (Nahm, 2016). In this study, a nonparametric test, Kruskal-Wallis H tests, was used to identify the significant differences among schools in relation to students' motivation and engagement in learning.

5. CONCLUSIONS

Of the four basic assumptions, normality, data type, and independently distributed errors were fulfilled; the assumption of homogeneity of variances was not. Therefore, it was decided to conduct parametric tests and non-parametric tests of the quantitative data.

Accordingly, t-tests were conducted on all the scales in relation to gender and ethnicity, t-test being robust for violations of normality (Heeren & D'Agostino, 1987; Sullivan & D'Agostino, 1992) and SPSS offers the capacity to account for non-normal distributions (Field, 2013)**. The** PM and FAA scales were considered for analyses in two-way MANOVA and follow-up two-way ANOVA. In one-way ANOVA, only the PM scale was considered for analyses. Further Kruskal-Wallis *H* tests were conducted for PE, FAA, and UC scales.

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