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Selecting Appropriate Statistical Methods for Small-Sample Continuous Measurement Data: A Comprehensive Review of Classical and Modern Approaches

Israa Abdulameer Resen [1]

[1] Department of Mobile communications and Computing Engineering, College of Engineering, University of Information Technology and Communications (UoITC), Baghdad, Iraq.
Email: israa.resen@uoitc.edu.iq

Abstract
In the fields of engineering and medical sciences, continuous measurement data based on small samples appear as a major problem, leading to the need for efficient and effective statistical tools. The problem of analysing data on the basis of small samples encourages the present review of the methods and ways for coordination of numerous statistical methods for analysis of small samples. The reviewed methodologies include all the ways from traditional statistical methods to advanced statistical techniques based on the developments of computing and artificial intelligence. T-test and Analysis of Variance (ANOVA) are among the most important methods of analysis of small samples. However, t-test and ANOVA and other traditional statistical techniques imply restrictive assumptions about normality and homogeneity of variances. It is well known that very often the previously mentioned assumptions do not hold in practice. Hence, statisticians had to find alternatives to the described traditional methods of analysing data, and nonparametric tests have become popular because of their effectiveness under the conditions when the basic assumptions of parametric methods do not hold true. The purpose of the research is to analyse the developing field of statistical techniques for small samples. Also, it is intended to describe the intersection, strengths and weaknesses of both traditional and modern techniques. With the help of computing and machine learning, modern statistical methods based on artificial intelligence have become powerful alternatives to traditional statistical techniques, especially for small samples. The scope of this paper is not limited to finding the best statistical techniques for small samples. It also reveals certain research gaps and the integration between the two techniques in this area.

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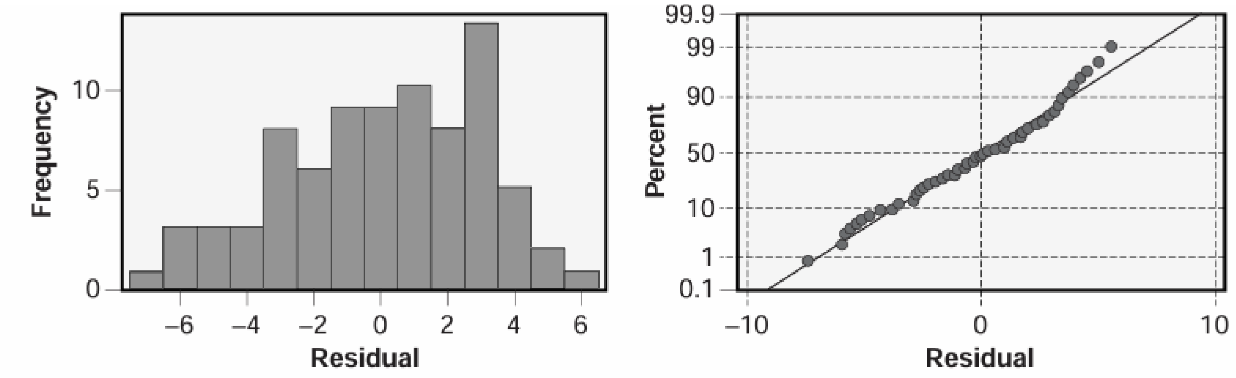
Introduction
The development of statistical methodologies and techniques has been driven by the fundamental need to draw valid inferences from limited measurement datasets. This evolution has been particularly significant in fields where collecting large quantities of data poses a major challenge.

Small sample sizes impose limitations on statistical surveys. These limitations create a barrier to the use of specific inferential methodologies from traditional statistics. These classical methodologies have played an important role in solving problems such as hypothesis testing and confidence interval estimation. However, numerous previous studies have shown that traditional methods lead to inaccurate conclusions when certain assumptions, such as normal distribution and the independence of variables, are not fully met. (Rigdon et al., 2024; Risan et al., 2024; Navidi, 2008; Bethea, 1995; Morgan, 2017; Stoudt et al., 2021). Modern datasets with their inherent complexities and rapid advancements in computing have paved the way for the emergence of advanced methodologies falling under the umbrellas of machine learning, deep learning, artificial intelligence, Bayesian statistics, and others. These modern methodologies aim to serve as alternatives to traditional approaches (Cao et al., 2024; Polas, 2024; Montgomery et al., 2007). In this extensive review, an analysis is presented regarding the various methodologies available for the analysis of continuously measured data from small data sets. The issue of the debate between conventional and modern statistics is also considered. Additionally, the importance of choosing an appropriate methodology for small data sets is emphasised. Although traditional methodologies have been widely used (Islam, 2024; Al Jamil et al., 2018), they often tend to lack the capability to control the natural variability in samples with small sizes. Old methods usually depend on ideas that apply to large samples, which might not be applicable in this case (Zhang et al., 2025). Bootstrap and Bayesian statistics have grown to be widely employed in the recent past. They provide some of the new ways of conducting analysis which are flexible and provide a means of incorporating extra information (Paiva & Reiter, 2017; Adam, 2011). Machine learning and deep learning methodologies have become common in the domain of inferential statistics. Therefore, combining the traditional and modern techniques can improve the decision-making process in many different areas. The assumption of normal distribution and outlier influence are crucial issues that need to be considered in choosing statistical methods in dealing with small samples (Kamal et al., 2024; Ater et al., 2025). As stated, it is evident that most of the statistical approaches presume certain types of distribution and therefore various methods of testing for normality have recently been gaining more interest in academic literature (Grafström & Schelin, 2014; Mathews, 2004; Benjamin & Cornell, 2014). Methods such as the Shapiro-Wilk test or graphical approaches including normal probability plots, histograms, and box plots (illustrated in Figure 1) are widely used to examine distributions. Furthermore, the presence and identification of outliers are of critical importance in statistics (Goodman, 2011; Lucy, 2013; Aitken & Stoney, 1991; Mathews, 2004).



(a) Histogram Plot (b) Normal Probability Plot

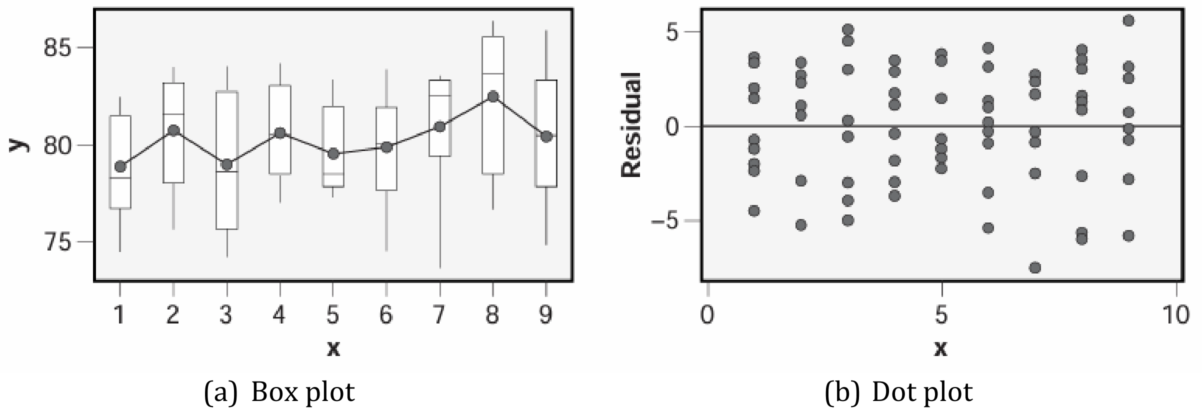
Fig. 1: Diagnostics plots for the data (Mathews, 2004)

To implement these types of advanced approaches, one needs to be thoroughly informed about the limitations that accompany such methodologies with respect to sample size (Kazanskaia, 2025). It is vital to deal with such limitations in light of the variation in results among different disciplines, a matter that proves the fundamental effect of the choice of the method on the result of research (Onwuegbuzie, 2024; Estrada et al., 2019). In this regard, this paper discusses the previous research done in this field and its applications, in addition to suggesting future research trends and the need for further research on advanced statistical methodologies (Mohajan, 2017; Chakraborty & Pant, 2025; Saari, 2025; Lee, 2023; van Doorn et al., 2021; Berry et al., 2010; Hollmann et al., 2025; Touvron et al., 2023).

This review paper is innovative in terms of analysing statistics of continuous data with a small sample size using an approach which not only analyses and compares various methods but also integrates them. This review paper not only presents the different approaches individually but also integrates the methods and analyses them along with their assumptions and limitations. In addition to this, another area of importance covered by this review paper is the lack of integration in the approaches as far as the selection of the best method is concerned. This review paper addresses the following research questions: (1) Which statistical methods are most appropriate for analysing continuous measurement data from small samples? (2) How do classical, non-parametric, resampling, Bayesian, and computational approaches compare in terms of their assumptions, advantages, and limitations? (3) What are the main methodological gaps and challenges in applying these approaches to small-sample data? and (4) How can traditional and modern statistical approaches be effectively integrated to support reliable statistical inference under small-sample conditions?

Descriptive Statistics of Small Measurement Data

Descriptive data analysis is essential before starting on more advanced inferential statistics. The descriptive statistics enable the researcher to clearly illustrate the underlying patterns in the target data. These dangers become more prevalent with smaller sample sizes. Measures of central tendency and dispersion in descriptive statistics are extremely essential tools for ensuring the reliability of data (Mathews, 2004; Risan et al., 2024). The measures of central tendency in the form of the arithmetic mean, median, and mode play an important role in determining the structure of data. Despite the arithmetic mean being the most popular measure, its major disadvantage lies in its vulnerability to outliers. In turn, the median acts as an important alternative to the arithmetic mean in case of small samples when outliers may affect the trends (Cao et al., 2024; Polas, 2024). Moreover, even though the usage of the "mode" is rare, it can offer valuable information regarding the most frequent values in the data (Rigdon et al., 2024). Another category of measures that is often used to explore the amount of dispersion of data includes the range, the interquartile range (IQR), variance, and standard deviation. It can be mentioned that the standard deviation is not always reliable in the case of small samples due to the variance inflation caused by the small number of data points. As a result, it is recommended to use both variance and standard deviation in conjunction with visual tools such as box plots and dot plots, which help to visualise the spread of data and identify outliers as demonstrated in Figure 2 (Zhang et al., 2025; Paiva & Reiter, 2017; Mathews, 2004).



(a) Box plot (b) Dot plot

Fig.2: Visual plots of data (Mathews, 2004)

It is considered to be a good practice while performing statistical analysis to repeat the measurements wherever possible. The first problem with small measurements is the scatter of the values obtained with a small number of measurements does not have to be representative of what can be expected from a larger number of measurements Second, the problem with the possible presence of the outlier value becomes more serious as well, its influence on the calculations of statistical parameters becomes relatively higher when working with a small sample (Adam, 2011; Risan et al., 2024). For example, we measure the diameter of any physical objects with three repeats {16.3,13.7,16.5} mm. The third value confirms the first one, so the second one seems to be an outlier. However, in the absence of a criterion for determining an outlier, using the second value, we obtain the mean value for the data set as "15.5" mm. When the validity of the mean is questionable, we might use the median of the data as another approach. Arranging them in the order of rank, we see that it is "16.3" mm. Using the median of three measurements should always be employed in order to avoid problems with a possible outlier in a small sample. It is better to use the median value rather than to exclude the suspected value and average the two remaining values as shown in Table 1. To estimate the spread of a small number of data points, three to ten, it is often convenient to use the range of values “R”. For the set of "n" measurements, where $3 \leq n \leq 10$ and arranged in order of increasing magnitude, a good approximation of the standard deviation is given by the range-estimated standard deviation $S_R \approx R/\sqrt{n}$. Using the median value and range-estimated standard deviation allows fast calculation of the descriptive statistics of the small data set with a reasonable reliability (Mathews, 2004; Adam, 2011; Risan et al., 2024).

Table 1: Descriptive statistics of small dataset

Small set of measurements $\{\mathbf{16.3, 13.7, 16.5}\}$		
$\boldsymbol{Mean\ of\ (16.3, 16.5) = 16.4}$	$Mean\ of\ (16.3, 13.7, 16.5) = 15.5$	$Median\ = 16.3$
$\boldsymbol{Range = 2.8}$	$S = 1.56$	$S_R = 1.6$

Skewness and kurtosis form basic indices of identifying asymmetry and peakiness of a dataset, correspondingly (Guerrier et al., 2019). Such features are important because they should be considered in relation to the following statistical test; if the distribution does not have the normal shape, then the use of non-parametric approaches can be required (Grafström & Schelin, 2014). The difficulties related to small samples and the problem of their variability and possible biases (Goodman, 2011; Kazanskaia, 2025) emphasise the necessity of using an effective approach. The application of a robust framework for the descriptive analysis is an essential part of dealing with such problems (Onwuegbuzie, 2024; Estrada et al., 2019; Mohajan, 2017; Chakraborty & Pant, 2025; Saari, 2025; Lee, 2023; van Doorn et al., 2021; Berry et al., 2010; Hollmann et al., 2025; Touvron et al., 2023).

Inferential Statistics of Small Measurement Data

The application of inferential statistics becomes significant in the case of data that has a small sample size. Such an approach allows concluding statistical populations on the basis of small sample sizes. Conventional approaches, which are based mainly on the assumption of large sample sizes, face difficulties while estimating small sample sizes. Thus, modification of these techniques and the development of some alternatives become necessary in order to overcome the limitations of small sample sizes. Even though conventional approaches (t-tests and analysis of variance) continue to be popular, they are limited due to the assumptions of normality and equal variance in the case of small sample sizes (Cao et al., 2024; Polas, 2024). Modern approaches make use of a Bayesian approach, which involves using prior information along with the observation of data (Rigdon et al., 2024; Zhang et al., 2025). The benefits of Bayesian modelling are not limited to the provision of flexibility in parameter estimation but also include the possibility of uncertainty calculation using confidence intervals. This property makes Bayesian models very important, especially in the fields of medicine and engineering where the accuracy of decisions is important (Paiva & Reiter, 2017). Non-parametric approaches, on the other hand, have become powerful tools for conducting inferential statistics based on small samples. The non-parametric approaches use some methods that are not so rigid regarding their parametric assumptions. For example, there are tests like the Wilcoxon rank-sum test and the Kruskal-Wallis test which are able to perform statistical analysis of group differences without the need for normal distribution of the data (Guerrier et al., 2019; Grafström & Schelin, 2014).

Table 2: Parametric tests and their non-parametric equivalents

Parametric test	Non-parametric tests
Mean	Median or mode
Standard deviation	Quartile or interquartile range
One-sample t-test	Wilcoxon test, sign test
Unpaired two-sample	Mann-Whitney U test
Paired two samples	Wilcoxon test, sign test
Chi-square test	Pearson's Chi-square test
Pearson's correlation test	Spearman's rank correlation coefficient
ANOVA	ANOVA on ranked data

The application of these methods is highly critical given the fact that in case of small samples, the probability of distribution skewing and the presence of outlier factors that will negatively impact results from conventional parametric statistical analysis will be present. Also, another type of resampling called the "bootstrapping" method has become increasingly popular as a good approach to calculate confidence intervals and test hypotheses in case of limited samples. With the help of bootstrapping, one can find out the sampling distribution of a particular statistic, which will allow making inferences from a set of samples which are too small for statistical testing (Goodman, 2011; Kazanskaia, 2025). Application of such alternatives in statistics can reduce the risk of errors in statistical inference from samples that do not meet optimal size criteria. Several studies, including those of Onwuegbuzie, 2024 and Estrada et al., 2019, have shown how such approaches have been successfully implemented and, therefore, their significance is highly relevant. In particular, in the case of medical research where the process of sample collection can be either unethical or financially unfeasible, application of Bayesian and nonparametric approaches has proved itself as being highly effective. However, the use of resampling methods makes the above observations even more convincing, especially in disciplines like engineering and medicine, where accurate predictions and good models are important for ensuring efficiency (Mohajan, 2017; Chakraborty & Pant, 2025). Despite the seemingly promising nature of using the above statistical techniques, it is critical to exercise caution when analysing the results obtained from small-sample datasets. The chances of making errors such as type I and II errors are bound to be high because, in their nature, small samples have high variance and are usually not representative of the target population (Saari, 2025). As such, more research into hybrid approaches that consider the unique features of the data and employ traditional, Bayesian and modern computational methodologies might bring interesting results and contribute to the development of improved methods of inferential statistics for small datasets (Lee, 2023; van Doorn et al., 2021; Berry et al., 2010; Hollmann et al., 2025; Touvron et al., 2023). To conclude, the use of inferential statistical methods, either traditional or modern, is an essential foundation for data analysis using small measurement datasets. The use of these methods in combination with Bayesian methodology, non-parametric tests, and resampling methods allows for drawing meaningful conclusions while taking into account the uncertainty of the limited samples.

Resampling Techniques and Outlier Detection of Small Sample Size

There are various problems associated with analysing small samples when discussing statistical methods. The two important issues related to statistical methods of analysing small samples are detecting the presence of outliers and the use of resampling methods. The significance of these areas of statistical methods is determined by the fact that using resampling methods like bootstrapping and cross-validation became an effective means of evaluating the validity of estimations made on the basis of small samples. It should be noted that bootstrapping allows generating the distribution of statistics by resampling the observed data, thus making it possible to estimate confidence intervals and reduce bias associated with small samples (Cao et al., 2024; Polas, 2024). Such a feature is highly important since outliers may greatly affect statistical analysis and, therefore, make it impossible to use regular techniques and lead to incorrect conclusions. With the help of computational means introduced recently, the application of resampling techniques becomes more promising in conjunction with the usage of algorithms designed to detect outliers based on machine learning techniques, such as Local Outlier Factor (LOF) and Isolation Forest (Rigdon et al., 2024; Zhang et al., 2025). Such algorithms enable detecting data points that do not follow the normal distribution even when there is an extremely small sample of data (Rigdon et al., 2024; Zhang et al., 2025). For example, with the help of the LOF algorithm, one may estimate the local density of data points and thus determine outliers compared to those around them (Paiva & Reiter, 2017). It is especially important in case the distribution of data points is irregular, which may occur in the case of data related to short-stature measures (Guerrier et al., 2019). Moreover, the isolation of outliers helps to better understand the results obtained from the data analysis in clinical and experimental research (Grafström & Schelin, 2014). The use of resampling methods is not restricted to boosting statistical power or detecting the presence of outliers but also involves ensuring that conclusions made from small samples are robust. Specifically, cross-validation involves assessing how well a predictive model works by splitting the data into different parts, using one set to train the model and another to test it (Goodman, 2011). Through such an approach, it becomes possible to evaluate the stability of models where the amount of available data is small (Kazanskaia, 2025). In particular, the "k-fold cross-validation" technique allows the systematic assessment of models, which makes it more favourable among statisticians and data analysts dealing with small sample sizes (Onwuegbuzie, 2024; Estrada et al., 2019). Table 3 demonstrates some methods for detecting outliers from small sample sizes. A visual representation of data can be useful for demonstrating the influence of outliers on statistical methods used with regard to a small-sized sample. For example, the use of visual techniques like Violin plots allows us to show a distribution considering the outliers. Thus, the use of these methods helps to identify possible outliers before using statistics in a study and increases the readability of the findings when communicated to stakeholders (Mohajan, 2017). Scatter plots are another helpful technique for analysing relationships between variables in a dataset as well as detecting outliers to investigate their correctness. Synthesising the current literature, one can conclude that although the use of resampling methods and outlier detection techniques is a promising solution for the problems related to small samples, there is a need for development in the field of implementation of these techniques in various disciplines. Further research needs to consider the establishment of common standards for integration of these methods into different paradigms, especially in fields of research where small sample data are often used, such as engineering or medicine. It is also necessary to mention that in terms of future evolution of statistical practice, the use of machine learning algorithms as an inevitable extension of traditional resampling techniques should be taken into account to successfully solve classification and prediction tasks when data are level-shift affected (Chakraborty & Pant, 2025; Saari, 2025; Lee, 2023).

Table 3: Outlier Detection Methods for Small Sample Sizes

Method	Description
Bootstrap	It is a resampling method for estimating the sampling distribution of a statistic using a sample where each data point is drawn from the original sample at random with replacement.
Jackknife	A type of resampling method where an observation is left out from the sample in a systematic way each time to estimate the sampling distribution, thereby helping in estimating bias and variance.
Multihalver	The delete-half jackknife method is used to detect the presence of any outliers by considering all the possible half samples in a dataset.
High-Breakdown Estimators (HBEs)	Robust regression methods, characterized by their reduced sensitivity to outliers, are effective when dealing with small sample sizes; however, they entail high computational costs.

Normality Assessment of Small Sample Size

When dealing with small samples, it is essential to test whether the data follows a normal distribution before selecting the appropriate analysis method. This is because several parametric tests are based on the assumption that the data is normally distributed. The significance of this assumption can be noted from the fact that violation of this assumption can produce inaccurate results in hypothesis testing. Testing for normality becomes especially difficult when the data is a small sample, as the low statistical power of tests makes them susceptible to errors. Statistical tests such as the "Shapiro-Wilk test" and "Kolmogorov-Smirnov test" are very popular. But these tests require the presence of sufficient sample sizes in order to achieve significance. This creates a paradox in the use of such tests (Cao et al., 2024; Polas, 2024). Graphical methods such as Q-Q plot, histograms are used in addition to the tests mentioned above, as they give an opportunity to visualise the shape of the data in comparison with the Gaussian distribution (Rigdon et al., 2024). However, the problem with these methods lies in the extreme difficulty of using them when the sample size is very small, as the visual characteristics of the graph can mislead the interpretation process (Zhang et al., 2025). The recent progress in bootstrapping methods is an alternative that can help to solve the problem of normality assessment. The bootstrapping method allows generating a huge amount of resampled data, which gives the opportunity to estimate the distribution of a certain statistic without the need to make any strong assumptions on the distribution of the original population (Paiva & Reiter, 2017). Thus, this approach improves the assessment of normality in cases when the result of using some tests is inconclusive because of a small sample size (limited observations). Moreover, new methods such as the Benjamini-Hochberg procedure can be used with bootstrapping techniques to control the false discovery rate when assessing normality in hypothesis testing (Guerrier et al., 2019). Modern approaches represent an adaptation of the methodology to overcome the restrictions of the traditional methods. The deep research conducted by Aitkin et al. proves the effectiveness of the modern methodology in cases when the sample size is limited (Grafström & Schelin, 2014). It is important to note that the power of normality tests is crucial when handling cases involving small sample sizes. This is because the normality tests can have low power with small sample sizes, making it more probable that the null hypothesis will not be rejected even if it is wrong. The Shapiro-Wilk test is among the most efficient and powerful normality tests. It is therefore imperative to take into account sample size and power while testing for normality. First, one cannot underestimate the significance of the Central Limit Theorem (CLT); this theorem explains theoretically why one can apply the assumption of normal distribution once the aggregated sample size reaches a certain level. At the same time, there are limitations to using the CLT in cases when sample sizes are small since there may be no convergence to a normal distribution. Such limitations lead researchers to consider using non-parametric methods—such as the Mann-Whitney U test and the Kruskal-Wallis test—that do not require the data to be normally distributed, particularly in cases involving small sample sizes (Goodman, 2011). Normality test methods for small sample sizes are presented in Table 4. Non-parametric methods may possess lower statistical power compared to parametric methods. This characteristic is considered the primary drawback of using non-parametric tests (Kazanskaia, 2025). However, when applying such tests in medicine and engineering, it is vital to assess whether the measurement data follow a normal distribution because, otherwise, it may lead to erroneous conclusions and scientific errors. For example, in the clinical trial of drugs, one will make false statistical conclusions and, therefore, may make incorrect clinical decisions if he/she assumes the normal distribution of data (Onwuegbuzie, 2024). In addition, in engineering cases, when small samples may occur due to limitations of experiments, the normal distribution may also lead to incorrect quality control because of false assumptions (Estrada et al., 2019).

Table 4: Normality Assessment Methods for Small Sample Sizes

Method	Sample Size Range	Recommended For	Notes
Shapiro-Wilk Test	5 to 2,000	Small samples	Most powerful test for small sample sizes; however, may become overly sensitive with larger samples, detecting trivial deviations from normality.
Shapiro-Francia Test	5 to 2,000	Small samples	Similar to Shapiro-Wilk but adjusted for skewness; may become overly sensitive with larger samples.
D'Agostino-Pearson Test	Over 100	Larger samples	Developed for larger samples; performance approaches that of Shapiro-Wilk for $n > 100$.
Anderson-Darling Test	Over 50	Larger samples	Performs well for sample sizes over 50; less sensitive to sample size variations.

Comparative Analysis of Existing Studies

Following the critical review of the methodologies presented in the preceding sections, it is now possible to conduct a detailed comparative analysis of existing scientific studies. This aims to develop a better understanding of the statistical approaches specifically designed to handle continuous variables derived from small-sized samples. It is worth noting that a review of the relevant literature reveals a growing trend toward the use of more sophisticated methods, despite the widespread application of traditional techniques employing the t-test and analysis of variance. For example, the benefits of resampling techniques, such as bootstrapping and permutation tests, have been studied as an alternative approach for use in situations where there is insufficient data and/or a non-normal distribution (Cao et al., 2024; Polas, 2024). Modern techniques have proven to be more effective than the traditional ones in many instances through the reduction in Type I and Type II errors, an assertion that is backed by empirical findings (Rigdon et al., 2024; Zhang et al., 2025). Moreover, the use of Bayesian statistics has received much attention in the past few years, especially in clinical and engineering practice; prior information makes it possible to steer posterior estimates, thus making it possible to conduct a more precise and elaborate interpretation of data obtained from small samples (Paiva & Reiter, 2017; Guerrier et al., 2019). For example, a review of psychological research based on small sample sizes found that the Bayesian approach was often more accurate compared to frequentist approaches when the assumptions about the normality of data distribution were not entirely fulfilled (Grafström & Schelin, 2014; Rigdon et al., 2024). In addition, an analysis dedicated to machine learning methods including Support Vector Machines (SVM) and decision trees shows their effectiveness in the case of small sample sizes since these approaches allow finding complicated patterns even with insufficient data (Goodman, 2011; Kazanskaia, 2025). When considering a comparative analysis of the aforementioned methods, decision-making approaches can be employed to select the appropriate technique for analysing continuous data with small sample sizes. Key considerations in this context include sample size, distribution characteristics, the presence of outliers, and the study's primary objective. Parametric methods may be used when all underlying assumptions are met; otherwise, non-parametric or robust approaches may be adopted. The conclusions drawn indicate important methodological advancements that allow more effective decision-making in empirical research conducted with a small sample size. On the other hand, some researchers stress the need to use both traditional and modern methods together, providing an example of using traditional parametric and non-parametric testing in order to confirm the reliability of the results achieved (Onwuegbuzie, 2024; Estrada et al., 2019). Such a comparison-based methodology helps not only to increase the level of reliability but also to identify any possible outliers and evaluate the distribution of the data. In addition, it has been shown recently by the findings of a meta-analysis that the efficiency of different statistical approaches may depend on the situation. Thus, the application of any method should be based on specific features of the data sample, such as its volume, distribution, and variation (Mohajan, 2017; Chakraborty & Pant, 2025). In engineering applications, the "small-sample" statistical approach can aid in material analysis and the conduct of structural and experimental studies. Such fields where limited sample sizes often prevent the use of traditional parametric statistical techniques. The same applies to medical applications, where this approach can be used to analyse clinical and diagnostic data while addressing issues such as normal distribution and outliers. For instance, robust statistics or nonparametric statistics can be employed in cases where the assumptions underlying parametric tests are not met. Although a lot of progress has been made in the study of small sample statistics, there are still some noticeable deficiencies in the academic research; for example, many research papers are mostly concerned with conventional or modern statistical methods, but fail to analyse their integration for achieving maximum benefit. Future studies should focus on approaches that call for a holistic approach towards small sample statistical methods. The developed approaches enable a more coherent understanding of the interaction of statistical models. Moreover, the application of these methods in important sectors, including healthcare, can have practical advantages for society where sound inferences need to be made based on small patient datasets (Saari, 2025; Lee, 2023). In summary, the comparative study of the literature shows how the development of statistical methods designed for continuous data collected from small samples has developed. The comparative study of the literature also shows how a combined analysis of conventional and modern methods makes one realise the developments in the area, which increase empirical validity. The use of Bayesian methods, hybrid analysis, and machine learning constitutes a fertile ground for future research.

Table 5: Comparison of Statistical Methods for Small Sample Continuous Data Analysis

Method	Design	Error Rate Type I	Power
The Paired t-test	Two eyes of a subject in two various comparison groups	Nominal	Higher
Linear Mixed Effects Model (LMM)	Two eyes of a subject in two various comparison groups	Nominal	Higher
Two-sample t-test (based on the average of two eyes)	Two eyes of a subject in the identical comparison group	Better control	Lower
Generalised Estimating Equations (GEE) Wald Test	Two eyes of a subject in any group of comparison	Inflated	Lower
Generalised Estimating Equations (GEE) Score Test	Two eyes of a subject in any group of comparison	Nominal	Lower

Current Challenges and Future Research Directions

The critical review of modern statistical methods indicates that there are numerous difficulties in this field, which should be researched in detail. First of all, the application of conventional approaches such as t-test and ANOVA is still very popular among scientists despite the restrictions that they have. The conventional approaches is caused by the necessity to make some assumptions about normal distribution of the data and its independence in case of the use of these methodologies. At the same time, such restrictions make this methodology less flexible in comparison with other modern approaches. Less flexible approaches are difficult to apply to samples, such as in engineering samples that usually are characterised by small group sizes. This is explained by the fact that it is hard to gather large samples due to certain restrictions on the availability of participants or materials (Cao et al., 2024). Besides, the development of new data analysis approaches, which include machine learning, deep learning, and artificial intelligence, generates the discrepancy, as traditional approaches cannot deal with complex data sets with complicated relations between observations (Polas, 2024). In order to solve the problem, it is necessary to learn thoroughly how to use modern methods, including the Bayesian approach and bootstrapping, to obtain more accurate results from such data (Rigdon et al., 2024). However, the usage of such methods in research practice has one problem connected with the lack of curricula, training materials, and sources of information for researchers unfamiliar with these methods (Zhang et al., 2025). First of all, the issue of how to deal with outliers is still a serious problem, especially when dealing with continuous measurement data from a small sample size. It is still a difficult task to identify and manage outliers without distorting the results of statistical analysis because existing detection strategies often depend on rigid statistical conditions (Paiva & Reiter, 2017). Some modern methods and techniques, such as using machine learning and deep learning algorithms in the process of detecting anomalies, are promising in terms of enhancing outlier monitoring and management. Nevertheless, their interpretation in the framework of small-sample data is still an open question (Guerrier et al., 2019). Machine learning algorithms and artificial intelligence techniques enable the generation of predictions, the identification of patterns, and the discovery of non-linear relationships, even when relying on small data samples. However, applying these algorithms and techniques to small samples presents several challenges, primarily stemming from data scarcity and the issue of "overfitting." These challenges are further compounded when employing multivariate analysis in scenarios where the sample size is smaller than the number of variables involved; data scarcity can lead to problems such as instability in the covariance structure, overfitting, and a reduced ability of the multivariate model to generalise. Consequently, specific techniques such as dimensionality reduction can be employed when dealing with small-sized samples. This is the reason why there is an urgent need to combine modern computing technologies with traditional statistical methodologies in order to create hybrid methods that will produce better results (Grafström & Schelin, 2014). In other words, integration of engineering and machine learning knowledge can help to develop new innovative statistical methods that will be more suitable for analysing small samples of continuous measurement data. Scientists should pay special attention to developing such tools that would increase both analytical and usability abilities of researchers who do not have deep knowledge in statistics. This means that special training courses and user-friendly software are necessary in order to bridge the gap in statistical literacy in clinical and engineering settings (Kazanskaia, 2025; Onwuegbuzie, 2024). In addition, changes in the methods of data collection make it necessary to reconsider statistical methodologies. One possible approach to a hybrid methodology proven effective for handling continuous small-sample data involves the sequential application of various techniques. One might begin with traditional methods to explore the data's structure and distribution and to identify any outliers. In cases where traditional methods are unsuitable for the available data, robust and nonparametric methods can be employed, alongside bootstrapping techniques to verify the stability of estimates. Furthermore, a Bayesian approach can be applied to leverage any available prior information, while machine learning techniques can be used to predict latent patterns within the data. The difficulties that the researcher encounters when choosing statistical methods for dealing with continuous measurement data obtained from small samples reveal the critical necessity of strengthening the process of development and innovation. The importance of development and expansion of statistical methods by means of modern methods is expected to contribute to the improvement of science and practice in this regard and make sure the statistics is relevant to the modern age (Estrada et al., 2019; Mohajan, 2017; Chakraborty & Pant, 2025). Generally, proper attention paid to these challenges and attempts to overcome them would bring about a more flexible, strong, and sophisticated statistical framework (Saari, 2025; Lee, 2023; van Doorn et al., 2021; Berry et al., 2010; Hollmann et al., 2025; Touvron et al., 2023). Further research is required to refine the aforementioned approaches into more sophisticated methods for analysing the impact of the variables in question and their interactions. Particularly when working with smaller sample sizes. Employing techniques such as regression analysis, resampling, and the Bayesian approach, among others, would yield additional insights into the effects of these variables. In addition, they prove valuable in interpreting the interactions between various factors within small samples. With respect to the computational implementation of the described methodologies. Commonly used statistical software tools like R, Python, SPSS, and SAS could be utilised. A pragmatic strategy would involve the step of exploring and validating assumptions before choosing one of parametric, non-parametric, re-sampling, or Bayesian methods based on sample size and other characteristics of the data. If necessary, additional steps would consist of the application of bootstrap or Bayesian methods in evaluating the uncertainty and robustness of the results obtained.

Conclusion

A survey of statistical techniques suitable for analysing continuous measurements using small samples shows an array of choices. The selection between these choices will be made depending on the different contexts and purposes of research. As the survey confirms, the continuous emergence of improvements in both classical and modern statistical techniques has great significance for researchers who face the challenges associated with small sample sizes. In the current study, classical techniques that are based on strict assumptions, including normality and equal variances, were compared to modern alternative techniques that use resampling approaches, deep and machine learning, and artificial intelligence. While classical t-tests and ANOVA allow getting accurate results in ideal circumstances, they might fail when applied to small samples which do not meet the mentioned assumptions; and this is where modern techniques come into play. The modern approach not only overcomes the shortcomings of the traditional one but also allows for additional flexibility in dealing with non-normal distributions. This additional flexibility gives the researchers an opportunity to find viable substitutes that will help in making sound conclusions. From the point of view of the practical applications of the approach, the reviewed literature demonstrates a number of scientific areas where modern methods have already been used. For example, machine learning, deep learning and artificial intelligence have proven effective in obtaining accurate outcomes in terms of recognising patterns in small samples, which is often done in biomedical and engineering research. This is the method that has improved diagnostics in a way that could hardly be achieved through the application of the traditional statistical approach. This review also emphasises the importance of conducting continuous research in relation to small samples in order to check the validity of the methodology used and its capacity to adapt to different fields. One of the major gaps in research that have been revealed through this particular review is the need to conduct further studies that will involve the development of hybrid models where both traditional and modern statistics will be combined. In summary, it can be seen from the above results of the literature review that there is immense importance in utilising proper statistical methods for analysing continuous measurement data in the case of small samples. In summary, this review presents a coherent framework for understanding and selecting appropriate statistical techniques for continuous measurement data in small samples. This is done based on the assumptions, advantages, and limitations of each technique. Selecting the suitable methodology requires consideration of sample size, distribution characteristics, the presence of outliers, and research objectives. Future research should address the development and validation of hybrid statistical frameworks. As well as multivariate analysis techniques should be investigated for small samples, with the robustness and reliability of machine learning methods and Bayesian approaches in data-limited contexts.

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