Comparison of Parametric and Nonparametric Test Results: Asian Demographics as Database

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ABSTRACT

Several studies used both parametric and nonparametric tests in the statistical analysis of data. A number of findings revealed varied results when both treatments were applied. In most cases, differences were due to wrong assumptions of normality of data distribution, the insufficient sample size, the inappropriate type of variables employed, etc. With these disparities, the researcher investigated the outcomes of the parametric and nonparametric tests if their respective data requirements are met and no assumptions are violated. To show fairness in handling data and procedure, the researcher used the published data on South-East Asian demographics.

Data were subjected to normality test using the normal probability plot and Kolmogorov-Smirnov test. Other data requirements were taken into account before the parametric and nonparametric statistics were applied. The parametric tests employed in this research are: (1) t-test for two correlated samples; (2) t-test for two uncorrelated samples; (3) analysis of variance or F-test for three samples; and (4)Pearson r for two correlated variables; with their corresponding nonparametric equivalents of Wilcoxon T, Mann-Whitney U, Kruskal Wallis H, and Spearman rho.

Though findings in this study revealed consistent parametric and nonparametric test results upon comparing the four sets of samples, it is essential, however, to note the observations of previous studies that the use of nonparametric tests comes at a cost in cases where a parametric test would be appropriate. The fewer assumptions in nonparametric tests make them less powerful than their parametric equivalents. Parametric test should be applied if normality is established because it gives a better chance of finding significances when they exist. Otherwise, a nonparametric test is a reasonable option.

Keywords: parametric statistic, nonparametric statistic, normality test, normal distribution

INTRODUCTION

Quantitative research is about explaining phenomena by gathering numerical data which are analyzed statistically. In planning to carry out such investigation it is necessary to examine first the distribution of data that has been collected prior to selection of treatments.

The data distribution has significant role in the choice of tests to be employed. The option will depend weather the data are normally distributed or not. A variety of statistics for testing normality may be employed such as Kolmogorov-Smirnov test , Shapiro-Wilk W test, and Lilliefors test. Moreover, the normal probability plots may also be considered to assess visually whether the data are accurately modeled by a normal distribution.

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If the data do not assume the outcome that is approximately normally distributed, then, there are distribution-free tests that may be applied. These treatments also known as nonparametric tests are called such because they rely on no or fewer assumptions. On the other hand, if data are observed to be normally distributed then parametric tests must be considered.

Several studies used both parametric and nonparametric tests in the statistical analysis of data. A number of findings revealed varied results when both treatments were applied. In most cases, differences were due to wrong assumptions of normality of data distribution, the insufficient sample size, the inappropriate type of variables employed, etc. With these disparities, the researcher investigated the outcomes of the parametric and nonparametric tests if their respective data requirements are met and no assumptions are violated.

METHODOLOGY

To show fairness in handling data and procedure, the researcher used the published data on South-East Asian demographics. The data were taken from the Statistical Yearbook for Asia and the Pacific 2013. The sample unit considered was not the individual population but the country population. The following variables pertaining to demographics were chosen: adult literacy and employment ratios; female and male youth literacy rates; primary, secondary and tertiary enrollment; and crude birth and death rates.

Data were subjected to normality test using the normal probability plot and Kolmogorov-Smirnov test. Other data requirements were taken into account before the parametric and nonparametric statistics were applied. The parametric tests employed in this research are: (1) t-test for two correlated samples; (2) t-test for two uncorrelated sample; (3) analysis of variance or F-test for three samples; and (4) Pearson r for two correlated variables; with their corresponding nonparametric equivalents of Wilcoxon T, Mann-Whitney U, Kruskal Wallis H, and Spearman rho.

REVIEW OF RELATED STUDIES

On the Efficiency of Parametric Statistics

Banks and Potter (2005) compared parametric and nonparametric estimation methods in the context of modeling using simulation studies. It was found that the parametric approach has obvious advantages when one has significant information on the distributions sought.

Nonparametric and parametric approaches have been proposed to estimate false discovery rate under the independent hypothesis testing assumption (Wu, 2006). The parametric approach has been shown to have better performance than the nonparametric approaches.

A simulation comparison of parametric and nonparametric dimensionality detection procedures was investigated (Mroch and Bolt, 2006). The procedures are compared by simulation across a range of conditions, including conditions in which the generating model differs from that assumed by the parametric model. Results revealed that the parametric method appears robust against model misspecification.

On the Efficiency of Nonparametric Statistics

A simulation study was conducted to explore the ability of parametric and nonparametric models to provide an adequate fit to count data (Krnjajić, et. al., 2008). Findings showed that the nonparametric models are able to flexibly adapt to the data, to offer rich posterior inference, and to provide, in a variety of settings, more accurate predictive inference than parametric models.

Another study used parametric and nonparametric methods to model total organic carbon, alkalinity, and pH after conventional surface water treatment (Towler, et. al., 2009). All models were evaluated in terms of their fit and predictive capability, and for all variables explored, the nonparametric local polynomial models outperformed their parametric linear least-squares counterparts.

To compare several parametric and nonparametric approaches to time series clustering, a simulation study was undertaken (Díaz and Vilar, 2010). Among all the measures studied, the nonparametric distances displayed the most robust behavior.

On the Consistency of Parametric and Nonparametric Statistics

Power comparison of parametric and nonparametric linkage tests in small pedigrees was studied (Sham, et. al., 2000). The outputs implied that both parametric and nonparametric methods are suitable for linkage analysis of complex disorders in small pedigrees.

A comparison of parametric and nonparametric methodologies was examined in evaluating cost and profit efficiency (Delis, et. al., 2009). The results suggested greater similarities in the predictions of cost and profit efficiency methods.

Another study compared the power of parametric and nonparametric test for testing means of several populations (Watthanacheewakul, 2011). The outcomes disclosed that the power of the two tests increases as sample size increases. When the differences among the population means are larger, higher power of them is obtained and they have the same power.

On the Inconsistency of Parametric and Nonparametric Statistics

A study of comparison of parametric and nonparametric methods for the analysis and inversion of immittance was conducted (Macdonald, 2000). Findings revealed that for discrete-line distributions, the parametric method used was found to be inferior in some ways to the nonparametric one, and it was concluded that the parametric one could not be employed to estimate continuous distributions at all. However, parametric method was shown to be far superior to the nonparametric one for the estimation of discrete-line distributions.

In comparing the performance of nonparametric and parametric test statistics when assumptions are violated (Finch, 2005), outputs implied that when the assumption of homogeneous covariance matrices is not met, the nonparametric approach has a lower type I error rate and higher power than the most robust parametric statistic. When the assumption of normality is untenable, the parametric statistic is robust, and slightly outperforms the nonparametric statistic in terms of type I error rate and power.

A study concerned with convergence issues in the identification of a static nonlinear function was investigated focusing on properties of the input signal that ensure convergence of the estimate (Hsu, et. al., 2006). Results showed that parametric offer sufficient conditions under which the estimated parameters converge to their true values almost surely. On the other hand, nonparametric offer necessary and sufficient conditions under which the estimated function converges almost surely to the true nonlinearity.

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RESULTS AND DISCUSSION

Comparison of Parametric and Nonparametric Test Results for Two Correlated Samples

Two correlated samples pertaining to adult literacy-to-population ratio and employment-to-population ratio were used to compare the test results derived from the parametric and nonparametric statistics. The succeeding discussion focuses not on the analysis of the South-East Asian demographics but rather on the comparison of the statistical outputs provided by the two said treatments.

The adult literacy rate as defined measures literacy among persons aged 15 years or older while the employment-to-population ratio refers to working-age population that is employed. For most countries, the working-age population is defined as persons aged 15 years or above (Table 1).

Table 1. South-East Asian Adult Literacy and Employment Ratios (Heyzer, 2013)

South-East Asian Countries	Adult literacy-to-population ratio (aged 15 and above)	Employment-to-population ratio (aged 15 and above)
Brunei Darussalam	95.4	63.5
Cambodia	73.9	81.4
Indonesia	92.8	63.2
Lao PDR	72.7	76.8
Malaysia	93.1	58.6
Myanmar	92.7	76.1
Philippines	95.4	60.1
Singapore	95.9	64.1
Thailand	93.5	71.1
Timor-Leste	58.3	54.5
Viet Nam	93.4	75.7

Since assessment of the normality assumption should be taken first into account before using the parametric test, the normality was examined visually using the normal probability plot. This method is a graphical way of assessing whether a set of data looks like it might come from a standard bell shaped curve, also known as normal distribution.

It must be noted that in a normal probability plot, the sorted data are plotted against values selected to make the resulting image look close to a straight line if the data are said to be approximately normally distributed. Deviations from a straight line indicate departures from normality.

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The normal probability plot shown in Figure 1 suggests that most of the observations fall not so far from the line. This means that there is no strong indication of non-normality.

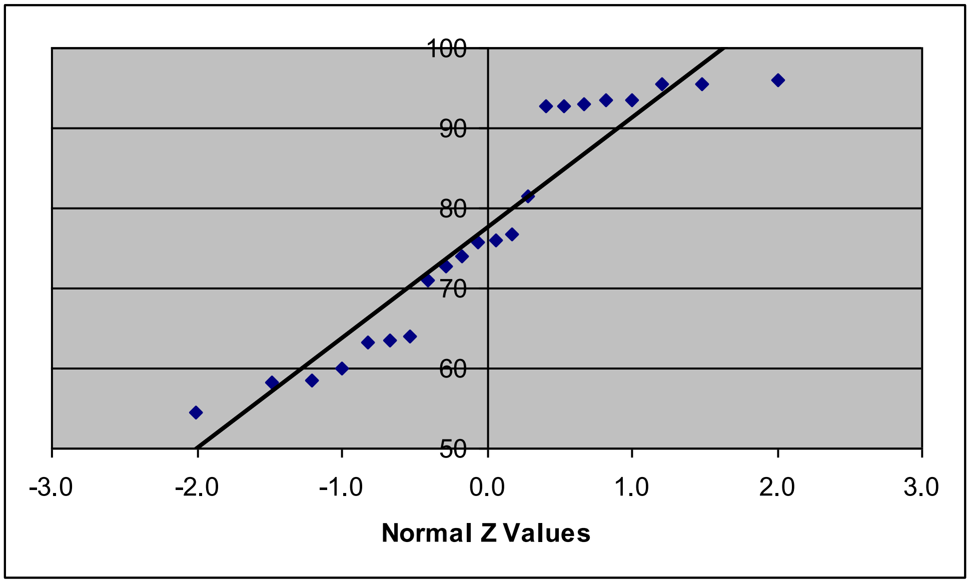

Figure 1. Normal Probability Plot for Adult Literacy and Employment Ratios

To further examine the nature of data distribution, the Kolmogorov-Smirnov test was computed to determine the degree of normality in the data. The value of this test provides a relative indication of normality, that is, as the value moves further away from zero, the data may be interpreted as it does not approximate a normal distribution. This test compares the set of scores in the sample to a normally distributed set of scores with the same mean and standard deviation.

Outcomes derived from Kolmogorov-Smirnov test posted a computed value of 0.1725, when compared to its critical value of 0.2844 at 0.05 level of significance, the data are interpreted as normally distributed (Table 2).

Table 2. Kolmogorov-Smirnov Normality Test for Adult Literacy and Employment Ratios

Demographic Variable	Kolmogorov-Smirnov Computed Value	Kolmogorov-Smirnov Critical Value at 0.05	Conclusion
Adult Literacy and Employment	0.1725	0.2844	Normally distributed

It is reasonable now to choose parametric statistics. To compare the two correlated samples, the parametric t-test was applied together with its nonparametric equivalent of Wilcoxon T test.

These treatments require two samples and it is necessary that those samples are to be paired. The said parametric and nonparametric tests are used when each observation in one group is paired with a related observation in the other group. Paired samples imply that each individual observation of one sample has a unique corresponding member in the other group.

It may be essential to note that the Wilcoxon T test has an advantage of using for it neither depends on the form of the data distribution nor on its parameters. It does not require any assumptions about the nature of the distribution. This test is often used as an alternative to t-test whenever the population cannot be assumed to be normally distributed (Sheskin, 2003).

Findings showed that the parametric t-test and nonparametric Wilcoxon T test are consistent in providing interpretation that the adult literacy ratio is significantly different from the employment ratio. Their computed values of 0.0022 (p-value for t-test) and 5 (Wilcoxon T) are smaller than their respective critical values at 0.05 level of significance (Table 3).

Table 3. Parametric and Nonparametric Test Results for Adult Literacy and Employment Ratios

Treatment	Statistic	Computed value	Critical value at 0.05	Conclusion
Parametric	t-test	0.0022*p-value	0.05	Significant
Nonparametric	Wilcoxon T	5	11	Significant

Comparison of Parametric and Nonparametric Test Results for Two Uncorrelated Samples

Comparison of two uncorrelated samples demands the choice of two independent samples and requires no overlap between the two groups.

Data samples are independent if they come from unrelated populations and the samples do not affect each other. For samples to be independent means the two categorical variables, such as male and female are mutually exclusive and exhaustive. A participant must either be male or female to be mutually exclusive and no other category for gender to be exhaustive.

Specifically, the independent samples considered in this study are the total number of female and total number of male in a given age group who can both read and write with comprehension a short simple statement about their everyday life; such figure expressed as a percentage of the female or male population in that age group. Missing data are not imputed (Table 4).

Table 4. South-East Asian Female and Male Youth Literacy Rates (Heyzer, 2013)

South-East Asian Countries	Youth literacy rate (% of population aged 15-24)	
	Female	Male
Brunei Darussalam	98.9	99.8
Cambodia	87.9	88.4
Indonesia	98.9	98.8
Lao PDR	88.1	89.2
Malaysia	97.2	98.4
Myanmar	95.8	96.3
Philippines	94.5	97.0
Singapore	99.4	99.7
Thailand	98.1	98.2
Timor-Leste		80.5
Viet Nam	95.6	97.5

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To examine the normality of the said samples, the normal probability plot was presented in graph. It may be recalled from the plot that strong deviations from the line would indicate non-normality. It has however been shown in Figure 2 that minor departures from normality was displayed.

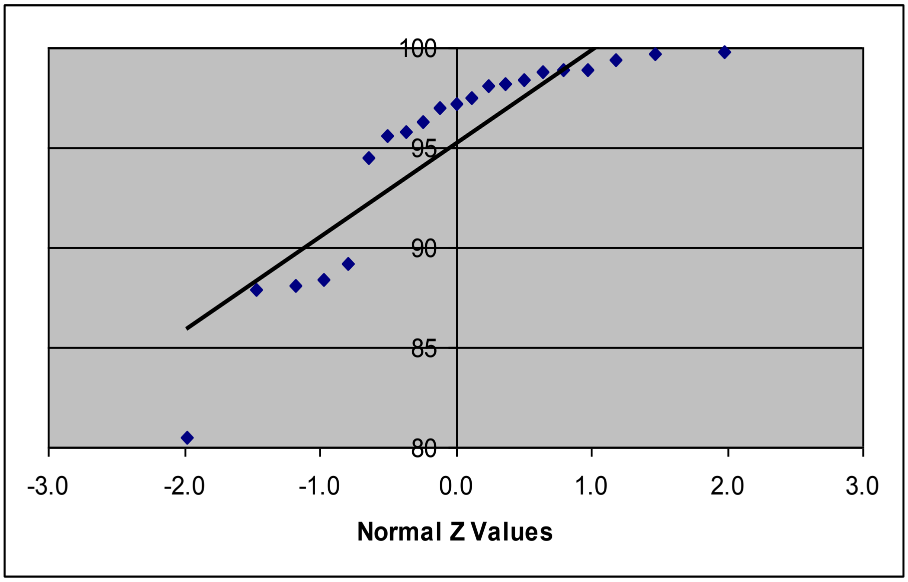

Figure 2. Normal Probability Plot for Female and Male Youth Literacy Rates

The Kolmogorov-Smirnov test further disclosed that the data are normally distributed as shown by the smaller computed value of the said statistic posted at 0.2009 compared to its corresponding critical value of 0.2892 at 0.05 level of significance (Table 5).

Table 5. Kolmogorov-Smirnov Normality Test for Female and Male Youth Literacy Rates

Demographic Variable	Kolmogorov-Smirnov Computed Value	Kolmogorov-Smirnov Critical Value at 0.05	Conclusion
Male and Female Youth Literacy	0.2009	0.2892	Normally distributed

Since the normality has already been established using the normal probability plot and Kolmogorov-Smirnov normality test, the use of parametric test may now be allowed.

To test for the significant difference between the two uncorrelated samples, the parametric t-test together with its nonparametric counterpart of Mann-Whitney U test were computed. Both treatments examine whether two independent samples are drawn from the same or identical distributions. An advantage with these tests is that the two samples under consideration may not necessarily have the same number of observations (Kvam and Vidakovi, 2007).

The greater computed values of 0.8134 (p-value) for the t-test and 49 for Mann-Whitney U test as compared to their corresponding critical values of 0.05 and 26 implied the same conclusion that there is no significant difference between the female and male youth literacy rates (Table 6).

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Table 6. Parametric and Nonparametric Test Results for Male and Female Youth Literacy Rates

Treatment	Statistic	Computed value	Critical value at 0.05	Conclusion
Parametic	t-test	0.8134*p-value	0.05	Not significant
Nonparametric	Mann-Whitney U	49	26	Not significant

Comparison of Parametric and Nonparametric Test Results for More than Two Samples

To compare the parametric and nonparametric test results for a case when three samples are given, the enrollment in the three levels of education were considered.

Table 7. South-East Asian Primary, Secondary and Tertiary Enrollment (Heyzer, 2013)

South-East Asian Countries	Enrolment in primary education (% of school age children)	Enrolment in secondary education (% of school age children)	Enrolment in tertiary education (% of school age children)*gross
Brunei Darussalam		99.0	19.6
Cambodia	98.2	37.6	14.5
Indonesia	99.0	74.4	24.9
Lao PDR	97.4	40.7	17.7
Malaysia		68.6	42.3
Myanmar		50.8	14.8
Philippines	88.7	61.6	28.2
Singapore			
Thailand	89.7	74.1	47.7
Timor-Leste	90.9	38.7	16.7
Viet Nam	99.4		24.4

The net enrolment in primary and secondary education as may be seen in Table 7 is referred to as the enrolment of the official age group for primary or secondary education expressed as a percentage of primary or secondary school age population. The gross enrolment in tertiary education is the total enrolment in tertiary education, regardless of age, expressed as a percentage of the eligible official school age population corresponding to tertiary education in a given school year. Missing data are not imputed.

To test the normality of distribution of data pertaining to the primary, secondary and tertiary enrollment, the normal probability was plotted in Figure 3. It may be interpreted from the

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graph that no strong deviations from the line were displayed. This further implied that normality of data distribution has been identified.

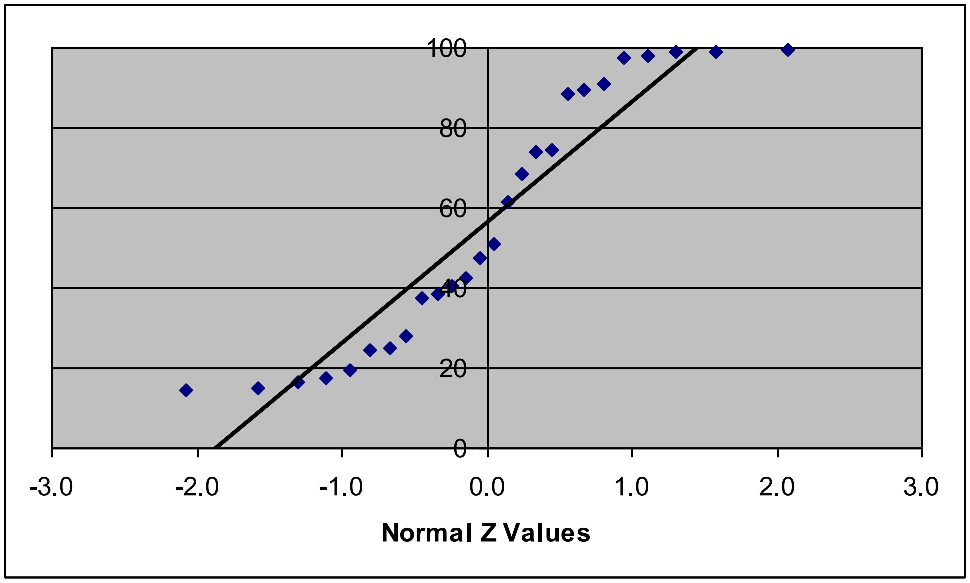

Figure 3. Normal Probability Plot for Primary, Secondary and Tertiary Enrollment

Again to support this observation, Kolmogorov-Smirnov normality test was applied. The computed value of -0.1307 compared to its corresponding critical value of 0.2640 disclosed the normality in data distribution (Table 8).

Table 8. Kolmogorov-Smirnov Normality Test for Primary, Secondary and Tertiary Enrollment

Demographic Variable	Kolmogorov-Smirnov Computed Value	Kolmogorov-Smirnov Critical Value at 0.05	Conclusion
Primary, secondary, and tertiary enrolment	-0.1307	0.2640	Normally distributed

To compare the normally distributed samples of three groups, the analysis of variance was used. This statistic, also known as F-test, examines if the value of a single sample differs significantly among others. One advantage of this treatment is that the number of observations need not be the same in each group.

If the analysis of variance is used to compare normally distributed samples of more than two groups, its parametric equivalent, Kruskal-Wallis test, compares ordinal or non-normal variables for more than two groups (Linebach et al., 2014).

Posted in Table 9 are the computed values of 247.8733 for F-test and 18.7684 for Kruskal Wallis H test which were found to be much greater than their corresponding critical values of 3.42 and 5.991 (Chi-square value) revealed that the two test results are consistent. They both interpreted that the primary, secondary, and tertiary enrolments differ significantly.

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Table 9. Parametric and Nonparametric Test Results for Primary, Secondary and Tertiary Enrollment

Treatment	Statistic	Computed value	Critical value at 0.05	Conclusion
Parametric	F-test	247.8733	3.42	Significant
Nonparametric	Kruskal Wallis H	18.7684	5.991*chi-square	Significant

Comparison of Parametric and Nonparametric Test Results for Two Correlated Variables

The two correlated variables employed in the study are crude birth rate and crude death rate. Crude birth rate refers to the number of births during a given period divided by the total number of person-years lived by the population during that period. The person-years for a calendar year is approximated as the midyear population. Crude death rate refers to the number of deaths occurring during a period divided by the person-years for that period (Table 10).

Table 10. South-East Asian Crude Birth and Death Rates (Heyzer, 2013)

South-East Asian Countries	Crude birth rate (Per 1,000 population)	Crude death rate (Per 1,000 population)
Brunei Darussalam	15.9	3.1
Cambodia	25.9	6.0
Indonesia	19.2	6.3
Lao PDR	27.3	6.1
Malaysia	17.6	4.7
Myanmar	17.4	8.5
Philippines	24.6	6.0
Singapore	9.9	4.7
Thailand	10.5	7.6
Timor-Leste	35.9	5.9
Viet Nam	15.9	5.7

It may be recalled that in the study of relationships, two variables are said to be correlated if change in one variable is accompanied by change in the other - either in the same or reverse direction. The two variables to be considered in computing the correlation may have independent units of measurement.

In this study, Pearson r is used to estimate the degree of association between two quantitative variables, the crude birth rate and crude death rate.

The nonparametric counterpart Spearman rho is likewise employed. This nonparametric statistic assumes that the variables under consideration are measured on at least an ordinal (rank order) scale (Gravetter, 2013).

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Table 11. Parametric and Nonparametric Test Results for Crude Birth and Death Rates

Treatment	Statistic	Computed value	Critical r value at 0.05	Conclusion
Parametric	Pearson r	0.0591	0.6021	Not significant
Nonparametric	Spearman rho	0.2114	0.6021	Not significant

The smaller computed values of 0.0591 for Pearson r and 0.2114 for Spearman rho as against their critical r value of 0.6021 implied that the parametric and nonparametric test results for the two said variables are the same. They are consistent in their interpretation that the crude birth rate and crude death rate are not significantly related (Table 11).

CONCLUSION AND RECOMMENDATION

When analyzing quantitative data for a research and confronted with a decision about what computational methods to perform, the selection of statistical treatment that should be employed must be carefully studied. It may be noted that if inappropriate test was chosen then this may lead to incorrect interpretation of data.

Before using the parametric statistics, it is essential to check the normality of data distribution. Parametric tests rely on the assumptions about the nature of the distribution, that is, it assumed a normal distribution. Unlike the nonparametric, they depend on no or few assumptions about data distribution.

Though findings in this study revealed consistent parametric and nonparametric test results upon comparing the four sets of samples, it is essential, however, to note the observations of previous studies that the use of nonparametric tests comes at a cost in cases where a parametric test would be appropriate. The fewer assumptions in nonparametric tests make them less powerful than their parametric equivalents. Parametric test should be applied if normality is established because it gives a better chance of finding significances when they exist. Otherwise, a nonparametric test is a reasonable option.

Moreover, it should be noted that it is necessary to examine the scale of the data. The nominal or ordinal data demands the use of nonparametric statistics while the interval or ratio data requires the use of parametric, however, when normality of data distribution cannot be assumed, nonparametric tests then again have to be applied.

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