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# Test for Significance of Pearson's Correlation Coefficient ($r$)

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**ABSTRACT**
This paper investigated the test of significance of Pearson's correlation coefficient. It provided an in-depth comparison of different methods of testing for the significance of Pearson's ($r$) as it is often called. The t-distribution, Fisher's z-transformation, and the Statistical Package for Social Sciences (SPSS) were employed. It was concluded that each of the methods provided good enough test for significance of correlation coefficients, which brings to rest the opposing views that the SPSS does not provide a test for significance of correlation coefficient. The SPSS was recommended ahead of the t-distribution and z-transformation due to its easy, robust, and wide applications. Researchers and academics were charged to expose their mentees to this great scientific discovery, the SPSS.
**Keywords**:

## INTRODUCTION

### Bivariate Distributionss - Correlation

Most persons are conversant with univariate distributions (single variable distributions): examples include students and their scores in English Language; or babies and their body weights at birth; or Nigeria and population growth rate; and so on. Bivariate distributions on the other hand involve two variables that can be compared to find relationships between them. Bivariate distributions deal with populations in which members are described in terms of two characteristics, say students and their scores in Mathematics and Physics.

Table 1 displays a set of bivariate data of scores of nine students in a quiz competition in Mathematics and Physics. In this set of data, each student has two scores: one for Mathematics and the other for Physics. We refer to this type of data as bivariate (two variables) as opposed to univariate data (one variable data). If more than two variables are involved, we refer to this as multivariate distribution. For instance, if we were dealing with exports in Nigeria, we might obtain data on crude oil, cotton, cocoa, cassava, man power, etc. This type of data is known as multivariate (each observation is measured in terms of many characteristics). However, the scope of this paper is bivariate distributions.

**Table 1: Students' scores in Mathematics and Physics**

| Student | Mathematics Score | Physics Score |
|---|---|---|
| A | 71 | 66 |
| B | 87 | 79 |
| C | 70 | 63 |
| D | 68 | 56 |
| E | 76 | 76 |
| F | 75 | 68 |
| G | 67 | 49 |
| H | 71 | 64 |
| J | 74 | 70 |

Correlation involves the measurement of association, or relationship, or correlation between two variables to ascertain whether they are positively or negatively related, or not related in any way whatsoever. Two variables are related if the changes in one variable affect or influence the changes in the other variable. To measure association or relationship between variables we use correlation coefficients to express the degree of association or relationship. In other words, correlation coefficients measure the strength (direction and magnitude) of association or relationship between two variables.

Correlation coefficients can be high or low (magnitude), and positive or negative (direction). Correlation coefficients vary from -1 to +1: whereas -1 and +1 indicate perfect negative and perfect positive correlation coefficients respectively, a correlation coefficient of 0 implies no correlation (zero relationship). Further, correlation coefficients lower that $\pm$0.40 (whether negative or positive 0.40) are said to be low, between $\pm$0.40 and $\pm$0.60 are moderate, and above $\pm$0.60 are high.

**Scatter Diagram or scatter plot**

It is fashionable to use the scatter diagram to isolate the correlation between two sets of bivariate data. The scatter diagram displays a set of data on the vertical axis and the other set on the horizontal axis. The values are plotted like is done with x, y coordinates in geometry.

If the values in Table 1 are plotted, we shall have the scatter plot below:

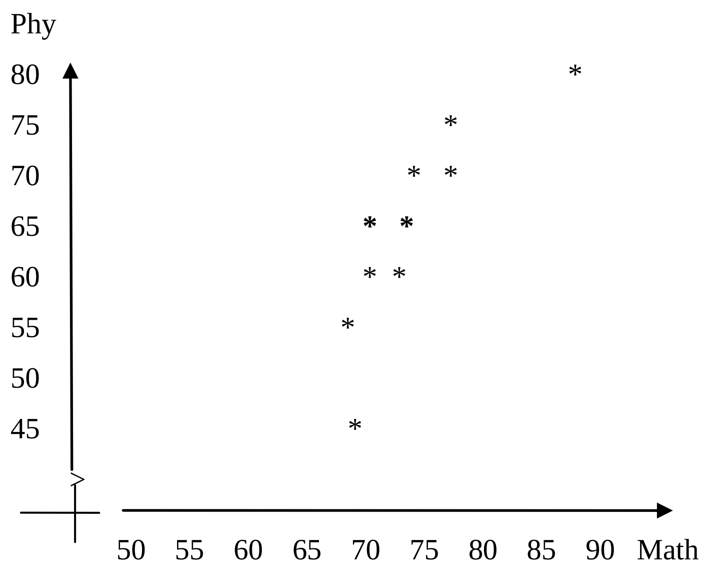


**Figure 1: Scatter diagram of Mathematics and Physics scores**

Figure 1 shows a cluster of plotted values rising from left to right indicating a direct proportional relationship between Mathematics and Physics. It shows that students who scored high marks in Mathematics most likely scored high marks in Physics and vice versa. When two variables have this type of relationship, they are said to be **positively correlated**.

Consider the following data and the associated scatter diagram:

**Table 2: Students' scores in Mathematics and History**

| Student | Mathematics Score | History Score |
|---|---|---|
| A | 42 | 79 |
| B | 60 | 65 |
| C | 58 | 75 |
| D | 80 | 50 |
| E | 54 | 85 |
| F | 73 | 63 |
| G | 84 | 52 |
| H | 50 | 68 |
| I | 81 | 47 |
| J | 70 | 53 |
| K | 59 | 59 |

In this case, the scatter diagram displays a cluster of plotted values rising from right to left indicating an indirect proportional relationship between Mathematics and History. It shows that students who scored high marks in Mathematics most likely scored low marks in History and vice versa. When two variables have this type of relationship, they are said to be **negatively correlated**.

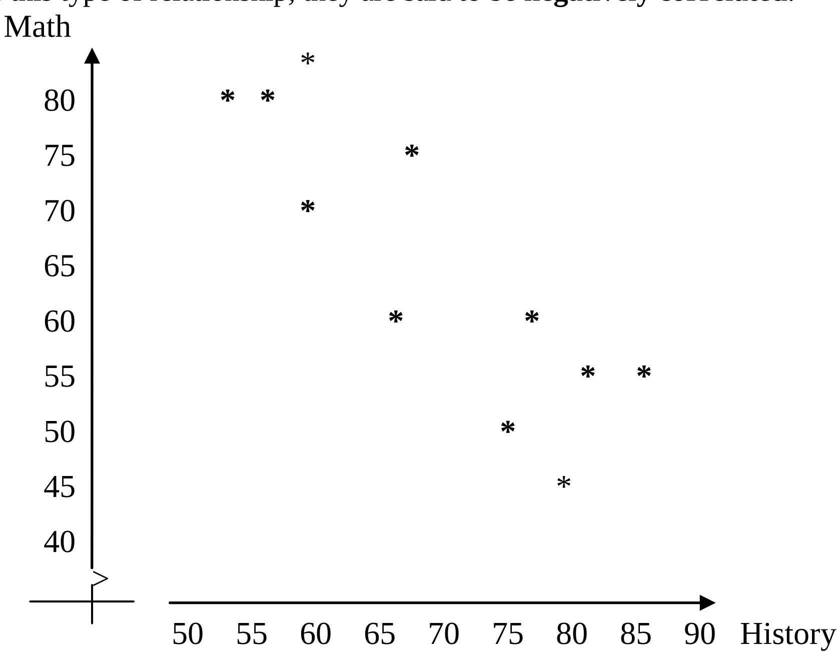


**Figure 2: Scatter diagram of Math scores and History scores**

Situations exist when the relationship between one variable and another is partly positive and partly negative. In other words, the relationship between the variables may be positive initially, and negative later. Or, it may be negative at first and later become positive. For instance, the relationship between age and physical ability of a man is positive from birth until a given time and becomes negative afterwards. When two variables have this type of relationship, they are said to have a **curve linear correlation**. The data and scatter diagram below show the cure linear relationship between the age of Peter and his ability to lift weights in kg.

**Table 3: Age and weights lifted**

| Age | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 | 55 | 60 | 65 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight ( kg) | 30 | 70 | 120 | 200 | 250 | 200 | 150 | 120 | 80 | 60 | 50 |

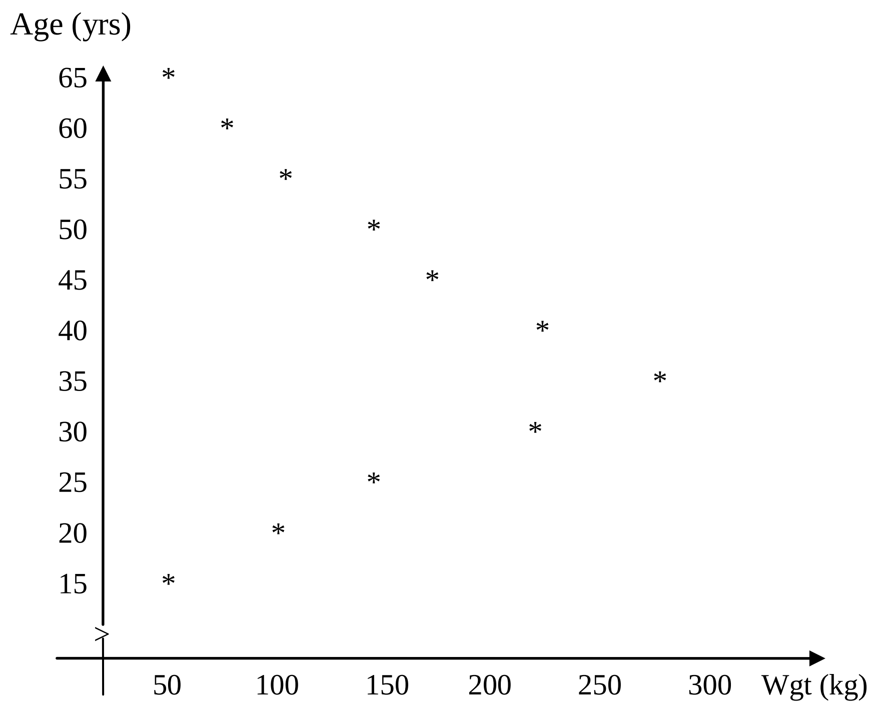


Figure 3: Scatter diagram of Peter's age and his ability to lift weights in kg

There also exist situations when the relationships are neither positive nor negative. In other words there is hardly any relationship at all. For instance, the relationship between heights of individuals and their intelligence quotient (IQ) is neither positive nor negative. Short people can have high IQ, low IQ or moderate level IQ. The same applies to tall people. Consider the frequency distribution below of heights of students (in cm) and their scores in Business Mathematics:

**Table 4: Students' heights and scores in Business Mathematics**

| Student | Height of Student (in cm) | Score in Business Math |
|---|---|---|
| A | 100 | 65 |
| B | 110 | 85 |
| C | 120 | 65 |
| D | 130 | 39 |
| E | 140 | 72 |
| F | 150 | 45 |
| G | 160 | 82 |
| H | 130 | 92 |
| I | 110 | 37 |

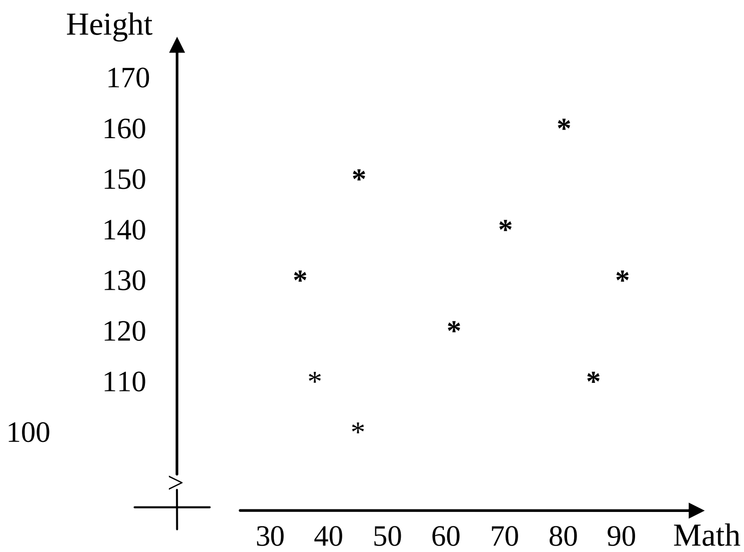


**Figure 3: Scatter Diagram of Students' Heights and Scores Math**

Figure 3 shows that there is no relationship between height of a student and his achievement in Business Mathematics. The scatter diagram shows a **zero correlation** between students' height and achievement. The plotted points almost formed a circle. This implies that both tall and short students can achieve either poorly or greatly; that height does not have anything to do with academic achievement.

There are various correlation statistics which include the Pearson's Product Moment Correlation (Pearson's r), Spearman's Rank Order Correlation [Spearma's $\rho$ (rho)], Kendall's Tau (T), Point Biserial Correlation (! b), Biserial Correlation, $\varphi$ (phi), and Tetrachoric Correlation. Pearson's r is appropriate for use when both variables represent either interval or ratio scales of measurement. Spearman's rho is appropriate when both variables represent the ordinal scale of measurement. Kendall's Tau is similar to Spearman's rho because it is suitable for use when the variables are in the form of ranks. The major difference between Kendall's tau and Spearman's rho is the former tends to be used when tied ranks. Point Biserial Correlation is appropriate when one variable is measured on the interval or ratio scale and the other variable is a dichotomous variable which takes values of 0's and 1's (e.g. scores for items on a multiple-choice test). The Point Biserial Correlation is a special case of the Pearson's Product Moment Correlation, and it is computationally a variant of the t-test. The Biserial Correlation is similar to the Point Biserial correlation, except that dichotomous variables are artificially created (that is "cutoff' values of a previously continuous variable are used). Phi correlations are used when both variables dichotomous. A Phi correlation, like the Point Biserial Correlation, is directly derived from the Pearson's Product Moment Correlation. Tetrachoric Correlations are used when each variable is created through dichotomising an underlying normal distribution. However, this paper discussed only the Pearson's Correlation. The Pearson's r was chosen as the focus of this paper because most readers are familiar with this test statistic. And very importantly, the assumptions for the use of the Pearson's r, with a few exceptions, are applicable to the other methods of correlation.

**Pearson's Product Moment Correlation (r)**

The Pearson's product Moment Correlation coefficient is a measure of the strength and direction of association that exists between two variables measured on at least an interval scale. A Pearson's correlation attempts to draw a line of best fit through the data of two variables, and the Pearson's correlation coefficient, r, indicates how far away all these data points are from this line of best fit.

When the Pearson's correlation is to be used, one must make necessary checks to ensure that the Pearson's correlation is the appropriate statistic. The way to do this is to ensure the following four assumptions are passed:

1. The two variables must be measured at the interval or ratio scale.
2. There is a linear relationship between the two variables.
3. There should be no significant outliers. Outliers are single data points within your data that do not follow the usual pattern.
4. The data should be approximately normally distributed.

**Computing the Pearson's $r$**

Given the bivariate set $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, the Pearson's Product Moment Correlation Coefficient (r) is defined as

$$r = \frac{S_{xy}}{S_x S_y}$$

where r = Pearson's Product Moment Correlation Coefficient

$S_{xy}$ = Covariance of x and y values (scores)

$S_x$ and $S_y$ = Standard deviations of x and y values (scores) respectively.

Given the above relationship, the Pearson's Product Moment Correlation Coefficient (r) can be written as

$$r = \frac{\frac{1}{N}\Sigma xy - \bar{x}\,\bar{y}}{\sqrt{\left(\frac{1}{N}\,\Sigma x^2 - \bar{x}^2\right)}\,\sqrt{\left(\frac{1}{N}\,\Sigma y^2 - \bar{y}^2\right)}}$$

where r = Pearson's Product Moment Correlation Coefficient

N = Number of pairs of values or scores

$\sum xy$ = Sum of the products of x and y

$\bar{x}$ = Mean of the x values (or x scores)

$\bar{y}$ = Mean of the y values (or y scores)

$\bar{x}\,\bar{y}$ = Product of the mean values (scores) of x and y

$\sum x^2$ = Sum of squares of x values (or x scores)

$\sum y^2$ = Sum of squares of y values (or y scores)

With the above equations of the Pearson's Product Moment Correlation Coefficient (r) a better computational equation can be written thus:

$$r = \frac{N\sum xy - (\sum x)(\sum y)}{\sqrt{\{N\sum x^2 - (\sum x)^2\}\{N\sum y^2 - (\sum y)^2\}}}$$

where r = Pearson's Product Moment Correlation Coefficient

N = Number of pairs of values or scores

$\sum xy$ = Sum of the products of x and y

$\sum x$ = Sum of the x values (or x scores)

$\sum y$ = Sum of the y values (or y scores)

$\sum x^2$ = Sum of squares of x values (or x scores)

$\sum y^2$ = Sum of squares of y values (or y scores)

$(\sum x)^2$ = Square of the sum of x values (or x scores)

$(\sum y)^2$ = Square of the sum of y values (or y scores)

Using the distribution of Economics and Commerce scores of SS2 students of Fazak International Secondary School below,

(i) Compute the Pearson's Product Moment Correlation Coefficient (r),

(ii) Interpret your result, and

**Table 5: Economics and Commerce scores of SS2 students of Fazak Secondary School**

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Economics | 10 | 12 | 15 | 14 | 12 | 10 | 9 | 11 | 14 | 10 | 16 |
| Commerce | 32 | 46 | 62 | 60 | 51 | 40 | 38 | 42 | 56 | 30 | 65 |

**Solution:**

(i) Recall that the computational formula is given by $r = \frac{N\sum xy - (\sum x)(\sum y)}{\sqrt{\{N\sum x^2 - (\sum x)^2\}\{N\sum y^2 - (\sum y)^2\}}}$

Now, the distribution above shall be set vertically to accommodate all the components needed to compute r. The various components are $N$, $\sum xy$, $\sum x$, $\sum y$, $\sum x^2$, $\sum y^2$, $(\sum x)^2$, and $(\sum y)^2$.

| Econs ($x$) | Comm ($y$) | $xy$ | $x^2$ | $y^2$ |
|---|---|---|---|---|
| 10 | 32 | 320 | 100 | 1024 |
| 12 | 46 | 552 | 144 | 2116 |
| 15 | 62 | 930 | 225 | 3844 |
| 14 | 60 | 840 | 196 | 3600 |
| 12 | 51 | 612 | 144 | 2601 |
| 10 | 40 | 400 | 100 | 1600 |
| 9 | 38 | 342 | 81 | 1444 |
| 11 | 42 | 462 | 121 | 1764 |
| 14 | 56 | 784 | 196 | 3136 |
| 10 | 30 | 300 | 100 | 900 |
| 16 | 65 | 1040 | 256 | 4225 |
| $\sum x = 133$ | $\sum y = 522$ | $\sum xy = 6582$ | $\sum x^2 = 1663$ | $\sum y^2 = 26254$ |

Substituting, we have $r = \dfrac{(11)(6582) - (133)(522)}{\sqrt{\{(11)(1663) - (133)^2\}\{(11)(26254) - (522)^2\}}}$

$$r = \frac{72402 - 69426}{\sqrt{\{18293 - 17689\}\{288794 - 272484\}}}$$

$$r = \frac{2976}{\sqrt{(604)(15946)}}$$

$$r = \frac{2976}{\sqrt{9631384}}$$

$$r = \frac{2976}{3103.45} = 0.9589$$

(ii) A positive correlation coefficient of 0.96 implies that Economics and Commerce are positively related. In other words, a student who scores highly in Economics is likely to score highly in Commerce and vice versa.

**Purpose of the Paper**

The purpose of this position paper is to show that test of significance of Pearson's correlation coefficient is not only possible with the t-distribution and z-transformation, but that the Statistical Package for Social Sciences (SPSS) perfectly does this with utmost ease and accuracy.

**Statement of the Problem**

The Pearson's Product Moment Correlation Coefficient, simply called the Pearson's $r$ when applied to a sample or Pearson's $\rho$ (rho) when applied to a population, is a measure of the degree (direction and magnitude) of the linear relationship between two variables. Though a very important measurement tool in Statistics, it does not measure the significance or otherwise of the linear relationship ("$r$" or "$\rho$") between variables.

But strong proponents of Null Hypothesis Significance Tests (NHSTs) agree that statistically significant results should be accompanied by one or more measures of practical significance test (Nix & Jackson Barnette, 1998a, 1998b; Thompson, 1996, 1998b, 1999; and Barnette & McClean, 1999). Nevertheless, relatively few researchers consistently report estimates of effect size (Levin, 1998; and McLean & Ernest, 1998). According to Thompson (1998a), many researchers appear to be under the delusion that p-values test result importance, test result replicability, and evaluate effect magnitude.

However, Student (1908) and Fisher (1915) have made rewarding efforts at testing for the significance of correlation coefficients using t-distribution and the Fisher's z-transformation. Yet there are clouds of uncertainty whether the Statistical Package for Social Sciences (SPSS) can be used to test for the significance of correlation coefficients. It is to clear these clouds that this paper x-rayed the usefulness of the SPSS in testing the significance of correlation coefficients. The paper also compared use of the t-distribution, the Fisher's z-transformation, and the SPSS in testing for the significance of correlation coefficients.

**RESULTS**

**Test for the significance of relationships between two continuous variables**

Pearson's correlation measures the strength of a relationship between two variables. But in research any relationship should be assessed for its significance in addition to its strength. The **strength** of a relationship is indicated by the correlation coefficient $\boldsymbol{r}$, but actually measured by the coefficient of determination $\boldsymbol{r^2}$. The significance of the relationship is expressed in probability levels $\boldsymbol{p}$ (where $p = .05;\ .01;\ etc$). The value of $\boldsymbol{p}$ tells how unlikely a given correlation coefficient $\boldsymbol{r}$ will occur given that no relationship exists in the population. It must be noted that the <u>larger</u> the correlation $\boldsymbol{r}$, the <u>stronger</u> the relationship, whereas a <u>smaller</u> $\boldsymbol{p}$-level indicates <u>more</u> significant relationship.

In testing for the significance of correlation coefficient, $\boldsymbol{r}$, some assumptions are necessary. First, let us assume that $\boldsymbol{r}$ is the correlation between two variables (x and y) in a given sample, and that $\boldsymbol{\rho}$ (rho) is the correlation between the same two variables (x and y) in the population from where the sample was taken. Next, let us assume that there is no relationship between x and y in the population (that is $\rho_{xy} = 0.0$). In correlation analysis, this means the null hypothesis that there is no significant relationship between x and y in the sample (that is $r_{xy} = 0.0$).

The test of significance of correlation coefficient $\boldsymbol{r}$ employed three methods in this paper. They are as follows:

(i) t-distribution
(ii) z-transformation
(iii) SPSS (which is the focus of this position paper)

The t-distribution formula for computing the appropriate t-value to test for the significance of correlation coefficient r is given by

$$t = r\sqrt{\frac{n-2}{1-r^2}}$$

Where, t = t-value required for the test of significance of the correlation coefficient $r$
n = sample size
r = the computed correlation coefficient being tested for significance.

For the z-transformation, the formula is given by

$$z = \frac{1}{2}log_e\left(\frac{1+|r|}{1-|r|}\right),$$ $r$ refers to the sample correlation coefficient.

$$\varepsilon = \frac{1}{2}log_e\left(\frac{1+|\rho|}{1-|\rho|}\right),$$ $\rho$ refers to the population correlation coefficient.

However, this paper focuses on the sample correlation coefficient, $r$, and not the populations correlation coefficient, $\rho$. Professor R. A. Fisher, the originator of this test statistic advised that this z statistic should be used to test

(i) Whether an observed value of r differs significantly from some hypothetical r value.
(ii) Whether two samples values of r differ significantly from each other.
(iii) Whether r differs significantly from zero. And that when this is the case, the t-test is preferable.

Recall that our null hypothesis is that there is no significant relationship between x and y (that is $r_{xy} = 0.0$). This is a two-tailed statistical test of significance which is used when the null hypothesis is non-directional (Goldsman, 2010; Kpolovie, 2011). Let us employ the data in Table 6, heights (in metres) and weights (in kilogramme) of some WWE wrestlers to discuss the test of significance of correlation coefficient using the t-distribution, Fisher's z-transformation, and the Statistical Package for Social Sciences (SPSS). The null hypothesis tested was that "**there is no significant relationship between heights and weights of WWE wrestlers".**

**Table 6: Heights and weights of some WWE wrestlers**

| Wrestlers | Height ($x$) | Weight ($y$) |
|---|---|---|
| 1 | 1.84 | 105 |
| 2 | 1.62 | 105 |
| 3 | 1.96 | 123 |
| 4 | 1.70 | 100 |
| 5 | 1.61 | 121 |
| 6 | 1.74 | 127 |
| 7 | 1.58 | 97 |
| 8 | 1.96 | 140 |
| 9 | 2.00 | 142 |
| 10 | 1.87 | 120 |
| 11 | 1.80 | 106 |
| 12 | 1.55 | 97 |
| 13 | 1.98 | 125 |
| 14 | 2.02 | 140 |
| 15 | 1.73 | 110 |
| 16 | 1.92 | 118 |

**Using the t-distribution:**

First, Pearson's Product Moment Correlation coefficient r was computed using the formula

$$r = \frac{N\sum xy - (\sum x)(\sum y)}{\sqrt{\{N\sum x^2 - (\sum x)^2\}\{N\sum y^2 - (\sum y)^2\}}} = 0.77$$

Second, the computed 0.77 was transformed to the t-distribution using the formula

$$t = r\sqrt{\frac{n-2}{1-r^2}} = (0.77)\sqrt{\frac{16-2}{1-(.77^2)}} = (0.77)(5.86) = 4.5122$$

Third, the degrees of freedom (df) was found thus: df = (n – 2) = 16 – 2 = 14

Fourth, the critical value table for t at 14 degrees of freedom (two-tailed test) was consulted and t = 2.145 was obtained. Since the calculated t = 4.512 > 2.145 critical t at 14 degrees of freedom and one-tailed test (indicating significant relationship), the null hypothesis that "there is no significant relationship between heights and weights of wrestlers" was rejected. In other words, there is a significant positive relationship between heights and weights of wrestlers.

**Using the Fisher's z-transformation:**

The Fisher's z-transformation was developed by Fisher to convert Pearson's r to the normally distributed variable z to enable the Pearson's r be tested for significance. Since the sampling distribution of the sample correlation coefficient for all values of the population correlation coefficient other than 0 is skewed, the sample correlation coefficient must be transformed in such a way that it has a sampling distribution which is approximately normal. This is appropriately carried out using the Fisher's z-transformation statistic which is defined as follows:

$$|z| = 0.5\, log_e \left(\frac{1+|r|}{1-|r|}\right)$$

Where:

$log_e$ = is the natural logarithm

"| |" = indication that the number contained in it can be either positive or negative.

r = calculated Pearson's r

Now, using the Pearson's r of 0.77 computed from Table 6, Fisher z-value which corresponds to r = 0.77 is

$$z = 0.5\, log_e \left(\frac{1+|0.77|}{1-|0.77|}\right) = 0.5\, log_e \left(\frac{1.77}{0.23}\right) = 0.5\, log_e\,(7.6957) = 1.0203$$

Next, the critical value table for z at 0.05 level was consulted and z = 1.960 (two-tailed test) was obtained. Since the calculated z = 1.020 < 1.960 critical z (indicating significant relationship), the null hypothesis that "there is no significant relationship between heights and weights of wrestlers" is rejected. In other words, there is a significant positive relationship between heights and weights of wrestlers.

Note that a very simple way of obtaining the Fisher z-values (instead of the rigorous computation using the natural logarithm) is to use the tables that are provided in many standard statistics textbooks. Such tables give the value of z for values of r from 0 to 1.00. When r is negative, the z-value obtained becomes negative. If the exact value of r is not listed, interpolation is used to obtain the corresponding z-value.

**Using the Statistical Package for Social Sciences (SPSS):**

Let us demonstrate this with the data in Table 6:

Step 1: Switch on your computer and allow it to boot fully.

Step 2: Click on the SPSS icon to start SPSS

Step 3: Type in your data in the data view window: all height values in VAR0001 and all weight values in VAR0002.

Step 4: Click on variable view and type height and weight values into the first and second rows respectively. Return to data view.

Step 5: Click analyse and move cursor to "correlate" to select "bivariate" and click.

Step 6: Move VAR0001 (now height values) and VAR0002 (now weight values) to the "variables" window.

Step 7: Check or mark Pearson's

Step 8: Test of Significance. You can select two-tailed or one-tailed probabilities. If the direction of association is known in advance, select One-tailed. Otherwise, select Two-tailed.

Step 9: Select "Flag significant correlations". In the result table, correlation coefficients significant at 0.05 level are identified with single asterisk, while those significant at the 0.01 level are displayed with two asterisks.

Step 10: Click option and select "means and standard deviations. Click "continue".

Step 11: Finally, click "ok" on the "bivariate correlations" window for SPSS to analyze data and generate output. The following results, among others, will display:

**Table 7: Descriptive Statistics**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| Height | 1.8050 | .16133 | 16 |
| Weight | 117.2500 | 15.17674 | 16 |

**Table 8: Correlations**

| | | Height | Weight |
|---|---|---|---|
| Height | Pearson Correlation | 1 | .772** |
| | Sig. (2-tailed) | | .000 |
| | N | 16 | 16 |
| Weight | Pearson Correlation | .772** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 16 | 16 |

**. Correlation is significant at the 0.01 level (2-tailed).

At the bottom of the 'Correlations' table (Table 8) is displayed "**Correlation is significant at the 0.01 level (2-tailed)". This implies that the Pearson's correlation coefficient $r = .772$ with N of 16 is statistically significant at 0.01 level ($p = 0.000$), which of course is also significant at 0.05 level. Thus, the null hypothesis that "there is no significant relationship between heights and weights of WWE wrestlers" is not accepted. In other words, there is a significant relationship between heights and weights of WWE wrestlers.

**CONCLUSION**

This paper has shown that the test of significance of correlation coefficients is very import in research because the degree of relationship alone is not sufficient to conclude that a computed correlation coefficient is adequate. It further revealed that each of the methods of test of significance (t-distribution, z-transformation, and SPSS) provided good enough test for significance of correlation coefficients, which brings to rest the opposing views that the SPSS does not provide a test for significance of correlation coefficient. Indeed, the SPSS is recommended ahead of the t-distribution and z-transformation due to its easy, robust, and wide applications. Researchers and academics should expose their mentees to this great scientific discovery, the SPSS.

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