International Journal of Future Generation Communication and Networking
Vol. 13, No. 1, (2020), pp.688 -702

The Pattern of Skewness And Kurtosis Using Mean Score And Logit In Measuring Adversity Quotient (AQ) For Normality Testing

Ewan Mohd Matore[1] , Ahmad Zamri Khairani[2]

[1]Faculty of Education
Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Malaysia
[2]School of Educational Studies
Universiti Sains Malaysia, 11800 Penang, Malaysia
effendi@ukm.edu.my[1], ahmadzamri@usm.my[2]

Abstract

This study aims to examine the pattern of skewness and kurtosis using mean and logit in measuring AQ for normality testing. Besides, the research also investigates the ability and potential of logit to meet the acceptance range of normality. The study uses survey design with questionnaires. A total of 1,845 students from five Malaysian polytechnics were selected using a proportionate stratified multistage cluster sampling. Instrument of IKBAR with 66 items of AQ and four CORE constructs were used after evaluated by 37 experts and analysed by Rasch model. The findings show that of the logit of skewness and kurtosis are higher than the mean. The difference in skewness shows the ranking of C-O-R-E while the kurtosis is C-E-R-O. The skewness of mean and logit indicates that Ownership records the largest value. The mean of kurtosis indicates Reach as the largest and Ownership for logit. Both skewness and kurtosis show that Control as the smallest for mean and logit. The pattern of skewness and kurtosis for mean and logit are in compliance with their best range. Results show that the skewness and kurtosis model have a strong linear relationship between mean and logit. The models also explain more than 70% of the variability of the response. Besides, the results mentioned about the linear moderate relationship between the differences and rate of changes of skewness between mean and logit, but inversely for kurtosis. Based on the results, it's clear that the patterns of logit have a great potential to be generating as normality testing besides mean. Nevertheless, the logit is greater than the mean and will be more difficult to meet the requirement of normality acceptance range. Further studies are proposed to explore the potential of logit from different contexts of study as well as suggesting the acceptance of specific normality ranges for logit.

Keywords*: normality, skewness, kurtosis, mean score, logits.*

1.0 Introduction

Many statistical tests require normally distributed data (Oztuna, Elhan, & Tuccar, 2006). Assessing the normality assumption should be taken into account for using parametric statistical tests (Ghasemi & Zahediasl, 2012). Neglect of testing normality by the researcher would have a very significant impact on the likelihood of error being made in the selection of statistical tests and thus affecting the final results of their findings. If the normality assumption is interrupted, interference and interpretation of data is likely to be invalid or unreliable (Nornadiah Mohd Razali & Wah, 2011). Assuming a normal distribution in a particular study is a common condition and usual requirement in most statistical techniques such as *t* tests, correlation, regression, and ANOVA (Chua Yan Piaw, 2006; Drezner, Turel, & Zerom, 2009; Hair, Celsi,

ISSN: 2233-7857 IJFGCN

Oritinau, & Bush, 2013; Mohd Rafi Yaacob, 2013). In many statistical analyses, normality is often conveniently assumed without any empirical evidence or test. But normality is critical in many statistical methods. When this assumption is violated, interpretation and inference may not be reliable or valid (Park, 2008). Therefore, it is very important to examine the distribution of the data before any decision can be made in choosing the appropriate statistical test for the data analysis (Lay Yoon Fah & Khoo Chwee Hoon, 2008).

One of the new instruments developed was *Instrumen Kecerdasan Menghadapi Cabaran* (IKBAR) using Rasch model, which to measure AQ in Malaysia using samples of polytechnic students (Mohd Effendi Mohd Matore & Ahmad Zamri Khairani, 2015, 2016). This instrument was using logits by Rasch in conducting their normality analysis. Based on the assumptions and measurement capabilities of classical test theory (CTT) on a rating scale, several limitations have been identified (Smith, Conrad, Chang, & Piazza, 2002). One of it is a data rating scale such as Likert scale, which is an ordinal type of data. This scale is ranking and when it is increases, so it does the trait. However, we cannot assume that increase in rank shows a similar increase between scales to another scale. Thus, “the difference in raw score between pairs of points does not necessarily imply the same number of constructs being studied” (Smith et al., 2002). Only the interval and ratio type of data can be used for the actual measurement or for parametric tests (that is, regression, analysis of variance (ANOVA), and others). Nonetheless, a rating scale such as the Likert scale for CTT analysis is often mistaken as an interval data and misused in parametric statistical procedures (Bode & Wright, 1999).

2.0 Research objectives

In this study, IKBAR uses a four-point Likert scale and the use of mean score as ordinal scales in normality analysis is tested as usual. However, this mean score is transformed into a Rasch logit to be tested for normality. This test will provide a different view of logit ability than the mean as regularly. Normally, we used the mean score through classical test theory in normality testing. The Rasch model through modern test theory able to transform the mean score to logits (which is interval data). The idea of this paper is to see the pattern of normality if we apply logit from Rasch using skewness and kurtosis method that suitable with large sampling.

The research objectives for this research are (a) How the logit can be used as data for normality testing of skewness and kurtosis by CORE? (b) How is the pattern of skewness and kurtosis of normality for logits and mean score by CORE? (c) What is the difference between the pattern of skewness and kurtosis for logit and mean score by CORE? (d) How the logit and mean in skewness and kurtosis able to fulfilling the normality acceptance range? (e) What is the relationship between the mean and logit of skewness and kurtosis by CORE? (f) What is the relationship between the differences and rate of changes of mean and logit for skewness and kurtosis by CORE?

3.0 Confusion in Normality Testing

Indeed, the sample size affects the normality of a data study. Previous study by Kamaruddin, Wah, Sayang and Jannoo (2017) stated that absolute measures (GFI, AGFI, RMSEA) are more affected by sample size while incremental fit measures such as TLI and CFI are less affected by sample size and non-normality. Conceptually, non-normality test is not on the observed data, but normality in the distribution of the population at random. Distribution characteristics in a random sample from a small population do

ISSN: 2233-7857 IJFGCN

not usually appear normal, especially when it involves small sample size. The distribution of larger samples tends to spread better and form a bell-shaped when the characteristics of the population are plotted based on the frequency. Confusion occurs when there is a sample from a normal population that does not show normal distribution; instead, only a few samples showed a seemingly normal distribution, especially with small sample size (Kim, 2012). We might be confused due to graph techniques or eyeball test and formal normality tests that may show inconsistent results for the same data. Some tests can only be applied to certain situations or assumptions. Furthermore, differences in normality tests often produce different results, for example when some tests reject and other tests fail to reject the null hypothesis of a hypothesis (Nornadiah Mohd Razali & Wah, 2011). To overcome this problem, skewness and kurtosis test methods are proposed to be used where it is relatively accurate for both small and large (Kim, 2013). These different findings have been an issue and have been misleading researchers and normality test selection must be given priority (Nornadiah Mohd Razali & Wah, 2011). For this research, we applied the skewness and kurtosis for large samples among 1,845 students from polytechnic using proportionate stratified multistage cluster sampling technique.

4.0 Type of Normality Testing

Normally distributed data means that there are a small percentage of extreme values that are too low or too high where most of the values would be around the mean value (Othman Talib, 2013). Basically, there are three methods to test the assumption of normality; the first is a method of testing graphically such as histogram, stem and leaf plot, boxplot, and normal Q-Q plot. Graphical method is also known as the eyeball test (Kim, 2012). The second method is through a more formal testing through numerical statistical methods such as skewness and kurtosis, and the third method is a computerised statistical software such as Shapiro-Wilk test (SW), Kolmogorov- Smirnov (KS), Anderson-Darling (AD), and Lilliefors (LF) (Nornadiah Mohd Razali & Wah, 2011). Meanwhile, it was categorised normality testing into two types, namely graphical method and numerical method (Park, 2008).

Skewness and kurtosis are categorised as descriptive statistics whilst tests such as SW, KS, and AD are theory-based methods (Nornadiah Mohd Razali & Wah, 2011). Although the graphics test methods can act as a normality test for independent samples of observation, it is still not sufficient enough to produce evidence that a datum is normally distributed. A more formal method should be carried out to support the graphical methods such as numerical methods and formal normality tests before making any conclusions about the data normality (Nornadiah Mohd Razali & Wah, 2011). Therefore, there is no one best method or gold standard for determining the normality of a datum (Kim, 2013). For this research context, we are using skewness and kurtosis values for normality testing because the different layers of acceptance range of normality and the suitability for large sample sizes.

Kim (2013) also stated that there are many formal normality testing methods such as statistical methods (Kolmogorov-Smirnov and Shapiro Wilk) or informal methods such as graphic or eyeball test (skewness and kurtosis, histogram, boxplot and Q-Q plot). However, none of the best methods to determine the normality of a data. Normality testing with formal methods such as statistical methods is more popular and well known. However, this method has its disadvantages: the Kolmogorov-Smirnov and Shapiro Wilk methods are not suitable for large sample sizes (n <300). For large samples, normality values that were not observed using the Kolmogorov Smirnov test (significant value greater than .05) were common (Pallant, 2011).

ISSN: 2233-7857 IJFGCN

Compared with the graphic or eyeball test, it is more suitable for medium to large samples (n> 50) and not suitable for small samples (Kim, 2012). Mistakes often arise when both methods of statistical testing show inconsistencies in the findings of the same data. Another suitable test method for this problem is to use the test of skewness and kurtosis distribution, where the relative accuracy of both small and large samples (Kim, 2013). Most parametric statistics for some data are seen as scattered near normal. This is because the frequency distribution is seen as bell shape, whereas most data has a high and low value in the middle range. This unsymmetrical distribution is called skewness. Therefore, it is important to examine the skewness. Normality is important when skewness or outliers affect correlation or significant value (especially in EFA and PCA) (Leech, Barrett, & Morgan, 2005). The kurtosis value is usually not taken into account as it does not have much effect on most statistical analysis (Leech et al., 2005).

Most statistical books do not provide suggestions to determine whether the variables are normal or not. SPSS suggests dividing the value of skewness with a standard error (with a value of less than 2.5 is considered normal). However, the disadvantages of this method are the use of calculators and standard error values depending on the size of the sample where most data with large samples are found to be not normally distributed (Leech et al., 2005). Therefore, the sample size of the study is closely related to the determination of the value of skewness and kurtosis for normality testing. In fact, sometimes when the sample used is large, the normality test is likely to be neglected as proposed by Field (2009) that explains the normality values based on both skewness and kurtosis (positive or negative) must not exceed 1.96 for small samples and not exceeding 2.58 for large samples (ie 200 or more). This test is ignored for very large samples.

There are some set of skewness and kurtosis values that are considered normal by researchers such as ± 1.0 (Leech et al., 2005) and a value of ± 2.0 (Chua Yan Piaw, 2008; Lomax & Hahs-Vaughn, 2012). For sample size greater than 300, the value of normality can be referred to the histogram and skewness and kurtosis values without considering the value of Z. The skewness value is less than two and the kurtosis does not exceed seven is considered normal (Kim, 2013). Based on Kline (2009), values above three for skewness are considered extreme for some researchers. For kurtosis values, values greater than 10 are considered problematic and become more serious when more than 20. Thus, the value of the acceptable range of values is less than 3 for skewness and less than 10 for kurtosis. The values fall within this range are considered normal for further analysis (Leech et al., 2005).

5.0 Skewness and Kurtosis for Normality Testing

Normality testing using formal methods such as statistical methods is more popular and well known. KS and SW normality tests can be used to test the null hypothesis which states that the observed data are a sample from the population that has a normal distribution. If the level of significance is large ($p > .05$), then the assumption can be made that the observed data are normally distributed. If the value of p is small ($p \leq .05$), the null hypothesis which states that the observed data are a sample from a normal population would be rejected. Such assumptions should be questioned (Lay Yoon Fah & Khoo Chwee Hoon, 2008). In simple language, if the significant value is less than 0.05, then the data is not normal (Chua Yan Piaw, 2006; Mohd Rafi Yaacob, 2013). This test is quite sensitive in that when the sample size is small, then the null hypothesis that should have been rejected would fail to be rejected.

ISSN: 2233-7857 IJFGCN

On the other hand, for large sample sizes, this test as suggested by Field (2009), who explained that the determination of normality is based on skewness and kurtosis (positive or negative) that must not exceed 1.96 for a small sample and not more than 2.58 for a large sample (i.e., 200 or more). For very large samples, these tests will be ignored. Through a large sample, skewness findings will not show different results to be considered in the analysis. Unlike kurtosis that has impact from the variance, this risk is reduced with large samples (over 200 samples) (Tabachnick & Fidell, 2008). For a large sample of 200 and more, it is more important to look at the shape of the distribution visually and examine the statistical skewness and kurtosis as compared to calculating its significance (Field, 2009).

There are some skewness and kurtosis value settings that are considered normal by previous researchers such as ± 1.0 (Leech, Barrett, & Morgan, 2005), value ± 2.0 (Chua Yan Piaw, 2008; Lomax & Hahs-Vaughn, 2012), and ± 3.0 (Othman Talib, 2013; Peat & Barton, 2005). For sample sizes greater than 300, the normality value can be referred to the histogram and the skewness and kurtosis value without considering the value of Z. Reference skewness value that is less than 2.0 and kurtosis not exceeding 7.0 are considered normal (Kim, 2013).

Table 1: Proposed Values for Skewness and Kurtosis Settings for Normality Assumptions

Skewness	Kurtosis	Proposed designation	Sample size (N)
± 1.00	± 1.00	(Leech et al., 2005)	
± 2.00	± 2.00	(Chua Yan Piaw, 2008; Garson, 2012; Lomax & Hahs-Vaughn, 2012)	
± 2.58	± 2.58	(Field, 2009)	N ≥ 200
± 1.96	± 1.96	(Field, 2009)	N < 200
± 3.00	± 3.00	(Othman Talib, 2013; Peat & Barton, 2005)	
< 2.00	< 7.00	(Kim, 2013)	N > 300
< 3.00	< 10.00	(Kline, 2009)	

Kline (2009) stated that the skewness value greater than 3.0 is considered extreme to some researchers. As for the kurtosis, the value greater than 10 is considered delinquent and become more serious when it is more than 20. Thus, the acceptable range of normality is less than 3 for skewness and less than 10 in value for kurtosis. Any value that falls within this range is considered normal for further analysis. Non-extreme value is necessarily expected to have no problem in answering all research questions (Leech et al., 2005). Basically, most of the scales used in the social sciences will have skewness whether positive or negative (Pallant, 2011).

6.0 Sources of Data Non – Normality's

The researchers need to take non normality seriously and start to report them along with means and variances. Reporting skewness and kurtosis with robust analysis can be made and increase the transparency of data analysis but also develop better techniques to deal with non-normality, improve statistical practices and conclusions in empirical analysis, and increase awareness and knowledge of the non-normality problem (Cain, Zhang, & Yuan, 2016). Harmon (2011) has clarified some of the causes for the non – normal distribution of data. Amongst them are the extreme outliers that can cause the

ISSN: 2233-7857 IJFGCN

distribution of data to easily skew. Researchers can identify and remove the extremes that cause errors in measurement or data entry. This method can assist in getting a normal distribution from skewness. However, these extreme values will only be removed if there is a specific reason that resulted in the existence of this value. Normally, the extreme value does exist and occur in a normal distribution. This value must be scrutinized with caution when the number exceeds the researcher's expectations.

Data distribution sometimes does not seem normal until the number of samples obtained is sufficient. Usually, the total sample of 30 is considered as the beginning of a large number. If researchers took 50 samples and the data are still not normally distributed, then it is recommended to take at least 100 samples before revaluation is done to the data normality in the study. If the data have a large number for a value close to zero or a natural limit, then the data will tend to be skewed. In this case, researchers can modify the data by adding a specific value of all data that are analysed and ensuring all will increase uniformly. It is very important to ensure that the samples taken represent the entire research process. If the sample taken is only specific to a certain subset, then it is not representative of the entire population and tends to be non – normal. Therefore, random and extensive sampling is encouraged.

By right, researchers should not rely solely on graphic techniques to make inferences about data distribution. It is recommended that consideration be made by combining graphic techniques with formal normality testing and inspection of the parameters such as skewness and kurtosis (Ghasemi & Zahediasl, 2012; Nornadiah Mohd Razali & Wah, 2011; Oztuna et al., 2006). It should be noted that the measurement of skewness and kurtosis is influenced by sample size. Researchers also need to be cautious that the four normality tests, namely SW, KS, LD, and AF do not work well on small sample sizes. Even until now, research continues to be conducted to identify new normality test that can function well for small sample sizes (Razali & Wah, 2011). The larger the sample size, the less important normality of the population distribution (Weaver, 2011). Although the existing normality tests do provide useful information, it is still not easy to identify whether a datum is able to fulfil the assumptions of a normal distribution or not (Kim, 2012). If the data are still not normally distributed, researchers can still choose non-parametric type of statistics (Harmon, 2011; Kim, 2013) or perform data transformations through logarithm (Kim, 2013; Tsai, Liou, Simak, & Cheng, 2017). The normality assumption also needs to be considered for validation of data presented in the literature as it shows whether correct statistical tests have been used (Ghasemi & Zahediasl, 2012). No one who is working with real data meets the assumptions of normality and homogeneity of variance (Weaver, 2011). Thus, the selection of normality test which coincides with the study features should be given attention by researchers to ensure the accuracy in the selection of test statistics and the validity in the final findings.

7.0 Methodology

The study was conducted by using quantitative survey approach. A total number of 1,892 respondents from 18,828 polytechnic students are identified as target of the population of the study. The return rate of the study was 97.52% (1,845 students) considered as acceptable (Christensen, Johnson, & Turner, 2011; Loewenthal, 2001). This study adopts a clustered multistage stratified proportional sampling technique involving five polytechnics in Malaysia.

ISSN: 2233-7857 IJFGCN

The selection of the polytechnics is based on geographical segregation according to zones, that is, Premier Polytechnic of Ungku Omar (PUO-Western), Polytechnic of Sultan Abdul Halim Mu'adzam Shah (POLIMAS-Northern), Polytechnic of Sultan Haji Ahmad Shah (POLISAS-Eastern), Polytechnic of Port Dickson (PPD-Southern), and Polytechnic of Kuching Sarawak (PKS-Borneo). This study adopts three distinct models based on the purpose of the study namely CORE model, Rasch model and instrument development model. The CORE model (Stoltz, 1997) provides a conceptualization of AQ while the instrument development model (Miller, Lovler, & McIntire, 2013) laid the foundation on how the instrument is developed.

RMM provides a framework for analysing and interpreting the measurement mode. This is conducted using the Mooney Problem Check List (MPCL) that measures 11 challenges usually faced by students - health, finance, recreation, courtship, social, personal, religion, family, career, education and learning (Mohd Effendi Mohd Matore & Ahmad Zamri Khairani, 2014; Mooney & Gordon, 1950). IKBAR used four main constructs namely CORE or Control, Ownership, Reach and Endurance. Table 2 shows the profile of respondents.

Table 2. Profile of respondents

Demography factor	Frequency	Percentage
Gender		
Male	994	53.9%
Female	851	46.1%
Year of study		
Year one	619	33.6%
Year two	287	15.6%
Year three	939	50.9%
Department		
Civil Engineering Department (JKA)	490	26.6%
Electrical Engineering Department (JKE)	294	15.9%
Mechanical Engineering Department (JKM)	383	20.8%
Petrochemical Engineering Department (JKPK)	32	1.7%
Marine Engineering Department (JKP)	9	0.5%
Commerce Department (JP)	442	24.0%
Food Technology Department (JTM)	53	2.9%
Information Technology and Communication Department (JTMK)	142	7.7%
Name of polytechnic		
Premier Polytechnic of Ungku Omar (PUO)	456	24.7%

ISSN: 2233-7857 IJFGCN

Polytechnic of Sultan Abdul Halim Mu'adzam Shah (POLIMAS)	393	21.3%
Polytechnic of Port Dickson (PPD)	375	20.3%
Polytechnic of Sultan Haji Ahmad Shah (POLISAS)	363	19.7%
Polytechnic of Kuching Sarawak (PKS)	258	14.0%
Total of respondents	1845	100.0%

8.0 Results and discussions

Table 3 show the normality values analysed using two different types of data namely mean score and logit. The mean score is obtained first and the logit is obtained from the mean score through WINSTEPS. The findings show the skewness and kurtosis of logits are higher than mean score.

Table 3: Normality using logits Rasch for IKBAR (N= 1845)

CORE Constructs	Type of Testing	Statistic (mean)	Normality Assumption	Statistic (logit)	Normality Assumption
Control	Skewness	- 0.328	Normal (Leech et al., 2005)	0.442	Normal (Leech et al., 2005)
	Kurtosis	0.039	Normal (Leech et al., 2005)	0.509	Normal (Leech et al., 2005)
Ownership	Skewness	- 0.092	Normal (Leech et al., 2005)	1.019	Normal (Leech et al., 2005)
	Kurtosis	0.171	Normal (Leech et al., 2005)	2.597	Normal (Peat & Barton, 2005)
Reach	Skewness	- 0.167	Normal (Leech et al., 2005)	0.973	Normal (Leech et al., 2005)
	Kurtosis	0.214	Normal (Leech et al., 2005)	2.469	Normal (Field, 2009)
Endurance	Skewness	- 0.236	Normal (Leech et al., 2005)	0.893	Normal (Leech et al., 2005)
	Kurtosis	0.113	Normal (Leech et al., 2005)	1.444	Normal (Garson, 2012; Lomax & Hahs-Vaughn, 2012)
AQ	Skewness	- 0.206	Normal (Leech et al., 2005)	1.047	Normal (Garson, 2012; Lomax & Hahs-Vaughn,

ISSN: 2233-7857 IJFGCN

					2012)
	Kurtosis	0.392	Normal (Leech et al., 2005)	4.147	Normal (Kim, 2013)

Figure 1 will show the normality expectations difference in Normal Q-Q Plot pattern for mean and logit based on CORE. The plots are clearly showing that the pattern of mean is more normal that logit for all CORE.

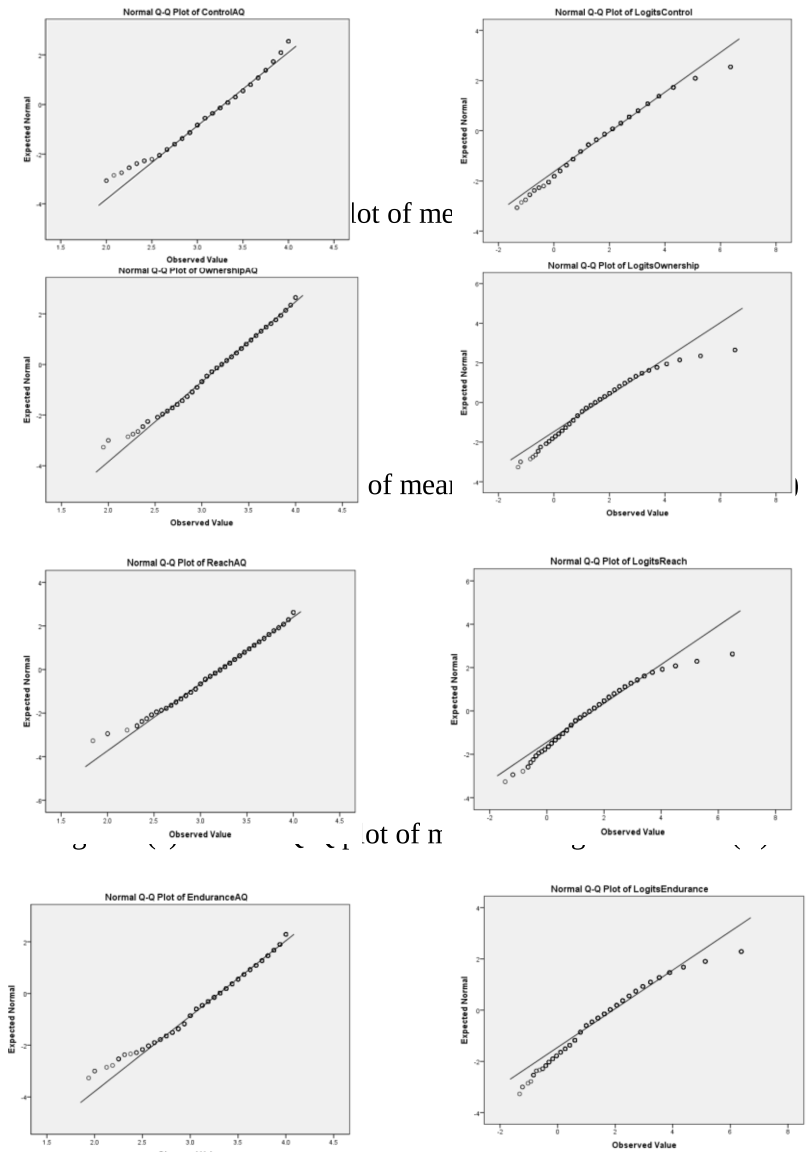


Figure 1(d) Normal Q-Q plot of mean and logit for Endurance (E)

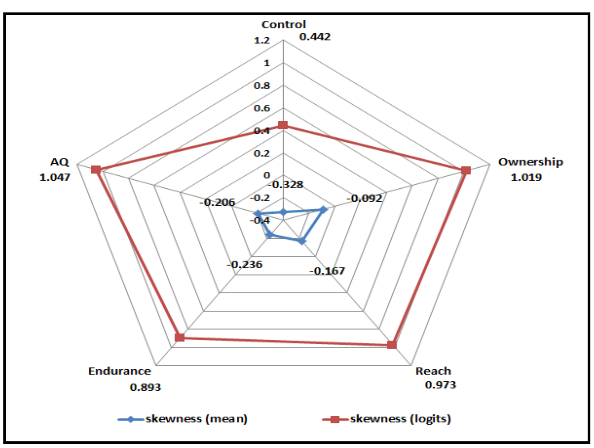
ISSN: 2233-7857 IJFGCN

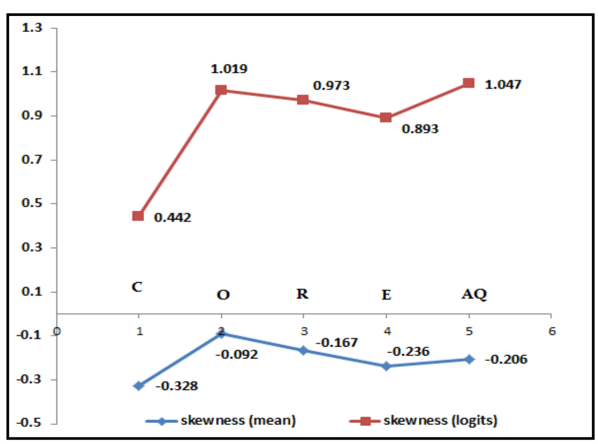
Table 4 shows the comparison of mean score and logit for skewness and kurtosis based on four CORE in AQ measurements. Results show the value of logit was exceeds the mean score for all constructs of skewness and kurtosis. Differences between skewness indicate the following rank arrangement of C-O-R-E (Control, Ownership, Reach and Endurance) and the rank for the kurtosis is as follows C-E-R-O (Control, Endurance, Reach, Ownership).

Table 4: Comparing mean score and logits for skewness and kurtosis (N= 1845)

CORE Constructs	Testing	Statistic (mean)	Statistic (logit)	Difference
Control	Skewness	- 0.328	0.442	0.77
	Kurtosis	0.039	0.509	0.47
Ownership	Skewness	- 0.092	1.019	1.111
	Kurtosis	0.171	2.597	2.426
Reach	Skewness	- 0.167	0.973	1.14
	Kurtosis	0.214	2.469	2.255
Endurance	Skewness	- 0.236	0.893	1.129
	Kurtosis	0.113	1.444	1.331
AQ	Skewness	- 0.206	1.047	1.253
	Kurtosis	0.392	4.147	3.755

Figure 5(a) show the skewness patterns for mean scores and logit based on the CORE model for measuring AQ. The Ownership shows the greatest value for the mean of -0.092 and the smallest value is the Control with mean of -0.328. Skewness pattern for logit shows Ownership dominated with mean of 1.019 and the smallest value is Control with mean of 0.442. Overall, the skewness of mean score is complying with a range of ± 1.00 and categorized as normal (Leech et al., 2005). Skewness for logit shows the changing values following CORE and found the normality range is obeyed (Chua, 2008; Field, 2009; Kim, 2013; Kline, 2009; Lomax & Hahs-Vaughn, 2012).





ISSN: 2233-7857 IJFGCN

Figure 5(a): The pattern of skewness by comparing their mean score and logit between CORE

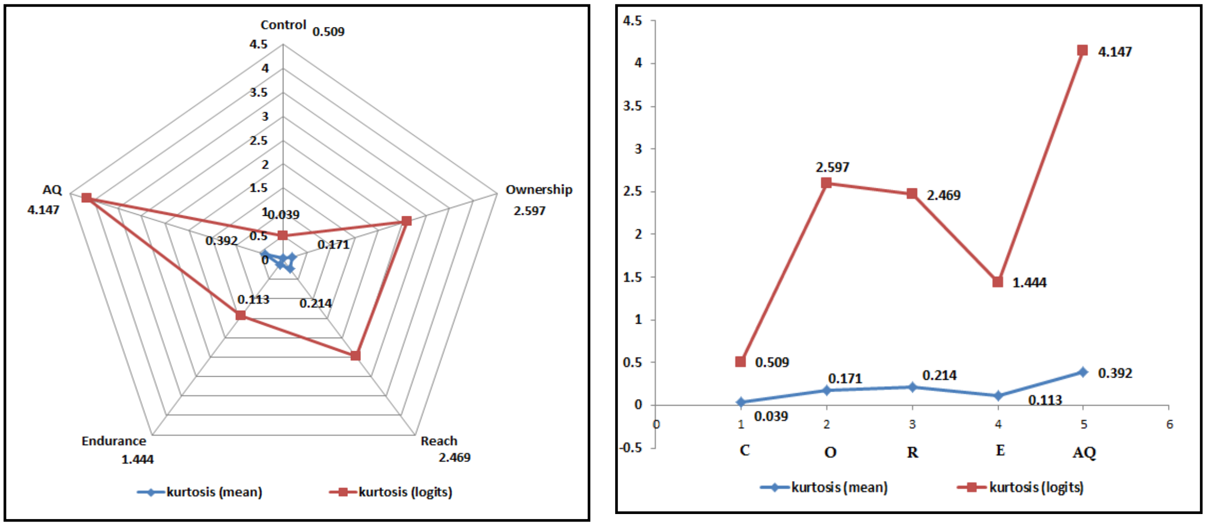


Figure 5(b): The pattern of kurtosis by comparing their mean score and logits between CORE

Figures 5(b) show the kurtosis patterns for mean scores and logit based on the CORE model for measuring AQ. The Reach shows the greatest value for the mean of 0.214 and the smallest is Control with the mean of 0.039. Kurtosis pattern for logit shows Ownership dominated with 2.597 logit and the smallest is Control with logit of 0.509. The kurtosis of logit is complying with a range of ± 2.00 and categorized as normal. Skewness for logit shows the changing values following CORE and found the normality range is obeyed (Chua, 2008; Field, 2009; Kim, 2013; Kline, 2009; Lomax & Hahs-Vaughn, 2012).

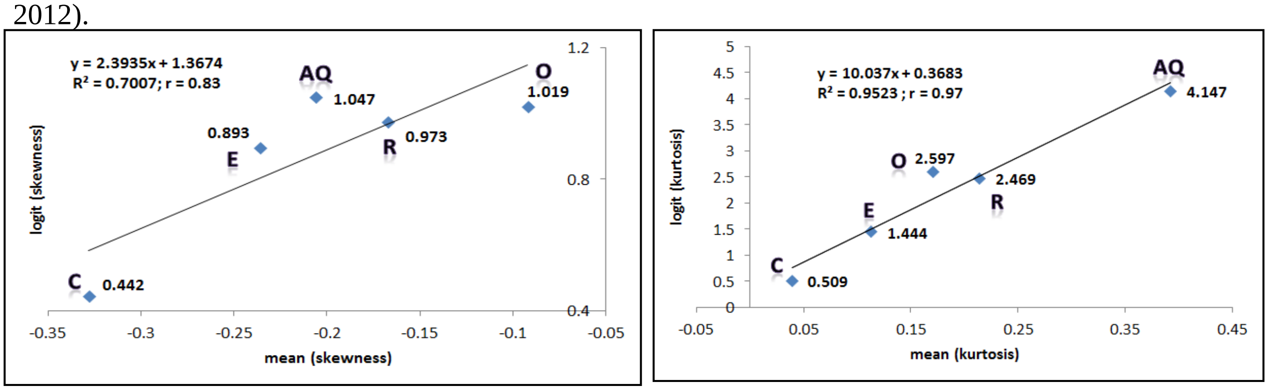


Figure 6: The scatter plot between the mean and logit of skewness and kurtosis by CORE

Figure 6 shows a scatter plot diagram showing how the skewness of mean and logit values affects each other (R^2). R-squared is a statistical relationship between two series of events and also the percentage of the response variable variation that is explained by a linear model. For skewness, figure 6(a) indicates that the model explains 70.1% of all the variability of the response data around its mean. It shows a strong linear relationship (r = +0.83) between the mean value and the logit for CORE. For kurtosis, figure

ISSN: 2233-7857 IJFGCN

6(b) indicates that the model explains 95.2% of all the variability of the response data around its mean. It also shows a very strong linear relationship (r = +0.97) between both. This suggests that this relationship is likely to be directly proportional to when the mean value increases; the logit value also increases in the case of skewness and kurtosis. This finding is quite clear that Rasch's logit is potentially to be used in normality testing, because the logit are in line with mean score (similar characteristics).

Table 5: Rate of changes of mean and logits for skewness (N= 1845)

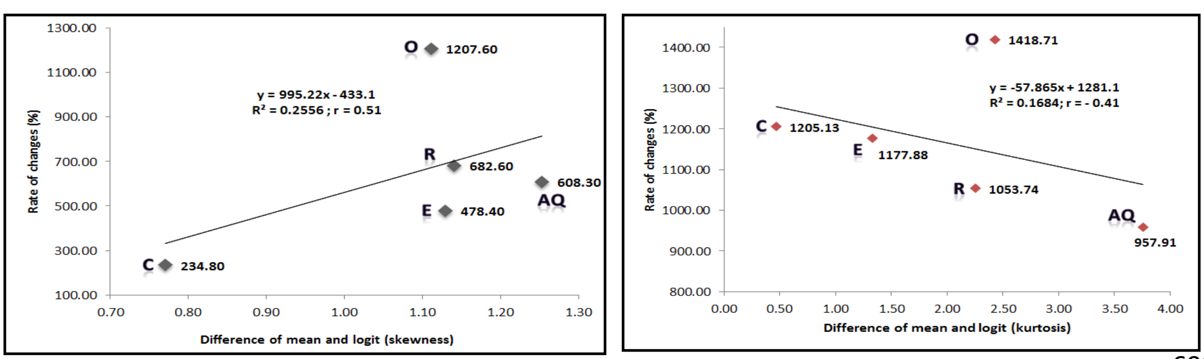
CORE Constructs	Statistic (mean)	Statistic (logit)	Difference	Rate of change (%)
Control	-0.328	0.442	0.77	234.80
Ownership	-0.092	1.019	1.11	1207.60
Reach	-0.167	0.973	1.14	682.60
Endurance	-0.236	0.893	1.13	478.40
AQ	-0.206	1.047	1.25	608.30

Table 6: Rate of changes of mean and logits for kurtosis (N= 1845)

CORE Constructs	Statistic (mean)	Statistic (logit)	Difference	Rate of change (%)
Control	0.039	0.509	0.47	1205.13
Ownership	0.171	2.597	2.43	1418.71
Reach	0.214	2.469	2.26	1053.74
Endurance	0.113	1.444	1.33	1177.88
AQ	0.392	4.147	3.76	957.91

Table 5 and 6 show that the increment in the rate of change that occurs between the mean and the logit. The positive value of the rate proves that the value of skewness and kurtosis for logit is greater than the mean for all CORE.

Figure 7 (a) shows that there is a linear moderate relationship (r = +0.51) between the difference and rate of changes of the mean with logit for skewness. When the difference increases, the rate of change also increases. Figure 7 (b) shows that there is a moderate relationship (r = -0.41) but inversely proportional between the difference and rate of changes of skewness for mean and logit. It shows that when the difference increases, the rate of change will be decreased with the moderate relationship.



ISSN: 2233-7857 IJFGCN

Figure 7(a) Figure 7(b)

Figure 7: The scatterplot between the differences and rate of changes of mean and logit of skewness and kurtosis by CORE

Although the normality findings show that not all CORE constructs of mean and logit are at the best range such as ± 1.0 (Leech et al., 2005), the value of ± 2.0 (Chua Yan Piaw, 2008; Lomax & Hahs-Vaughn, 2012) or ± 2.58 (Field, 2009). Even though the logit are larger than mean, the pattern of logit for skewness and kurtosis are not much different. In fact, most scales and measurements used in social sciences will indeed experience either positive or negative declines (Pallant, 2011). Generally, normality testing based on the value of skewness and kurtosis for mean and logit shows that CORE in AQ is normally distributed and complies with the acceptance range of normality.

9.0 Conclusions

This study has proven that the ability of logit through Rasch's model is able to apply for normality testing as the mean score. The findings show logit is greater than the mean score, but the skewness and kurtosis pattern is quite uniform. This pattern is supported by a linear relationship of the mean and logit of skewness and kurtosis according to the CORE. Although there is a large difference in the percentage of the rate of change between mean and logit, the value still meets the normality acceptance range. The study suggests that a standardized normality of range is produced especially for the logit, rather than just the mean as it is now. Researchers can also use logit for their normality tests but they need to face the risk of getting a higher value than the mean score. The implication is the logit will make them harder to meet the best range of normality. Some future studies can be carried out by implementing logit setting and mean for different contexts, comparing the logit capabilities in a different total of sampling and examining whether there is a significant difference between logit capability with the mean score.

10.0 Acknowledgment

This research was supported by the Universiti Kebangsaan Malaysia under grant of GG-2019 -034 and GGPM-2017-088.

References

[1] Bode, R. K., & Wright, B. D. (1999). Rasch measurement in higher education. In J. C. Smart & W. G. Tierney (Eds.), *Higher Education: Handbook of Theory and Research* (Vol. 14, pp. 287 – 316). Dordrecht: Springer Netherlands. http://doi.org/10.1007/978-94-011-3955-7

[2] Cain, M. K., Zhang, Z., & Yuan, K.-H. (2016). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior Research Methods*. http://doi.org/10.3758/s13428-016-0814-1

[3] Christensen, L. B., Johnson, R. B., & Turner, L. A. (2011). *Research methods, design and analysis* (11th ed.). Boston: Pearson Education.

[4] Chua Yan Piaw. (2006). *Asas statistik penyelidikan (Buku 2)*. Bentong: McGraw Hill.

[5] Chua Yan Piaw. (2008). *Asas Statistik Penyelidikan: Analisis Data Skala Ordinal dan Skala Nominal (Buku 3)*. Kuala Lumpur: McGraw Hill.

[6] Drezner, Z., Turel, O., & Zerom, D. (2009). *A modified Kolmogorov-Smirnov test for normality*

(No. 14385). Fullerton, CA. Retrieved from http://mpra.ub.uni-muenchen.de/14385/
[7] Field, A. (2009). *Discovering statistics using SPSS*. London: SAGE Publications.
[8] Garson, G. D. (2012). *Testing Statistical Assumptions*. Asheboro, NC: Statistical Associates Publishing.
[9] Ghasemi, A., & Zahediasl, S. (2012). Normality tests for statistical analysis: a guide for non-statisticians. *International Journal of Endocrinology and Metabolism*, *10*(2), 486–9. http://doi.org/http://dx.doi.org/10.5812/ijem.3505
[10] Hair, J. F., Celsi, M. W., Oritinau, D. J., & Bush, R. P. (2013). *Essentials of marketing research* (3rd ed.). New York: McGraw Hill.
[11] Kamaruddin, A. A., Wah, Y. B., Sayang, M. D., & Jannoo, Z. (2017). Sample Size and Non-normality Effects on Goodness of Fit Measures in Structural Equation Model. *Pertanika Journal Science & Technology*, *25*(2), 575–586.
[12] Kim, H.-Y. (2012). Statistical notes for clinical researchers: assessing normal distribution (1). *Restorative Dentistry & Endodontics*, *37*(4), 245–8. http://doi.org/http://dx.doi.org/10.5395/rde.2012.37.4.245
[13] Kim, H.-Y. (2013). Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry & Endodontics*, *38*(1), 52–4. http://dx.doi.org/10.5395/rde.2013.38.1.52
[14] Kline, R. B. (2009). *Becoming a behavioral science researcher: a guide to producing research that matters*. New York: Guilford Press.
[15] Lay Yoon Fah, & Khoo Chwee Hoon. (2008). *Pengenalan kepada analisis statistik dalam penyelidikan sains sosial: Siri 2*. Batu Caves: Venton Publishing (M) Sdn. Bhd.
[16] Leech, N. L., Barrett, K. C., & Morgan, G. A. (2005). *SPSS for intermediate statistics: use and interpretation* (2nd ed.). Mahwah, New Jersey: Lawrence Erlbaum Associates.
[17] Loewenthal, K. M. (2001). *An introduction to psychological tests and scales* (2nd ed.). Philadelphia: Taylor and Francis.
[18] Lomax, R. G., & Hahs-Vaughn, D. L. (2012). *An introduction to statistical concepts* (3rd ed.). New York: Taylors and Francis.
[19] Miller, L. A., Lovler, R. L., & McIntire, S. A. (2013). *Foundations of psychological testing: a practical approach* (4th ed.). California: SAGE Publications Inc.
[20] Mohd Effendi Mohd Matore, & Ahmad Zamri Khairani. (2014). Mengenal pasti cabaran pelajar politeknik di Malaysia menerusi model Rasch. *Journal of Quality Measurement and Analysis*, *10*(1), 59–74.
[21] Mohd Effendi Mohd Matore, & Ahmad Zamri Khairani. (2015). Psychometric assessment on Adversity Quotient instrument (IKBAR) among polytechnic students using Rasch model. In N. E. Mastorakis, I. Rudas, M. V. Shitikova, & Y. S. Shmaliy (Eds.), *Proceedings of the International Conference on Education and Educational Technologies (EET 2015)* (pp. 52–57). Barcelona, Spain: Institute for Natural Sciences and Engineering. Retrieved from http://www.inase.org/library/2015/barcelona/EDU.pdf
[22] Mohd Effendi Mohd Matore, & Ahmad Zamri Khairani. (2016). Correlation between Adversity Quotient (AQ) with IQ , EQ and SQ Among Polytechnic Students using Rasch Model. *Indian Journal of Science and Technology*, *9*(47). http://doi.org/10.17485/ijst/2016/v9i47/ 108695
[23] Mohd Rafi Yaacob. (2013). *SPSS 20 for Business and Social Science Students*. Kota Bharu: Eduserve Resources.

ISSN: 2233-7857 IJFGCN

[24] Mooney, R. L., & Gordon, L. V. (1950). *Manual: The Mooney problem checklists*. New York: Psychological Corporation.

[25] Nornadiah Mohd Razali, & Wah, Y. (2011). Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests. *Journal of Statistical Modeling and Analytics*, *2*(1), 21–33. Retrieved from http://instatmy.org.my/downloads/e-jurnal 2/3.pdf

[26] Othman Talib. (2013). *Asas penulisan tesis penyelidikan dan statistik*. Serdang: Universiti Putra Malaysia.

[27] Oztuna, D., Elhan, A. H., & Tuccar, E. (2006). Investigation of Four Different Normality Tests in Terms of Type 1 Error Rate and Power under Different Distributions. *Turkish Journal of Medical Sciences*, *36*(3), 171–176.

[28] Park, H. M. (2008). *Univariate Analysis and Normality Test Using SAS, Stata, and SPSS*. Retrieved from http://www.indiana.edu/~statmath/stat/all/normality/index.html

[29] Peat, J., & Barton, B. (2005). *Medical Statistic: A guide to data analysis and critical appraisal*. USA: Blackwell publishing Ltd. http://doi.org/http://dx.doi.org/10.1002/9780470755945

[30] Smith, E. V., Conrad, K. M., Chang, K., & Piazza, J. (2002). An introduction to Rasch measurement for scale development and person assessment. *Journal of Nursing Measurement*, *10*(3), 189–206.

[31] Stoltz, P. G. (1997). *Adversity quotient: turning obstacles into opportunities*. Canada: John Wiley & Sons.

[32] Tabachnick, B. G., & Fidell, L. S. (2008). *Using multivariate statistics* (5th ed.). Boston: Pearson Education.

[33] Tsai, A. C., Liou, M., Simak, M., & Cheng, P. E. (2017). On hyperbolic transformations to normality. *Computational Statistics and Data Analysis*, *115*, 250–266. http://doi.org/10.1016/j.csda.2017.06.001

[34] Weaver, B. (2011). Silly or Pointless Things People Do When Analyzing Data: 1. Conducting a Test of Normality as a Precursor to a t-test. In *Northern Health Research Conference*. Sudbury, Ontario: Northern Ontario School of Medicine. Retrieved from http://www.helsinki.fi/~komulain/SPSS-kurssi/Weaver, Bruce_Silly or Pointless Things.pdf

ISSN: 2233-7857 IJFGCN