APPROPRIATE ANALYSIS

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Periodically, the profession should examine the fundamentals related to our analysis procedures. The author does not purport to be a scholar of statistics. He has continued to study the topic beyond the mandatory preparation for a terminal degree because he believes that "if you are green you are growing, but, if you are ripe; then you are ready to rot." In short, the last time he spent many hours reading about statistics has been more recent than when he completed a doctorate. Such study is done because a professional needs to remain competent, because he has taught statistics and research methods at the university level, because the graduate students advised deserve knowledgeable assistance, and because of a belief that professors should not place the decision making for data analysis only in the hands of statistical consultants and computer analysis assistants.

We do research. Statistics are the tools of the researcher and we need to know our tools. Tractor mechanics, artists, and masons have their tools and they must know how to use them. We, likewise, need to know how to use ours. You are challenged to get "checked-out" again on your tools; that is, devote some of your personal inservice or professional development time to renewing, maintaining, and improving your skills. Are you "green and growing?'

The writer would purport to have a working understanding of how to apply statistics. He could not provide derivations offormulas any longer, and, frankly, has no interest in doing so. He thinks he understands where and when these tools -- statistics-- should be used. In case some concept is presented that is contrary to your thinking, let me reiterate a statement often made by Dr. Al Krebs, our esteemed, retired colleague: "You don't have to agree with everything I say, but you should understand it."

One can easily find many contradictions in the statistical literature. Does the violation of "Assumption ` destroy the power of a test? Some say "yes" and some say "no." So, "pat answers" do not exist. What the author will attempt to present are what makes sense to him. If he has had any comparative advantage as a professional, perhaps it has been the ability to reduce the abstract to the understandable. Most of all, he would profess to be a teacher; one who can illustrate, explain, and show application. Therefore, any success or reputation enjoyed in the research area is probably due more to pedagogical and humanistic considerations than statistical competence. Further, being able to work alongside some remarkable researchers has, over the years, provided innumerable advantages. As our colleague, Dr. Glen Shinn, often says: "no one of us is as smart as all of us." Let us begin to use the *JAE* as a forum to discuss some of these issues, share with each other and improve our research.

When discussing the proper use of statistics, given the preceding, one must deal as often with the absence of analysis as with misuse. Absence constitutes, or precipitates in many cases, the misuse, a lack of clarity in describing findings, expressing results, or meeting assumptions.

The author most often teaches by story, example, analogy and metaphor. Thus, using one here, statistics are tools and are conceptualized as fitting into three tool boxes. The first box is labeled "Descriptive", the second is labeled "Correlation/Regression" and the third box is labeled "Inferential".

Box #1 is filled with measures of central tendency (mean, median, and mode), dispersion (variance, standard deviation, range, average deviation, semi-interquartile range), and visual tools such as symmetry, graphs, scatterplots, polygons, and charts.

Box #2 has two compartments: (A) correlation and (B) regression. The correlation compartment has a variety of tools such as the Pearson, Spearman, Kendall, point biserial, tetrachloric, or eta and each has a specific use. The regression compartment has tools like hierarchial, stepwise, or moderated.

Box #3 also has two compartments: (A) parametric and (B) nonparametric. The parametric compartment has tools such as t-tests, F-tests, or Anova. The nonparametric compartment contains tools such as Chi Square, sign test, Wilcoxon, Mann-Whitney, Kruskal-Wallis, or log linear analysis.

These tools, coincidentally, correspond with the purposes of research (Table 1). The purpose of a study and its objectives drive the selection of a statistical tool, not vice versa. Then, level of measurement, number of groups, and research design help the researcher select the appropriate tool. Please understand that many tools are parallel, but just be sure the ones selected are appropriate, i.e., do they meet the assumptions? Do not rely just on a statistical consultant or a computer programmer to make the right decisions. After all, the one doing the research will be the person who ultimately has to make sense out of the results of the analysis.

Descriptive statistics: tool box #1

Most of us are relatively familiar with measures of central tendency and dispersion. While some of us have studied and/or used statistics to varying depths, most have studied and adequately understand these tools. Table 2 provides a brief refresher of when to use which. The misuse most often encountered in this tool box results from a failure to consider the scale of measurement of the data upon which the tool is to be used.

A mean calculated on social security numbers would make little sense, nor would a mean generated from coding “men” as a one (1) and “women” as a two (2) for analysis purposes; what would a 1.4 be? A mean calculated on ordinal data would similarly be nonsensical.

Another concern is that we could do a lot more to describe data with graphs and other visuals to help the readers/consumers conceptualize and understand the results. Pie charts, bar graphs, or polygons could often provide clarity and assist with communication. Software programs are available for microcomputers and have made the preparation of such visuals less laborious. This should be a positive step for advancing the clarity of our dissemination and interpretation efforts if we do not overuse them

Table 1. Types of Research

Purpose or End Sought		
Explore/Describe	Explain/Predict	Control
Type of Research: Survey	Type of Research: Correctional/Ex Post Facto	Type of Research: Experimental (True and Quasi)
Analysis Used: Descriptive Statistics	Analysis Used: Correlations/ Regression	Analysis Used: Inferential

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Table 2. Descriptive Statistics

Measure	Scale of Measurement		
	Nominal	Ordinal	Interval or Ratio
Central Tendency (Location: score or category that best represents all in the distribution)	Modal Category	Median (50^{th} percentile)	Mean Median if skewed distribution
Variability (Spread: dispersion, heterogeneity, or scatter in the distribution)	Relative frequencies of categories	Semi-interquartile range $Q = \frac{Q_3 - Q_1}{2}$ Q_1=25th percentile Q_2=50th percentile (median) Q_3=75th percentile	Variance Standard Deviation Range
Symmetry (Shape: degree to which the distribution is asymmetrical)			Skewness values indicating symmetrical distribution negatively skewed positively skewed

Correlation/regression: tool box #2

Some might prefer that these tools be placed in Box #1 particularly the correlations,’ and others might like to see the regression placed in the inferential box; but, conceptually, it makes sense to the author to keep them stored separately. Then, they are handy when needed to analyze data to explain/predict (Table 1). These tools are principally used with correlational and ex post *facto* (relational/associational) research. Relational research is conducted to explain/predict phenomena. Correlation statistics address the explain portion and regression statistics address the predict component.

One could also argue that each of the compartments in the box have descriptive and inferential components, and be right. For, in the correlational compartment, there is the descriptive purpose of the correlation coefficients themselves and the inferential component would be to test the null hypothesis that Rho is equal to zero. (See Miller, L.E. “Correlations: Description or Inference? *Journal of Agricultural Education,* **35(3),** pp 5-7). One could reasonably argue that the inferential function is of little value in addressing questions in our discipline. In the regression compartment, the descriptive components would be beta and R squared, while the inferential components would be to test the null hypotheses that Beta is equal to zero or that R squared is equal to zero.

Correlation

Tables 3 and 4 present a system for determining which tools to use, based upon the scale of measurement for each variable (characteristic) studied. Were space available in these tables, numerous other tools could be listed.

The most common analysis is conducted with the Pearson product moment correlation coefficient **(r)** because it is used when both variables are interval or ratio in scale of measurement. But, sometimes, **r** is used whether or not it is appropriate. Two assumptions of the Pearson are sometimes violated, seldom reported, and lead to the misuse of the tool. Remember, the first thing to do when calculating this correlation is to construct a scatterplot? The scatterplot can be examined to see if the assumptions have been met for **r** of (1) linearity and (2) homoscedasticity. If the scatterplot is not linear (but curvilinear) and not homoscedastic (but heteroscedastic), then the **r** is not the appropriate tool to use. If the scatterplot is curvilinear, one would use Eta, a measure of curvilinear association / relationship.

Table 3. Correlations (Linear)

Scale of Measurement (Variable 1)	Scale of Measurement (Variable 2)		
	Nominal	Ordinal	Interval or Ratio
Nominal	Phi coefficient (2 X 2 table) Cramer's statistic (R X C Table) Hays, pp. 743-745)		
Ordinal	Rank-biseral correlation coefficient Glass and Stanley pp. 179-181	Spearman rank-correlation coefficient Hays, pp. 788-792 Kendall Tau Coefficient Hays, pp. 792-800	
Interval or Ratio	Point-biserial correlation coefficient Glass and Stanley pp. 163-165	Convert interval scores to ranks and calculate Spearman rank-correlation or Kendall Tau	Pearson product-moment coefficient Hays, pp. 63 l-636

Table 4. Correlations (Contingency Tables)

Scale of Measurement (Variable 1)	Scale of Measurement (Variable 2): Nominal — Dichotomous	Nominal — Multichotomous	Ordinal (Ordered Categories)
Nominal			
Dichotomous	Phi coefficient Hays, pp. 743-745	Cramer's statistic Hays, pp. 743-745	Convert ordered categories to nominal scale and calculate phi coefficient or Cramer's statistic
Multichotomous	Cramer's statistic Hays, pp. 743-745	Cramer's statistic Hays, pp. 743-745	
3rdinal Ordered Categories	Convert ordered categories to nominal scale and calculate phi coefficient or Cramer's statistic		Kendall Tau b (Square contingency tables) Kendall Tau c (rectangular contingency tables) Nie. et al., pp. 227-228.

When running CROSSTABS on SPSS and in lieu of plotting, an Eta and an **r** can be calculated. If Eta is of similar magnitude to **r,** then linearity can probably be assumed. However, if Eta is high and **r** is low, then do a scatter-plot because a curvilinear distribution probably exists.

Heteroscedastic distributions are also problematic. If a scatterplot is not plotted, about all that can be done is to "eyeball" the data to see if the variability in Y is rather uniform across each value of X. Analogies might be helpful to visualize (imagine) the appearance of the scatterplots: homoscedastic plots might look like pencils, bratwurst, cucumbers, depending upon the magnitude of the correlations; while heteroscedastic distributions might look like ping-pong paddles, dog bones, or bar bells.

One should further note that when one variable is nominal (e.g., men and women) and the other variable is interval (e.g., GRE scores), a point biserial is appropriate. However, it always seems to make more sense to not determine the relationship (with the point biserial) between gender and GRE scores, but to determine if there is a significant difference between men and women on GRE scores. One would, of course, use an inferential statistic such as a t-test for that analysis. Comparing the means for the men and women would be the descriptive dimension. If one tests a statistical hypothesis about the population means, then the analysis is inferential. Of course, if you wish to include a nominal variable as one of several variables in regression, then the point biserial is appropriate for the correlation and dummy coding for the regression.

Correlational tools answer the question of "how do two things vary together?" The output, the number, must also be interpreted correctly or misuse occurs. See Table 5 for a convention to use as a guideline for describing the magnitude. Another type of analysis error sometimes occurs because number, must also be interpreted correctly or misuse occurs. See Table 5 for a convention to use as a guideline for describing the magnitude. Another type of analysis error sometimes occurs because Pearson **r's** have been reported on tables in our national professional meeting that exceed the limit of an **r, e.g.,** a number such as 1.23 has been observed. How would this occur when the upper limit is l? Simple! Someone messed up!

Table 5. Describing Magnitude [a]

r	Adjective
1.0	Perfect
0.70 - 0.99	Very High
0.50 - 0.69	Substantial
0.30 - 0.49	Moderate
0.10 - 0.29	Low
0.01 - 0.09	Negligible

a Davis, J. A. Elementarv Survev Analvsis. Englewood, NJ: Prentice-Hall. 197 1.

The next problem seen with correlations is misuse via the interpretation of the significance of a correlation coefficient. Researchers often have a correlation of low magnitude (e.g., **r =** .15), which indicates two "things" really are not varying together, but report the correlation as "significant". The availability of information on the computer printouts is often partially to blame for this because the matrix generated by the computer will often list the **r** and directly under it will be listed the "p", the probability level. A naive researcher who is frantically searching for something important to result/report from a study may examine the **r's,** find none of very high magnitude; but, alas, some are "significant". This author perceives that many do not even realize what null hypothesis is being tested to produce this "p", and then they make a "big deal" about the significant correlation. A correlation can be very small and of little practical importance but still be "statistically significant" because statistical significance is a function of sample size. Reporting and interpreting a coefficient of determination (**r^2**) would be much more appropriate. Perhaps our research is too often concerned with finding something "statistically significant" and too seldom concerned with "practical significance." Our papers and journals are replete with the phrase "significant correlation" when they add nothing to the meaning and should not be reported.

Regression

The tools in this compartment are used primarily to help explain/predict. However, some correctly profess that they can serve an inferential function as well. The principal question which identifies them is "how well can I predict Y from knowledge of X (or several X's)?" This is the second question of relational/associational studies (those that explain/predict) and is the "predict" component (Table 1). Further, one must clearly understand that the method of collecting data, such as with a mailed questionnaire, does not dictate the type of research. What does identify the type of research conducted is the purpose of the study and if the purpose of a study is to explain/predict, then the study that uses a mailed questionnaire can be relational/associational A questionnaire can be mailed to gather data for a relational study and it would not be called survey research. [Note: One does not mail out a survey (a type of research) but one mails out a questionnaire, instrument or opinionaire.] Of course, documentary analysis, secondary data analysis and many other means can be used to supply data for relational research.

Numerous tools exist to examine the ability to predict. This compartment of the tool box has many tools each with specific purposes. Regression is appropriate when the dependent variable is interval or ratio in scale of measurement. Discriminant function analysis would be appropriate if the dependent variable is dichotomous (i.e., did youth drop out of the FFA or remain a member), and other tools such as logit analysis, probit analysis or canonical correlations have specific uses. These latter tools are becoming much more visible in the literature of the profession. Perhaps more recent graduates have had more training in these procedures and are more comfortable with them.

A practical concern with the use of these tools is with persons who, once again, forget the assumptions of the tools which permit their usage and proper interpretation. Many who use regression, for example, report significance and do not really explain what null hypothesis has been tested. One could suspect such authors do not know whether they should report the t-test or the F-test, and they do not fully understand what has been tested with each. Many writers may not know of the problems generated by multicolinearity, or the implications of a truncated distribution or non-normal distribution. Some also seem to have trouble in constructing a table to adequately convey the data needed to properly permit a reader to interpret the results. Properly prepared tables for an article or paper should be expected with any statistical analysis.

Inferential: tool box #3

The tools in this box address the question of "what are the chances that I got my results by chance?" In other words, what are the chances that the difference found between the groups was because of some quirk in my random assignment of experimental units to groups and not because the treatment made any difference; or, that there is any real difference between the groups other than what may have occurred by chance alone. Given all the many tools and complex formulas, this simple question seems minuscule, but is the real essence of what is being tested by inferential statistics. These tools test hypotheses such as with studies conducted to control (Table 1) as with experimental research.

Note, above, the use of the words "experimental unit (EU)". In our discipline, researchers have sometimes randomly assigned classrooms of students to a level an independent variable. For example, method of teaching is the independent variable in a study with level one being Computer Assisted Instruction (CAI) and with level two being the Conventional (Con) method.

The researcher randomly assigns three classrooms of ten students each for a total of 30 subjects to CAI and three classrooms to Con for a total of 30 students. Sixty (60) students are in the study. The EU, however is classrooms and, thus, the unit of analysis is also classrooms and there are six (6). The degrees of freedom **(df),** as N-1, (6-l) would be five (5). Students are often reported as the EU and the **df** is reported (60-1= 59) incorrectly, and this makes the analysis incorrect as well.

Each of the tools in this tool box has its own set of assumptions that must be met and reported before that tool is utilized. The researcher has the responsibility of assuring the reader that they have been met. So, be sure they have been met and described in the reports, papers or articles about the research. Appropriate information about the design of the study and the nature of the data must be used to determine which test is appropriate. The basic purpose of these tools is to infer the properties of a population (parameters) from knowledge of the properties of a sample (statistics). These inferences are never made with certainty as there is always some risk of an incorrect decision. There is always the risk of making a Type I or Type II error. Helpful ways to avoid these errors are provided in most statistics books.

The second concern which the profession must address is with the difference between statistical significance and practical significance. For example, one might be using a 4-point Likert-type scale and find the mean of one group to be 2.27 and the mean of the second group to be 2.38 when averaged across 300 subjects in each group on a 100 item questionnaire. If the sample sizes are large enough, then this small numerical difference of 11 can be statistically significant. However, the question is "whether or not it is of any practical significance" as the means of both groups, on the average, has fallen near the midpoint between the scale points of agreeing and disagreeing. Practically, how does the researcher interpret such a finding? Some writers might go to great detail in describing how the groups are significantly different when there is no practical significance. Tools are available such as omega squared and eta squared which can be used to assess practical significance and researchers in the profession ought to be "checked-out" on them. The idea of effect size can be meaningful in enhancing our interpretation of data.

Summary

The writer believes that, by omission, we also "under-use" interval estimation. We could easily calculate confidence intervals in many cases, but fail to do so. Such calculations would be another way by which we could aid in the reporting of our research. Constructing confidence intervals around a sample statistic and on a population parameter would often add to our reports. This is an error of omission, and perhaps we do it because we were so thoroughly grounded in hypothesis testing that we just do not think to do it.

Two other concerns seem almost paradoxical. The first is with the researcher who uses statistics to try to overwhelm the reader, and the second is with the person who underutilizes the tools.

In the first instance, research problems may be of small consequence or the objectives questionable, or perhaps the researcher really did not find anything; but proceeds to use some high powered statistical tool such as a canonical correlation, MANOVA factor analysis, cluster analysis, probit analysis, logit analysis, analysis of covariance; whether or not it is needed to address the objectives of the study. One could say the data are massaged in order to try to find "something." Oh, those tools have their place, do not misinterpret what is implied, but, if they are misused given the purpose of the study, then we should be critical. Often, when these studies are presented for consideration for journals or research conferences, the referees do not even know what was done with the data. The referees must take the initiative to look it up and study the procedure to determine its appropriateness even if it means spending several hours learning about it (e.g., Generalizability Theory) in order to properly make a judgement. Each referee, as a professional, has to assume the responsibility because the Editors of ourjournals cannot be expected to know the level of statistical sophistication of each referee. Complicated statistics do not make something scientific or important and trivial questions should not be masked by them.

The second person, who underutilizes statistics, may posit hypothesis which imply that the results will be analyzed, for example, to determine whether or not one group is superior to another group on a given criterion. The data are subsequently reported only in descriptive ways, i.e., that the mean of one group is higher than the other. The reader is essentially asked to judge whether or not there is sufficient difference between the means for the outcome to be meaningful. Such thinking, the writer believes, led Kerlinger and others to indicate that *ex post facto* research must propose hypotheses and provide more than just descriptive information. The example provided would necessitate the testing of hypothesis, and the reader should not be left to make an independent judgment based solely on descriptive data.

Since the topic of hypothesis testing is being discussed, let us examine a personal "pet peeve". Alpha levels should be set *a priori*, tested at that level, and reported at that level. Once again, the computer is partially to blame because most printouts from inferential analysis now list the "p" level. The researcher may have set an alpha level of .05 *apriori*, but when the computer prints out a "p" level of .001 the researcher asterisks the observed score for the test of significance and lists .001 at the foot of the table. Why? This author is particularly perplexed when the bottom of the table contains a whole array of probability levels ranging from 10 to .001 This is particularly worrisome when the precision of our measurement is not very precise and it already looks as though the researchers are using an electron microscope to examine data collected with a steamshovel (using the example of Dr. Jim Key). Granted, less of a problem would exist with subjecting data to a more robust test, for example, reporting alpha levels which put the data to a more stringent test, but to go from .05 to .10 would not be appropriate. The 1986 article in the *Educational Researcher* which presents a conceptual and comparative discussion of alpha levels and "p" would be appropriate reading for many in the profession as well as the March 1996 issue (p 26).

Another concern which surfaces is the use of statistics when one is studying a population. One must remember that statistics are characteristics of a sample and parameters are characteristics of a population. Statistics are symbolized by Latin or English letters and parameters are symbolized by Greek letters. Two scenarios will be drawn. The first is when a researcher is studying a finite population, such as 16 state FFA officers, where every member of the population is being studied. When the data are analyzed in this situation, the researcher has parameters, and statistics are not used. Remember, that inferential statistics essentially asks the question of whether or not the data were the result of chance sampling. If every member of a population was studied, then no chance exists that the data are the result of chance sampling because no sampling was used. Therefore, no statistics are needed. Still, one frequently sees inferential statistics used when a population is being studied.

A second scenario would be when one comparison group in a study is a population and the second group is a sample as one might do in comparing the attitudes of a population of state FFA officers with a random sample of local chapter officers. This example has a sample of one group and a population of the other. The appropriate analysis procedure would be to construct confidence intervals around the sample statistic to determine if it captures the parametric value. The problem of using parameters or statistics could also be addressed logically from the standpoint of arguing that the data determined from the population are really statistics since the data are from a sample of time and not a sample of people. That is, the data are collected at one point in time: that this set of state FFA officers is a sample of others which will exist or have existed at other points in time, and then use inferential statistics instead of construction confidence intervals. The major point is that the researcher has the responsibility to develop, in writing, a logical argument for analyzing and interpreting the data.

An advantage of being a Regional Editor of the *JAE* is that one can share personal biases and preferences. Essentially, the biggest concern is with whether or not we, as professionals and researchers, do enough to keep ourselves up-to-date in the area of analysis. Statistics may not be the favorite late-night reading for any of us, but we need to devote as much attention to these skills as we do to the technical skills of teaching, or the study of one of our content areas. Remember, we need to be "green and growing" when it comes to the study of statistics, too.

An additional caution was shared relative to the assumptions of any statistical procedure. The problem essentially is that we too often quickly decide what our analysis procedure will be before we have really examined our hypothesis, the design of our study, or the nature of our measurement to determine which is the single best tool. We all have known people whose only tool in the house was a pair of pliers and, thus, they used the pliers as a hammer, or as a screwdriver to extract or insert screws. We need to be sure that Anova, or some other tool, is not our only pair of pliers. My Mother used to believe that a mixture of lard and kerosene, as a salve, could cure most anything, from scrapes and scratches to congestion from a cold. We now have more than homemade salve. We need to learn to use the new medications as well.

The author would leave a final thought we should develop: research is an exciting endeavor. It can be fun, if you know the rules and procedures. We need to convey this enthusiasm to more of our graduates. Let us light their candle for conducting high quality research and prepare the next generation ofresearchers for agricultural education. Let us help them be persons who really love to do research and not people who see it as drudgery and a necessary evil of being employed, promoted or tenured in higher education. Help prepare them to be wise consumers of research. A legacy we can give future members of our profession is not only the skills to properly conduct research but a refreshing vision that they can help contribute to knowledge and the application of that knowledge to help solve the real problems of people.

Numerous improvements can be made in our research. Analysis is only one component. Future articles, under this editorial team. will attempt to address some of them.