Normality of Data: An Essential Tool for Effective Research Study

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ABSTRACT

Statistical analysis is guided by a set of assumptions that ensure the validity and reliability of research findings. One of the most critical assumptions is the normality of data, particularly in the application of parametric statistical techniques. Despite its importance, many empirical studies either overlook normality testing or fail to report the results. This paper presents a conceptual review of data normality, its relevance in statistical analysis, and the implications of non-normal data for research conclusions. The review discusses graphical and statistical methods for assessing normality and examines strategies for handling non-normal data, including data transformation, non-parametric testing, robust methods, and bootstrapping. The paper concludes that assessing and reporting data normality are essential for methodological rigour, transparency, and valid inference in social science research.

Keywords: data, non-normal, non-parametric, normality, parametric

INTRODUCTION

Errors in statistical analysis are common in published research. According to Curran-Everett and Benos (2004), more than half of empirical studies contain at least one statistical error. A major source of these errors is the violation of fundamental statistical assumptions, including normality, linearity, and homogeneity of variance. Failure to satisfy these assumptions undermines the validity, reliability, and accuracy of research findings.

Among these assumptions, data normality plays a central role in statistical inference. Many parametric statistical techniques such as the t-test, correlation analysis, regression analysis, and analysis of variance (ANOVA) require that data follow a normal distribution (Ghasemi & Zahediasl, 2012). Without adequate consideration of data normality, research conclusions may be biased or misleading (Field, 2009).

Despite its importance, the assumption of normality is frequently overlooked or inadequately addressed in empirical studies. In many cases, researchers apply parametric methods without testing or reporting whether the data meet the normality assumption. This paper therefore seeks to conceptually highlight the importance of data normality as an essential tool for effective research and to discuss appropriate methods for assessing and addressing non-normal data distributions.

Statement of problem

Parametric statistical tests are widely used in research because of their efficiency and statistical power. However, these tests rely on several assumptions, including the normal distribution of data (Kim & Park, 2019). When the assumption of normality is violated, test results may become unreliable and lack generalizability (Zach, 2021).

Despite this well-established requirement, many studies apply parametric techniques without verifying whether their data satisfy the normality assumption. This practice undermines the credibility of research findings and increases the risk of erroneous conclusions. There is therefore a need to re-emphasize the role of data

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normality in statistical analysis and to provide clear guidance on how researchers can appropriately assess and handle non-normal data. This study addresses this gap by conceptually reviewing the importance of data normality in effective research.

Objectives of the study

The objectives of this conceptual review are to:

1. Explain the concept of data normality and its relevance in statistical analysis.
2. Describe the methods used to assess the normality of data.
3. Examine appropriate strategies for handling normal and non-normal data distributions.

Nature of the Study

This paper adopts a conceptual and narrative review approach. Relevant literature was selected based on its theoretical contribution to the understanding of data normality, statistical assumptions, and methods for handling non-normal data. Peer-reviewed journal articles, textbooks, and methodological papers focusing on normality testing and statistical analysis were included.

LITERATURE REVIEW

Conceptual Review

Normality and Non-Normality of data

In statistical research, normality refers to a specific probability distribution known as the normal or Gaussian distribution. A random variable is said to be normally distributed when its values are symmetrically distributed around the mean, forming a bell-shaped curve. The assumption of normality is central to statistical inference because many commonly used statistical techniques rely on it (Singh & Masuku, 2014).

The validity, reliability, and precision of empirical research findings largely depend on whether the data—or the sampling distribution of the test statistics—conform to a normal distribution. Consequently, testing for normality has become a routine requirement in empirical analysis, particularly when parametric statistical methods are employed.

Normality of Data

A normal distribution is a continuous probability distribution characterized by symmetry around its central tendency (Guzik & Więckowska, 2023). In a perfectly normal distribution, the mean, median, and mode are equal, and the distribution is fully described by two parameters: the mean (μ) and the standard deviation (σ). The standard normal distribution has a mean of zero and a standard deviation of one (Mishra, Pandey, Singh, Gupta, Sahu, and Keshri, 2019).

In a normal distribution, most observations cluster around the mean, while fewer observations occur toward the extreme ends of the distribution. This property makes the mean a meaningful and representative measure of central tendency. Kim and Park (2019) note that data are considered normally distributed when their probability distribution peaks at the center and gradually declines symmetrically toward both tails.

The initial step in data analysis typically involves assessing whether the data follow a normal distribution, as this determines whether parametric or non-parametric statistical methods should be applied. When data deviate substantially from normality, the mean may no longer serve as an appropriate summary measure, thereby limiting meaningful comparison across groups.

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Hypothesis of Normality

The normality of data is commonly assessed through hypothesis testing, where the null hypothesis assumes that the data follow a normal distribution:

- **H_0:** The data are normally distributed.
- **H_1:** The data are not normally distributed.

This assumption is closely linked to the Central Limit Theorem, which states that the sampling distribution of the mean approaches normality as sample size increases. However, even with large samples, assessing normality remains important, particularly when data exhibit extreme skewness or outliers.

Importance of Normal Distribution in Research

Normality is a key assumption underlying many parametric statistical methods, including regression analysis, correlation analysis, and analysis of variance (ANOVA) (Mohammad, Haneen, Sa'd, & Abdulazziz, 2022; Mishra et al., 2019). When this assumption is violated, statistical estimates and hypothesis tests may yield biased or misleading results.

Mishra et al. (2019) argue that when data deviate from normality, the sample mean may not accurately represent the underlying data. Similarly, Indrayan and Satyanarayana (1999) caution that using an inappropriate measure of central tendency can lead to incorrect statistical inferences. Therefore, verifying data normality is essential for determining whether parametric methods are appropriate and whether research conclusions are valid.

Mathematical Representation of the Normal Distribution

The normal distribution can be represented using a probability density function, which allows researchers to calculate the probability of a variable taking on a specific value. The total area under the normal curve equals one, representing the complete probability distribution.

Equation (1): Normal Probability Density Function

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- $f(x)$ = probability
- x = value of the variable
- μ = mean
- σ = standard deviation
- σ^2 = variance

Proper estimation of the mean and standard deviation allows the normal curve to be fitted to empirical data.

Non-normality of Data

Non-normal data refer to continuous variables that do not conform to the normal distribution. Such distributions may be skewed, have heavy tails, or contain extreme values (Sainani, 2012). Non-normal distributions lack symmetry and may be either flatter or more peaked than the normal distribution.

When data are non-normally distributed, the assumptions underlying parametric tests are violated. Researchers must therefore assess normality prior to analysis and adopt alternative analytical strategies when necessary.

Parametric and Non-Parametric Tests

Statistical tests are broadly classified into parametric and non-parametric methods (Ukponmwam & Ajibade, 2017). The distinction between these approaches is largely based on the distributional assumptions they require (Albassam, Khan & Aslam, 2021; Orcan, 2020).

Parametric Test

Parametric tests assume that data are drawn from a population with a specific distribution, typically the normal distribution. Common parametric tests include the t-test, analysis of variance (ANOVA), and Pearson’s correlation coefficient. These tests are generally more powerful and efficient when their assumptions are satisfied, enabling researchers to make population-level inferences based on sample data.

Non-Parametric Test

Non-parametric tests do not rely on assumptions about the underlying population distribution. Examples include the Mann–Whitney U test, Wilcoxon signed-rank test, Kruskal–Wallis test, and Spearman’s rank correlation. Although non-parametric tests are more flexible and robust to skewness and outliers, they typically have lower statistical power than parametric tests.

Tests of Normality

Normality tests are statistical tests utilised to verify the normal distribution of a random variable (Babalola, Obubu, Oluwaseun & Obiora-ilono, 2018). Data normality can be assessed through two approaches: visual methods and statistical methods.

1. Visual/Graphical Methods

Visual methods involve employing a rapid and casual approach to assess if a dataset follows a normal distribution. Graphical methods are not statistical tests in the proper sense, but rather subjective approaches for evaluating normality (Hernandez, 2021). Oztuna, Elhan, and Tuccar (2006) asserted that the visual approach can be employed to assess data normality, but caution that this method may lack reliability and can potentially lead to misleading results. Mishra et al. (2019) suggested that the graphical approach of checking data normality can provide reliable judgement in cases where statistical tests may be excessively or insufficiently sensitive. They noted, however, that assessing normality using graphical approaches requires a significant amount of expertise to avoid drawing incorrect findings.

Data normality can be visually assessed using the following instruments:

i. Frequency Distribution (Histogram)
ii. Probability-probability plot (P-P plot)
iii. Quantile-quantile plot (Q-Q plot)
iv. Boxplot

Frequency distribution (histogram)

A frequency distribution graphically represents the observed values and their corresponding frequencies, allowing for a visual assessment of the data's normalcy in the distribution (Peat & Barton, 2005). Kim (2013) defines a histogram as a visual representation of the probability distribution of a continuous quantity. The data is presumed to follow a normal distribution if the graph exhibits a nearly bell-shaped distribution and displays symmetry with respect to the mean. If a histogram of a data distribution exhibits a bell-shaped curve, it indicates that the data follows a normal distribution. The major advantage of the histogram is that it displays the shape and spread of distributions, however interpreting it can be tricky. Hernandez (2021) asserted that in

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some cases the bell shape is clearly observed for normal data, but some other cases it is not perfectly clear; and other distributions may present a bell-like shape giving the erroneous idea of normality. Figure 1 illustrates the histogram of a normally distributed dataset, showing symmetry around the mean.

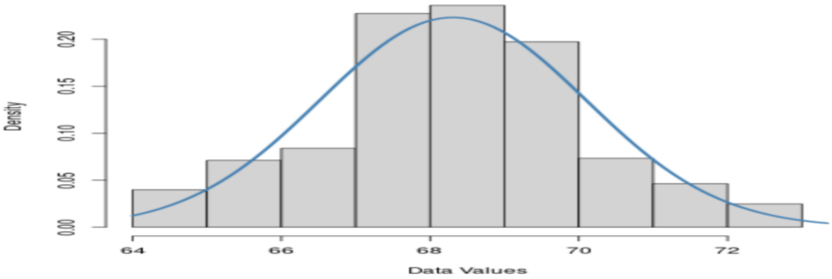

Figure 1: Histogram of a Normally Distributed Dataset

Probability-probability plot (P-P plot)

A P–P plot is a graphical technique utilised to assess the level of agreement between two data sets, namely the actual and predicted data. In the case of normally distributed data, a linear diagonal line is observed, whereas any deviation from this line indicates that the data does not follow a normal distribution. According to Field (2009), the P-P plot is a method for estimating the cumulative probability of a variable compared to a specific distribution. The data is arranged in order and assigned a z-score, which represents the expected value of the score in a normal distribution. The observed z-scores are graphed in comparison to the predicted z-scores. A uniformly distributed dataset would yield a linear relationship, resulting in a straight diagonal line. Figure 2 illustrates the P-P plot of a normally distributed dataset, showing a linear diagonal line.

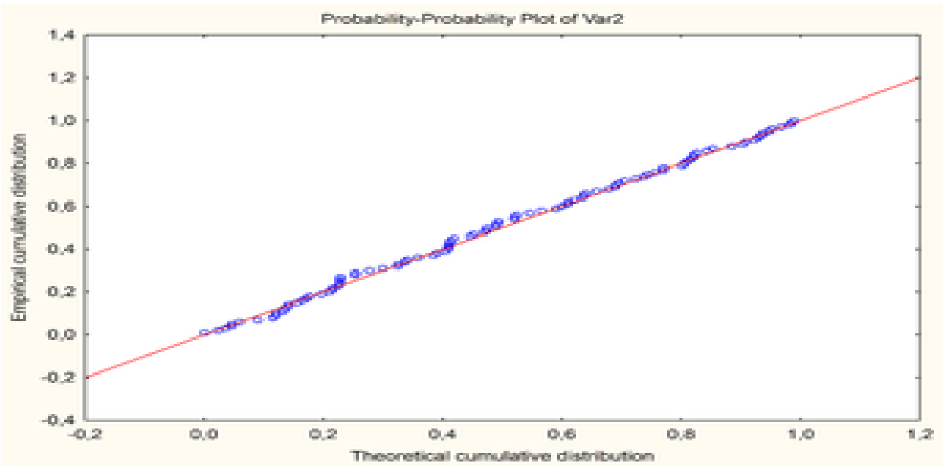

Figure 2: A P-P plot of a Normally Distributed Dataset

Quantile-quantile plot (Q-Q plot)

The Q-Q plot is analogous to the P-P plot, with the distinction that it represents the quantiles (values that divide a data set into equal parts) of the data set rather than each individual score within the data. A Q–Q plot is generated by graphing the quantiles of two sets (seen and predicted) against each other. If the data points exhibit a linear trend, it is inferred that the data follows a normal distribution. Figure 3 illustrates the Q-Q plot of a normally distributed dataset.

Field (2009) states that Q-Q plots are more easily interpretable when dealing with high sample sets. Hernandez (2021) asserted that the superiority of the plots graphs is that it is easier to determine whether the data points follow a straight line than comparing bars on a histogram to a bell-shaped curve. These plots are easy to interpret and also have the benefit that outliers are easily identified (Singh & Masuku, 2014).

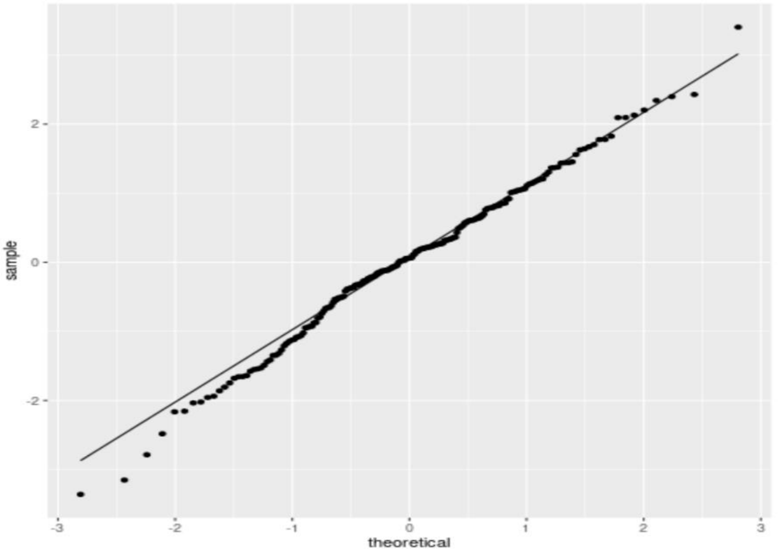

Figure 3: A Q-Q plot of a Normally Distributed Dataset

Boxplot

A box and whisker plot, also referred to as a boxplot, is a graphical representation that provides a concise summary of a dataset. The boxplot visually represents the distribution of the data and identifies any outliers. Comparing diverse sets of data can be facilitated by the ability to generate many boxplots on a single graph, making it a valuable analytical tool.

If the data is sampled from a normal distribution, the box plot will exhibit symmetry, with the mean and median positioned at the centre. If the data conforms to the premise of normalcy, there should be a minimal number of outliers.

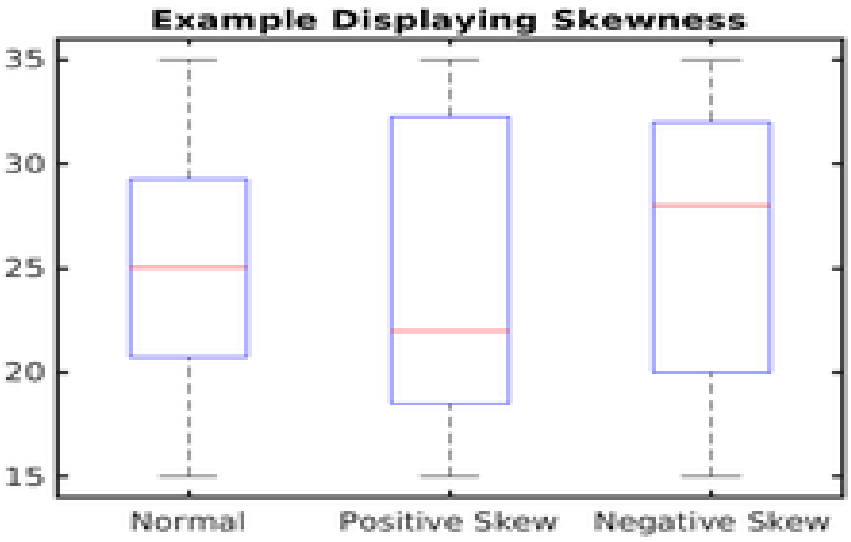

Figure 4: Boxplots diagram of data distribution

Statistical methods of normal distribution test

Statistical tests formally evaluate whether data deviate significantly from a normal distribution. They are tests that can be employed to assess the normality of data (Elliot & Woodward, 2007). The statistical tests include Kolmogorov-Smirnov (K–S) test, Shapiro-Wilk test, Lilliefors corrected K–S test, Anderson-Darling test, D'Agostino skewness test, Cramer-von Mises test, D'Agostino-Pearson omnibus test, Anscombe-Glynn kurtosis test, and the Jarque-Bera test (Mohammed *et al.*, 2022). Hernandez (2021) stated that there are over 50 analytical tests of determining normality of data. However, the common tests include the Kolmogorov-

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Smirnov (K-S) test, Shapiro-Wilk test, Jarque-Bera test, and Skewness and Kurtosis (Zhang, Yan, Tian & Fei, 2022; Babalola *et al*., 2018).

The K-S and Shapiro-Wilk normality tests can be performed using the statistical software "SPSS" by navigating to the "analyse" menu, selecting "descriptive statistics," then "explore," followed by "plots," and finally "normality plots with tests."

In these tests, a p-value greater than 0.05 indicates failure to reject the null hypothesis of normality.

Kolmogorov-Smirnov (K-S) test

The KS test is employed when there is a requirement to compare an observed sample distribution with a theoretical distribution. It is use to check for any difference in two samples coming from two populations. Oztuna et al., (2006) state that the K-S test is used to compare the cumulative distribution function of a variable with a predetermined distribution.

According to Okeniyi, Okeniyi and Atayero (2015), determining the normality of data using the KS test entails analytical processes that necessitate a profound understanding of statistics or mathematics. The Kolmogorov-Smirnov test is specifically employed for sample sizes more than or equal to 50 (Biu, Nwokuya & Wonu, 2019).

Shapiro-Wilk test

The Shapiro-Wilk test, as described by Peat and Barton (2005), relies on the correlation between the data and their respective normal scores. The Shapiro-Wilk test demonstrates superior statistical power compared to the K-S test, even when the Lilliefors correction is applied (Steinskog, 2007). Thode (2002) stated that power is the predominant metric used to assess the effectiveness of a test in determining if a sample is derived from a non-normal distribution. The Shapiro-Wilk test is recommended by several researchers (Yap & Sim, 2011; Nor, Teh, Abdul-Rahman & Che-Rohani, 2011; Marmolejo-Ramos & Gonza'Lez-Burgos, 2012; Mayette & Emily, 2013) as the most suitable method for assessing the normality of data. The Shapiro-Wilk test is the preferred method for small sample sizes (less than 50 samples), although it can also be applied to higher sample sizes (Mishra et al., 2019).

Jarque-Bera Test

The test is named after Carlos Jarque and Anil K. Bera, as established in their publication in 1980. Jarque Bera is a statistical test used to assess the normality of a distribution. It is utilised to assess whether a particular dataset exhibits skewness and kurtosis that align with a normal distribution. Ukpomwan and Ajibade (2017) proposed that this test can be used to assess if data from a sample exhibits the skewness and kurtosis characteristics of a normal distribution. According to Stephanie (n.d), the test is commonly employed for extensive data sets, as alternative normalcy tests lack reliability when the sample size exceeds 2000. The test statistic is consistently positive, and if it deviates significantly from zero, it indicates that the sample data does not conform to a normal distribution. The decision rule is to accept the null hypothesis if the test value is not statistically significant ($P > 0.05$); otherwise, reject the null hypothesis.

Dealing with Non-normal Data

When the assumption of normality is violated, researchers may adopt several strategies:

1. Transform the data.

Transformation of data to make it normally distributed can be done using any of the following:

- **Log Transformation:** Transform the data from y to log(y).
- **Square Root Transformation:** Transform the data from y to $\sqrt{y}$

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- **Cube Root Transformation:** Transform the data from y to $y^{1/3}$
- **Box-Cox Transformation:** Transform the data using a Box-Cox procedure.

By performing these transformations, the distribution of data values typically becomes more normally distributed. If an adequate transformation can be achieved, then researchers can run standard statistical tests on the transformed data. After transformation is done, the normality test must be conducted again. If the data is still not normal or normality is not enough, other methods can be considered (Mohammed *et al*., 2022; Bridges, Calkin, Kenyon & Saltzman, 2020).

Non-parametric tests

If the data is not normally distributed and cannot be transformed or normalised, an alternative approach is to analyse the data using "nonparametric" tests, which do not rely on any assumptions about the underlying distribution of the data. If the assumption of normality is violated, the researcher can examine the data using non-parametric tests. The non-parametric tests that can be employed are:

1. One Sample Wilcoxon Signed Rank Test

2. Mann-Whitney U Test

3. Two Sample Wilcoxon Signed Rank Test

4. Kruskal-Wallis Test

Robust Methods

Employing a resilient technique to process data is an alternative approach for analysing non-normal data that cannot be adequately transformed or normalised. Robust approaches refer to statistical models and tests that exhibit reduced sensitivity towards issues such as skewness and outliers (Liu, Cosman & Rao, 2018).
Robust methods of data analysis give a more reliable results in a situation when there is presence of outliers, non-normal distribution of data and other departures from classical statistical assumptions (Wilcox & Rousselet, 2023). Techniques such as Huber regression, M-estimation and least trimmed squares (LTS) regression are robust alternatives to ordinary least squares (OLS) regression (Priya, 2024).

Bootstrapping

Field (2009) suggested that an alternative approach to address deviations from normality is to employ a method known as bootstrapping. According to Zimmerman (2014), it is non-parametric and does not rely on assumptions about the population distribution. It can be applied to a wide range of statistics and also provide more accurate estimates for complex distribution (Wilcox & Rousselet, 2023). The bootstrap is a general-purpose method for estimating the sampling distribution of any statistic computed from independent observations (Lumley, Diehr, Emerson & Chen, 2002).

CONCLUSION

For correct research conclusion, it is important to ascertain the distribution of the data. The normality assumption is one important assumption in carrying out a parametric statistical test. Hence, Researchers must ensure that the assumption of normality is not violated in order to reach a meaningful conclusion and make valid inferences. Normality of data should be ascertained using statistical tests and graphs. Determining normality using graphs can be subjective but not so with statistical tests. Where the assumption on normality is violated, the Researcher can transform the data, conduct a non-parametric test, use robust method or do a bootstrap analysis. For reliability and validity of the analysis result, normality test result must be shown.

RECOMMENDATIONS

Based on the conclusion of this review, it is recommended that to promote transparency, Researchers and Analysts should always report normality test result. Both the graphical methods and statistical tests should always be used to test for normality of data as this will improve decision on the normality of data. Also, the normality of a transformed data should be checked before using it for analysis. Lastly, justification should be given for the choice of using either the non-parametric test or robust method to analyze the data.

REFERENCES

1. Albassam, M., Khan, N., & Aslam, M (2021). Neutrosophic D'Agostino test of normality: An application to water data. Journal of Mathematics. https://doi.org/10.1155/2021/5582102
2. Babalola, M.A., Obubu, M., Oluwaseun, A.O., & Obiora-Ilono, H. (2018). Selection and validation of comparative study of normality test. American Journal of Mathematics and Statistics, 8(6): 190-201. DOI: 10.5923/j.ajms.20180806.05
3. Biu, E.O., Nwakuya, M.T., & Wonu, N. (2019). Detection of non-normality in data sets and comparison between different normality tests. Asian Journal of Probability and Statistics. 5(4): 1-20.
4. Bridges, W.C., Calkin, N.J., Kenyon, C.M., & Saltzman, M.J. (2020). Log transformations: what not to expect when you're expecting, Theory. Methods Commun. Stat. Theor. M. 1–8.
5. Curran-Everett, D., & Benos, D.J. (2004). Guidelines for reporting statistics in journals published by the American Physiological Society. Am JPhysiol Endocrinol Metab, 287(2), 189-91.
6. Elliott, A.C., & Woodward, W.A. (2007). Statistical analysis quick reference guidebook with SPSS examples (1st ed.). London: Sage Publications.
7. Field, A. (2009). Discovering statistics using SPSS (3rd ed.). London: SAGE publications Ltd.
8. Ghasemi, A., & Zahediasl, S. (2012). Normality tests for statistical analysis: A guide for non-statisticians. Int J Endocrinol Metab, 10(2):486-9. DOI: 10.5812/ijem.3505
9. Guzik, P., & Więckowska, B. (2023). Data distribution analysis: A preliminary approach to quantitative data in biomedical research. Journal of Medical Science, 92(2); doi:10.20883/medical.e869
10. Hernandez, H. (2021). Testing for normality: What is the best method? ForsChem Research Reports, 6(5), 2 – 38.
11. Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics Letters, 6(3): 255–259. doi:10.1016/0165-1765(80)90024-5.
12. Kim, H.Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution using skewness and kurtosis. Restor Dent Endod. 38:52-4.
13. Kim, T.K., & Park, J.H. (2019). More about the basic assumptions of t-test: normality and sample size. Korean Journal of Anesthesiology, 72(4).
14. Liu, J., Cosman, P. C., & Rao, B. D. (2018). Robust linear regression via L0 regularization. IEEE Transactions on Signal Processing, 66 (3):698–713. doi:10.1109/TSP.2017.2771720
15. Lumley, T., Diehr, P., Emerson, S., & Chen, L. (2002). The importance of the normality assumption in large public health data sets. Annu. Rev. Public Health. 23:151–69. DOI: 10.1146/annurev.publheath.23.100901.140546
16. Marmolejo-Ramos, F., & Gonza´lez-Burgos, J. (2012). A power comparison of various tests of univariate normality on ex-Gaussian distributions. European Journal of Research Methods for the Behavioural and Social Sciences. DOI: 10.1027/1614-2241/a000059. www.hogrefe.com/journals/methodology
17. Mayette S., & Emily A. B. (2013). Empirical power comparison of goodness of fit tests for normality in the presence of outliers. Journal of Physics. Conference Series 435 (2013) 012041.doi:10.1088/1742-6596/435/1/012041
18. Mishra, P., Pandey, C.M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. Ann Card Anaesth; 22:67-72.
19. Mohammad, M.H., Haneen, A., Sa'd, H., & Abdulaziz, A. (2022). Ultra-fine transformation of data for normality. Heliyon 8, e09370

20. Nor A. A., Teh S. Y., Abdul-Rahman O., & Che-Rohani Y. (2011). Sensitivity of normality tests to non-normal data. Sains Malaysiana. 40(6): 637–641.
21. Okeniyi, J.O., Okeniyi, E.T., & Atayero, A.A. (2015). Programming development of Kolmogorov-Smirnov goodness-of-fit testing of data normality as a Microsoft ExcelR library function. Journal of Software & Systems Development, DOI: 10.5171/2015.238409
22. Orcan, F. (2020). Parametric or non-parametric: Skewness to test normality for Mean comparison. International Journal of Assessment Tools in Education, 7(2), 255–265 https://doi.org/10.21449/ijate.656077
23. 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):171-6.
24. Peat, J., & Barton, B. (2005). Medical statistics: A guide to data analysis and critical appraisal. Blackwell Publishing.
25. Priya, C. (2024). Robust Statistics, WallStreetsMojo
26. Sainani, K.L. (2012). Dealing with non-normal data. The American Academy of Physical Medicine and Rehabilitation. 4, 1001-1005. http://dx.doi.org/10.1016/j.pmrj.2012.10.013
27. Singh, A.S., & Masuku, M.B. (2014). Assumption and testing of normality for statistical analysis. American Journal of Mathematics and Mathematical Sciences, 3(1), 169-175
28. Steinskog, D.J. (2007). A cautionary note on the use of the Kolmogorov-Smirnov test for normality. American Meteor Soc. 135:1151-7.
29. Stephanie, G. (n.d). Jarque-Bera test from StatisticsHowTo.com: Elementary statistics for the rest of us! https://www.statisticshowto.com/jarque-bera-test/
30. Ukponmwan, H.N., & Ajibade, F.B. (2017). Evaluation of techniques for univariate normality test using Monte Carlo simulation. American Journal of Theoretical and Applied Statistics. Special Issue: Statistical Distributions and Modeling in Applied Mathematics, 6(5-1): 51-61. doi: 10.11648/j.ajtas.s.2017060501.18
31. Yap B. W. & Sim C. H. (2011). Comparisons of various types of normality tests. Journal of Statistical Computation and Simulation, 81(12), 2141-2155, DOI:10.1080/00949655.2010.520163
32. Wilcox, R. R., & Rousselet, G. A. (2023). An updated guide to robust statistical methods in neuroscience. Current Protocols. 3. doi: 10.1002/cpz1.719
33. Zhang, W., Yan, S., Tian, B., & Fei, D. (2022) Statistical assumptions and reproducibility in psychology: Data mining based on open science. Front. Psychol. 13:905977. doi: 10.3389/fpsyg.2022.905977
34. Zimmerman, D.W. (2014). Robust statistical tests. In: Michalos, A.C. (eds) Encyclopedia of Quality of Life and Well-Being Research. Springer, Dordrecht. https://doi.org/10.1007/978-94-007-0753- 5_2529