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# A Two-Step Approach for Transforming Continuous Variables to Normal: Implications and Recommendations for IS Research

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### Abstract:

This article describes and demonstrates a two-step approach for transforming non-normally distributed continuous variables to become normally distributed. Step 1 involves transforming the variable into a percentile rank, which will result in uniformly distributed probabilities. Step 2 applies the inverse-normal transformation to the results of the first step to form a variable consisting of normally distributed z-scores. The approach is little-known outside the statistics literature, has been scarcely used in the social sciences, and has not been used in any IS study. The article illustrates how to implement the approach in Excel, SPSS, and SAS and explains implications and recommendations for IS research.

**Keywords:** math modeling, discipline, interdisciplinary, reference theory, contributing theory

# A Two-Step Approach for Transforming Continuous Variables to Normal: Implications and Recommendations for IS Research

## I. INTRODUCTION

Traditionally, data transformations (e.g., power and logarithm) have been pursued by improving normality incrementally using a trial-and-error approach. Unfortunately, it is rarely the occasion that a researcher may actually achieve statistical normality as indicated by accepted diagnostics tests (e.g., Kolmogorov-Smirnov, P-P plot, skewness, kurtosis). This research demonstrates a simple yet powerful approach herein referred to as the Two-Step, which may be used to transform many non-normally distributed continuous variables toward statistical normality (i.e., satisfies the preponderance of appropriate diagnostics tests for normality). The proposed transformation can achieve statistically acceptable kurtosis, skewness, and an overall normality test in many situations and improve normality in many others. With the exception of two limitations described later, the approach optimizes normality of the resulting variable distribution. The Two-Step offers an ideal standard for transforming variables toward normality and a new perspective on MIS research.

In studies on the effects of non-normality on association tests, prior research has used simulated data [e.g., Figelman, 2009], whereas the proposed Two-Step procedure will enable the use of observed variables. For example, the *Productivity Paradox* is a term that describes the perplexing inability of information systems (IS)[1] researchers to uncover relationships between a range of information technology (IT) investment criteria and organizational productivity. Within this topic, a tremendous amount of multidisciplinary scholarly effort has been expended to better understand specific streams, such as the relationship between IT investment and financial performance [Brynjolfsson and Hitt, 2003]. Despite the enormity of effort and its prominence across disciplines, very little resolution has been made to the *Paradox* and, surprisingly, studies on the subject rarely mention the distributional aspects of underlying data. Simulation studies, which use data devoid of theory to study normality implications, cannot directly advance the *Paradox* stream. By contrast, the Two-Step offers the potential to transform observed variables toward statistical normality and the realization of downstream effects on study findings, such as main effect sizes.

Among the dozens of generic distributions available, the normal distribution has the most applications in quantitative research. Many parametric statistical procedures (e.g., multiple regression, factor analysis) used in quantitative research are sensitive to normality. For instance, the presence of normality has been shown to improve the detection of between-groups differences in both covariance and components-based structural equation modeling [Qureshi and Compeau, 2009]. Improved normality will reduce the heteroscedasticity shown in P-P plots [Hair et al., 2010], thereby increasing the level of statistical correlation observed between two variables.

The proposed approach addresses at least four voids that may be observed in IS research. First, as will be demonstrated in the following section, normality has barely been addressed in IS studies that should address the issue. Second, the Two-Step transformation approach presented here has not been used at all in IS research to date. Consequently, researchers have had no exposure and have been unaware of the technique. For the first time, this tutorial makes the approach available to the IS community as a method and subject of research. Third, recent trends in pervasive computing, remote sensing, and cloud computing are making dramatically more data available to more organizations and members of the "information society." The greater availability of data will only increase the societal reliance on analyses of such data. For example, data mining is proliferating and raising the importance of causal testing in practice. Fourth, due to the availability of less expensive and more comprehensive electronic databases, researchers are more interested in data reduction than ever. Consequently, rigorous formative index construction studies, which rely heavily on the results of intercorrelation tests between logically grouped variables, is more important. While the Two-Step approach is relevant in studies utilizing any continuous data, it is perhaps more useful to those in the highly multidisciplinary IS research community.

The purpose of this tutorial is to illuminate a transformation approach that promises to help advance any topic constrained by the non-normality of continuous data. The significance of the article is in its description of a novel procedure and its potential for providing a new perspective on IS research. While each step has been used disparately in the social sciences, the originality of this manuscript lies in its description of two steps for transforming observed variables toward normality. In particular, the algorithm introduced here has not been described or studied

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[1] Similarly, productivity paradoxes also exist in other fields, such as human resources management [Wigblad et al., 2007] and manufacturing [Skinner, 1986].

in published research. Therefore, the article serves as a means by which IS researchers can access the approach to determine if it will improve theoretical understandings and rates of scientific advancement in the IS discipline.

This article provides a background of foundational concepts, explains a logical algorithm researchers may follow, illustrates its use in three common software applications, and provides examples of its application to observed data. The article then discusses its implications for IS scholarship, uses of the approach and recommendations for researchers, and a brief conclusion.

## II. BACKGROUND

This section explains the research context, which involves the current state of normality research in IS and other social sciences disciplines. While normality remains a significant issue in IS and other disciplines, it goes largely unaddressed in studies that should address the issue. An *EBSCO Host*[TM] *Business Source Premier* journal article search was performed to find business-related studies that should address normality issues. The sample frame included only articles that contained both of the the phrases "corporate financial performance" (CFP) and "structural equation modeling" (SEM) in the full text. Measures of CFP are known to universally depart severely from normality [Barnes, 1982; Deakin, 1976] and studies including these measures should address the extent of normality in all cases. SEM is an analytical method that is sensitive to the normality assumption [Qureshi and Compeau, 2009] and studies using the approach should also address normality. The results indicate that normality has barely been mentioned in studies that combine both subjects. Of the seventy-nine articles including both phrases in the text, twelve (15 percent) included the word *skewness,* eight (10 percent) included "kurtosis," and fifteen (19 percent) included "normality." This analysis indicates that authors are not addressing normality in articles that should and many are working with non-normally distributed data. Furthermore, it has become common and accepted practice to *not* report attempted variable transformations in analyses in final publications [see Massetti, 1998].

An evaluation of IS and strategic management literature reveals an ongoing "normality burden" faced by quantitative researchers. For example, Saeed et al. [2005] tested the relationship between e-commerce competence and CFP. They dutifully transformed two CFP variables (Tobin's q and economic value added) using the Box-Cox transformation to address heteroskedasticity in model association tests. The researchers do not report any pre- or post-transformation normality diagnostics. Subsequently, little is known about how such a change in distributions would have improved heteroskedasticity in model association tests, nor how much the study effect sizes would have improved had the variables been transformed toward statistical normality. Another example is Choi and Wang [2009], who tested the relationship between stakeholder relations and CFP, which was indicated by return on assets and Tobin's q. In this study, there was no report of distributional diagnostics or any attempt at transformation toward normality. Finally, Tanriverdi [2005] tested the association between information-technology mediated knowledge management aspects and CFP (return on assets and Tobin's q). Despite using SEM, Tanriverdi [2005] reports no attempt to transform CFP nor normality diagnostics. While association test results were significant, attempts to improve findings through increased normality were not reported.

Each of the above three examples are exemplary and rigorous studies on many accounts. The examples show the diverse ways in which normality is addressed in studies that presumably should address the topic. They also show the common situation of researchers faced with uncertainty regarding how much non-normality threatens the results, statistical power, and reliability of quantitative studies.

## III. TRANSFORMATION ALGORITHM

This section provides the origins, logic, and limitations of the Two-Step transformation algorithm. It concludes with a section describing how it is distinct from other procedures that are more common in IS research.

### Origins

Researchers and practitioners across disciplines have traditionally used distribution functions to produce random variables for simulation studies [e.g., Yuan and Chen, 2009] and assessing the distributional fit of original variables [Fishman, 2003]. Unfortunately, most original continuous data from real-world phenomena can be shown to be arbitrarily distributed. That is, the data does not statistically conform to one of the generic distributions (e.g., normal, chi-square, F, Pereto) produced by a known cumulative distribution function (CDF). When CDFs are inverted (called inverse cumulative distribution functions), they may be used to calculate random numbers that conform to that generic distribution. For example, to generate normally distributed random variables, simulation researchers generate random probabilities (ranging from 0 to 1) that are then transformed using the inverse-normal CDF. It is from this tradition that the proposed approach was conceived, although the math, several peripheral issues, and implications differ between random normal variate generation and the Two-Step transformation toward normality.

Another important generic distribution is the uniform distribution, which characterizes variables produced by random number functions. *The uniform distribution is assumed before successfully transforming to any generic continuous distribution.* As prescribed below, transformation of observed variables toward uniformity does not involve the use of an inverse distribution function.

## Logic

Figure 1 illustrates the Two-Step algorithm (including procedures A through K) for transforming arbitrarily distributed continuous variables to normal. The approach classifies all variables using three categories:

1. Normal-Original—the extremely rare case that the original values are found to be statistically normal (i.e., satisfies the preponderance of normality diagnostics)

2. Normal-Feasible—the case that the original variable is found to be non-normal, but is transformable to normal

3. Normal-Infeasible—the case that the original variable is found to be non-normal and is not transformable to normal

This categorization scheme is useful because the calculus of the Two-Step causes any transformed continuous variable to approach perfect normality. The technique is limited by two distributional characteristics described in greater detail in the Limitations section below. In many cases, the approach causes transformation results to satisfy "statistical normality" (i.e., the variable will satisfy the preponderance of appropriate normality diagnostics tests), which is an extremely high standard for IS and other sciences. Researchers may alternatively bypass this proposed algorithm and simply apply the Two-Step for exploration purposes (e.g., to identify distributional properties that may be limiting its efficacy).
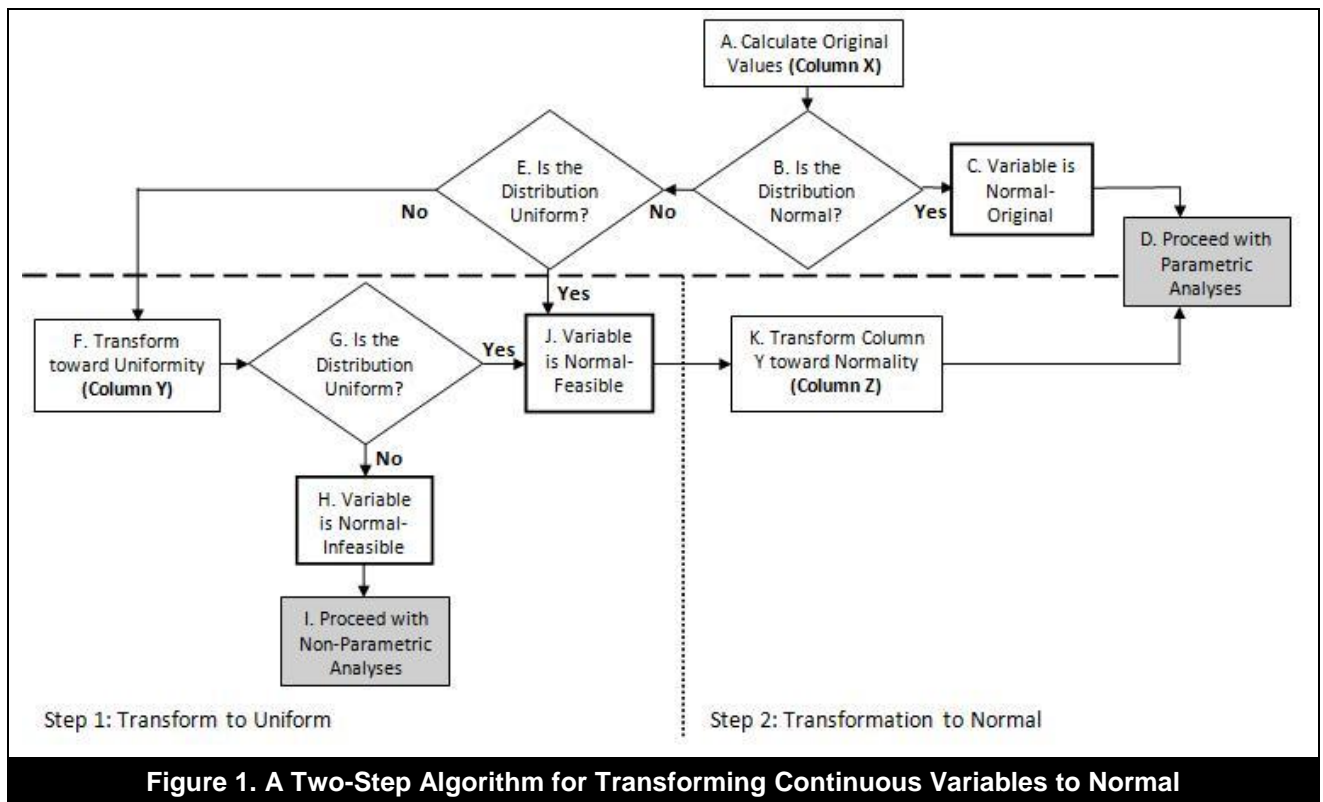


**Figure 1. A Two-Step Algorithm for Transforming Continuous Variables to Normal**

### Step 1: Transformation to Uniformity

The first step involves transforming the original variable toward statistical uniformity (i.e., satisfies the preponderance of diagnostics tests for uniformity) by calculating the percentile (or fractional) rank of each score. In an attempt to aid in its interpretability, three representations of variables will be used:

1. Column X—original variable

2. Column Y—result of transforming Column X to uniform probabilities (Step 1)

3. Column Z—result of transforming Column Y to normally distributed values (Step 2)

The approach begins with the calculation of original values for a continuous variable (starting with Procedure A in Figure 1) that will be referred to as Column X. If diagnostic tests show that Column X is normal (Procedure B), it is classified as Normal-Original (Procedure C) and the researcher may proceed with parametric statistical tests (Procedure D). If tests show that Column X is not normal, the researcher should conduct diagnostic tests for uniformity (Procedure E). If found to be uniformly distributed, Column X proceeds to Step 2 for transformation to normal. If not found to be uniform, Column X is computed to uniform using the percentile rank function (Procedure F, resulting in Column Y). A basic formula for percentile rank, which results in values ranging from 0 to 1, is (1):

$$Percentile\ Rank = 1 - [Rank(X_i) / n] \tag{1}$$

Where,

$Rank(X_i)$ = rank of value $X_i$

n = sample size

For example, Generic Company reports an annual profit rate of 1.3, which ranks seventh among 100 companies. The percentile rank is $1 - (7/100) = .93$, which is interpreted to mean that 93 percent of sample observations have profit rates below that of Generic Company. The achievement of statistical uniformity is a prerequisite for the achievement of statistical normality using the Two-Step procedure. Therefore, if Column Y does not show statistical uniformity (Procedure G), the original variable (Column X) is categorized as Normal-Infeasible (Procedure H) and the researcher should consider non-parametric statistical procedures (Procedure I).

Step 1 is a critical step since the achievement of statistical uniformity is required before Step 2 will result in statistical normality. Some situations will not allow for the achievement of statistical uniformity, which is a very high standard according to the norms of social sciences (and IS) research. If Step 1 fails to achieve statistical uniformity, researchers have at least four options:

1. Tolerate less than the "statistical uniformity" standard and proceed to Step 2 (which will not reach the standard of "statistical normality."

2. Use the traditional trial-and-error transformation approach to optimize uniformity, then proceed to Step 2.

3. Consider the association to be multi-functional and split the sample accordingly; one part of the sample will likely perform better than other parts; retry Step 1 with the amenable parts of the sample.

4. Only where logical to do so, replace mode values of zero with missing values [Andrés et al., 2010] and retry Step 1.

## Step 2: Transformation to Normality (from Uniformity)

Any variable found to conform to statistical uniformity is Normal-Feasible (Procedure J). Uniform probabilities (Column Y) may be transformed to normal (Procedure K, resulting in Column Z) using the inverse normal distribution function shown in (2):

$$p = \mu + \sqrt{2}\ \sigma\ erf^{-1}(-1 + 2\Pr) \tag{2}$$

Where,

| | | |
|---|---|---|
| $p$ | = | z-score resulting from Step 2 |
| $\mu$ | = | mean of $p$ (recommendation is 0 for standardized z-scores) |
| $\sigma$ | = | standard deviation of $p$ (recommendation is 1 for standardized z-scores) |
| $erf^1$ | = | inverse error function |
| $\Pr$ | = | probability that is the result of Step 1          [Source: Abramowitz and Stegun, 1964] |

For example, a researcher wants to transform the results of Step 1 (Column Y) into a variable conforming to the normal distribution (Column Z). Three parameters are necessary for the normal-inverse function: (1) a probability ($\Pr$, in Column Y), (2) the expected mean (μ) of the resulting variable (Column Z), and (3) the expected standard deviation (σ) of Column Z. Researchers may consider any values for μ and σ to approach normality. To produce z-scores, the researcher uses $\Pr$ = *variablename*, μ = 0, and σ = 1 as parameters. A value of .025 will be transformed to a z-score of −1.96.

As described above, each of these two steps is explained in some statistics sources and appears in analytic software tools. Regardless, the social sciences has ignored applying both steps in succession to transform observed variables.

## Limitations

There are two limitations of the efficacy of the described Two-Step procedure. To the extent that variables are not characterized by these two limitations, the Two-Step will produce transformations with perfect normality characteristics. The limitations are: (1) the presence of a low number of levels and (2) the presence of influential modes.

### Number of Levels

The approach will be successful to the extent that the original variable is continuous (which means that a meaningful cumulative probability can be obtained). Therefore, order among levels is necessary and therefore nominal (categorical) data types cannot logically be transformed into normal distributions using the approach. Ordinal and interval data types with greater numbers of levels will be more successful and ratio data is most amenable to successful transformations using the approach. As examples, the approach will have very little impact on variables represented by 5-point and 7-point Likert scaled responses. To improve normality in these studies, social scientists will need to design scales with many more levels, such as 30, or perhaps 100. While scales with so many levels is certainly not the norm, a low number of levels severely limits the efficacy of the Two-Step. Further research on the practicality of such scales is significant to the extent that normality is an important assumption in statistical procedures.

### Influence of Modes

When using the technique, researchers should be conscious of the frequency and influence of mode values. Variables are diverse in the location and relative frequency of their modes. In all research contexts, researchers should consider removing subjects that are meaningless in the study of causal relationships [Shadich et al., 2002]. Likewise, researchers should ensure that only those mode values relevant to the theory tested are retained in the analysis. If modes are found to impair results, researchers should investigate and consider replacing mode values with missing values and retry the transformation. In count variables, influential modes are typically represented by values of zero. There is a general relationship between the number of levels and the influence of modes. By definition, a variable with a low number of levels usually has highly influential modes. A variable with a high number of levels may or may not have one or more influential modes.

Experience shows the Two-Step is more effective at transforming variables with both a high number of levels and with less influence of high-frequency modes (e.g., excessive zeros). As examples, financial and economic data can be readily amenable to the approach while binary[2] data (e.g., gender) will not.

## Distinctions

The Two-Step is distinct from random number generation and standardization. Users of the Two-Step approach may correctly note that random number generation also uses two steps and that the second step (application of the inverse-normal function) is identical to that used in random number generation. However, the purpose and calculus for Step 1 is what differentiates the two procedures. During random number generation, the first step involves the generation of uniformly distributed probabilities. This operation does not occur in the Two-Step, which transforms *observed* variables toward uniformity using a percentile rank. Random number generation starts with no values, while the Two-Step is applied to observed values. Accordingly, random number generation aimed at the production of random normal variates will always approach statistical uniformity after the first step, and statistical normality after the second step. This is not the case with the proposed Two-Step approach, which may not achieve statistical uniformity after the first step.

Researchers should also note that the Two-Step is distinct from standardization, which is the calculation of z-scores for all values. Standardizing has the intentions of (1) making variables comparable by setting all units of measurement to be one standard deviation and (2) accurately representing the original distribution. The Two-Step also achieves unit standardization and z-score units are recommended above. Therefore, researchers using the Two-Step as described here will not need to use z-score standardization.

## IV. USE IN STATISTICAL SOFTWARE

Both steps necessary to complete the above transformation are easily accessible in modern statistical software packages. This section provides the functions available in three popular analytical tools: Excel, SPSS, and SAS. Each illustration uses the CitationsPerPublication variable as the example, with results of the transformation

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[2] When binary dependent variables are involved, researchers are referred to Probit analysis methods, which often involve the PROBIT function. See Borooah (2002) for introductory guidelines on conducting probit analysis. Researchers may also find value in Doyle [1977], who compares probit analysis to logit and tobit analyses in a marketing context. Probit analysis can be generalized to ordinal variables, such as Likert scales as described in a review by Daykin and Moffatt [2002].

illustrated later. In each example, note that the results of Step 1 must be in probability units ranging between 0 and 1 (exclusive) in order to complete Step 2. Furthermore, the achievement of statistical uniformity resulting from Step 1 is a prerequisite for transformation to statistical normality during Step 2.

## Excel

To accomplish Step 1 in Excel, use the PERCENTRANK function, which has the following syntax and argument definitions:
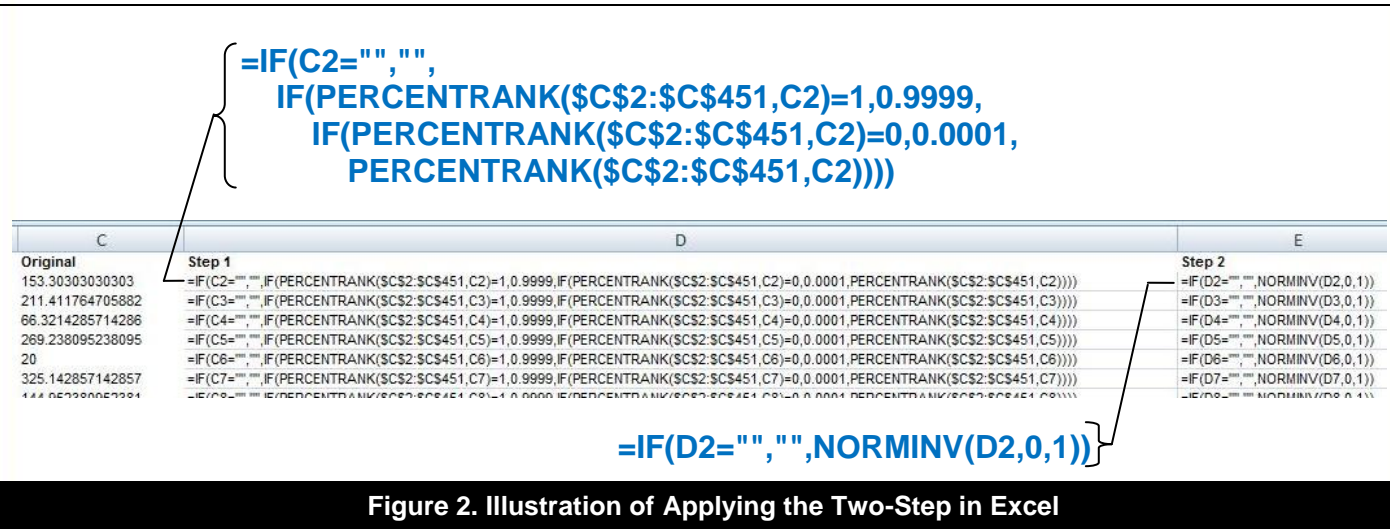
PERCENTRANK(original series, original value)

Where,

Original series = reference to the original variable to be transformed

Original value = the cell, or single value, to be transformed

Unless otherwise specified (using a third argument), PERCENTRANK produces probabilities using three digits (0.NNN). Use of this function is illustrated in the column labeled "Step 1" (Column D) in Figure 2. The illustration shows that logic was necessary to avoid three potential pitfalls during transformation:

1. The first IF function is necessary to avoid applying the function to an empty cell, which would otherwise cause an error.

2. The second IF function is necessary to replace any resulting 1's with .9999. Otherwise, an error would occur during the second step.

3. Likewise, the third IF function replaces any resulting 0's with .0001. An error would occur during the second step otherwise.

In the cases of #2 and #3 above, replacement is much less drastic than removal, and allows for the retention of all variable values.

=IF(C2="","",
    IF(PERCENTRANK($C$2:$C$451,C2)=1,0.9999,
        IF(PERCENTRANK($C$2:$C$451,C2)=0,0.0001,
            PERCENTRANK($C$2:$C$451,C2))))



=IF(D2="","",NORMINV(D2,0,1))

**Figure 2. Illustration of Applying the Two-Step in Excel**

To accomplish Step 2 in Excel, use the NORMINV() function, having the following syntax:

NORMINV(Step 1 result, imposed mean, imposed standard deviation)

Where,

Step 1 result = the result of Step 1, which must be in probability form
Imposed mean = mean of the variable resulting from the transformation
Imposed standard deviation = standard deviation of the resulting variable

The mean and standard deviation arguments are arbitrary in that they will not affect the shape of the resulting distribution. Again, in order to standardize in units of z-scores, set the mean equal to 0 and the standard deviation equal to 1.

Use of this function is illustrated in the column labeled "Step 2" (Column E) in Figure 2. The IF function is necessary to avoid applying the function to an empty cell, which would otherwise cause an error. This will happen when the result of Step 1 is a blank cell.

## SPSS

Step 1 is accomplished in SPSS by selecting Rank Cases from the Transform option in the main menu. After selecting the variable and moving it to the Variable(s) box, as shown in Figure 3, select the Rank Types command button. In the Rank Cases form, the "Display summary values" checkbox is irrelevant to the transformation results. As shown in Figure 4, deselect Rank, select Fractional Rank, and select the Continue command button. The "Smallest value" radio button should be selected for the Assign Rank 1 To control. Selecting the OK command button will generate values for a new variable, which is now viewable in both the Data View (which depicts values in relational format) and Variable View (which depicts variable properties in relational format). Users should note three caveats: (1) the type of the input variable must be numeric for the operation to work, (2) missing original values will result in missing transformed values, and (3) replacing resulting 0's and 1's after Step 1 must be done manually in SPSS. The SPSS code for Step 1 is shown below:

```
GET
   FILE='FileName.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.
RANK VARIABLES=CitationsPerPublication (A)
   /RFRACTION
   /PRINT=NO
   /TIES=MEAN.
```
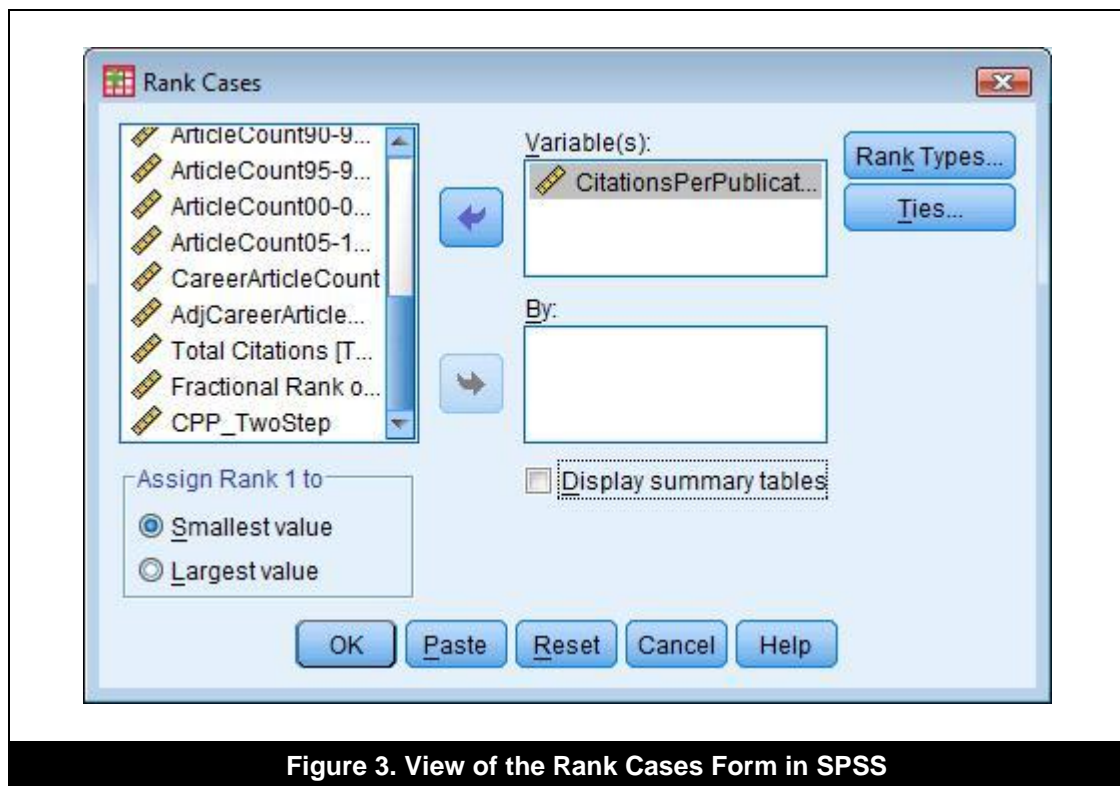


**Figure 3. View of the Rank Cases Form in SPSS**
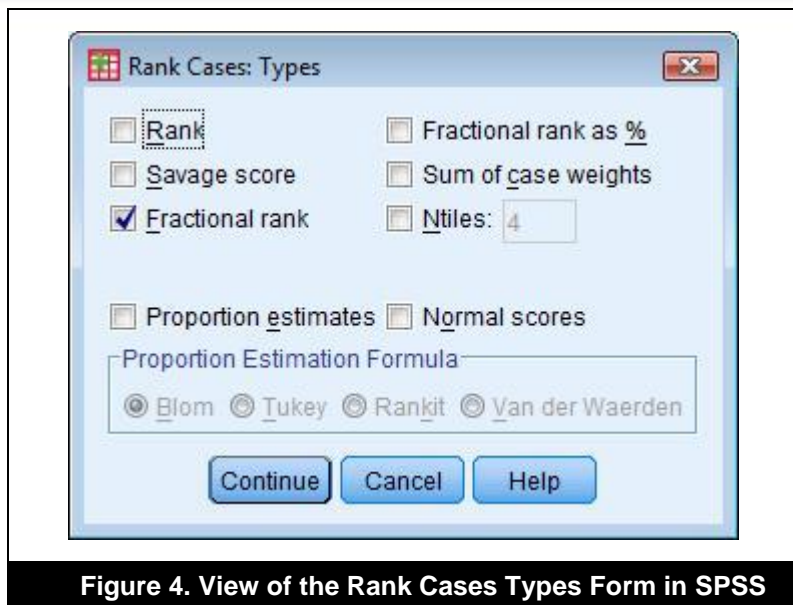
**Figure 4. View of the Rank Cases Types Form in SPSS**

Step 2 involves selecting Transform from the main menu, then Compute Variable. From the Compute Variable form (Figure 5), select Inverse DF as the Function Group and select Idf.Normal from Functions and Special Variables to build the function. The first parameter is the result of Step 1, the second can be any desired mean, and the third can be any desired standard deviation. For ease of interpretation, we suggest using 0 (zero) as the first argument and 1 (one) as the third argument. This will produce standardized z-scores that are transformed toward normality to the extent the original variable allows. Below is the SPSS code to complete Step 2:

```
COMPUTE CPP_TwoStep=IDF.NORMAL(RCitatio,0,1).
EXECUTE.
```
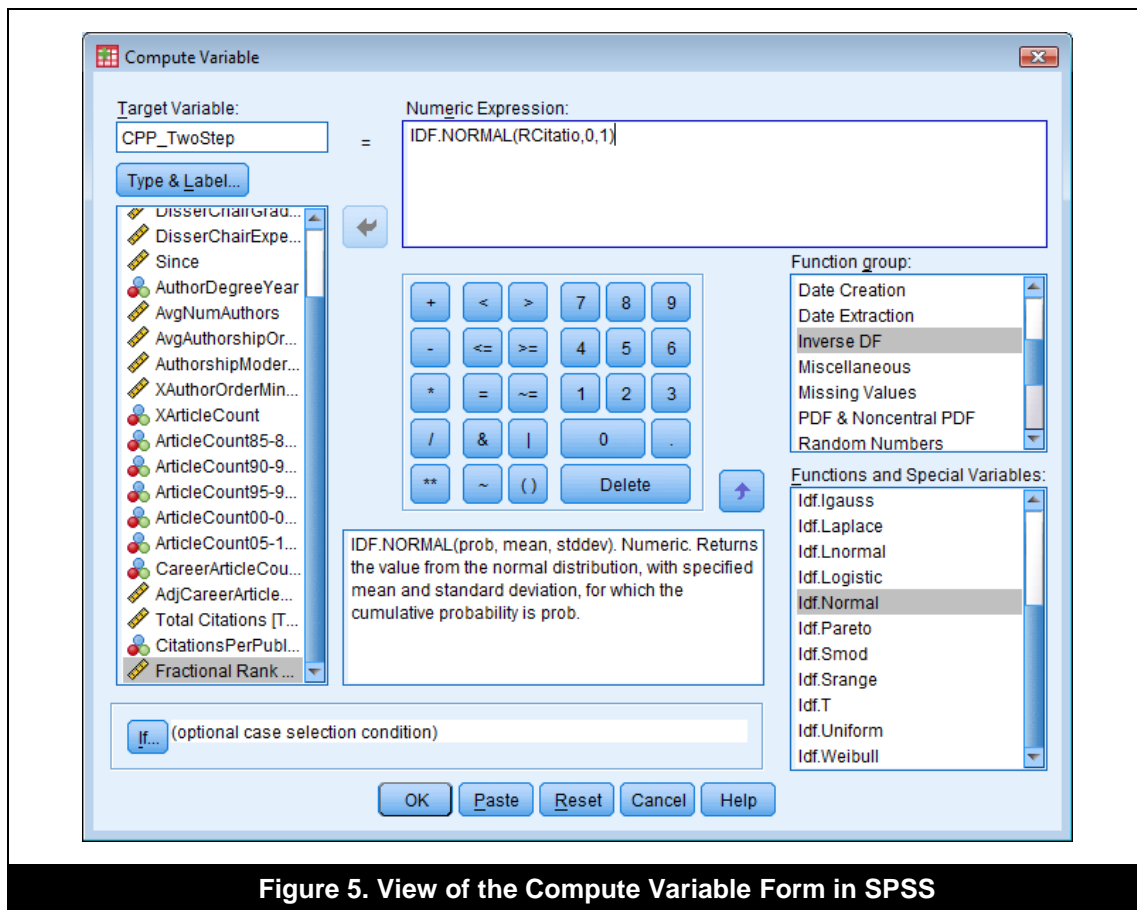


**Figure 5. View of the Compute Variable Form in SPSS**

## SAS

Use PROC RANK with the FRACTION option to complete Step 1 in SAS:

```
PROC RANK
  DATA=inputfilename
  OUT=outputfilename
  FRACTION
  TIES=MEAN;
RANKS step1result;
var step1result;
RUN;
```

Users should consult the SAS syntax guides to customize the code for the situation at hand. For example, the DECENDING option may be used to reverse the order of values (i.e., the highest value has a rank of 1).

To complete Step 2, use the PROBIT function, which transforms from uniform probabilities to normal:

```
step2result=PROBIT(step1result);
```

## V. ILLUSTRATIVE EXAMPLES

The Two-Step is useful across all types of continuous variables, for applications ranging from exploration to the achievement of almost perfect normality. To illustrate how the algorithm in Figure 1 is applied during research, a data set including a diverse range of variable characteristics was sought. The author used a data set recently collected in the field of scientometrics applied to the IS field. It includes a sample of 450 faculty contained in the *AIS Faculty Directory*[3] who also graduated from 1985–1990 with a terminal degree (i.e., Ph.D.s and DBAs). The data set included variables on authorial experiences and career performance and two variables are included in this illustration: (1) Citations Per Publication and (2) Total Citations. Citations Per Publication is the number of career citations attributed to articles each author published in the study journal basket divided by the number of those same articles. Total Citations is the total number of career citations attributed to those same articles. For our purposes, the definition of these variables is less important than the characteristics of the distributions that influence normal feasibility. As described below, Citations Per Publication was found to be easily transformable to normality, and Total Citations was not, using the algorithm. This section concludes by illustrating the importance of addressing high-frequency values before using the algorithm (i.e., in procedure A of Figure 1).

Table 1 defines the criteria used to evaluate normality and uniformity for all three versions of variables used as examples. Note that, depending on the software tool used, the highest and/or lowest value(s) within a variable may be transformed to 0 or 1 at the completion of Step 1. These values are not allowed as inputs into the inverse–normal function. So that neither of these values is lost in transformation, it is recommended here to replace any 0 with .0001 and any 1 with .9999 after Step 1. This will allow Step 2 to be completed so that all subjects are retained and with minimal effects on distributional shape or test results.
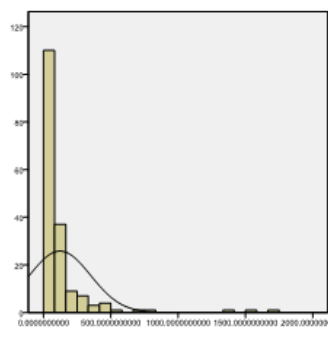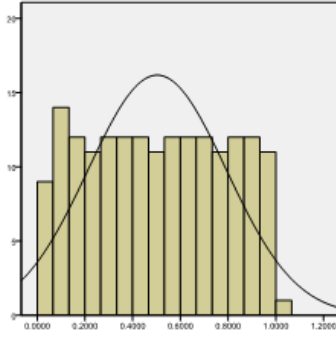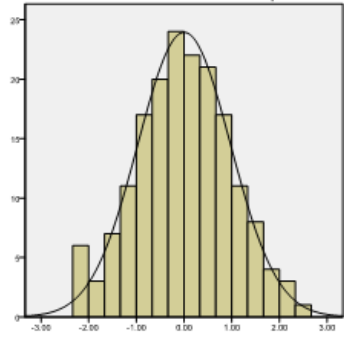
| Table 1: Test Criteria and Definitions | | |
|---|---|---|
| **Criteria** | **Definition (source)** | **How Interpeted** |
| Skewness p-value | Skewness is the degree and direction of asymmetry. The skewness p-value is the probability that a skewness statitistic is less than the observed value for that variable | p-value < .05 (extreme negative values) or > .95 (extreme positive values) indicate significant deviation from 0 (kurtosis or skewness) |
| Kurtosis p-value | Kurtosis is the degree to which the sizes of the distribution tails deviate from normality. The kurtosis p-value is the probability that a kurtosis statistic is less than the observed value | |
| Kolmogorov-Smirnov Significance, test for normality | Tests to determine whether the variable distribution is significantly different from the normal distribution | p-value > .05 indicates that the distribution is the test distribution (normal or uniform) |
| Kolmogorov-Smirnov Significance, test for uniformity | Tests to determine whether the variable distribution is significantly different from the uniform distribution | |

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[3] *The AIS Faculty Directory* web interface is available here: http://home.aisnet.org/displaycommon.cfm?an=1&subarticlenbr=339.

## Analysis Resulting in Normal-Feasibility

Table 2 depicts the versions of Citations Per Publication as it progresses through the three stages of the Two-Step: (1) the original variable, (2) transformation toward uniformity, and (3) transformation toward normality. Calculation of the original values (Procedure A in Figure 1) resulted in the original distribution (see "Original" column in Table 2). Tests (Procedure B in Figure 1) showed that the original variable was found to have significant skewness (p-value = 1.000) and kurtosis (p-value = 1.000), and to depart significantly from normality according to the K-S test (p-value = .000). Since the variable was not statistically normal, the K-S test for uniformity was observed (procedure E in Figure 1) and the variable found to significantly depart from uniformity (p-value = .000). Therefore, the variable was transformed toward uniformity (Procedure F, Figure 1) resulting in the distribution shown in the "Step 1" column in Table 2. Subsequent testing (Procedure G) indicated that the variable was statistically uniform (p-value = .987), so the variable was classified as Normal–Feasible (Procedure J). The variable was then transformed to normal (Procedure K) according to the K-S test (p-value = .200) and parametric analyses should proceed (Procedure D).

| Table 2: Three Versions of Citations Per Publication as Transformed Using the Two-Step | | | |
|---|---|---|---|
| Version | Original | Step 1 (Fractional Rank) | Step 2 (Inverse-Normal) |
| Histogram |  |  |  |
| N | 176 | 176 | 176 |
| Skewness p-value | 1.000 | .502* | .580* |
| Kurtosis p-value | 1.000 | .001 | .183** |
| K-S – normality | .000 | .047 | .200*** |
| K-S – uniformity | .000 | .987**** | .000 |

Key: *acceptable skewness; **acceptable kurtosis; ***distribution is normal; ****distribution is uniform

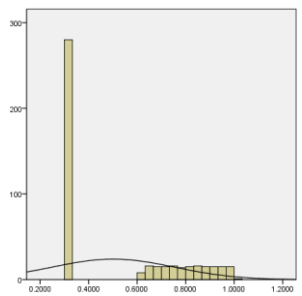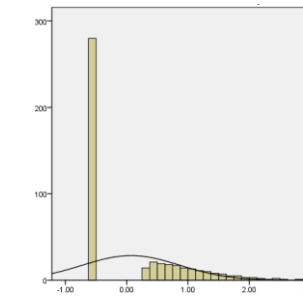## Analysis Resulting in Normal-Infeasibility
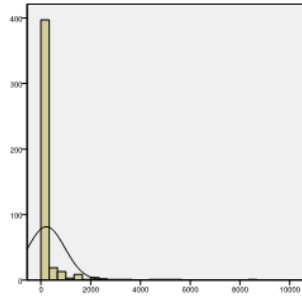
Table 3 depicts the versions of Total Citations as it progresses through the three stages of the Two-Step. Calculation of the original values (Procedure A in Figure 1) resulted in the distribution shown in the "Original" column. Tests (Procedure B in Figure 1) showed that the variable was found to have significant skewness (p-value = 1.000) and kurtosis (p-value = 1.000), and to depart significantly from normality according to the K-S test (p-value = .000). Since the variable was not statistically normal, the K-S test for uniformity was observed (Procedure E in Figure 1) and the variable found to significantly depart from uniformity (p-value = .000). Therefore, the variable was transformed toward uniformity (Procedure F, Figure 1) resulting in the distribution shown in the "Step 1" column in Table 3. Subsequent testing (Procedure G) indicated that the variable departed from statistically uniformity (p-value = .000), so the variable was classified as Normal-Infeasible (Procedure H). The algorithm suggests that non-parametric analyses should be used (Procedure I).

Table 3 shows the results of applying Step 2 to the results of Step 1—the variable is found to have significant skewness (p-value = 1.000), acceptable kurtosis (p-value = .577), and to depart from normality (p-value = .000). The distributions show graphically how influential modes cause non-normality, and these deviations are reflected in the K-S distributional tests indicating statistical non-normality.

## Examination of Modes to Improve or Achieve Statistical Normality

In a study testing the relationship between Total Citations and Article Count, the researcher may conclude that it is illogical to include all records with values of zero for both variables. The researcher may justify replacing these zeros with missing values by arguing that authors having no publications (within a given journal basket) will always have no citations and that including these records would not be useful to those interpreting the findings. Of the 450 authors in the Total Citations example, 268 were found to have zero publications and zero citations. Table 4 shows the progression of Total Citations, with most zeros replaced by missing values, through the Two-Step algorithm.

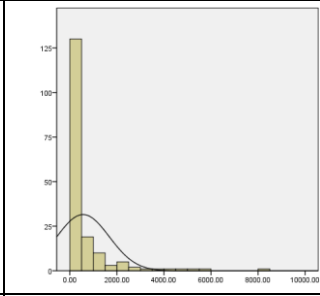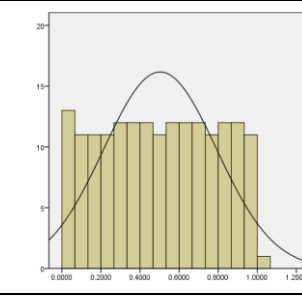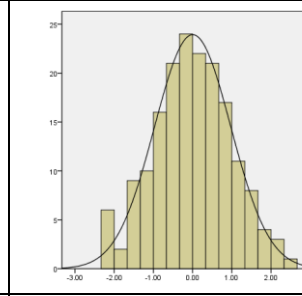| Table 3: Three Versions of Total Citations as Transformed Using the Two-Step | | | |
|---|---|---|---|
| **Version** | **Original** | **Step 1 (Fractional Rank)** | **Step 2 (Inverse-Normal)** |
| Histogram |  |  |  |
| N | 456 | 456 | 456 |
| Skewness p-value | 1.000 | 1.000 | 1.000 |
| Kurtosis p-value | 1.000 | 0.000 | 0.577** |
| K-S – normality | .000 | .000 | .000 |
| K-S – uniformity | .000 | .000 | .000 |

Key: *acceptable skewness; **acceptable kurtosis; ***distribution is normal; ****distribution is uniform

Replacing these values with missing values reduced the frequency of zeros from 274 to 6 and the sample size from 450 to 182 and drastically improved the results of the Two-Step transformation. The six zeros not replaced with a missing value were associated with authors having at least one career article but no citations attributed to those articles. Thus, these zeros could not be justifiably removed from the analysis acording to the aforementioned logic.

This example illustrates how a justifiable elimination of influential mode values can change the path a variable takes through the Two-Step algorithm shown in Figure 1 and improve normality after transformation. While researchers may not find justification to replace all influential mode values in their datasets, this example shows that mode values should be replaced where justified before using the Two-Step (or any statistical procedure). It should be emphasized that researchers may find justification for replacing with missing a fraction or all of the mode values. Whatever the justification, whether it centers on achieving normality through the Two-Step or some other, the justification should be reported within the study so that subsequent researchers may find reliability in the results.

| Table 4: Three Versions of Total Citations (with most zeros replaced by missing) as Transformed Using the Two-Step | | | |
|---|---|---|---|
| **Version** | **Original** | **Step 1 (Fractional Rank)** | **Step 2 (Inverse-Normal)** |
| Histogram |  |  |  |
| N | 175 | 175 | 175 |
| Skewness p-value | 1.000 | 0.501* | 0.578* |
| Kurtosis p-value | 1.000 | 0.001 | 0.183** |
| Kolmogorov-Smirnov Sig. | .000 | .095*** | .200*** |
| K-S – uniformity | .000 | .987**** | .000 |

Key: *acceptable skewness; **acceptable kurtosis; ***distribution is normal; ****distribution is uniform

This example emphasizes two aspects of modes that negatively influence results of the transformation. First, a relatively high percentage of mode values negatively affect transformation success. Researchers should be wary of any and all high-count values in variables they are attempting to transform using the technique. Second, modes are especially confounding the further they are away from the mean. Had the mode value in the original value of Total Citations (see Step 1 in Table 3) been closer to the mean, the efficacy would have been better. However, even if the mode value was equal to the mean, it may still negatively influence the efficacy of the Two-Step.

## VI. DISCUSSION

The following sections encourage future research, propose implications for the IS discipline, and summarize recommendations for using the proposed Two-Step transformation.

### Implications for Scholarly Topics

It is expected that the procedure will have implications for IS research on at least three levels. First, the technique is expected to change the methodological choices, outcomes, and value of findings within studies. The technique promises to simplify transformation toward normality whereas trying a diverse range of options has been encouraged. Furthermore, the relevance of statistical procedures for association tests hinges in part on the underlying distributions of variables. In general, transformations-to-normal among study variables are expected to improve statistical power [Baroudi and Orlikowski, 1989] and Type I error—effects that will in turn reduce required sample size. Enhanced normality increases the applicability of computing confidence bounds and improves the normality of residuals in linear regression. In factor analysis, transformations to normal will increase measures of sampling adequacy and communality. Improved normality in studies will often change the total variance explained, parsimoniousness, representativeness, and stability of factor structures.

Second, the procedure may change the rate of advancement within research streams. By reducing heteroscedasticity in association tests, the procedure will improve the strength of main effects. In some streams, this may influence theoretical understanding. For example, economic data is renowned for poor normality across datasets. The method may help with the construction of economic indices, the development of which depends on the findings of association tests. In this example, decisions regarding the indicators used in indices may be reconsidered. Because tests of association can improve, so may the probability of replication [Killeen, 2005] and hence the value of research streams employing the technique.

Third, the transformation technique may affect the numerous diverse topics across the IS discipline among others. The procedure is applicable to any topic using continuous data that suffers from non-normality. Continuous data can be observed in the output of a wide range of organization-relevant phenomena (e.g., counting events, production processes, financial transactions). Many of these data, especially in efficiency ratios (e.g., financial performance), have shown extreme departures from normality.

### Implications for Causal Inferences

A review of multidisciplinary literature indicates that the Two-Step can improve each of four validity categories impacting causal inference in studies [Cook et al., 1990]. These validity categories are (1) statistical conclusion, (2) internal, (3) construct, and (4) external. As a transformation approach, the Two-Step has the most implications for improving the statistical conclusion validity of causal inferences.

*Statistical conclusion validity* includes threats to inferring from hypothesis and effect size tests. Because the order of values do not change when the transformation is made, inferences using parameters (such as p-values) remain valid. The retention of the order of values means that when the population distribution is believed or assumed to be normal, inferences may be *more* accurate for variables transformed using the Two-Step compared to the same inferences made using severely non-normally distributed variables. The use of transformation methods to mitigate outliers in financial ratios has been shown to improve statistical conclusion validity [Watson, 1990]. The Two-Step has the advantage over competing procedures (e.g., truncation) of retaining outliers. It is well-known that non-normality causes heteroscedasticity in regression tests and produces bias in statistical results. Such bias should be mitigated as much as possible in statistical analyses [Schweder and Hjort, 2002] and is minimized as variable distributions approach normality. The Two-Step is demonstrated to improve the reliability of measures aspect of statistical conclusion validity in van Albada and Robinson [2007].

Statistical conclusion validity depends on the appropriate application of statistical tools [Straub et al., 2004]. Therefore, researchers should select appropriate statistical approaches that maximize statistical power and parametric tests are more powerful than non-parametric tests [Baroudi and Orlikowski, 1989]. The Two-Step transforms variables toward the distributional shape that is assumed when making statistical inferences about populations and will, therefore, often improve statistical power. As examples, SEM and PLS are two prominent statistical approaches containing procedures that are sensitive to normality: "both techniques struggle with the prediction of a highly skewed and kurtotic dependent variable" [Qureshi and Compeau, 2009, p. 197].

The literature also shows that the Two-Step can improve the *internal validity* aspect of causal inferences. Internal validity is concerned with whether inferred findings are attributable to causality. For example, it is known that outliers negatively influence statistical regression bias [Zeis et al., 2009], an important aspect of internal validity. By retaining and bounding extreme values, use of the Two-Step results in the mitigation of an important threat to internal validity.

Transformations toward normality using the Two-Step can also enhance *construct validity*, which is the extent to which measures are operationalized in theory-relevant terms. In modern survey research, a common problem arises when there are confounding relationships between a low number of construct levels. For example, in a scale with four levels, the first and fourth level may be uncorrelated, but the second and third correlated. Using items having distributions homogenized by the Two-Step addresses this issue: "when the distributional shapes of two paired variables are different, the resulting coefficient is understated (i.e., biased)" [Shumate et al., 2007, p. 360]. Coincidentally, Nunnally and Bernstein [1994] also argue that reducing this bias depends on increasing the number of measurement levels. This agrees with the recommendation herein to design survey scales with as many as 100 levels, which is easily amenable to transformations to statistical normality using the Two-Step.

Finally, the literature also indicates that the Two-Step can improve the *external validity* of causal inferences. External validity is the extent to which a causal relationship can be generalized to other samples. Outliers may be the result of historical effects interacting with treatments. For example, several outlying accounting measures may be the result of a catastrophic weather event. By moving these values from an extreme toward the center of the distribution, the Two-Step makes variables more content valid [Brito and de Vasconcelos, 2009, p. 124] and consequently mitigates any history-treatment interaction.

## Implications for Future Research on the Two-Step Approach

Due to changing technology (e.g., the increasing deployment of streaming data systems), continuous data will gain even greater prominence in IS research. The multidisciplinary IS research community, situated in all matters involving information and data processing, should take a more prominent role in addressing normality issues that pervade all social sciences. Future research is needed to advance understanding about the merits and limitations of transformations to normal. In general, what effect does the transformation of observed data toward normality have on association tests? While this question cannot be answered with Monte Carlo simulations, the proposed Two-Step will allow such an investigation. More generally, the Two-Step transformation provided here allows for investigations concerning the efficacy of normality when applied to data representing real-world phenomena.

## Uses of the Approach

Figure 6 depicts a framework researchers can use to design measures to be more amenable to the Two-Step. Variables will lie anywhere on this conceptual map constructed from the two limitations of the approach (except the arc drawn across Boxes 1 and 3 indicates that variables with an extremely low number of levels cannot have low influence and, therefore, may not lie to the left of the arc).
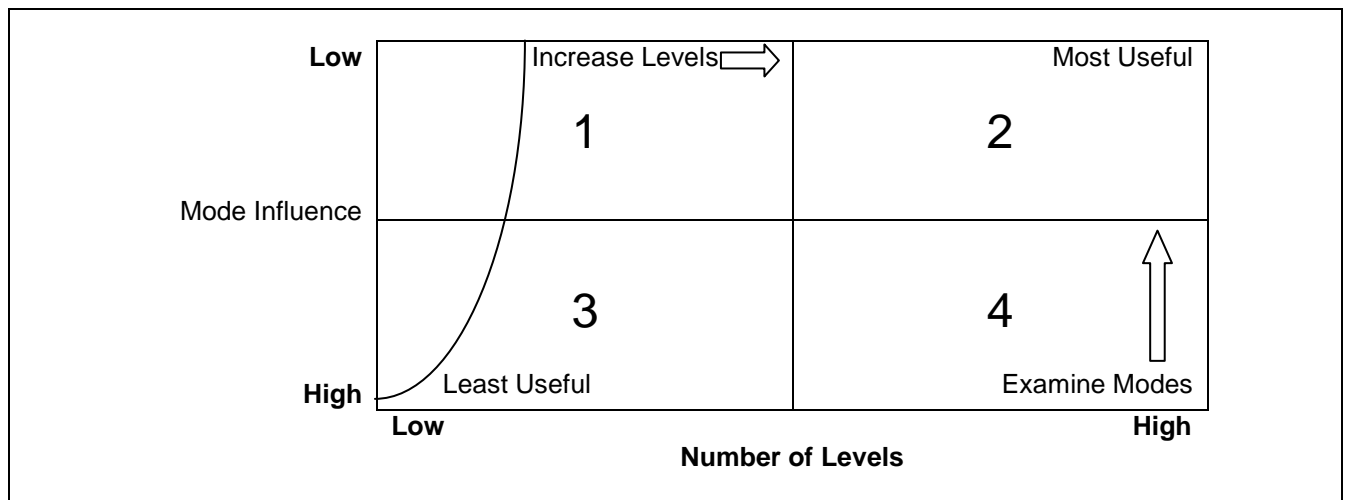


**Figure 6. Application Framework for the Two-Step**

### Box 1

In the extreme case of only two levels (binary variables such as gender or participation in a dichotomous treatment program), the Two-Step will have *no* usefulness in transforming toward normality. Variables with lower levels (e.g., a 5- or 7-point Likert scale) will naturally have higher mode influence, as all levels act as influential modes in these cases. In order to "escape" Box 1, researchers should design instruments (e.g., perceptual questionnaire scales or remote sensors) with many more levels than are often the current practice.

Variables in the extreme top right of the matrix (high number of levels and low extent of mode influence) are the most amenable to the technique. A depiction of such ideal situations is shown in Table 2. Variables characterized by extremely low influence of modes and an extremely large number of levels will reach "statistical normality" when transformed using the Two-Step. Researchers should design instruments with many levels to potentially transform variables to unprecedented levels of normality and its associated downstream effects.

Variables in the extreme bottom left of the matrix (low number of levels and high mode influence) will not be very successfully transformed toward normality using the Two-Step. In the extreme, binary variables by definition have highly influential modes and coincidentally cannot be improved using the approach. Count variables are often characterized as having a low number of levels and highly influential mode values of zero. Both aspects will diminish normality improvements, although researchers will often observe improvements toward normality.

In the case of a high number of levels and high mode influence, researchers will observe distributional changes as shown in Table 3. In order to alleviate the situation, researchers should consider removing mode values where justified. When the influence of modes has been diminished, such variables would be reclassified as Box 2 variables. An example of such a reclassification is Total Citations and the effects of such changes are shown by comparing Tables 3 and 4.

## Recommendations

Table 5 summarizes important recommendations for researchers using the Two-Step technique. The recommendations are grouped into aspects that may be of interest to adopters of the approach.

| Table 5: Recommendations for Researchers Using the Two-Step | |
|---|---|
| **Researcher Concern** | **Recommendation** |
| When do I use the transformation? | Any continuous variable may be transformed using the Two-Step. Variables with a high number of levels and non-influential modes will show the most improvement toward normality. |
| When do I not? | The procedure is not applicable to nominal (categorical data). Binary variables will show no change in distribution or improvement based on normality diagnostics. |
| How do I use the approach? | See Figure 1 and associated explanation for the logic of the Two-Step approach.<br><br>Functions for transforming variables using percentile (fractional) ranks and the normal-inverse function are available in many modern statistical software packages. Avoid applying any function to an empty cell.<br><br>Step 1: Depending on the software tool used, the highest and/or lowest value(s) within a variable may be transformed to 0 or 1. If this happens, replace any resulting 1's with .9999 and 0's with .0001.<br><br>Step 2: The Two-Step may produce z-score units by using arguments $\mu$ =0 and $\sigma$ =1 in the inverse-normal function. |
| What are implications towards the results that I will get? | In ideal situations, the results of the Two-Step will approach perfect normality according to appropriate diagnostic tests. Improvements to the validity of causal inferences will generally depend on the degree to which normality was improved using the procedure. |
| What is the value of using the approach? | The transformation may improve causal inferences, including statistical power, hypothesis tests, effect sizes, and generalizability. Consequently, it can reduce required sample size. |
| What are challenges I should note? | The efficacy of the technique depends on two distributional characteristics:<br><br>Influential Modes: In the original variable version, the negative influence exhibited by a given mode is due to 1) the proportion of values it represents in the sample and 2) its distance from the mean. Only those mode values relevant to the theory tested should be retained in the analysis.<br><br>Low Number of Levels: Variables with a low number of levels will not be as amenable to success. Consequently, Likert scales of 5- and 7-points is discouraged and should be replaced with scales containing a high number (up to 100) of levels. |

# VII. CONCLUSIONS

A vast amount of emphasis has been placed on the importance of univariate and multivariate normality in statistics courses, published studies and conference presentations. However, studies in IS and other social sciences rarely report descriptive statistics on the underlying distributional properties of data. The extent of normality of a given study variable can have tremendous influence on a wide range of statistical tests that influence findings and understanding about the subject matter [Berger, 2000].

This article offers a new perspective on normality by providing a means for approaching perfect statistical normality in variables most amenable to the Two-Step Transformation. The approach will transform any variable with a high number of levels and negligible influence of modes toward statistical normality. Based on literature reviewed here, IS researchers should achieve greater statistical results in association tests when the approach is successfully used. That is, researchers should experience more significant findings, greater effect sizes, less threats to causal inferences (especially statistical conclusion validity), and more reliable results as a consequence of using the Two-Step.

Researchers should be aware of the two limitations of the approach (a low number of levels and high influence of modes). Measures should be designed accordingly and it is recommended that perceptual survey instruments be constructed to take advantage of the Two-Step. Furthermore, researchers should we conscious of influential modes in study variables and remove them where justified. Empirical research on the efficacy of the Two-Step and its implications on downstream effects on studies is strongly encouraged.

## ACKNOWLEDGMENTS

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