Study of the Effectiveness of Hypopressive Abdominal Training as Physiotherapeutic Treatment in Lumbosciatica in Adults Using Neutrosophic Statistics

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Abstract

This work was developed at the Dr. Publio Escobar Gómez Hospital in Ecuador. The objective is to reduce pain and tone the abdominal and back muscles in adults with lumbosciatica through the application of hypopressive abdominal training to help reintroduce the adult to their work and social activities. We worked with a population of 25 male and female adult patients, with an age range from 30 to 50 years old. To process the collected data, we determined that classical statistics are too restrictive in terms of the hypotheses to fulfill. For example, the initial evaluation employing the Visual Analogue Scale (VAS) that assesses the intensity of pain is subjective and depends on the pain threshold of each patient, moreover, the size of the population is not large (<30), therefore it is not possible to carry out a study with the rigor required by classical statistics to infer. That is why we have decided to use neutrosophic statistics to process the data, which will consist of pain scales in the form of intervals, which will contain indeterminacy. The statistical test selected was the T-test for paired samples. In addition to the fact that neutrosophic statistics admit the principles of De Finetti's subjective probabilities and the statistics derived from it, where objective evidence through a random sample is not needed to reach valid conclusions.

Keywords: Lumbosciatic pain; Hypopressive abdominal training; Neutrosophic Statistics; Subjective probability; T-test.

1. Introduction

Low back pain is the pathology most diagnosed by health professionals worldwide. This manifests itself at any age and gender and considerably influences public health since it is the main cause of work absenteeism due to its high prevalence.

Lumbosciatic pain, according to the World Health Organization (WHO), defines it as lower back pain, it is a constant pain in the anatomical area of the back, causing deep levels of discomfort and disability. These discomforts are common worldwide; it is a social and labor problem that affects the working adult population.

Hypopressive techniques were originally designated diaphragmatic suction techniques. The pioneer of them was the physiotherapist Marcel Caufriez, who began to develop it in the year 1980 in the urogynecological area and for toning the abdominal muscles in women after childbirth. It is a safe technique that does not cause any discomfort and pain, the patient can perform the exercises at any time without interrupting daily activities.

Doi: https://doi.org/10.54216/IJNS.210405
Received: February 05, 2023 Revised: May 09, 2023 Accepted: July 11, 2023

The objective of this article is to measure the effectiveness of applying hypopressive abdominal training to reduce pain and tone the abdominal and back muscles in adults with lumbosciatica who attend the Dr. Publio Escobar Gómez Hospital.

To this end, there was a population size that is not high. On the other hand, we have the drawback that the pain scale depends on the pain threshold of each individual and it is, therefore, a subjective index. A painful stimulus of the same intensity can be very painful for some individuals and not very painful for others. That is why we determined that a pain measurement scale based on numerical values is not accurate enough and we prefer to use values in the form of intervals.

In addition, because the sample size is not large, data processing with the help of classical statistics presents limitations, since it is mainly based on a frequentist and objective vision for data analysis and it needs to have a large sample size. This is how we determined that the fundamentals of Neutrosophic Statistics are more adequate to solve this problem. Neutrosophic Statistics generalizes the methods of classical statistics for the case in which the data is given in the form of intervals and not numerical values [1].

Neutrosophic Statistics is also based on less rigid principles than classical statistics, since it is based on neutrosophic logic, and therefore it can be considered that it generalizes Bruno de Finetti's theory of subjective probabilities, since the results obtained from it take into account the indeterminacy of knowledge, which is mostly incomplete, and where the measurements are indeterminate [2].

We affirm that Neutrosophic Statistics not only contains the principles of subjective probabilities but also generalizes it, because in the neutrosophic context, there are no restrictions as in Finetti's Theory, since here the sum of the probabilities of mutually exclusive events and exhaustive, not only is less than or equal to 1, this sum also admits a value greater than unity because it means that there is a contradiction in the way of measuring the probabilities, such that we should be dealt with it instead of avoid it, according to the perspective of the neutrosophy. Neutrosophic Statistics has been applied in many fields as can be read in [1, 3-10].

In other words, to achieve greater accuracy and to deal with a "fairly large" sample size, we worked with a pain threshold reported by the patients on an interval-shaped scale, instead of the traditional numerical scale. The effectiveness of the treatment was determined with the help of the T test for paired samples, where the data are given as intervals. This makes it possible to better deal with the indeterminacy given by the subjectivity produced by the pain threshold.

This paper is divided into the following sections; Section 2 is dedicated to explaining the basic notions of the theories that are applied, mainly Neutrosophic Statistics and subjective probabilities. Section 3 contains the results of the statistical study of patients diagnosed with lumbosciatica. The last section contains the conclusions of the investigation.

2. Related work

A. Notions on Neutrosophic Statistics

Neutrosophic statistics refers to a set of data, such that the data or a part of it is indeterminate to some degree, and to the methods used to analyze these data [1].

In classical statistics all data is determined; this is the distinction between neutrosophic statistics and classical statistics. In many cases, when the indeterminacy is zero, the neutrosophic statistics coincide with the classical statistics. Neutrosophic measurement can be used to measure indeterminate data. *Neutrosophic statistical methods* will allow us to interpret and organize neutrosophic data (data that may have some indeterminacies) to reveal underlying patterns. Many approaches can be used in neutrosophic statistics.

In *neutrosophic probability*, indeterminacy is different from randomness. While classical statistics is concerned solely with randomness, neutrosophic statistics is concerned with both randomness and especially indeterminacy.

Doi: https://doi.org/10.54216/IJNS.210405
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Neutrosophic descriptive statistics consists of all the techniques for summarizing and describing the characteristics of neutrosophic numerical data. Since neutrosophic numerical data contain indeterminacies, *neutrosophic line plots*, and *neutrosophic histograms* are plotted in 3D space, rather than 2D space as in classical statistics. The third dimension, in addition to the Cartesian XOY system, is that of indeterminacy (I). From unclear graphical data, we can extract (unclear) neutrosophic information.

Neutrosophic inferential statistics consists of methods that allow the generalization of a neutrosophic sampling to a population from which the sample was drawn.

Neutrosophic data are data containing some indeterminacy. In a similar way to classical statistics, it can be classified as:

- *Discrete neutrosophic data*, if the values are isolated points; for example $6 + I_1$, where $I_1 \in [0,1]$,7, $26 + I_2$, where $I_2 \in [3,5]$;

- and *Continuous neutrosophic data*, if the values form one or more intervals, for example: [0, 0.8] or [0.1, 1.0] (i.e., not sure which).

Other classification:

- *Quantitative* (*numerical*) *neutrosophic data*;

For example a number in the interval [2, 5] (we don't know exactly), or; 47, 52, 67, or 69 (we don't know exactly);

- and *Qualitative* (*categorical*) *neutrosophic data*; for example: blue or red (we don't know exactly), white, black or green or yellow (we don't know exactly). Also, we can have:

- *Univariate neutrosophic data*, that is, neutrosophic data consisting of observations on a single neutrosophic attribute;

- and *Multivariate neutrosophic data*, that is neutrosophic data consisting of observations on two or more attributes. In particular cases, we mention *bivariate neutrosophic data* and *trivariate neutrosophic data*.

A *neutrosophic statistical number* N has the following form:

$N = a + bI$, where a is the determinate (sure) part of N, and b is the indeterminate (unsure) part of N.

The arithmetic operations between these numbers are summarized below:

Given $N_1 = a_1 + b_1 I$ and $N_2 = a_2 + b_2 I$ two neutrosophic numbers, some operations between them are defined as follows, [1, 11]:

- $N_1 + N_2 = a_1 + a_2 + (b_1 + b_2)I$ (Addition);
- $N_1 - N_2 = a_1 - a_2 + (b_1 - b_2)I$ (Difference),
- $N_1 \times N_2 = a_1 a_2 + (a_1 b_2 + b_1 a_2 + b_1 b_2)I$ (Product),
- $\frac{N_1}{N_2} = \frac{a_1 + b_1 I}{a_2 + b_2 I} = \frac{a_1}{a_2} + \frac{a_2 b_1 - a_1 b_2}{a_2(a_2 + b_2)} I$ (Division).

For example, $a = 5 + I$, where $I \in [0, 0.4]$, is equivalent to $a \in [5, 5.4]$, so safely $a \geq 5$ (meaning that the determinate part of a is 5), while the indeterminate part $i \in [0, 0.4]$ means the possibility that the number a is slightly greater than 5. For example, if we have the following neutrosophic data: $6 + I_1$, with $I_1 \in (0, 0.2)$; $7 + I_2$ with $I_2 \in [2,3]$; $6 + I_3$, with $I_3 \in [0,1]$; $9 + I_4$, with $I_4 \in [1.1, 1.5)$; $9 + I_1$.

A *neutrosophic sample* is a chosen subset of a population, a subset that contains some indeterminacy: either concerning several of its individuals (who may not belong to the population we are studying or may only partially belong to it) or for the subset as a whole.

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While classical samples provide precise information, neutrosophic samples provide vague or incomplete information. By abuse of language, it can be said that any sample is a neutrosophic sample since it can be considered that its indetermination is equal to zero.

Neutrosophic survey results are survey results containing some indeterminacy. A *neutrosophic population* is a population not well determined at the membership level (i.e., it is not sure whether some individuals do or do not belong to the population). For example, as in the neutrosophic set, a generic element x belongs to the neutrosophic population M as follows, $x(t,i,f) \in M$ which means: x is t% in the population M, f% of x is not in the population M, while i% membership of x in M is indeterminate (unknown, unclear, neutral: neither in the population nor outside).

A *simple random neutrosophic sample* of size N from a classical or neutrosophic population is a sample of N individuals such that at least one of them has some indeterminacy.

A *neutrosophic normal distribution* of a continuous variable X is a classical normal distribution of x, but such that its mean μ or its standard deviation σ (or variance σ^2), or both, are imprecise. For example, μ, or σ or both can be set to two or more elements. The most common distributions are when μ, σ, or both are intervals.

The formula for the *neutrosophic frequency function* is the same, except that it is replaced μ_N by μ and σ_N by σ:

$X_N \sim N_N(\mu_N, \sigma_N^2) = \frac{1}{\sigma_N\sqrt{2\pi}} \exp(-\frac{(x-\mu_N)^2}{2\sigma_N^2})$, where X_N means that the variable X can be neutrosophic (i.e., have some indeterminacy), and similarly $N_N(\cdot,\cdot)$ means that the normal distribution $N(\cdot,\cdot)$ can be neutrosophic (i.e., have some indeterminacy). Instead of one bell-shaped curve, we can have two or more bell-shaped curves that have common and unusual regions between them and lie above the x-axis. Each of them is symmetric about the vertical line through the mean ($x = \mu$).

As a first neutrosophic example of the normal distribution, consider a normal distribution with $\mu = 15$ and $\sigma = [2, 3]$. Therefore, the standard deviation is indeterminate.

“Within one standard deviation of the mean” is translated in this first example as $\mu \pm \sigma = 15 \pm [2,3] = [15-3, 15+3] = [12,18]$, or about 68% of the values are in $x \in [12,18]$.

“Within two standard deviations of the mean” translates to $\mu \pm 2\sigma = 15 \pm 2 \cdot [2,3] = 15 \pm [4,6] = [15-6, 15+6] = [9,21]$, or approximately 95.4% of the values lie in $x \in [9,21]$. We could also calculate the last interval as: $[12,18] \pm \sigma = [12,18] \pm [2,3] = [12-3, 18+3] = [9,21]$.

Similar to classical statistics, a *neutrosophic null hypothesis*, denoted by NH_0, is the statement initially assumed to be true. While the *alternative neutrosophic hypothesis*, denoted by NH_a, is the other hypothesis.

When carrying out a test of NH_0 versus NH_a there are two possible conclusions: to reject NH_0 (if the sample evidence strongly suggests that NH_0 is false) or do not reject NH_0 (if the sample does not support evidence against NH_0).

Examples:

$NH_0: \mu \in [90,100]$ $NH_a: \mu < 90$,

$NH_a: \mu > 100$ $NH_a: \mu \notin [90,100]$, where μ represents the classic average IQ of all children born since January 1, 2001.

B. Some notes on subjective probabilities

Bruno de Finetti was one of the founders of the theory of subjective probabilities [2, 12]. In this theory, the frequentist principle of probability is violated, where it is necessary to carry out a random experiment from a sample large enough to guarantee the objectivity of the results. De Finetti broke with this tradition and established that a probability theory could be built where a person is the one who establishes the probabilistic values according to his/her experience.

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However, the only restriction that is imposed in this theory is that the sum of the probabilities of pair-wise mutually exclusive events is always less than or equal to 1, this is the so-called Principle of Coherence. This avoids in decision theory a decision made where there will always be a loss, as is the case with the Dutch Book.

The authors of this article consider this theory important because it makes more flexible the quite strong conditions of the different tests used in classical statistics. This is following Neutrosophy, which takes into account knowledge in all its variants, including paradoxical and irrational ones. That is why we consider that in the light of neutrosophy, there should be no restriction for the sum of probabilities of mutually exclusive events, since a sum greater than 1 means that there is a contradiction in the probability measurements, which is possible in the field of knowledge.

3. The statistical study

Of the total of 25 patients in the study that make up the population, 48% correspond to the ages between 40 and 45 years, which is the most frequent age range in suffering low back pain.

Table 1: Age of the patients to whom the treatment was applied. Source: Data obtained from the Basic Hospital Dr. Publio Escobar Gómez

AGE	FREQUENCY	PERCENTAGE
30-35	3	12%
36-40	5	20%
41-45	12	48%
46-50	5	20%
TOTAL	25	100%

Table 2: Gender of the patients to whom the treatment was applied. Source: Data obtained from the Basic Hospital Dr. Publio Escobar Gómez

GENDER	FREQUENCY	PERCENTAGE
FEMALE	16	64%
MALE	9	36%
TOTAL	25	100%

Of the total number of patients, 64% correspond to the female gender, it is the most prevalent gender in suffering low back pain since women have had several pregnancies, and are dedicated to agriculture, livestock, and housework.

Table 3: Summary of the pain evaluation of the patients to whom the treatment was applied. Source: Data obtained from the Basic Hospital Dr. Publio Escobar Gómez

FINAL VAS SCALE	FREQUENCY	PERCENTAGE
MILD PAIN LESS THAN 3	21	84%
MODERATE PAIN BETWEEN 4 and 7	4	16%

Doi: https://doi.org/10.54216/IJNS.210405
Received: February 05, 2023 Revised: May 09, 2023 Accepted: July 11, 2023

SEVERE PAIN HIGHER THAN 8	0	0%
TOTAL	25	100%

According to Table 3, in the majority of patients, after the application of hypopressive exercises, an improvement in their quality of life was noted. These patients achieved good results due to their perseverance and discipline when performing the exercises, demonstrating that hypopressive abdominal training acts as a physiotherapeutic treatment.

The previous result is limited since it is based on classical statistics, which is very restrictive. That is why it can only be inferred about the progress of the population that was studied, which is not a large number of individuals. However, when Neutrosophic Statistics is introduced, more general results can be inferred, as we will do below.

Now on, we will apply the following scheme of research:

1. To fuzzify the data and to convert the data from crisp to interval-valued. So, we will count with a pair of interval-valued data (for both, before and after to achieve the treatment).
2. To prove the normality of the two sample data, before and after the treatment by using the Kolmogorov-Smirnov test.
3. To carry out the T-test for the paired interval-valued data.
4. Additionally, we asked three experts for their opinions about the effectiveness of the treatment, by using the principles of subjective probabilities. This step is only made to confirm our results with neutrosophic statistics.

The first measurement that can be generalized is the VAS, such that it is considered an interval instead of a numerical value. This makes it possible to take into account the error that is made in the assessment of pain by the patient. It is known that the same painful stimulus, for example being pricked by a needle, is perceived differently by two individuals, which depends on the pain threshold of each of them. That is why we will generalize the numerical data by the interval whose lower limit is one degree less on the pain scale if it does not exceed the established range, while the upper limit will be one degree higher than the numerical value if it is not exceeded the established range. That is, a numeric value 8 is substituted by $[7, 9]$, 10 is substituted by $[9, 10]$ and 0 is substituted by $[0, 1]$. Let us recall that a Visual Analogue Scale (VAS) for pain goes from the value 0 of no pain to the value 10 of maximum pain.

So, the scale of discrete values between 0 and 10 is replaced by a continuous interval of values $I \subset [0, 10]$. Thus, we fuzzified the results in the manner of fuzzy random number theory [13], where we defined a triangular membership function with the following equation:

$$\mu_m(x) = \begin{cases} \min(1, 0.5x + (1 - 0.5m)), if\ x \in [0, m] \\ \max(0, -0.5x + (1 + 0.5m)), if\ x \in [m, 10] \\ 0, otherwise \end{cases} \quad (1)$$

In this case, for a VAS value equal to m, it is fuzzified as $\mu_m(m) = 1$ and $\mu_m(m - 1) = \mu_m(m + 1) = 0.5$, as long as m-1 and m+1 remain in the interval $[0, 10]$.

Otherwise, when one of the two cases holds, either m=0 or m=10, the following membership functions are defined:

$$\mu_0(x) = \begin{cases} 1 - 0.5x, if\ x \leq 2 \\ 0, otherwise \end{cases} \quad (2)$$

$$\mu_{10}(x) = \begin{cases} 0.5x - 4, if\ x \geq 8 \\ 0, \text{otherwise} \end{cases} \quad (3)$$

See Figure 1 for the graphical representation of the functions $\mu_0(x)$, $\mu_5(x)$, and $\mu_{10}(x)$.

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Received: February 05, 2023 Revised: May 09, 2023 Accepted: July 11, 2023

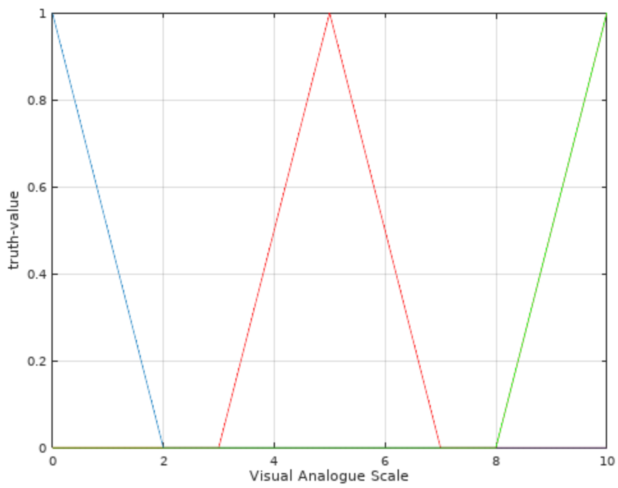

Figure 1: Graphical representation of $\mu_0(x)$(in blue), $\mu_5(x)$(in red), and $\mu_{10}(x)$(in green)

Let us note that from these functions we will take the closures of their 0.5-cuts within the interval $[0, 10]$, as the statistical data. Specifically, we will apply the T-test of paired samples on the data in the form of intervals before and after the treatment. This test is used in cases like this one we are studying, to measure the effectiveness of a treatment. Although it was verified that there was an improvement in the patients in the majority of the cases, it was not inferred that this improvement is significant as a general study for future cases. If the 25 patients are taken as the sample to infer the result of the treatment in future patients, the results are paired in the form of an interval before and after the treatment, and the T-test of paired samples is applied to them, whose statistic is shown in Equation 4 [14, 15].

$$t = \frac{\bar{X}_D - \mu_0}{S_D/\sqrt{n}} \quad (4)$$

Where:

$\bar{X}_D$: is the mean of the differences between the pairs,

S_D: is the standard deviation of the differences between the pairs,

μ_0: is the mean of the population with which we want to compare the mean of the results. We fix $\mu_0 = 0$.

That is to say, we have a set of paired interval-valued data. E.g., let us suppose the interviewed M has a VAS equal to $[4, 5]$ before the treatment and he/she has had $[2, 3]$ after the treatment, so $X_D(M) = [4, 5] - [2, 3] = [4 - 3, 5 - 2] = [1, 3]$.

Let us note that we do not use the difference $[4, 5] - [2, 3] = [4 - 2, 5 - 3] = [2, 2]$ to avoid emptiness.

Next, to calculate $\bar{X}_D$ we apply Equation 5:

Such that, given $X_D = \{[a_1, b_1], [a_2, b_2], \cdots, [a_{25}, b_{25}]\}$, then:

$$\bar{X}_D = \left[\frac{\sum_{i=1}^{25} a_i}{25}, \frac{\sum_{i=1}^{25} b_i}{25}\right] \quad (5)$$

Thus, the mean of the intervals X_D is the interval with the lower limit equal to the mean of every lower limit of the data, and its upper limit is the mean of the upper limits of the data.

The standard deviation is calculated by using Equation 6:

$$S_D = \sqrt{\frac{\sum_{i=1}^{25} (X_{Di} - \bar{X}_D)^2}{25}} \quad (6)$$

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In this formula above, the interval difference between every data and the mean is calculated and squared, later these values are summed up, the result is multiplied 1/25 times, and finally, the square root is obtained. E.g., $[1,3]^2 = [1^2, 3^2] = [1,9]$, $\left(\frac{1}{25}\right) \cdot [1,3] = \left[\frac{1}{25}, \frac{3}{25}\right]$, and $\sqrt{[1,3]} = \left[\sqrt{1}, \sqrt{3}\right] = \left[1, \sqrt{3}\right]$. Also, we substituted $\mu_0 = 0$ by $\mu_0 = [0,0]$.

First of all, we must test the normality of the data, both before and after the treatment. For this, the Kolmogorov-Smirnov test for normality can be used. This test consists of calculating the statistic in Equation 7 [3, 16]:

$$D = max_i |F_n(x_i) - F_0(x_i)| \quad (7)$$

Where:

x_i: is the ith value observed in the sample,

$F_n(x_i)$: is an estimator of the probability of observing values less than or equal to x_i,

$F_0(x_i)$: is the probability of observing values less than or equal to x_i when H_0 is true.

Specifically, $F_n(x)$ is the sampling distribution function and $F_0(x)$ is the theoretical function corresponding to the normal population specified in the null hypothesis.

To apply the Kolmogorov-Smirnov test (KM test) we were supported by the statistical package in Matlab. Then we applied the test for the lowest limit values of the data by achieving a p-lower value of the KM test, later, for the upper limit we calculated a p-upper value, so we obtained an interval-valued p-value. This algorithm was repeated twice, once for the data corresponding to before the treatment, and once for the data after the treatment.

This test resulted in a p-value equal to 0.0303749 for the sample before the treatment, while the p-value for the sample after treatment is the interval $[0.021577, 0.071020]$, therefore the null hypothesis is not rejected in any case if it is taken $\alpha = 0.1$, because, $[0.021577, 0.071020] < 0.1$.

When applying Equation 4 to the results by intervals, we have that $t = [8.5733, 9.6540]$.

Let us now take the values of the t-Student distribution with $df = 25 - 1 = 24$ degrees of freedom and $\alpha = 0.05$ which is equal to $t_{0.05,24} = 1.7109$.

From the inequality $t = [8.5733, 9.6540] > 1.7109$, it follows that in any case the null hypothesis is rejected such that $H_0: \mu_0 = [0,0]$. That is, the improvement of the patients is always significant.

See in Figure 2 the graphical representation of the membership function obtained for the statistics t.

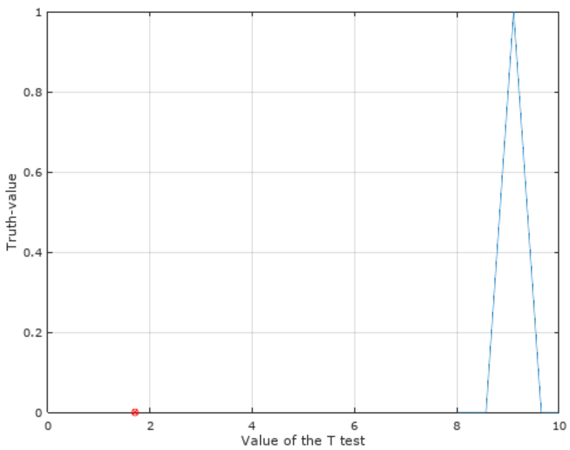

Figure 2: Graphical representation of the fuzzified interval obtained for the statistic t (Equation 4) in the T-test.

Doi: https://doi.org/10.54216/IJNS.210405
Received: February 05, 2023 Revised: May 09, 2023 Accepted: July 11, 2023

In Figure 2 we have represented in blue line the triangular membership function of the statistic t and the red point is the theoretical value of the t-Student distribution. Let us note that the point is smaller than any point in the membership function with a nonzero truth value.

Finally, new knowledge can be obtained by applying the theory of subjective probabilities, which deals with the probabilities that human beings use to evaluate the conditions of daily life, without taking into account their mathematical knowledge. In this case, we use our common sense that is tied to our unconscious. On the other hand, it is not always possible to have a completely random sample of a sufficiently large size. For this reason, three experts were asked if they had to "bet" on their belief in the probabilities of improvement of the patients after treatment, with a value from 0 to 100 in each case, in such a way that the sum of all bets is less than or equal to 100. These results are shown in Table 4. Let us note that we use the term “bet” to follow De Finetti's term used in decision-making.

Table 4: Subjective probabilities in percent associated with pain reduction after treatment according to the opinion of three specialists. Source: Data obtained from the Basic Hospital Dr. Publio Escobar Gómez

VAS PREDICTED BY THE EXPERTS	EXPERT 1	EXPERT 2	EXPERT 3
MILD PAIN LESS THAN 3	62%	67%	60%
MODERATE PAIN BETWEEN 4 and 7	32%	25%	30%
SEVERE PAIN HIGHER THAN 8	6%	8%	10%
TOTAL	100%	100%	100%

It can be inferred that, according to specialists, it can be expected $[60, 67]\%$ that patients who pass the treatment will have mild pain or no pain, the probability of ending up with moderate pain is $[25, 32]\%$, while the probability of remaining in severe pain is $[6, 10]\%$. In any case, according to these results, there is an improvement in the treatment. Let us note that the two limits of the intervals are formed by both, the minimum and maximum percent of the experts’ criteria.

The degree of indeterminacy can be calculated by Equation 8:

$$DI([a, b]) = b - a \qquad (8)$$

So, these subjective probabilities have $DI([60, 67]) = DI([25, 32]) = 7\%$, and $DI([6, 10]) = 4\%$ of accuracy. Figure 3 contains the Neutrosophic Chart Graphic of these results.

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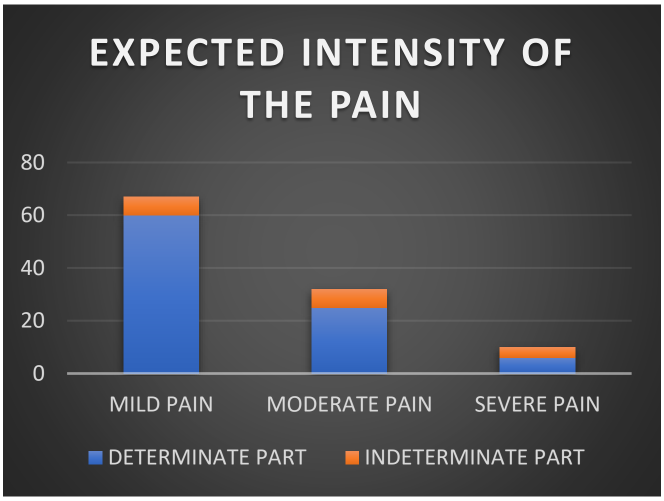

Figure 3: Graphical representation of the expected intensity of the pain after the treatment, according to the experts' subjective probabilities.

6. Conclusion

In this paper, in the first place, we proved that the Physiotherapeutic treatment of Adult Lumbociatalgia in patients of the Dr. Publio Escobar Gómez hospital in Ecuador offers considerable improvement. On the other hand, no less important, is that we benefit from the advantages of using Neutrosophic Statistics and neutrosophic theory in general to obtain more results than the processing based only on classical statistics. Some interesting approaches to this topic can be found in [17, 18]. In the example, we convert crisp values into intervals of values to apply statistical tests such as the Kolmogorov-Smirnov normality test or the T-test for paired samples. We also established how De Finetti's probability theory can be understood in the field of neutrosophy and illustrated this relationship within the case study. These techniques allowed us to generalize the results of the collected data and ensure that they are valid beyond the studied population. In future works, we will delve further into the advantages of using Neutrosophic Statistics and neutrosophy with other statistical tests.

Funding: "This research received no external funding"

Conflicts of Interest: "The authors declare no conflict of interest"

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