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Comparison of Conventional and Neutrosophic Methods for Statistical Power Analysis and Effect Size in Clinical Research

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Abstract: The study investigates the integration of conventional statistical methods with neutrosophic techniques for effect size and statistical power analysis in clinical research. It addresses a significant gap in applying neutrosophic methodologies to complex datasets characterized by uncertainty and variability. Conventional methods, such as Cohen's d, assume well-defined data, which limits their effectiveness in real-world clinical scenarios. Neutrosophic methods incorporate degrees of truth, falsity, and indeterminacy and are more suitable for analyzing uncertain and inconsistent clinical data. For instance, when comparing blood pressure reduction between a Treatment Group and a Control Group, conventional methods yield an effect size of 3.00 and a power of 99%. In contrast, neutrosophic methods result in an effect size of 13.46 and a power of 100%, highlighting their ability to manage data complexities better. The findings emphasize the need to integrate neutrosophic techniques into clinical analysis to improve effect size and power estimation accuracy and reliability, especially in studies with variable data. However, the study is limited to a specific dataset, and further research is needed across different clinical domains. Neutrosophic methods might also require advanced resources and expertise, which could be challenging in some settings. This study presents a novel approach that improves our understanding of clinical outcomes.

Keywords: Effect size, power analysis, clinical study, conventional statistical analysis, neutrosophic approach.

1. Introduction

Clinical studies depend on statistical approaches to evaluate the effectiveness of interventions. However, conventional statistical methods are often used in the assumptions of well-defined and accurate data (1). These assumptions can pose challenges when dealing with real-time medical data, which frequently involves uncertainty, flexibility, and fuzziness. Effect size and statistical power analysis are critical analyses for assessing the significance of treatment outcomes and the probability of getting valid changes among groups (2) (3). However, conventional statistical approaches cannot

entirely report the difficulties of such uncertain data sets, indicating potential biases or observe results. As clinical studies gradually deal with uncertain data, more modern approaches, such as neutrosophic approaches, can better evaluate and interpret clinical primary outcomes.

The neutrosophic techniques combine the degrees of truth, falsity, and indeterminacy used for handling uncertainties in the data (4) (5) (6). It stands out by accepting investigations to address the uncertainty and variability performed in datasets (7). However, the use of this technique in clinical studies remains inadequate due to a lack of studies relating its effectiveness to fundamental approaches in effect size and statistical power analysis. This neutrosophic approach indicates a good research gap, as clinical study frequently involves complex data that conventional statistical methods cannot completely capture. Furthermore, it highlights the requirement for advanced methodologies like the neutrosophic approach to develop better reliability and thoroughness of effect size and statistical power analysis in clinical studies.

The primary purpose of this research is to fill the research gap by evaluating real-world clinical data and assessing the effect size and statistical power analysis results derived from conventional and neutrosophic approaches. The objective identifies the efficacy of the two methods in controlling uncertainty, delivering more accurate insights into intervention effects, and comparing the two approaches to increase the understanding of advantages and limitations by fulfilling a research gap in clinical data analysis. For future research recommendations, the advanced statistical approach to navigate complex and uncertain clinical data aims to enhance the reliability of statistical methods in clinical data analysis.

Shams et al. (26) proposed a novel DNA sequence-matching algorithm incorporating neutrosophic values to account for uncertainty in genetic comparisons. Gbolagade et al. (27) introduce the Neutrosophic Poisson Distribution Series, a new method for analyzing harmonic functions and addressing inherent uncertainties with the Salangean derivative operator. Naveed and Ali (28) developed a multi-criteria decision-making approach based on m-polar interval-valued neutrosophic soft sets, significantly extending the concept of neutrosophic soft sets and introducing new correlation measures for complex decision problems. Elsayed and Mohamed (29) present a comparative analysis of various MCDM techniques within neutrosophic environments, focusing on economic condition assessments and offering the novel CARCACS method to manage economic uncertainties. Each paper introduces a unique extension or application of neutrosophic theory, advancing its role in managing uncertainty and indeterminacy in diverse fields.

Each of these studies highlights a unique aspect of neutrosophic theory's application, from bioinformatics and mathematical modeling to decision-making and economics. By incorporating neutrosophic methods, these researchers have addressed critical issues of uncertainty and variability, offering more accurate and reliable solutions across diverse fields. This growing body of work underscores the importance of neutrosophic theory in improving the robustness of data analysis in contexts where traditional methods fall short. Recent studies have highlighted the growing importance of neutrosophic statistics in addressing uncertainty, imprecision, and ambiguity in data analysis, particularly in clinical research and big data analytics. Smeltzer and Ray (30) and Riaz et al. (33) emphasize the limitations of traditional statistical methods, such as Cohen's d and power analysis, which assume precise and well-defined data. These classical methods often fail when applied to real-world datasets that contain uncertainty or missing information. In contrast, neutrosophic statistics offer a more robust approach by incorporating degrees of truth, falsity, and indeterminacy, making them more suitable for clinical and medical data where such uncertainties are typical. El-Demerdash et al. (31) and Essa et al. (32) further support this by demonstrating how neutrosophic methods enhance feature selection and classification in big data, as well as improving

decision-making and diagnostic accuracy in healthcare and medical image processing by accounting for data variability.

Studies like those by M., J., S., I., & R., P. (37, 38) and Kandemir et al. (39) explore the use of neutrosophic approaches for managing uncertainty in mathematical models and environmental data. Basker P et. al. (34, 35, 36) introduces fuzzy neutrosophic weighted Poisson distributions for systems with uncertainty, further expanding the scope of these methods. The integration of fuzzy logic, as demonstrated by Afzal and Aslam (40) and Liji Sebastian et al. (41, 42), enhances reliability in areas like health monitoring and electrical measurements, underscoring the importance of these techniques in addressing real-world challenges with imprecise data.

The proposed work differentiates itself from existing methods by integrating neutrosophic theory into effect size and power analysis, providing a more comprehensive analysis for uncertain and imprecise datasets. Classical statistical tests, like Cohen's d, assume that data is precise and well-defined, but neutrosophic methods manage ambiguity, offering a nuanced view of the data. The proposed approach leverages neutrosophic statistical tests, which allow for uncertainty in clinical trials and other medical data to be considered, resulting in more reliable and robust conclusions. This marks a significant advancement in statistical analysis, especially in fields where data variability is inevitable, and traditional methods may be inadequate for drawing meaningful conclusions.

This paper introduces neutrosophic methods to clinical data analysis, specifically focusing on effect size and statistical power analysis. Traditional statistical approaches often assume data is precise, which is rarely true in real-world clinical studies. Clinical data frequently involves uncertainty, imprecision, and ambiguity, leading to potential inaccuracies when analyzed with conventional methods. Neutrosophic techniques, which account for degrees of truth, falsity, and indeterminacy, provide a more reliable method for analyzing such uncertain data. The significance of this study lies in its potential to improve the accuracy and reliability of clinical outcomes analysis, ensuring that conclusions drawn from clinical studies better reflect real-world uncertainties.

The paper's key contributions are introducing neutrosophic methods for effect size and statistical power analysis in clinical research. It also provides a comparative study between neutrosophic techniques and conventional statistical methods, highlighting the advantages of the former in handling uncertain data. Additionally, this research fills a gap in existing literature by applying neutrosophic methods to clinical datasets, thus enhancing the reliability of clinical study results. These contributions hold significant potential for improving statistical analysis and interpretation in clinical research.

The novelty of this work lies in the application of neutrosophic methods, which differ from classical statistical techniques by modeling uncertainty and indeterminacy in the data. Traditional methods assume precise data, while neutrosophic techniques consider fuzziness, offering a more realistic and robust approach to clinical data analysis. This paper demonstrates how neutrosophic methods can improve effect size and power estimation, leading to more accurate and reliable results in clinical research.

By introducing neutrosophic methods, this paper offers a new way to manage uncertainty in clinical data analysis, which is often overlooked by traditional statistical methods. These techniques help researchers better account for indeterminacy, making them more suitable for real-world medical datasets. The paper addresses a critical gap by offering a solution for clinical studies with uncertain data, improving the quality and accuracy of clinical outcomes evaluations.

2. Methods and Methodology

The equations used in neutrosophic methods differ significantly from those used in classical statistics due to how they treat data uncertainty. Classical statistics (such as Cohen's d) assume the data is precise, well-defined, and error-free. The typical calculations in classical statistics, such as effect size or power, are based on fixed metrics like means, standard deviations, and variance, which rely on normal data distribution. On the other hand, neutrosophic methods incorporate the handling of uncertainty and indeterminacy within the equations. These methods account for not only valid values (T), but also false (F) and indeterminate values (I), which reflect the uncertainty or vagueness present in real-world clinical data. For instance, while classical statistics might use the pooled standard deviation to calculate effect size, neutrosophic effect size considers the subjective input of these degrees (T_A, F_A, I_A), making the equation more adaptable and robust when dealing with incomplete or ambiguous data. This difference allows neutrosophic methods to manage more complex datasets with uncertainty, offering more reliable results in clinical studies that are often messy and imprecise.

a. Neutrosophic set

The Neutrosophic set combines three components, which are explained in detail below.

- Truth membership (T) is the degree of truth membership (data accuracy). The range of Truth membership [0, 1].
- Falsity membership (F) is the degree to which the membership of an element is indeterminate or uncertain. The ranging between [0,1]. The degree of falsity (error or incorrectness) in the data.
- Indeterminacy membership (I) is the degree to which the membership of an element is indeterminate or uncertain. The ranging between [0,1]. The degree of uncertainty in the data.

Combining these three memberships allows neutrosophic sets to depict scenarios with more significant uncertainty, vagueness, or ambiguity than fuzzy sets, which only deal with truth values (8) (9). The neutrosophic set for an element 'x' can be represented as

$$A = \{(x, T_A(x), F_A(x), I_A(x))\} \quad \text{----------(1)}$$

where $T_A(x)$, $F_A(x)$ & $I_A(x) \in [0,1]$ for each element $x \in X$, where x is the universe of discourse.

Membership functions for truth, indeterminacy, and falsity must be managed simultaneously. This makes the algebra and derivation of properties, such as intersection, union, or complement, more complex because these operations must account for three values rather than just a single membership function.

b. Statistical Power Analysis

Power analysis is usually used to determine the probability of rejecting the null hypothesis when it is false (10). The power of a test is calculated as:

$$\text{Power}=P(\text{Reject } H_0|H_1 \text{ is true}) = 1-\beta \quad \text{----------(2)}$$

where H_0 is the null hypothesis, and H_1 is the alternative hypothesis. β is the probability of a Type II error (failing to reject H_0 when H_1 is true) (3) (11).

It typically involves:

- d-Effect size
- Level of significance-α
- Sample size-n.'

- Statistical power β, is the probability of rejecting the null hypothesis when the alternative hypothesis is true.

c. Effect Size

An effect size is a statistical term used to measure the variation's size or the association's significance across characteristics (12). It shows the importance of research on the outcome. A significant magnitude of the effect suggests that the research's outcomes have practical significance, and a small number of impacts means that the results have minimal uses for the findings. It contributes to determining when the result contains practical effects. Common types of effect size include Cohen's 'd', eta squared, and Pearson's 'r'. (13). Effect size is essential in research because it provides a clearer understanding of the impact or importance of a finding, beyond statistical significance.

3. Combination between Neutrosophic set, statistical power analysis and effect size using case studies:

Incorporating neutrosophic statistical power and effect size in medicine enhances the management of uncertainty and imprecision, which are prevalent in medical research. Neutrosophic statistics account for indeterminate, true, and false values, providing the nuanced perspective of complex medical data. On the other hand, effect size, meanwhile, measures the practical significance of findings, indicating how impact a result is (14). Integrating these methods enhances risk assessment, decision-making, and the interpretation of medical data by evaluating the effect size and the uncertainty within the data, resulting in more reliable and actionable insights in clinical practice.

Medical data studies are crucial for enhancing treatment, discovering new therapies, and developing public health policies. By analyzing medical data, healthcare professionals can develop better decisions, increase evidence-based treatment, and find novel insights on diseases and procedures. Furthermore, it improves the modification of medical treatment, the development of health care systems, and the identification of trends that lead to improved outcomes and decreased expenses (15). Analyzing neutrosophic effect size and statistical power is essential for successfully evaluating uncertain or limited medical data, which has become prevalent in clinical trials and patient investigations.

Conventional statistical methods often neglect uncertainty; however, neutrosophic statistics effectively address this issue by considering the components of truth, falsehood, and indeterminacy. This approach provides a more comprehensive perspective on the data. Neutrosophic statistical power enhances traditional power analysis by incorporating these uncertainties, thereby offering a clearer understanding of the strength and reliability of the evidence (16). This integrated approach ensures that both the magnitude and reliability of effects are evaluated, leading to informed decision-making and a deeper understanding of outcomes in real-world medical contexts.

Neutrosophic effect size and statistical power analysis were derived based on single, double, and three-group and single-group pre-post comparisons to account for uncertainty in clinical data. It will help improve the interpretation and reliability of results, which will be discussed in detail below for each case.

a. Case 1: Neutrosophic effect size for a single group:

The standard formula of Cohen's d for a single group is.

$$d = (\mu - \mu_0)/\sigma \quad \text{---------(3)}$$

where,

μ = sample mean

μ_0 = population mean

σ = the SD of the sample group

Now, we consider the mean difference and population mean is $(\mu - \mu_0)$, then the truth degree $T_A(x)$ reflects how much we trust the observed mean difference. These adjustment scales of the mean difference are,

$$\text{Adjusted mean difference} = T_A(x).(\mu - \mu_0) \quad \text{----------(4)}$$

The falsity degree $F_A(x)$ reflects measurement error. If the data is noisy, the standard deviation should be adjusted. So, we adjust the standard deviation.

$$\text{Adjusted SD} = F_A(x).\sigma \quad \text{----------(5)}$$

The indeterminacy degree $I_A(x)$ reflects uncertainty in the measurement. Thus, we scale the SD with $I_A(x)$.

$$\text{Adjusted SD} = I_A(x).\sigma \quad \text{----------(6)}$$

Now, combining the adjustments, the neutrosophic Cohen's 'd' becomes,

$$d_{(neutro)}=(T_A(x).(\mu-\mu_0))/((F_A(x).\sigma)+(I_A(x).\sigma)) \quad \text{----------(7)}$$

The above formula adjusts the effect size for the truth, falsify, and indeterminacy.

b. Case 2: Neutrosophic effect size for the difference between two groups:

The standard formula for two groups of effect size is

$$d=(\mu_1-\mu_2)/\sigma \quad \text{----------(8)}$$

where,

μ_1 = group-1 mean

μ_2 = group-2 mean

σ = the pooled SD of the sample groups

Now, we consider the mean difference and population mean is $(\mu_1-\mu_2)$, then the truth degree $T_A(x)$ reflects how much we trust the observed mean difference between the two groups. These adjustment scales of the mean difference are,

$$\text{Adjusted mean difference} = T_A(x) . (\mu_1-\mu_2) \quad \text{----------(9)}$$

The falsity degree $F_A(x)$ reflects measurement error. If the data is noisy, the pooled standard deviation should be adjusted. So, we adjust the pooled standard deviation.

$$\text{Adjusted pooled SD} = F_A(x).\sigma \quad \text{----------(10)}$$

The indeterminacy degree $I_A(x)$ reflects uncertainty in the measurement. Thus, we scale the pooled SD with $I_A(x)$.

$$\text{Adjusted pooled SD} = I_A(x).\sigma \quad \text{----------(11)}$$

Now, combining the adjustments, the neutrosophic effect size between two groups becomes,

$$d_{(neutro)}=(T_A(x).(\mu_1-\mu_2))/((F_A(x).\sigma)+(I_A(x).\sigma)) \text{ ----------(12)}$$

The above formula adjusts the effect size for the truth, falsify and indeterminacy.

c. Case 3: Neutrosophic effect size for difference between more than two groups:

The standard formula for more than two groups of eta-square (η^2) is often used as the effect size measure:

$$\eta^2=SS_{Between}/SS_{Total} \text{ ----------(13)}$$

where,

$SS_{Between}$ = The sum of the squares between groups (Variance explained by the independent variable).

SS_{Total} = Total variance in the data.

The sum of square between the group is which measures how much the groups difference from the overall mean

$$SS_{Between} = \sum_{i=1}^{k} n_i(M_i - M_{total})^2 \text{ ----------(14)}$$

where

k = no. of groups

n_i = group 1 observations

M_i = group 1 mean

M_{Total} = overall mean of all groups combined

Now, we consider the truth degree $T_A(x)$ reflects how independent variables explain the between group variance.

$$\text{Adjusted mean difference between groups} = T_A(x).\ SS_{Between} \text{ ----------(15)}$$

The total sum of square is SS_Total, which represents the total variance in the data.

$$SS_{Total} = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - M_{Total})^2 \text{ ----------(16)}$$

where,

M_{Total} = Overall mean of the data

k = no. of groups

n_i = group 1 observations

x_{ij}= each and every observations in group 1

The falsity degree $F_A(x)$ adjusts the total variance based on measurement error.

$$\text{Adjusted } SS_{Total} = F_A(x).SS_{Total} \text{ ----------(17)}$$

The indeterminacy degree $I_A(x)$ adjusts the total variance based on uncertainty.

$$\text{Adjusted } SS_{Total} = I_A(x).SS_{Total} \text{ ----------(18)}$$

Now combining the adjustments, the neutrosophic effect size between three groups becomes,

$$\eta^2_{(neutro)} = (T_A(x).\ SS_{Between}) / ((F_A(x).\ SS_{Total}) + (I_A(x)\ .SS_{Total})) \text{ ----------(19)}$$

The above formula adjusts the effect size for the truth, falsify and indeterminacy.

d. Case 4: Neutrosophic effect size for single group (pre & post) test

The standard formula of Cohen's d for a single group is.

$$d=(\mu_{post}-\mu_{pre})/\sigma \text{ ----------(20)}$$

where,

μ_{pre} = the pretest mean

μ_{post} = the posttest mean

σ = the SD of the pretest and post test

Now, we consider the mean difference and population mean is $(\mu_{post}-\mu_{pre})$, then the truth degree $T_A(x)$ reflects how much we trust the observed mean difference. These adjustment scales of the mean difference are,

$$\text{Adjusted mean difference} = T_A(x) . (\mu_{post}-\mu_{pre}) \text{ ----------(21)}$$

The falsity degree $F_A(x)$ reflects measurement error. If the data is noisy, the standard deviation should be adjusted. So, we adjust the standard deviation.

$$\text{Adjusted SD} = F_A(x).\sigma \text{ ----------(22)}$$

The indeterminacy degree $I_A(x)$ reflects uncertainty in the measurement. Thus, we scale the SD with $I_A(x)$

$$\text{Adjusted SD} = I_A(x).\sigma \text{ ----------(23)}$$

Now combining the adjustments, the neutrosophic Cohen's 'd' becomes,

$$d_{(neutro)}=(T_A(x). (\mu_{post}-\mu_{pre})) / ((F_A(x).\sigma)+(I_A(x) .\sigma)) \text{ ----------(24)}$$

The above formula adjusts the effect size for the truth, falsify and indeterminacy.

e. Case 5: Neutrosophic effect size for difference between two groups pre and posttest:

The standard formula for two groups of effect size is

$$d_{(neutro)} = ((\mu_{post1}-\mu_{pre1}) - (\mu_{post2}-\mu_{pre2})) /\sigma \text{ ----------(25)}$$

where,

$(\mu_{post1}-\mu_{pre1})$ = the pre-posttest means of the sample group-1

$(\mu_{post2}-\mu_{pre2})$ = the pre-posttest means of the sample group-2

σ = the pooled SD of the groups

Now, we consider the mean difference and population mean is $(\mu_{post1}-\mu_{pre1})$ & $(\mu_{post2}-\mu_{pre2})$, then the truth degree $T_A(x)$ reflects how much we trust the mean difference of two groups pre-posttest. These adjustment scales of the mean difference are,

$$\text{Adjusted mean difference for group 1} = T_A(x). (\mu_{post1}-\mu_{pre1}) \text{ ----------(26)}$$

$$\text{Adjusted mean difference for group 2} = T_A(x) . (\mu_{post2}-\mu_{pre12}) \text{ ----------(27)}$$

The falsity degree $F_A(x)$ reflects measurement error. If the data is noisy, the pooled standard deviation should be adjusted. So, we adjust the pooled standard deviation.

$$\text{Adjusted pooled SD} = F_A(x).\sigma \text{ ----------(28)}$$

The indeterminacy degree $I_A(x)$ reflects uncertainty in the measurement. Thus, we scale the pooled SD with $I_A(x)$

$$\text{Adjusted pooled SD} = I_A(x).\sigma \text{ ----------(29)}$$

Now combining the adjustments, the neutrosophic effect size between two groups becomes,

$$d_{(neutro)} = (((T_A(x).(\mu_{post1}-\mu_{pre1})) - (T_A(x).(\mu_{post2}-\mu_{pre2})))/ ((F_A(x).\sigma)+(I_A(x).\sigma)) \text{ ----------(30)}$$

The above formula adjusts the effect size for the truth, falsify and indeterminacy.

f. Case 6: Neutrosophic effect size for difference between more than two groups pre and posttest:

The standard formula for two groups of effect size is

$$d=(\mu_{post1}-\mu_{pre1})- (\mu_{post2}-\mu_{pre2})- (\mu_{post3}-\mu_{pre3})/\sigma \text{ ----------(31)}$$

where,

$\mu_{post1}-\mu_{pre1}$ = the pre-posttest means of the sample group-1
$\mu_{post2}-\mu_{pre2}$ = the pre-posttest means of the sample group-2
$\mu_{post3}-\mu_{pre3}$ = the pre-posttest means of the sample group-3
σ = the pooled SD of the sample groups

Now, we consider the mean differences and population mean is $(\mu_{post1}-\mu_{pre1})$, $(\mu_{post2}-\mu_{pre2})$ and $(\mu_{post3}-\mu_{pre3})$ then the truth degree $T_A(x)$ reflects how much we trust the observed mean difference between more than two groups. These adjustment scales of the mean difference are,

$$\text{Adjusted mean difference for group 1} = T_A(x).(\mu_{post1}-\mu_{pre1}) \text{ ----------(32)}$$
$$\text{Adjusted mean difference for group 2} = T_A(x).(\mu_{post2}-\mu_{pre2}) \text{ ----------(33)}$$
$$\text{Adjusted mean difference for group 3} = T_A(x).(\mu_{post3}-\mu_{pre3}) \text{ ----------(34)}$$

The falsity degree $F_A(x)$ reflects measurement error. If the data is noisy, the pooled standard deviation should be adjusted. So, we adjust the pooled standard deviation.

$$\text{Adjusted pooled SD} = F_A(x).\sigma \text{ ----------(35)}$$

The indeterminacy degree $I_A(x)$ reflects uncertainty in the measurement. Thus, we scale the pooled SD with $I_A(x)$

$$\text{Adjusted pooled SD} = I_A(x).\sigma \text{ ----------(36)}$$

Now combining the adjustments, the neutrosophic effect size between two groups becomes,

$$d_{(neutro)}=(T_A(x).(\mu_{post1}-\mu_{pre1}) - T_A(x).(\mu_{post2}-\mu_{pre2}) - T_A(x).(\mu_{post3}-\mu_{pre3}) / ((F_A(x).\sigma) + (I_A(x).\sigma)) \text{ ------(37)}$$

The above formula adjusts the effect size for the truth, falsify and indeterminacy.

g. General non-centrality parameter

The power analysis formula is fundamentally the same across all methods,

$$\lambda = |d| \times \sqrt{n} \text{ ----------(38)}$$

$\lambda = (d_{neutro}.\sqrt{n})/2$ (For all cases except more than 2 groups) ----------(39)
$\lambda = (d_{neutro}.\sqrt{n})/\sqrt{2}$ (For more than 2 groups and more than two groups pre and posttest) -----(40)
$n = (2\lambda)/d_{neutro}$ ----------(41)

but the difference lies in the effect size calculation d_{neutro} used in the formula. Each experiment design will use a different effect size formula based on the specific method like t test, F test, correlation, etc., still the power analysis procedure is consistent once you have the effect size.

4. Comparison between conventional methods and Neutrosophic method for effect size and statistical power analysis:

This comparison explores the differences between conventional and Neutrosophic methods in effect size and statistical power analysis. While conventional methods assume precise, well-defined data, Neutrosophic methods accommodate uncertainty and inconsistency, making them suitable for complex medical datasets. We will compare both methods using the example problem given below:

The problem involves comparing the blood pressure reduction between two groups: the Treatment Group (Group 1) with data values 15, 12, 14, 16, 13, 18, 17, 19, 20, 15 and the Control Group (Group 2) with data values 10, 8, 9, 7, 12, 6, 8, 9, 6, 8. The analysis aims to assess the difference in blood pressure reduction using conventional statistical methods (mean, standard deviation, Cohen's d) and neutrosophic statistical methods, accounting for uncertainty in the data.

In this section, we compare the results obtained from conventional statistical methods with those derived from neutrosophic methods. Using the example of comparing blood pressure reduction between two groups (Treatment vs. Control), classical statistical methods (e.g., Cohen's d) yield an effect size of 3.00, indicating a large effect. Additionally, the conventional power analysis for this dataset shows a power of approximately 99%, suggesting an extremely high probability of detecting a true effect under the assumption of well-defined data. These results are consistent with the typical analysis of clinical studies with precise data.

However, when we apply neutrosophic methods, the effect size calculated is significantly higher at 13.46, reflecting the added complexity introduced by uncertainty in the data. Neutrosophic methods account for truth, falsity, and indeterminacy, which are critical when dealing with uncertain or imprecise clinical data. Furthermore, power analysis with neutrosophic methods results in 100% power, meaning there is a near-perfect ability to detect a true effect. This higher power reflects the robustness of neutrosophic methods in handling uncertainty. In conclusion, while classical methods perform well with precise data, neutrosophic methods provide a more reliable and accurate analysis for clinical studies involving uncertain or ambiguous data. The comparative results highlight the advantages of neutrosophic methods in real-world applications where data variability is common.

The goal is to determine the effectiveness of the treatment and evaluate statistical power.

a. Effect Size:

1. Conventional statistical methods:

The above dataset shows that the average blood pressure reduction is 15.9 mm Hg for the treatment group, 8.5 mm Hg for the control group, and a pooled standard deviation of 2.47, which combines the variability of both groups. Using equation (8), the conventional Cohen's d value is calculated and is 3.00, indicating a large effect size. This shows a significant difference in blood pressure reduction between the groups.

2. Neutrosophic effect size:

This approach considers the data's truth, falsity, and indeterminacy, making it more robust to uncertainty. This method is calculated using the equation (12). The values $T_A(x) = 0.9$, $F_A(x) = 0.05$, and $I_A(x) = 0.05$ are assumptions made by the researcher to model the uncertainty in the data, reflecting the degrees of truth, falsity, and indeterminacy. These values are subjective and can vary

depending on the analysis context. Based on the above equation and mean and SD values, the neutrosophic effect size is calculated, and the answer is 13.46. This result shows that the neutrosophic effect size for one participant is 13.46. This value reflects the additional complexity of the uncertainty in the data. The average neutrosophic effect size would be significantly higher for the entire group.

b. Power Analysis

1. Conventional Statistical Power Analysis

In this case, Cohen's d= 3.00 & n=10 influences the test's power. Power refers to the probability of correctly rejecting the null hypothesis if one exists. To estimate the power of the test, the non-centrality parameter (λ) is calculated (17). The effect size (Cohen's d), and n is the sample size per group. Using the values of d and n above, the non-centrality parameter is 9.49 using equation (38).

Once the non-centrality parameter is calculated, it is used to determine the power of the test (18). We refer to a non-central t-distribution table or use statistical software to do this. For this analysis, the degrees of freedom (df) are 18, calculated by $df=n_1+n_2-2=18$. With $\lambda=9.49$ and df = 18, looking up the values in a statistical table or using software reveals that the power of the test is approximately 99%. This result means there is a 99% possibility of appropriately identifying an actual difference between the groups if it happens. With such a high power, the test can identify a real effect, reducing the risk of a Type II error (failing to detect a true effect). Hence, the power analysis indicates the observed variance in the blood pressure reduced in each group is of statistical significance and consistent.

2. Neutrosophic Statistical Power Analysis

In this case, the effect size, measured by the Neutrosophic Effect Size d_{neutro}, was calculated to be 13.46 for one participant, with a sample size of 10 per group. This effect size is significantly larger than the conventional Cohen's d, reflecting the additional complexity introduced by uncertainty factors such as truth (T), falsity (F), and indeterminacy (I). Power refers to the probability of correctly rejecting the null hypothesis if there is an actual effect. To estimate the power of the test, the non-centrality parameter λ is calculated. Using the values of d_{neutro} and n above, the non-centrality parameter is calculated as 21.35 using the equation (39).

Once the non-centrality parameter is calculated, it is used to determine the power of the test. We refer to a non-central t-distribution table or use statistical software to do this. For this analysis, the degrees of freedom (df) are 18, calculated as $df = 2n - 2$, where n=10. With $\lambda = 21.35$ and df=18, using statistical software or a non-central t-distribution table reveals that the power of the test is approximately 100%. This result means there is a 100% chance of correctly detecting a true difference between the Treatment and Control groups if one exists. With such a high power, the test can identify a real effect, minimizing the risk of a Type II error (failing to detect a true effect). Therefore, this Neutrosophic power analysis suggests that the difference in blood pressure reduction between the groups is statistically significant and highly dependable, even considering uncertain factors.

The above example shows that the conventional method is highly effective for precise data. Still, if uncertainty is present, the neutrosophic method provides a more complete and nuanced understanding of the effect size and power.

5. Practical Application

Statistical power analysis and effect size was calculated based on the dataset from Prabu Raja et al. (2023) (19). for both conventional and neutrosophic methods. The study examined the impact of fascial manipulation (FM) and sequential yoga poses (SYP) on pain, function, and fear-avoidance

behavior in individuals with mechanical neck pain, showing significant improvements in the intervention and control group. Based on the real-world data uncertainties are evaluated and the results are presented below:

a. Pain (NPRS):

For conventional power analysis, using Cohen's d = 1.00 (absolute value), and assuming a sample size of 30 per group, the non-centrality parameter (λ) is calculated using the above equation and the value is 2.74 with degrees of freedom (df) = 58 (for two groups of 30 participants), the power of the test (using non-central t-distribution) is approximately 99%, meaning there is a 99% chance of detecting a true difference in pain levels of groups.

For neutrosophic power analysis, using the Neutrosophic Effect Size of 6.67 and the same sample size (n = 30), the non-centrality parameter is 18.23 with df = 58, this results in a power close to 100%, indicating near-perfect certainty that the difference between the groups in pain reduction is reliable, even after considering uncertainty factors.

b. Range of Motion (EEROM):

For conventional effects and power analysis, using Range of Motion (EEROM), the conventional Cohen's d is 1.00, indicating a significant positive effect. For conventional power analysis, with Cohen's d = 1.00, the non-centrality parameter (λ) is 2.74 with df = 58, the power is approximately 99%, suggesting a high probability of detecting a true difference in range of motion of groups.

For neutrosophic power analysis, using the Neutrosophic Effect Size of 45.0, the non-centrality parameter is 123.25. This leads to an almost perfect power of 100%, indicating an extremely high probability that the difference in range of motion between the groups is highly dependable, even after considering uncertainty.

c. Fear-Avoidance Beliefs (FABQ):

For conventional power analysis, with Cohen's d = 1.05, and a sample size of 30 per group, the non-centrality parameter (λ) is 2.87 with df = 58, the power is approximately 99%, indicating a very high probability of detecting the true effect of the intervention on fear-avoidance beliefs.

For neutrosophic power analysis, using the Neutrosophic Effect Size of 9.00, the non-centrality parameter is 24.75. This results in a power of approximately 100%, indicating that the difference in fear-avoidance beliefs of groups is highly dependable, even considering uncertainty.

Outcome Variable	Traditional Effect Size	Non-centrality Parameter (λ)	Degrees of Freedom (df)	Power of Test	Neutrosophic Effect Size	Non-centrality Parameter (λ)	Power of Test (Neutrosophic)	Difference in Effect Size (Traditional vs Neutrosophic)
NPRS	1.00	2.74	58.00	0.99	6.67	18.23	1.00	5.67
EEROM	1.00	2.74	58.00	0.99	45.00	123.25	1.00	44.00
FABQ	1.05	2.87	58.00	0.99	9.00	24.75	1.00	7.95
PSFS	1.50	4.10	58.00	0.99	99.00	271.46	1.00	97.50

d. Patient-Specific Function (PSFS):

For conventional power analysis, with Cohen's d = 1.50, and a sample size of 30 per group, the non-centrality parameter (λ) is 4.10 with df = 58, the power is approximately 99%, indicating a high probability of detecting a true difference in function between the groups.

For neutrosophic power analysis, using the Neutrosophic Effect Size of 99.00, the non-centrality parameter is 271.46. This results in a power close to 100%, indicating almost complete certainty that the intervention significantly affected patient-specific function, even when uncertainty is accounted for.

Through the conventional statistical approach, significant and large effects were observed for all four variables, with high power (around 99%), indicating the ability to detect true effects reliably. Larger effect size is identified from the neutrosophic statistical approach for all measures, suggesting that this approach offers a more comprehensive understanding in real-world scenarios.

6. Discussion

The classical approach relies heavily on the assumption that the data is precise and free from ambiguity. This approach is effective when data is well-controlled, and measurements are accurate. However, in the real-world, data often includes factors like human error, imprecision in measurement instruments, or participant variability that classical methods do not capture easily. Methods such as Cohen's d are commonly employed across various medical disciplines, including psychology (20), neuro (21), and other fields (22). Additionally, traditional power analysis techniques are widely used and well-understood (23). They clearly interpret statistical significance and effect sizes, making them suitable for studies with precise data. They are particularly valuable in experimental designs where uncertainty is minimal or controlled.

The neutrosophic approach, in contrast, offers a more flexible framework for managing these uncertainties. By incorporating indeterminate, uncertain, or incomplete data, neutrosophic methods provide a more holistic understanding of the true effect size and the power of the test. This is particularly valuable in medical fields where variability in patient responses and measurement instruments is common (24). Thus, this provides an additional layer of insight, reflecting the complexity of real-world data. By accounting for uncertainty, neutrosophic methods can provide a more nuanced and comprehensive interpretation of the data, improving the understanding of treatment effects in clinical settings.

In summary, while the traditional methods offer precise and statistically significant results, the neutrosophic methods provide a deeper and more flexible understanding of the data. The significant difference in effect sizes and power between the two methods highlights the importance of considering data uncertainty (25). Traditional methods work best in controlled environments with precise data. In contrast, neutrosophic methods excel in scenarios where uncertainty and variability are inherent, offering a more complete understanding of the effect size and statistical power. This comparison suggests that the neutrosophic approach is especially valuable when working with real-world, imprecise data, while traditional methods continue to be the standard for well-defined datasets.

7. Conclusion:

The current study is significant in the clinical data because it highlights the significance of combining conventional approaches with neutrosophic analysis to address inconsistencies in complicated clinical data. The evaluation with conventional and neutrosophic methods for effect size

and statistical power analysis indicates that conventional approaches work effectively using accurate datasets. Still, neutrosophic methods gives a more reliable strategy by considering uncertainties, leading to a deeper comprehension of the effects of treatment in real-life situations. Future studies might investigate the combination of neutrosophic approaches in many clinical scenarios, especially when data is uncertain or complicated, while comparing it with more advanced techniques in statistics. The research's most significant limitation is that it depends on a single data set, which can fail to reflect the variation of different populations or situations. Also, inaccurate variables applied to the neutrosophic analysis, which include degrees of truth, falsehood, and indeterminacy, may add bias and change the findings' generalization. Further investigations using more extensive and more diversified datasets is needed to confirm the use of neutrosophic approaches in clinical trials.

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