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Assessing Students Performance Using Neutrosophic Tool

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Abstract

Recently, a lot of educational as well as academic researchers have shown their ultimate interest in educational data mining techniques. Thus, several studies that can definitely contribute to the improvement of the educational process are conducted. The results of this lead to several issues that have to be addressed if the students general academic performances are to be improved. In this paper, we investigate the academic performance of a set of students in their core subjects. This we did by using the concept of the neutrosophic frequency, as well as the neutrosophic relative frequency distribution for the class of scores for the set of students. The results give some form of expectation for their general performance. This case serves as a means to enhance the educational process of the chosen set of students by identifying the students at risk of failure or dropping out and predicting the students' academic level at an early stage to provide the necessary support for the at-risk students.

Keywords: Neutrosophic Statistics, Classical Statistics, Crisp Numbers, Neutrosophic Frequency, Netrosophic Relative Frequency.

1 | Introduction

In recent years, eminent and passionate researchers in the field of educational developments have indicated their ultimate interest in educational data mining techniques. Thus, several studies that can definitely contribute to the improvement of the educational process are conducted. The results of this lead to several issues that have to be addressed if the students general academic performances are to be improved. In this paper, we investigate the academic performance of a set of students in their core subjects. This we did by using the concept of the neutrosophic frequency as well as the neutrosophic relative frequency distribution for the class of scores for the set of students. The results give some form of expectation for their general performance. This exercise serves as a means to enhance the educational process of the chosen set of students by identifying the students at risk of failure or dropping out and predicting the students' academic level at an early stage to provide the necessary support for the at-risk students [10]. Studies involving the exploitation of the concepts and techniques of neutrosophic inference that rely on neutrosophic logic are very useful in evaluating the level of human resource performance in economics, institutions, and other working enterprises, such as in the field of food industries. This logic is an extension of fuzzy logic and is characterized by its

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ability to deal with indeterminate information that carries different degrees of truth, falsehood, neutrality, and uncertainty. This can be further followed by the application of computer software, which produces a neutrosophic inference system for human resource data that can be related to qualifications, experiences, skills, productivity, absence, discipline, and others. In [6] (Haitham I. A. Ward et al., 2023), data were converted into neutrosophic values using membership, comparison, and action functions. Then neutrosophic rules were used to calculate human resource performance scores in terms of truth, falsehood, neutrality, and uncertainty. The results of the study showed that the level of human resource performance in the institution was average in general. Hence, based on their results, some recommendations were presented in order to improve human resource performance in the institution, such as developing training, motivation, evaluation, and reward programs.

Education is generally regarded as a necessary and essential requirement for human development. It is central to socioeconomic and technological advancements, and it is critical to the self-generating process of positive transformation in modern society. Education is partially about primary socialization and partly about the process of imparting knowledge for progress and development, both at the individual and group levels. Education is not just about literacy and enlightenment. It is about value formation, value generation, and orientation. Having critically examined the word "study," what is the perception or attitude of students towards study? This leads us to the meaning and effect of this perception towards study. Attitude or perception, as defined by a researcher, is a mental or neural state of readiness organized through experience exerting a directive or dynamic influence upon the individual response to all subjects and situations with which it is related. In 1996, a researcher defined attitude as a kind of mental state, representing a predisposition to form an opinion. Attitude is one of the determining factors that aid the development of interest, which guides action, and the type of attitude that students have developed towards learning has been directed to a great extent by their academic performance. Thomas (1977) observed that students who have a positive perception of a subject teacher perform better than those who have a negative perception of their subject. There are also some attitudes that can affect students learning and have implications for their performance. These attitudes include students' expectations, self-concept, cultural differences, and motivation [4]. Sodipo (2015). We enjoin our readers to refer to [10]–[86] of our references.

An extension of classical statistics is modern neutrosophic statistics. In classical statistics, the data is known and formed by crisp numbers, while in neutrosophic statistics, the data may have some forms of indeterminacy. Multiple problems, such as attributes in decision-making processes, are often solved using hesitant, fuzzy linguistic information. In the case of the neutrosophic statistics, the data may not be so direct. It may seem vague, ambiguous, incomplete, imprecise, or even unknown.[2] (Florentin Smarandache, 2014). In practice. Sets (such as intervals) [1] in neutrosophic statistics are used instead of crisp numbers in classical statistics. In addition, the neutrosophic concepts are undoubtedly very applicable to a host of important statistical and mathematical ideals and concepts [5, 9].

2 | Preliminaries

Since the advent of neutrosophic statistics through the concerted efforts of Prof. Dr. Florentin Smarandache, many other significant and essential concepts have continually been developed. This includes, among others, the introduction of the Neutrosophic Descriptive Statistics (NDS), the Neutrosophic Inferential Statistics (NIS), the Neutrosophic Applied Statistics (NAS), and the Neutrosophic Statistical Quality Control (NSQC). Neutrosophic statistics is also a generalization of interval statistics. This is because while interval statistics is based on interval analysis, neutrosophic statistics is based on set analysis (meaning all kinds of sets, not only intervals). Hence, the neutrosophic statistics seem to be more elastic when compared with the classical statistics. For instance, if all the data and inference methods are determinate, then the neutrosophic statistics coincide with the classical statistics. In reality, our world possesses more indeterminate data than determinate data. Hence, there is definitely a need for more neutrosophic statistical procedures than classical ones.

3 | On Neutrosophic Statistics

In neutrosophic statistics, the data may be ambiguous, vague, imprecise, incomplete, or even unknown. Instead of crisp numbers used in classical statistics, one uses sets (that respectively approximate these crisp numbers) in neutrosophic statistics [2] (Florentin Smarandache, 2014).

Also, in neutrosophic statistics, the sample size may not be exactly known (for example, the sample size could be between 30 and 80; this may happen because, for example, the statistician is not sure about the 50 sample individuals if they belong or not to the population of interest, or because the 50 sample individuals only partially belong to the population of interest while partially they don't belong) [8].

In this example, the neutrosophic sample size is taken as an interval n = [30, 80], instead of a crisp number n = 30 (or n = 80) as in classical statistics. Neutrosophic statistics refers to a set of data, such that the data or a part of it is indeterminate in some degree, and to methods used to analyze the data (Florentin Smarandache, 2014) [2]. In classical statistics, all data are determined; this is the distinction between neutrosophic statistics and classical statistics. In many cases, when indeterminacy is zero, neutrosophic statistics coincide with classical statistics. We can use the neutrosophic measure for measuring indeterminate data. Neutrosophic data is data that contains some indeterminacy. Similarly 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, $26 + i_2$, $i_2 \in[3,5]$;

- and continuous neutrosophic data, if the values form one or more intervals, for example: [0,0.4] or [0.2 ,1.4] (i.e. not sure which one).

Another classification: - quantitative (numerical) neutrosophic data; for example: a number in the interval [2, 5] (we do not know exactly), 47, 52, 67 or 69 (we do not know exactly); - and qualitative (categorical) neutrosophic data; for example: blue or red (we don't know exactly), white, black or green or yellow (not knowing exactly (Florentin Smarandache , 2014) [2]. Also, we may have: - univariate neutrosophic data, i.e. neutro-sophic data that consists of observations on a neutrosophic single attribute; and multivariable neutrosophic data, i.e. neutrosophic data that consists of observations on two or more attributes. As a particular cases we mention the bivariate neutrosophic data, and trivariateneutrosophic data. A Neutrosopical Statistical Number N has the form: $N = d + i$, where d is the determinate (sure) part of N, and iis the indeterminate (unsure) part of N. For example, $a = 5 + i$, where $i\in$ [0, 0.4],is equivalent to $a\in$ [5, 5.4], so for sure $a \geq 5$ (meaning that the determinate part of a is 5), while the indeterminate part $i\in$ [0,0.4] means the possibility for number "a" to be a little bigger than 5. While the Classical Statistics deals with determinate data and determinate inference methods only, the Neutrosophic Statistics deals with indeterminate data, i.e. data that has some degree of indeterminacy (unclear, vague, partially unknown, contradictory, incomplete, etc.), and indeterminate inference methods that contain degrees of indeterminacy as well (for example, instead of crisparguments and values for the probability distributions, charts, diagrams, algorithms, functions etc. Neutrosophic Numbers of the form N = a+bI have been defined by W.B. Vasantha Kandasamy and F. Smarandache in 2003, and theywere interpreted as "a" is the determinate part of the number N, and "bI"as the ndeterminate. In Imprecise Probability, the probability of an event is a subset T in [0,1], not a number p in [0, 1], what's left is supposed to be the opposite, subset F (also from the unit interval [0, 1]); there is no indeterminate subset I in imprecise probability (F. Smarandache, 2013)[3] .The function that models the Neutrosophic Probability of a random variable x is called Neutrosophic distribution: NP(x) = (T(x), I(x), F(x)), where T(x) represents the probability that value x occurs, F(x) represents the probability that value x does not occur, and I(x) represents the indeterminate / unknown probability of value x. It could be deduced that the Neutrosophic idea is continuous within the interval while the crisp idea is discrete. And so, combining the cases we have as required and indicated: NP(x) = (T(x), I(x), F(x)). A true neutrosophic number contains the indeterminacy I with a non-zero coefficient. According to M. Mahmud etal (2020) [7], the generalization of the Fuzzy set and Intuitionistic Fuzzy set concept is called as neutrosophic set. This is a powerful general formal framework. The components in neutrosophic set has a degree of truth (T), indeterminacy (I) and falsity (F).The value of this components are between [0,1], respectively. A neutrosphic set has a general formal framework for analysing uncertainty in data set or undetermined information. Not only uncertainty, neutrosophic set can also analyse large information sets or big data sets as well. Single Valued Neutrosophioc sets (SVNs) was introduce to be used expediently to deal with real problems and it is appropriate in solving data mining problem and make a decision for the problem. In their paper, titled " Student engagement and attitude in mathematics achievement using single valued neutrosophic set ", Single valued neutrosophic set (SVNs) was proposed to measuring factors impact on student engagement and attitude in mathematics achievement based on Trends in International Mathematics and Science Study TIMSS 2015 for ASEAN countries. Although the neutrosophic statistics has been defined since 1996, and published in the 1998 book Neutrosophy/ Neutrosophic Probability, Set, and Logic, it has not been developed since now. A similar fate had the neutrosophic probability that, except a few sporadic articles published in the meantime, it was barely developed in the 2013 book "Introduction to Neutrosophic Measure, Neutrosophic Integral, and Neutrosophic Probability". Neutrosophic Statistics is an extension of the classical statistics,and one deals with set values instead of crisp values. Neutrosophic Statistics refers to a set of data, such that the data or a part of it are indeterminate in some degree, and to methods used to analyze the data. In Classical Statistics all data are determined; this is the distinction between neutrosophic statistics and classical statistics.

Tables 1 - 5 below show the (percentage) performance of some sets of six classes of science students in a particular high school in selected five core subjects for the sciences.

Table 1. shows the percentage performance of some sets of six classes of science students in a particular high school in the core subjects: English.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	39-62	44-61	56–64	54-60	50-63	37-73

Table 2. shows the percentage performance of some sets of six classes of science students in a particular high school in the core subjects: mathematics.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	54-66	63-67	60-72	58-67	68-76	47-94

Table 3. shows the percentage performance of some sets of six classes of science students in a particular high school in the core subjects: physics.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	34-50	44-60	53-67	62-73	44–68	37-76

Table 4. shows the percentage performance of some sets of six classes of science students in a particular high school in the core subjects: chemistry.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	52-67	48-65	45-68	46-68	40–70	36-80

Table 5. shows the percentage performance of some sets of six classes of science students in a particular high school in the core subjects: biology.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	56-68	48-72	55-67	54-76	45–70	37-92

4 | Neutrosophic Frequency Distribution

A neutrosophic frequency distribution is a table displaying the categories, frequencies, and relative frequencies with some indeterminacies. Most often, indeterminacies occur due to imprecise, incomplete, or unknown data related to frequency. As a consequence, relative frequency becomes imprecise, incomplete, or unknown too. The frequencies are not crisp numbers as in classical statistics, but between some limits. In real life, we cannot always compute or provide exact values for the statistical characteristics, but we need to approximate them. This is one way of passing from classical to neutrosophic statistics.

An example of the neutrosophic frequency distribution concerning the range of scores for five core subjects for science students in a certain high school is done subject by subject as follows using Tables 6–10:

Table 6. shows the neutrosophic frequency distribution and the neutrosophic relative frequency distribution concerning the range of scores for the science students in a certain high school in the core subject: english.

CLASSES	Neutrosophic frequency	Neutrosophic relative frequency
JSS1	[39 , 62]	[0.102, 0.221]
JSS2	[44 , 61]	[0.115, 0.218]
JSS3	[56 , 64]	[0.146, 0.229]
SS1	[54 , 60]	[0.141, 0.214]
SS2	[50 , 63]	[0.131, 0.225]
SS3	[37 , 73]	[0.097, 0.261]
TOTAL : JSS1 – SS3	[280 , 383]	[0.731, 1.368]

From here , the minimum neutrosophic frequency for the English classes of scores could be calculated as follows :

$Min_{\mathrm{nf(e)}}$ = 39 + 44 + 56 +54 +50 +37 = 280 and $Max_{\mathrm{nf(e)}}$ = 62 + 61 + 64 +60 + 63 + 73 = 383

Also, for the neutrosophic relative frequency, we have as follows:

The $Min_{\mathrm{nf(e)}}$ and $Max_{\mathrm{nf(e)}}$ [39 , 62] ÷ [280 , 383] = [0.102, 0.221]

Table 7. shows the neutrosophic frequency distribution and the neutrosophic relative frequency distribution concerning the range of scores for the science students in a certain high school in the core subject: mathematics.

CLASSES	Neutrosophic frequency	Neutrosophic relative frequency
JSS1	[54 , 66]	[0.122, 0.189]
JSS2	[63 , 67]	[0.142, 0.191]
JSS3	[60 , 72]	[0.136, 0.206]
SS1	[58 , 67]	[0.131, 0.191]
SS2	[68 , 76]	[0.154, 0.217]
SS3	[47, 94]	[0.106, 0.266]
TOTAL : JSS1 – SS3	[350 , 442]	[0.791, 1.260]

For the JSS1 class , we have the calculations as follows:

$Min_{\mathrm{nf(e)}}$ = 54 + 63 + 60 +58 +68 +47 = 350 and $Max_{\mathrm{nf(e)}}$ = 66 + 67 + 72 +67 +76 + 94 = 442

Also, for the neutrosophic relative frequency, we have as follows:

The $Min_{\mathrm{nf(e)}}$ and $Max_{\mathrm{nf(e)}}$ = [54 , 66] ÷ [350 , 442] = [0.122, 0.189]

Other calculations are thus obtained analogously and recorded in the respective cells of the tables.

In order to make our calculations easier, we quickly give the approximate total neutrosophic relative frequencies as recorded in the tables.

Table 8. shows the neutrosophic frequency distribution and the neutrosophic relative frequency distribution concerning the range of scores for the science students in a certain high school in the core subject: physics.

CLASSES	Neutrosophic frequency	Neutrosophic relative frequency
JSS1	[34 , 50]	[0.086, 0.183]
JSS2	[44 , 60]	[0.117, 0.219]
JSS3	[53 , 67]	[0.135, 0.245]
SS1	[62 , 73]	[0.157, 0.266]
SS2	[44 , 68]	[0.112, 0.248]
SS3	[37 , 76]	[0.094, 0.277]
TOTAL : JSS1 – SS3	[274 , 394]	[0.701, 1.438]

Table 9. shows the neutrosophic frequency distribution and the neutrosophic relative frequency distribution concerning the range of scores for the science students in a certain high school in the core subject: chemistry.

CLASSES	**Neutrosophic frequency**	**Neutrosophic relative frequency**
JSS1	[52 , 67]	[0.124 . 0. 251]
JSS2	[48 , 65]	[0.115 . 0.244]
JSS3	[45 , 68]	[0. 108. 0. 255]
SS1	[46 , 68]	[0.110 . 0. 255]
SS2	[40 , 70]	[0.096 . 0. 262]
SS3	[36 , 80]	[0. 086. 0. 300]
TOTAL : JSS1 – SS3	[267 , 418]	[0.639 .1.567]

Table 10. shows the neutrosophic frequency distribution and the neutrosophic relative frequency distribution concerning the range of scores for the science students in a certain high school in the core subject: biology.

CLASSES	Neutrosophic frequency	Neutrosophic relative frequency
JSS1	[56 , 68]	[0. 126 . 0. 231]
JSS2	[48 ,72]	[0. 108. 0. 244]
JSS3	[55 , 67]	[0.124 . 0. 227]
SS1	[54 , 76]	[0.121 . 0. 258]
SS2	[45 , 70]	[0. 101. 0. 237]
SS3	[37 , 92]	[0.083 . 0. 312]
TOTAL : JSS1 – SS3	[295 , 445]	[0.663 .1.509]

5 | Classical Statistical Frequency Distribution

Another idea for solving this problem would be to transform the neutrosophic data into classical data, either by taking the midpoint of each set or. In classical statistics, all data are determined; this is the distinction between neutrosophic statistics and classical statistics. While classical statistics refers to randomness only, neutrosophic statistics refers to both randomness and especially indeterminacy.

While the classical samples provide accurate information, the neutrosophic samples provide vague or incomplete information. Neutrosophic statistics is an extension of classical statistics. While in classical statistics the data is known and formed by crisp numbers, in neutrosophic statistics the data has some indeterminacy. In neutrosophic statistics, the data may be ambiguous, vague, imprecise, incomplete, or even unknown. Instead of crisp numbers used in classical statistics, one uses sets (that respectively approximate these crisp numbers) in neutrosophic statistics.

In Tables 11–15, the neutrosophic form data has been transformed into a crisp format. This is done by finding the average mean for each subject in the entire set of classes of the students under the assessment.

Table 11. shows the neutrosophic form data transformed into a crisp format for the core subject: English.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	39-62	44-61	56–64	54–60	50-63	37-73
Class average score	50.5	52.5	60.0	57.0	56.5	55.0
Total	331.5 Average = 331.5 ÷ 6 = 55.25					

Table 12. shows the neutrosophic form data transformed into a crisp format for the core subject: mathematics.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	54-66	63-67	60-72	58-67	68-76	47–94
Class average score	60	65	66	62.5	72	70.5
Total	396 Average = 396.0 ÷ 6 = 66.00					

Table 13. shows the neutrosophic form data transformed into a crisp format for the core subject: physics.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	34-50	44-60	53-67	62-73	44-68	37–76
Class average score	42	52	60	67.5	56	56.5
Total	334 Average = 334.0 ÷ 6 = 55.67					

Table 14. shows the neutrosophic form data transformed into the crisp format for the core subject: chemistry.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	52-67	48-65	45-68	46- 68	40-70	36-80
Class average score	59.5	56.5	56.5	57.0	55.0	58.0
Total	342.5 Average = 342.5 ÷ 6 = 57.10					

Table 15. shows the neutrosophic form data transformed into a crisp format for the core subject: biology.

Class	JS1	JS2	JS3	SS1	SS2	SS3
Students score range	56-68	48-72	55-67	54-76	45-70	37-92
Class average score	62.0	60.0	61.0	65.0	57.5	64.5
Total	Average = 370.0 ÷ 6 = 61.67					

6 | Analysis

If we are to judge the performances by the highest attainable score for each subject , clearly , it could easily be observed that 1.567 > 1.509 > 1.438 > 1.368 > 1.260, and accordingly, the order of performance from the highest to the lowest can be in this order Chemistry > Biology > Physics > English > Mathematics Going by the classical statistical mean average for each subject for the sets of classes, we have the level of performance represented in the following manner: Mathematics. 1 (66.00) > Biology. 2 (61.67) > Chemistry. 3 (57.10) > Physics. 4 (55.67) > English. 5 (55.25).

7 | Interpretation

From the analysis of the event, the following observations emerge: (i) The classical statistics predict that the students are good in mathematics but very weak in English. (ii). The neutrosophic statistics predict that the students are poor in mathematics but very good in chemistry. If we go by the prediction of classical statistics, one may be deceived to believe that the academic performance of this set of students is okay for their chosen career since their mathematics as a core subject is on good ground. But the prediction of the neutrosophic statistics is very much in order, at least to be on the server side. This is because if one believes that the students performance in mathematics is poor, then efforts would be put in place to improve them and give them more of what it takes to prepare them for further future examinations.

8 | Conclusion

The classical statistical analysis may be faulty and not able to supply the required information necessary for the expected demand, whereas the neutrosophic statistics help in providing what could be of advantage for necessary improvements for future expectations.

For future research, the authors are proposing the following:

(i). Taking care of the other categories of measures of central tendencies involving neutrosophic statistics is also to be considered for the assessment and evaluation of students academic performance and other spheres of performance assessment.

(ii). Putting in more of the Multi-Criteria Decision-Making (MCDM) analysis and subsequently the evolving algorithms on the subject.

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Author Contributaion

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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