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Research Paper

Re-examination of the limitations associated with correlational research

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Abstract. Correlational research is a type of quantitative research method that some researchers wrongly apply in a given academic study. It is time to highlight and address this problem by the way of publication in very reputable Journal. The paper is meant to re-examine the limitations and uses of correlational studies. At the end of the day, researchers are alerted to weigh various methods of quantitative research before making decision on the method suitable for their research objectives. Desktop approach that reviewed, critiqued and synthesized representative literature on a topic in an integrated way such that new frameworks and perspectives on the topic are generated was adopted. Books and articles were used as well. The revelation was that despite the challenges associated with using correlation, it was found very useful in bi-variate data analysis method used for predictions in some cases. Complex correlational statistics such as path analysis, multiple regression and partial correlation "allow the correlation between two variables to be recalculated after the influence of other variables is removed, or 'factored out or 'partialed out'. Even when using complex correlational designs, it is important that researchers make limited causation claims.

Keywords: Correlational studies, research methodology, quantitative research

INTRODUCTION

The term correlation is one of the most common and useful statistical concepts applied in scientific studies. A particularly important tool of the social sciences for enhancing the understanding of the social world is a host of statistical techniques that can be broadly described as correlational analysis. These statistical innovations were developed by social scientists in the late nineteenth century and came into widespread use in the twentieth century. Francis Galton (1822 - 1911) conceived the idea of correlation in 1898 but Karl Pearson was the person who developed and promoted it as scientific concept of universal significance (Aldrick, 1995). The aim behind its development was to help get a handle on one of the most difficult problems confronting social sciences: How to account for the often bewildering number of variables that potentially influence social phenomena. Isolating the effects of particular variables in the social realm presents a formidable challenge to social scientists, owing to the difficulty – and sometimes impossibility – of conducting controlled experiments.

Correlational research is a type of quantitative research method within the positivism paradigm (Anderson and Arsenault, 1998). It includes explaining phenomena by collecting numerical (quantitative) data that are analyzed using mathematically based methods (in particular statistics) (Aliaga and Gunderson, 2000).

Quantitative data is based on precise measurements using structured and validated data- collection instruments and involves statistical report with correlations, comparisons of means, and statistical significance of findings (Johnson and Christensen, 2008; Given, 2008). Other types of quantitative research approaches are descriptive survey research, experimental research, single-subject research, causal-comparative research method (Lodico et al., 2010).

In general, a correlational study is a quantitative method of research in which two or more quantitative variables from the same group of subjects are taken through series of computations to determine if there is a relationship (or covariance) between variables (a similarity between them, but not a difference between their means). Correlational research, therefore, represents a general approach to research that focuses on assessing the covariance among naturally occurring variables. It is also known as associational research in which relationships among two or more variables are studied without any attempt to influence them. There is no manipulation of variables in correlational research. Theoretically, each two quantitative variables can be correlated. It is not reasonable to collect and analyze data scientifically when there is little reason to think the two variables would be related to each other (e.g. Sexual Aggression and Pornography) or to determine if there is a correlation between breastfeeding and test performance among high school students.

We have two forms of variables in correlational research namely: predictor variable (independent variable) and criterion variable (dependent variable or output variable). Independent variable is a variable that is believed to predict the outcome. Dependent variable is the variable to be predicted. Phi correlation is used when both predictor and the criterion variables are natural dichotomies (two categories). When the predictor variable is a natural (real) dichotomies (two categories) and the criterion variable is interval or continuous, the biserial correlation is used. But if the dichotomies are artificial, the tetra choric correlation is used.

Survey, direct observation of behavior or compiling research from earlier studies, rating scales, scores on various tests and demographic information are some of the methods used to gather data for correlation studies. One can perform multiple correlations using such approaches as partial correlation, multiple regressions, discriminant analysis and factor analysis. Correlation research process usually follows the patterns as stated below. Identifying the variables to be studied; establishing questions or hypothesis; selecting appropriate samples; collecting data; calculating correlations; and reporting the results.

Justification and objectives of the study

The types of research approaches used (in correlational research) depend on the goal of the research, the research paradigm, and statistics needed for data analysis. There are cases that researchers use the wrong research method for a given academic study and deploy wrong research paradigm and data analysis method thus making findings from research unreliable, unrealistic and irrelevant. This paper discusses the challenges involved in the application of correlation in social science research. Generally, correlational research attempts to measure or determine the *nature* and *degree* of the relationship between two variables. For example, a researcher may want to find out the relationship between obese people and the level of their blood pressure or to know how smoking affects the health of a smoker or how to determine the degree of association between the health status of smokers and non-smokers. Here, a correlation coefficient could be calculated and the values obtained are used to establish the relationship.

Methodology

Desktop research involving an integrated literature review was used for collecting data. An integrative literature review is a form of research that “reviews, critiques, and synthesizes representative literature on a topic in an integrated way such that new frameworks and perspectives on the topic are generated” (Torraco, 2005:356). Relevant articles in peer reviewed Journals, text books and other academic papers were accessed and reviewed.

Data analysis method

Since the method for this research was purely desktop approach, textual analysis was used to analyze data.

Analysis of findings (revelations)

Textual analysis

It was found out that for each individual correlational research there must be at least two measures, or it will be impossible to calculate correlation. A statistically positive correlation could still be weak or low. This means it has no practical significance. There are two values in correlation research that must be reported. A correlation is reported as *‘r’* and a statistic probability is reported as *‘p’.*

Correlation value ranges from -1.00 to +1.00 that is perfect inverse relationship to a perfect linear relationship. However, because practically we cannot have a perfect correlation, we can restate it as + or -0.01 to + or – 0.99. When one variable increases and the other variable increases as well or a decrease of one variable leads to the decrease of the other, it is called *positive* correlation. When a variable increases, while the other variable decreases, it is known as *negative (inverse)* correlation. We have other situations where there is no correlation at all. A correlation coefficient close to +1.00 indicates a strong positive correlation. A correlation coefficient close to -1.00 indicates a strong negative correlation. A correlation coefficient of 0 indicates no correlation. No correlation indicates no relationship between the two variables.

We may describe correlation to have weak, moderate, strong or very strong based on the range they fall into. Such as +*or* - 0.0 to +*or* - 0.20 as very weak, +*or* - 0.21 to +*or* - 0.40 as weak, +*or* - 0.41 to +*or* - 0.60 as moderate,

Table 1. Cost and sales relationship.

Product	Cost	Sales
A	7	15
B	9	6
C	5	7
D	11	10
E	2	8
F	4	7
G	4	12
H	3	11
I	8	9
J	11	8

+or - 0.61 to *+or* - 0.80 is strong, and *+or* - 0.81 to *+or* - 0.99 is very strong correlation.

There are several methods applied to measure correlation. Scatter diagram is used to represent correlation between two variables by showing the location of points saying x and y on a rectangular coordinate system. In applying this method, the given bi-variate data is plotted on a graph paper and the degree of correlation is determined with the help of spreading points. In other words, the scatter plot diagrams are dot graphs to show how the scores of two variables, x and y, are distributed in order to have a graphical and visual representation of the extent to which the two variables may correlate (Asamoah, 2012).

Some diagrams could be obtained after plotting the data on the graph sheet. Advantages of scatter diagram are that it is very simple to use and understand and unlike many mathematical methods, is not influenced by extreme values. The limitations are that scatter diagram gives an idea about the direction of relation and whether it is high or low but the exact degree cannot be ascertained, because the visual examination of the scatter plots are largely subjective.

One of the frequently reported statistical methods involves correlational analysis where correlation coefficient is reported representing the degree of linear association between two variables. The Product Moment Correlation (Karl Pearson's Correlation Coefficient) is used when both the criterion and the predictor variables contain continuous interval data such as test scores. Excel with statistical functions could be used to calculate Pearson Product Moment Correlation (PPMC), Statistical Package for Social Sciences (SPSS), a statistical software programme for personal computers, could also be used. This method is the most widely used one in practice and usually denoted by the symbol (r*).*The formula for computing this coefficient is based on the assumption that the bivariate data involved are *quantitative* (Asamoah, 2012).

For example, If x_i and y_i (where i=1, 2...n.) are the observations of two variables xy then the Pearson's correlation coefficient is given as:

$$r = \frac{\sum_{i=1}^{n}(x_{i-\bar{x}})(y_{i-\bar{y}})}{\sqrt{\sum_{i=1}^{n}(x_{i-\bar{x}})^2 \sum_{i=1}^{n}(y_{i-\bar{y}})^2}}$$

A more simpler and practical formula is:

$$r = \frac{\boldsymbol{n\sum xy - (\sum x)(\sum y)}}{\sqrt{(\boldsymbol{n\sum_x 2 - (\sum x)^2})}\,(\sqrt{\boldsymbol{n\sum_y 2 - (\sum y)^2}})}$$

Where:
$\boldsymbol{n}$Represents the number of pairs of data presented
$\sum \boldsymbol{x}$Denotes the sum of all-values
$\sum_x \boldsymbol{2}$Indicates that each x-value should be squared and then those squares added
$(\sum \boldsymbol{x})^2$ Indicates the x-values should be added and then the total value squared
$\sum \boldsymbol{xy}$ indicates that each x-value should first be multiplied by its corresponding y-value. After obtaining all such products, find their sum.
$\boldsymbol{r}$Represents the linear correlation coefficient for a sample

The method is symmetric, it gives us one single value that expresses the direction and the degree of relation between the variable. It is quite easy to compute. The value of **r** is affected by extreme values. The mathematical computation can be a bit tedious with large data.

Example

The manager of a multiproduct firm wants to know the relationship between the costs of producing the product and sales using the Pearson's Correlation Coefficient. Table 1 shows the data.

Plugging the data in Table 2 into our formula, we arrive at -0.0765.

$$r = \frac{10(589) - (64)(93)}{\sqrt{[10(506) - (64)^2][10(933) - (93)^2}} = -0.0765$$

This implies that there exists a very low negative correlation between costs of production and sales.

Unlike the Pearson's correlation coefficient, which assumes that the variables involved are quantitative and measurement can be made, in many cases that variables are qualitative where measurement cannot be made but can be *ranked* the Spearman's Rank Correlation is applied. Thus with quantitative data we rank them in order of preference or in a way appropriate to what we need. A rank is a number assigned to an individual sample item according to its order in the sorted list. The formula given in this method is:

Table 2. Solution- using Pearson's correlation coefficient.

Product	Cost X	Sales Y	X^2	Y^2	XY
A	7	15	49	225	105
B	9	6	81	36	54
C	5	7	25	49	35
D	11	10	121	100	110
E	2	8	4	64	16
F	4	7	16	49	28
G	4	12	16	144	48
H	3	11	9	121	33
I	8	9	64	81	72
J	11	8	121	64	88
	$\sum X = 64$	$\sum Y = 93$	$\sum X^2 = 506$	$\sum Y^2 = 933$	$\sum XY = 589$

Table 3. Relationship between examination score in mathematics and daily expenditure.

Examination score (X)	Daily expenditure Y)
24	136
36	121
52	436
16	126
33	422
33	257
16	103
11	451
32	421

$$r_s = 1 - \frac{6\sum_d 2}{n(n^2-1)}$$

Where
$\boldsymbol{n}$ represents the number of observation
$\boldsymbol{d}$ represents the difference between ranks of corresponding pair of observations
$\boldsymbol{r_s}$ denotes Spearman's correlation coefficient

In ranking the observations, if a pair of observation has the same value, we assign them to the mean rank. The interpretation for the correlation coefficient for the Spearman is the same for the Pearson's correlation coefficient.

An example is presented as follows: Assuming an adult education researcher wants to know the relationship between JHS student's examination score in mathematics and their daily expenditure. He randomly selects nine students and obtains the following data (Table 3): It is determined by using the Spearman's Rank correlation.

It is started by ranking the values of X and Y in ascending order. When the same value appears more than once, their mean values are assigned.

Then the difference between the ranks and finally the sum of the squares of the difference are found and plugged into the formula to calculate the answer (Table 4).

$\sum_d 2$ =105.5

$r_s = 1 - \frac{6(\sum_d 2)}{n(n^2-1)} n = 9$

$r_{s=1-\frac{6(105.5)}{9(81-1)}}$

$r_{s=0.12}$

This implies that there exist a weak positive correlation between x and y.

With the use of Excel, calculating correlations is probably the easiest way to analyze data. In Excel, we set up three columns: Subject #, Variable 1 (e.g. hours of study), and Variable 2 (e.g. exam scores). Then we enter our data in these columns. We then select a cell for the correlation to appear in and label it. We click "fx" on the toolbar at the top, then "Statistical", then "Pearson". When it asks highlight each of the two columns of data in turn, we click "Finish", and our correlation will appear. In any statistics textbook, charts can tell us if the correlation is significant, considering the number of participants.

DISCUSSION

Correlation does not imply causality. In other words, while this type of research could be used to determine if two variables have a relationship, it does not allow researchers to determine if one variable causes changes in another variable. Where we want to know the relationship between obese people and the level of their blood pressure or to know how smoking affects the health of a smoker, even if we are able to find out that there exists a significant relationship between them, we cannot base on that finding and draw a conclusion that obesity

Table 4. Solution.

X	Y	r_x	r_y	$d\ (r_x - r_y)$	d^2
24	136	4	4	0	0
36	121	8	2	6	36
52	436	9	8	1	1
16	126	2.5	3	-0.25	0.625
33	422	6	7	-1	1
33	257	6	5	1	1
16	103	2.5	1	1.5	2.25
11	451	1	9	-8	64
33	421	6	6	0	0

causes high blood pressure or high blood pressure causes obesity.

Stated differently, while correlational studies can suggest that there is a relationship between two variables, they cannot prove that one variable causes a change in another variable. In other words, correlation does not equal causation. For example, a correlational study might suggest that there is a relationship between academic success and self-esteem, but it cannot show if academic success increases or decreases self-esteem.

Other variables might play a role, including social relationships, cognitive abilities, personality, socio-economic status, and myriad other factors. Correlation can never tell researchers whether one variable *causes* changes in another variable. This is so even if a one-to-one correspondence between variables is uncovered. For it is always possible that there is an unknown third variable that is the true cause behind changes in the variable that investigators seeks to explain. For example, suppose statistical analysis demonstrates a strong and stable correlation between individuals' average television-viewing hours and violence: the more television individuals watch, the more likely they are to commit violent acts. But such evidence by itself cannot tell researchers whether watching television makes people more inclined to commit acts of violence or whether the violence-prone are more likely to watch television. Perhaps an unaccounted for third factor – say, poor social skills or unemployment – is the true cause of the violence and the increased television viewing.

Explaining the cause of some phenomenon requires understanding the causal mechanism that produces it. This correlation analysis cannot provide it. It can, however, tell social scientists when a causal connection does not exist. Correlation does not entail causation, but causal connections always produce correlation. So failure to uncover a correlation between certain variables can inform researchers that there is no causal connection between them. In this way, correlation analysis provides an important tool for falsifying hypotheses. As the correlation cannot be used to draw inferences about the causal relationships between and among the variables, the greatest challenge of correlational research is the problem of interpreting causal relationships.

Besides, one must be very careful about how to use the correlation coefficient to predict outcomes. This is because it is difficult to predict the results unless the selection of the variables to be correlated is guided by a theoretical or practical rationale. This explains the reason for calculating the co-efficient (Badu-Nyarko, 2011).

Another challenge is the area of probability and the use of inferential statistics where the use of representative sample is used for generalization to the entire population under study. Correlation falls within descriptive statistics and therefore cannot handle inferential statistics that enables the use of representative samples and generalization to the actual population.

In addition, according to Gupta and Gupta (1993), statistical method (including correlative statistics) cannot be applied in all kinds of phenomena and cannot answer all kinds of questions. Correlation, being a statistical measurement, deals with only those subjects that are capable of being quantitatively measured and numerical expressed. Correlational research does not deal with one (uni-variate) phenomenon of study; it is a bi-variate statistical measure.

Poor selections of subjects and application of misappropriate data analysis may render correlation results wrong and unreliable.

In looking at how dependent is one variable on the other without looking at the strength or association between them, it is the chi square that could be used instead of correlation. The chi square is a bi-variate and nonparametric measurement that cross tabulates between two variables but can be used for categorical, nominal, and ordered data. Again, in an experimental design, where we need to see the effect of intervention, where we need to establish the difference between two means, or to know whether there is a statistical difference between two groups, we cannot use correlation but *t*-test.

On a more serious note when we want to establish or find out the difference of mean between three or more variables or the difference within variables, correlation cannot be used. In this case, ANOVA model is applicable. Multivariate regression analysis, structural equation modeling, and other sophisticated statistical tools address this problem by giving social scientists the ability to gauge with mathematical precision on the impact of multiple variables on social phenomena. For example, suppose criminologists wish to shed light on the factors influencing the rate of violent crime. A host of potential social variables might plausibly be thought to do so, including poverty, education, sex, race, population density, gun-control laws, television viewing, and so forth. Multivariate regression, which provides the ability to hold multiple variables artificially constant, allows researchers to determine how strongly each of these variables is associated with violent crime. Such analysis might be able to tell us, for example, that poverty, sex, and education level accounts for 60% of the variance in crime and that gun control laws have no effect.

Multivariate regression can even help gauge the interactive effects of various factors, perhaps showing that education level alone has little effect on crime but does have an impact when combined with poverty and high-population density.

Pearsonian text book described a problem with the use of correlation, that is, 'it is possible to obtain a significant value for a coefficient correlation when in reality, the two functions are absolutely uncorrelated (Elderton, 1907:22, cited in Aldrick, 1995).

Despite the challenges or limitations associated with using correlation, correlation statistics has greatly enhanced social scientists' understanding of the social world. Correlation is important because it permits researchers to determine the strength and direction of a relationship between different sets of variables or to predict scores on one distribution based on the knowledge of scores of another (Badu-Nyarko, 2011:157). With correlation, one is able to obtain a measure of the degree of association or relationship between two variables. That is, whether the variables are positively related, negatively related or not related; that is, how a variable turn to reflect or influence the other. It also helps to reduce uncertainties. It helps to understand related events, conditions and behaviours, for example, finding out if there is a relationship between community health education and malaria prevention. Correlation helps us to predict how one variable might predict another, for example, ascertaining how high school grades could be used to predict university grade.

Although correlation cannot prove a causal relationship, it can be used to predict a phenomena, support a theory, and measure test-retest reliability. According to Runyon et al. (1996) cited in Badu-Nyarko (2011), one of the uses of correlation is to measure reliability. The test-retest reliability is determined by administering a test to a group of subjects on one occasion and then retesting the same subjects some time later. This determines the stability of the measurement device (questionnaire). It allows testing the expected relationships between and among variables and making predictions. Correlation could be used to assess these relationships in everyday life events (Stangor, 2011). The results of correlational research also have implications for decision makers, as reflected in the appropriate use of actuarial prediction.

Stanovich (2007) points out the following as the relevance for correlational analysis:

> "First, many scientific hypotheses are stated in terms of correlation or lack of correlation, so that such studies are directly relevant to these hypotheses…. Second, although correlation does not imply causation, causation does imply correlation. That is, although a correlational study cannot definitely prove a causal hypothesis, it may rule one out. Third, correlational studies are more useful than they may seem, because some of the recently developed complex correlational designs allow some very limited causal inferences.
>
> …some variables simply cannot be manipulated for ethical reasons (for instance, human malnutrition or physical disabilities). Other variables, such as birth order, sex, and age are inherently correlational because they cannot be manipulated and, therefore, the scientific knowledge concerning them must be based on correlational evidence."

When we know a score on one measure, we can make a more accurate prediction of another measure that is highly related to it. The stronger the relationship between/among variables, the more accurate the prediction is. Practically, evidence from correlation studies can lead to testing that evidence under controlled experimental conditions. Correlational studies are a stepping-stone to the more powerful experimental method, and with the use of complex correlational designs (path analysis and cross-lagged panel designs), allow for very limited causal inferences. Correlational research is beneficial because it helps researchers to see the relationship between two or more things. It helps narrow down possible causes for diseases, behaviors, etc. For example, discovering the correlation between smoking and cancer has led to much research and literature informing smokers about their increased chance to cancer.

Correlation could help scholars to test the significance of r when they want to know whether there is a significant relationship between two variables. The following steps are followed: You establish the null hypothesis, H0 to indicate there is no relationship between variables, say A and B, then you formulate an alternative hypothesis H1, to show there is relationship between A and B. Then you select the level of significance, for example, 0.05 level of significance. Next, you determine the test distribution to use. The t-test or t-distribution table is used and the degree of freedom to apply (n2) when there are only two variables. Then you define the rejection or critical region. The t-value for one tailed test is n-2 or 4 degrees of freedom at the 0.05 level which is 2.132. The next step is to state the decision rule. Reject the null hypothesis in favor of the alternative if the test statistic is greater than or equal to 2.132. Otherwise, you fail to reject H0 (The Null hypothesis). Finally, you compute the test statistic (Badu-Nyarko, 2011).

CONCLUSIONS AND RECOMMENDATION

Correlational research is designed to discover relationships between variables and allow the prediction of future events from present knowledge. In contrast to descriptive research, which is designed primarily to provide static pictures, correlational research involves the measurement of two or more relevant variables and an assessment of the relationship between or among variables. For instance, the variables of height and weight are systematically related (correlated) because taller people generally weigh more than shorter people. In the same way, study time and memory errors are also related, because the more time a person is given to study a list of words, the fewer errors he or she will make. When there are two variables in the research design, one of them is called the 'predictor variable' and the other the 'outcome variable'. Correlational research is not an 'experimental research'. An experimental research is a kind of study in which initial equivalence among research participants in more than one group is created followed by a manipulation of a given experience for these groups and a measurement of the influence of the manipulation.

The goal of experimental research design is to provide more definitive conclusions about the causal relationships among variables in the research hypothesis than in correlational designs. In an experimental research design, the variables of interest are called the 'independent variable' *(*or variables*)* and the 'dependent variable'. The independent variable in an experiment is the causing variable that is created (manipulated) by the experimenter. The dependent variable in an experiment is a measurable variable that is expected to be influenced by the experimental manipulation. The research hypothesis suggests that the manipulated independent variable or variables will cause changes in the measured dependent variables. We can diagram the research hypothesis by using an arrow that points in one direction. This demonstrates the expected direction of causality. Experimental designs have two very noticeable features. For one, they guarantee that the independent variable occurs prior to the measurement of the dependent variable. This eliminates the possibility of reverse causation. Second, the influence of common-causal variables is controlled and thus eliminated by creating initial equivalence among the participants before manipulating. Experimental research differs significantly from correlational research methods. Correlational research is predictions and is mostly based on statistics, whereas experimental research is based on experiment and explanation.

There are two major problems when attempting to infer causation from a simple correlation. First, directionality problem: before concluding that a correlation between variable 1 and 2 is due to changes in 1 causing changes in 2, it is important to realize that the direction of causation may be the opposite, thus, from 2 to 1; second, third-variable problem: the correlation in variables may occur because both variables are related to a third variable.

Complex correlational statistics such as path analysis, multiple regression and partial correlation “allow the correlation between two variables to be recalculated after the influence of removing, ‘factoring out” or ‘partialing out’ other variables” (Stanovich, 2007:77). Even using complex correlational designs, it is important for researchers to make limited causation claims. Experimental research is the key to uncovering causal relationships between variables. In experimental research, the experimenter randomly assigns participants to one of two groups: the control group and the experimental group. The control group receives no treatment and serves as a baseline. Researchers manipulate the levels of some independent variables in the experimental group and then measure the effects. Because researchers are able to control the independent variables, experimental research can be used to find causal relationships between variables which correlation cannot handle.

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