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# Some of the Most Common Questions Asked of Statistical Consultants: Our Favorite Responses and Recommended Readings

DAVID B. ALLISON
BERNARD S. GORMAN
LOUIS H. PRIMAVERA

ABSTRACT. We addressed some of the most common questions or concerns encountered when consulting with applied researchers: detecting and managing outliers; handling missing data; multiple comparisons and familywise alpha rate protection; the disadvantages of dichotomization; the nature of the general linear model; writing the results section; determining the number of factors to retain in factor analysis; power analysis; parametric versus nonparametric statistics; appropriate numbers of predictor variables for use in multiple regression; variable selection procedures in multiple regression; interpreting interaction effects; and alternative analyses for pretest-posttest control group designs. We offer brief responses, not exhaustive theoretical expositions, but we believe they will help fellow consultants, teachers, and researchers to answer their own questions and those of their consultees, students, and associates.

IN DISCUSSIONS ABOUT RESEARCH DESIGN and statistical analysis with applied researchers in the social, behavioral, and medical sciences, we have observed common questions or concerns among many different consultees. We have written this article for researchers with some background in statistics and research methods, who prefer to be and should be involved in both the conceptualization and conduct of the analyses and often wish to be directed to readings that are relevant and comprehensible to someone with only modest statistical training. Our purpose in this article was not to introduce new statistical techniques but to offer some guidance on commonly confronted issues.

Herein, we have described some commonly encountered questions or some concerns, offered brief responses, and listed our favorite sources

recommended to clients. These responses are intended to be brief and not exhaustive theoretical expositions. As such, interested readers will often find themselves wanting more detail than we have provided on particular questions. This is where our "favorite" sources come in. Sources have been selected using several criteria: brevity, recency, and, most important, readability. As brevity is a consideration, articles or chapters have generally been preferred over books. In some cases, an exceptionally useful piece of software has also been cited.

## Questions

*How do I find out if I have outliers and what do I do if I have them?*

To be able to interpret results of statistical analyses unambiguously, one needs to insure that the results are not distorted by the presence of outliers. Outliers are cases (usually subjects) that come from different populations than do most of the other cases in the sample. Some investigators also consider unusual observations that result from erroneous data generation, collection, or transcription procedures to be outliers. The general principle governing outlier detection methods is that extreme scores occur rarely. Therefore, cases with extreme scores are likely to be outliers. However, it is important to note that it is not possible to definitively determine whether an extreme case is actually an outlier or "just an extreme case." We will return to this point shortly.

The first step in checking for outliers is to examine the univariate distributions. This can easily be accomplished by obtaining frequency distributions, histograms, and box plots from most major statistical packages. Cases that stray far from other cases in graphic displays or are more than three standard deviations from the mean are suspect as univariate outliers.

After checking for univariate outliers, the next step is to check for bivariate outliers. Bivariate outliers are cases that stray far from the "swarm" of other cases in two-dimensional space. They can frequently be identified visually by examining scatterplots. Numerically, just as a case more than three standard deviations from the mean may be a univariate outlier, cases with standardized residuals from the regression line may be bivariate outliers. Again, most major statistical packages will produce scatterplots and compute standardized residuals. It is important to remember that even though a case is not a univariate outlier on either variable, it can still be a bivariate outlier. For example, imagine a survey respondent who reports being 12 years old and earning $30,000 per year. Neither figure alone is unusual but the combination is quite rare.

One may also wish to check for multivariate outlets. We focus here on outliers in the context of multiple regression, as this is probably by far the most used multivariate statistical technique. However, most of these procedures are germane to other analytic strategies. Three types of outliers can occur in multiple regression: outliers on the criterion, outliers among the predictors and outliers that have undue influence on the regression equation. When checking for outliers on the criterion, one simply needs to compute the multiple regression equation and calculate standardized residuals with any standard statistics package. As in the bivariate case, cases with standardized residuals greater than three (absolute value) are possible outliers. Stevens (1984) offers a more sophisticated but still readable treatment of this topic including significance tests for outliers on the criterion.

Regarding outliers on the predictors (or for that matter, any *set* of variables), one can obtain a measure of the distance of each case from the centroid of all cases. The centroid is a multivariate average of all variables (i.e., the coordinates describing the center of a "swarm" in the $p$-variate hyperspace, where $p$ is the number of predictors). The measure of distance is referred to as Mahalanobis' $D^2$ and is a generalization of a z-score. Tabachnick and Fidell (1989) point out that Mahalanobis' $D^2$ can be interpreted as a chi-square with $p$ degrees of freedom and recommend testing each $D^2$ at $p = .001$. Cases with significant $D^2$ are considered potential outliers.

Finally, Cook's Distance (*CD*) is a measure of how much the regression equation would change if the case under consideration were dropped. *CD* is a measure of the joint influence of any case on both the criterion variable and the predictors. In this way, *CD* may be the most important indicator of potential outliers, because it indicates how much a case will influence the results of analysis. Cook and Weisberg (1982) suggest that a *CD* of about 1.0 be considered large.

Detecting potential outliers is all well and good. However, what does one do with them once detected? First, we recommend careful checking of the raw data for entry, transcription, coding, and transformation errors. This often accounts for a substantial amount of presumed outliers. If outliers are not merely the result of some data handling error, four broad options are available: (a) ignore them; (b) eliminate them; (c) transform them (e.g., Winsorize, see Cook & Weisberg, 1982); or (d) perform the analyses both with and without the outliers.

As we mentioned earlier, there is no sure way to tell if an outlier is actually from a different population or just extreme. Therefore, we do not favor elimination of cases. Rather, of the four options, we decidedly favor the fourth alternative. In the event that both sets of analyses give essential-

ly the same results, this can be mentioned and results obtained with the outliers can be reported. In our experience, this is almost always the case with samples of any reasonable size. In the event that different results are obtained with and without the outliers, then both can be reported.

Regarding sources, virtually all the plots and statistics we have been discussing can be easily obtained from any of the major statistical packages (e.g., SPSS, SAS, BMDP) and we therefore recommend their use in detecting outliers. For investigators using factor analysis, a program by Comrey (1985) may be helpful in identifying multivariate outliers that may affect the factor solution. For readings, we highly recommend Stevens (1984) as a thorough and comprehensible source. Other helpful sources are Barnette (1978) and Johnson (1985).

### *How do I handle missing data?*

Missing data is one of the most common problems encountered in research. Although survey and archival studies are probably most prone to this, the problem can also be present in experimental research (Welch, Frank, & Costello, 1983). The appropriate handling of missing data involves a two-stage decision process.

In the first stage, one must decide whether or not the data are believed to be missing at random. The assumption that data are missing randomly, that is, that "the available data and missing data for each item [variable] are each random subsets of the data for the complete sample" (Hertel, 1976, p. 460) is essential to the use of "imputation" methods described below. Imputation can be defined as the estimation of a missing value and the subsequent use of that estimate in statistical analyses.

Although there is no sure way to determine if data are missing randomly, two heuristics are available. One is a rule of thumb suggesting that if "too many" data are missing from any one variable, the data should *not* be assumed to be missing randomly. In this case, the variable in question should be dropped if at all possible. What is "too much" missing data is debatable, but Hertel (1976) suggested a 15% cut-off point. That is, if 15% or more of subjects are missing data on any one variable, then the variable may be excluded from the analysis.

A somewhat more sophisticated method, devised by Cohen and Cohen (1983), consists of dummy coding a new variable for the presence or absence of missing data on the variable in question. This dummy variable can then be entered into correlations or regression equations as a predictor of other variables. To the extent that the dummy variable is correlated with other variables, data cannot be assumed to be missing randomly.

In the event that some data are missing but are believed to be missing randomly, several methods of handling this problem are available. The simplest methods involve deleting subjects having missing data. Listwise deletion entails excluding a subject from any analysis in which he or she is missing a value for any variable involved in the analysis. The advantage of this method is its simplicity. The disadvantage is that, if the amount of missing data is at all substantial and multivariate procedures are in use, it will result in a substantial loss of subjects and, consequently, power.

In pairwise deletion, a correlation or variance-covariance matrix is computed "by using for each pair of variables ($X_i$, $X_j$) as many cases as have values for both variables" (Cohen & Cohen, 1983, p. 278). Multivariate procedures can then be performed on the resulting matrix. This method has the advantage of not losing any data. The disadvantage is that it is possible for the resulting matrix to be somewhat "ill-conditioned" or even a matrix that could not possibly occur with real data. This is particularly likely if data are missing in nonrandom ways. Pairwise deletion should be used with extreme caution, particularly if more than a small portion of data is missing.

Missing data imputation methods are generally superior alternatives to deletion. There are three primary methods for the imputation of missing data. In the first method, referred to as "mean imputation," one simply enters the mean value of a variable for any subject who is missing data on that variable. Although this method is the simplest of the three, it is *not* recommended, because it will artificially reduce the variability around the mean and potentially attenuate observed relationships among variables in the study. On the other hand, it is a conservative approach, inasmuch as relationships that are not strong will not be found. The reader might adopt this procedure when a bit of "extra" conservatism is desired.

The second method is referred to as "random imputation" or "sequential hot deck imputation" (Little & Rubin, 1987). Although there are several variations of this procedure, the basic method entails randomly ordering the records in one's data file and then assigning "to any missing score the value of the nearest preceding available nonmissing score for that item [variable]" (Hertel, 1976, p. 470). The advantage of this method is that it does not affect the variances of individual variables in a systematic way. However, since it does introduce more *random* variance ("noise"), it can also attenuate relationships between variables.

The third method is regression estimation. In this method, one computes a regression equation with one or more variables as predictor(s) and the variable with missing data as the criteria. The resulting equation is then used to predict what values the missing data would have taken

were they not missing, and these values are imputed. The advantage of this method is that it provides the most accurate estimates of missing values. There are two disadvantages. The first is computational complexity. The second is that when there is a distinction between independent (or predictor) variables and dependent (or criterion) variables, one cannot be used to estimate the other as this would artificially inflate the research findings (Raymond, 1986).

Cohen and Cohen's (1983) dummy coding can be helpful in this process. Specifically, Cohen and Cohen suggest that one might use imputation methods but assess the relations among variables with imputed values *after* partialing out the effects of missing data with the dummy coded variable. Cohen and Cohen (1983), Hertel (1976), and Raymond (1986) are excellent sources on this topic.

### *If I am doing multiple comparisons, should I use some adjustment procedure to protect my familywise alpha rate and if so which one?*

The appropriate handling of the multiple comparison situation has caused considerable consternation among researchers and statisticians alike. In part, this may be because there are two distinct issues at the heart of the controversy, one epistemological, the other statistical. We have tried to graphically depict the decisionmaking process at hand via the decision tree in Figure 1.

On the epistemological level, one must decide if one wishes to protect/control the familywise alpha level. The problem is simple (although the solution is not). Using Fisherian statistics, when we reject the null hypothesis at the prespecified alpha level (e.g., $p = .05$), we are stating that there is only a 5% chance that we have made a Type I error. If the appropriate assumptions are met, our statement would be correct *for any one comparison.* However, suppose that in a given study, we are testing 20 comparisons. The probability of making at least one Type I error becomes $1 - (.95^{20})$ or .64. Moreover, the expected number of Type I errors is 1.0; many find this unacceptably high.

In contrast, others (e.g., Saville, 1990) argue that

> the natural unit is the comparison, not the experiment. An experiment is no more a natural unit than a program consisting of several projects. Clearly, it is unsatisfactory to have the size of the experiment, or the number of experiments in a project, influencing the probability of detecting a particular pairwise difference. (p. 177)

In other words, changing the probabilities associated with a particular hypothesis test because the researcher is testing other hypotheses seems

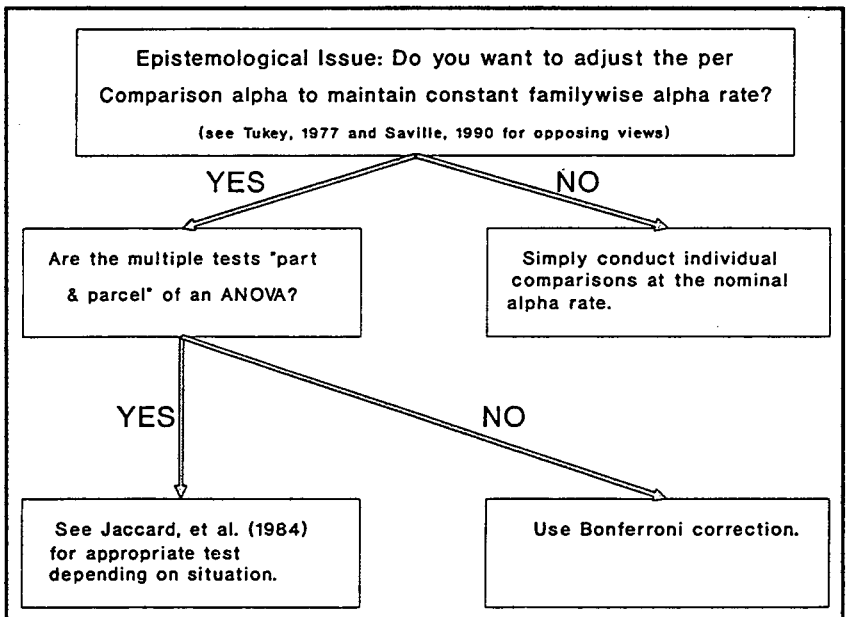


**FIGURE 1. Decision tree for multiple comparison question.**

not only irrelevant, but also punishes researchers for ambitious multifactorial studies.

This issue is of great concern to many applied researchers who are equally concerned with Type II and Type I errors (David & Gaito, 1984). Neither the logic of the "nonmultiple comparisonist" (e.g., Saville, 1990) nor the classic "multiple comparisonist" (e.g., Tukey, 1977a) is flawed. The only advice we can provide is that each individual researcher must ultimately "cut the Gordian knot," as Saville (1991, p. 167) states, and simply choose an epistemological position. Darlington (1990, chap. 11) presents a cogent discussion of the philosophical issues involved. In the event that the researcher chooses *not* to "protect" the familywise alpha rate, we recommend simply using the nominal alpha rate for each comparison or using the unrestricted least significant difference (LSD; see Saville, 1990).

In contrast, if one decides to protect the familywise alpha rate, a second set of decisions has to be made. Most often, multiple comparison procedures (MCPs) are discussed in the context of analysis of variance (ANOVA), because this is historically where they were developed (Klockars & Sax, 1986). However, multiple comparisons occur in other

situations as well. An illustrative situation occurred when Weiss et al. (1980) studied the behavioral effects of artificial food dyes on the disruptive behavior of 22 children. Weiss et al. conducted randomized single-subject alternating treatments designs (Barlow & Hersen, 1984) with each child. Data were analyzed via nonparametric randomization tests (Edgington, 1987). As 10 dependent variables were separately examined for each of 22 subjects, 220 comparisons were made, raising the familywise alpha rate to $1 - (.95^{220})$ or .999987. This figure would hardly be acceptable to anyone concerned about familywise alpha inflation.

In this situation (where tests are truly independent and not part of an ANOVA), the primary MCP available is the Bonferroni correction (Darlington, 1990). The Bonferroni correction is probably the easiest to use. One simply divides the nominal alpha level (e.g., .05) by the total number of comparisons being made. In the Weiss et al. (1980) case, if .05 was the chosen alpha level, the per comparison alpha level would be set at .05/220 or .00023. Although this is an extremely stringent test, for one of the 22 children, 5 of the 10 dependent variables did have associated $p$ values that exceeded the specified level. Thus, for that one child, Weiss et al. could confidently state that the food dyes did have an effect.

Another situation occurs when one is testing differences among means in ANOVA-type designs. Here, there are many procedures available. Jaccard, Becker, and Wood (1984) thoroughly reviewed all major MCPs that hold the familywise alpha rate at or below the nominal alpha level in terms of a variety of Type I and Type II errors. They review the major alternatives and provide recommendations for between-groups designs, within-groups designs, and mixed designs, under both optimal conditions (equal $n$s, normality, homogeneity of variance) and suboptimal conditions (unequal $n$s, nonnormality, heterogeneity of variance). The Newman-Keuls test, the least significant difference test (LSD), the restricted LSD, and Duncan's test were not recommended. Specific recommendations varied with the situation. We refer the reader to Jaccard et al. (1984).

### *If I have a continuous independent variable, should I do a median split and compare "low" and "high" groups to each other?*

This is one of the few issues on which there is generally a clear and simple answer: No! In responding to this question, we are reminded of Einstein's oft quoted remark, "Keep things as simple as possible, but not simpler." The desire to make things simple generally seems to underlie the intention to dichotomize (or otherwise make categorical) continuous

variables. However, the outcome of this procedure does not make things simpler at all for four major reasons.

First, dichotomizing continuous variables can drastically lower statistical power ($1 - \beta$; or the likelihood of rejecting the null hypothesis when it is actually false). A detailed discussion and proof of this phenomenon can be found in Cohen (1983). Cohen showed that dichotomizing one variable (e.g., the independent) at the mean results in power losses equivalent to discarding 38% of one's subjects. Even greater losses in power occur when variables are dichotomized at points above or below the mean or when the dependent variable is also dichotomized. Given the low power typically available in many researches (Rossi, 1990), any practice that unnecessarily lowers power further seems unconscionable. Compensation for this practice would necessitate collecting data on a substantially greater number of subjects. In the long run this can hardly be considered "simpler."

Second, dichotomizing continuous variables into "high" and "low" groups based on median, mean, or other splits of one's sample data in no way insures that groups defined as "high" or "low" correspond to groups so labeled in other studies or in the population overall. Imagine, for example, performing a median split on the distribution of IQ scores among members of the Mensa Society and labeling the lower half of the distribution as the "low IQ group." The absurdity of this example may be obvious. However, the practice of dichotomization is quite common among other highly selected and nonrepresentative samples (e.g., college students). Thus, dichotomization makes the interpretation of one's basic constructs less simple.

Third, dichotomizing two continuous predictor variables and treating them as independent variables in an ANOVA model potentially creates a nonorthogonal design. If the predictor variables are correlated, ANOVA cell sizes will be unequal, creating interpretive difficulties. Main effects can no longer simply be added together. Although this is equally true in regression analyses, the decision-making and interpretive process involved in multiple regression more explicitly acknowledges and was designed for this colinearity (Humphreys & Fleishman, 1974).

Finally, with multiple predictors, dichotomization can play havoc with interaction effects among the predictors. Veiel (1988) has shown quite eloquently that both the magnitude and direction of interaction effects can be greatly dependent on and distorted by dichotomization. Furthermore, the type and degree of distortion will vary with different and essentially arbitrary cut points.

In sum, as Humphreys (1978b) stated, research on individual differences requires correlational analysis, not ANOVA. Although regression

and multiple regression may seem more complex, it can be shown that ANOVA is a special case of regression (Pirot & Lustig, 1984; see next section). In the long run, the use of regression/correlation analysis will make research with continuous variables far simpler.

Unfortunately, in our experience, the belief in the appropriateness of dichotomization seems fairly resistant to change. So that skeptical readers may convince themselves (or their research associates) that these are not the opinions of just one statistician, we have cited several excellent discussions of these issues by several different authors (Cohen, 1983; Falzer, 1974; Humphreys, 1978a, 1978b; Humphreys & Fleishman, 1974; Veiel, 1988).

At this point, the reader may wonder "Are there *ever* situations in which dichotomization is warranted or better?" Our opinion is that the answer is yes when there is a strong theoretical rationale *and* the distribution can be shown to be significantly bimodal by an appropriate statistical test (e.g., Hartigan & Hartigan, 1985). In this case, nature has "dichotomized" the distribution for us and the sample should be split at the nadir, between the two modes, not at the median or any other arbitrarily selected value. We also believe that these situations occur rarely and that many dichotomies based on theoretical distinctions between groups are not supported by inspection of data that prove to be continuous and unimodal. For an example of this argument, see Eysenck (1970) on the value of a depressed/nondepressed dichotomy.

Finally, it should be noted that dichotomizing data after the fact should not be confused with the use of the "extreme groups design" to increase power. Under many circumstances, the latter is an appropriate and powerful method for testing weak to moderate relationships with expensive measures (Feldt, 1961). It should also be noted that even in the extreme groups design, the analysis of variance approach is still inferior to regression/correlation (Abrahams & Alf, 1978; Alf & Abrahams, 1975).

*What do you mean when you say that ANOVA, regression,* t *tests, discriminant function analysis, and so on, are really all the same?*

These techniques differ on whether variables are categorical or continuous and on how many independent and dependent variables there are. However, they are all subsumed under the general linear model and can be seen as special cases of canonical correlation (Knapp, 1978). Baggaley (1981) intelligibly portrays the relationships among these techniques (and several others) graphically, whereas Tabachnick and Fidell (1989, chap. 13) provide an excellent verbal description of the general linear model.

Canonical correlation analysis (CCA) is a multivariate technique for relating a set of $p$ independent or predictor variables to $g$ dependent or criteria variables. They may be either categorical or continuous (Share, 1984). Multiple regression is a special case of CCA when there is only one dependent variable. When one has only one independent variable, multiple regression become simple bivariate regression/correlation. If the one independent variable is a dichotomous categorical variable (e.g., gender), the resulting $r$ is a point-biserial correlation coefficient, $r_{pb}$. The significance test for this correlation is equivalent to the significance test for a $t$ test and $r_{pb}$ can be converted to $t$ (Rosenthal & Rosnow, 1991). It is well known that $F = t^2$ (in the case of the pooled variance $t$). Thus, this $t$ test can be seen as a special case of ANOVA with one between-groups factor having two levels. In turn, the ANOVA is a special case of multiple analysis of variance (MANOVA) in which there is only one dependent variable. Finally, we come full circle when we see MANOVA as a special case of CCA in which all independent variables are categorical.

We find that understanding these connections helps one understand the meaning and output of various statistical analyses. In addition, it helps researchers to be more flexible in their choice of data analytic strategy rather than relying rigidly on only one technique.

*How should I write my results?*

This question really requires three different responses at three different levels. First, there is the response at the broadest level, really a response to the question "How do I do good scientific writing?", most often asked by graduate students tackling one of their first research projects. For this we recommend some combination of several sources. One is the APA Publication Manual (American Psychological Association, 1983). In addition, both Rosenthal and Rosnow (1991, Appendix A) and Kidder and Judd (1986, chap. 17) have sections on writing research reports. Checklists of good reporting practices (an excellent example is Maher, 1978) can be helpful reminders, even to experienced researchers.

Often consultees are comfortable writing research reports in general. But on a more specific level, they ask what constitutes good or appropriate "statistical writing" in the results section. Again, the APA Publication Manual is a good source, but our favorite may well be Bailar and Mosteller (1988). Although their article is nominally aimed at medical journals, their suggestions and discussions apply equally well to educational and psychological research.

Finally, the researchers are often unsure about how to describe specific statistical techniques and their output. Although this can happen with

any technique, it occurs most often with multivariate statistical techniques (e.g., ANOVA, MANOVA, multiple regression, discriminant analysis, etc.). Here, we have found Tabachnick and Fidell (1989) to be an excellent source. At the end of each chapter discussing a specific multivariate technique, a sample report of a hypothetical analysis is presented. The reports are invariably well written, clear, comprehensible, and detailed without being verbose.

*If I'm doing a factor analysis, how should I decide how many factors to retain?*

This is a question that has been the subject of much thought. Although research on this issue will undoubtedly continue, some consensus appears to be developing. At this time, Zwick and Velicer (1986) have published what may be the most comprehensive and up-to-date work in this area. They conducted a Monte Carlo comparison of five of the most common rules for determining the numbers of meaningful factors or components. The five rules were Horn's parallel analysis (PA), Velicer's minimum average partial (MAP), Cattell's scree test, Bartlett's chi-square test, and the Guttman-Kaiser eigenvalue greater than 1.0 rule (K1).

Zwick and Velicer (1986) summarize their findings in the following:

> . . . PA was clearly the most frequently accurate method followed by MAP and scree. The tendency of K1 to overestimate was marked. The K1 method never underestimated. The Bartlett test was quite inaccurate and variable. . . . (p. 439)

One of the most important points is which rules *not* to use. Given the inaccuracy of the Bartlett test, it is clearly not recommended. Of even greater note is the performance of the K1 rule. Despite its empirical shortcomings (Zwick & Velicer, 1986) and the fact that it has been shown to be theoretically unsound (Cliff, 1988), it is probably the most commonly used rule. We suspect, like Zwick and Velicer (1986), that this occurs because it is the default procedure in SPSSx, BMDP, and SAS. Readers are cautioned against the blind use of this rule.

In terms of what rules to use, obviously the PA criterion is empirically sound. However, two practical concerns may mitigate against its use. First, the theoretical rationale for the method is complex and may be difficult to communicate to research associates and consumers. Moreover, to the best of our knowledge, no major statistical package incorporates PA (although programs which perform PA have been written; Velicer, Fava, Zwick, & Harrop, 1988). Thus PA may not be accessible to many users.

In contrast, MAP not only performs quite well under most circumstances but has recently been included in an easily accessible user-friendly

statistics package (Gorsuch, 1990). Thus our primary recommendation is use of the MAP criterion with Gorsuch's program. For researchers without access to this program, the scree test is simple and easy to apply and is still fairly accurate, particularly when component saturation (the magnitude of the loading of each variable on a component) is high (Zwick & Velier, 1986). Thus, the scree test represents a good "backup" method.

*How many subjects do I need? Do I have enough power?*

This is undoubtedly the single most commonly asked question of statistical consultants (Kraemer, 1985). At the risk of being flippant, we have been tempted to respond "Whatever your question about power analysis is, the answer is 82." Although this is clearly an oversimplification, it actually approximates an appropriate response in many (but by no means all) applied psychological researches. Our rationale is as follows. Power is a direct function of sample size ($n$), alpha levels ($\alpha$), and effect size ($\delta$). Conceptually, effect size is defined as the impact of one variable (or set of variables) on another variable (or set of variables). If any three of these parameters are held constant, the fourth is determined.

Most applied researchers are willing to operate at $\alpha = .05$. Most researchers would also like the power of their investigations to be at least .99; that is, they would like to have a 99% chance of rejecting the null hypothesis if it is in fact false. However, sample sizes for this power level are usually prohibitively large. In practice, Cohen (1988) recommends a power level of .80 and most researchers find this acceptable. The third parameter, effect size, is what Lipsey (1990) refers to as "the problematic parameter." It is on this parameter that the calculation of the required $n$ usually hangs. Although there are many indicators of effect size, we find Friedman's (1982) $r_m$, conceptually equivalent to a product moment correlation coefficient, to be easily interpretable. When we ask applied researchers if they are interested in finding small effects or primarily moderate to large effects, most select the latter. Cohen (1988) defines a moderate effect as equivalent to $r_m$ of .30.

Entering Friedman's power tables with $\alpha = .05$, $r_m = .30$, and power $= .80$, we find that the required sample size is 82. The reader may now see the basis for our earlier flippant response. Moreover, the reader may discern our favorite source in this area. Friedman (1982) provides a single table that will easily answer many questions about power analysis and requires the reader to perform little or no calculation. Clearly, we do not mean to imply that Friedman's article will answer all questions, but it is certainly an excellent starting point.

Readers interested in a more general but still brief and readable introduction to power calculations may find Muenz (1989) or Kraemer and

Thieman (1987) quite helpful. Bird and Hall (1986) present an excellent source for researchers planning studies involving protected post-hoc comparisons. Bartko, Pulver, and Carpenter (1988) introduce extremely simple nomograms for power analyses involving either paired or independent sample *t* tests. Finally, for readers interested in the full range and complexity of power calculations, there is no better source than the classic Cohen (1988).

Recently, some helpful software has been developed. Here no one or two sources can be recommended since no program calculates power in all relevant situations. Readers may wish to consult Goldstein (1989) for a review of software and also consider some programs made available since Goldstein's review (e.g., Allison & Gorman, in press; Borenstein, Cohen, Rothstein, Pollack, & Kane, 1990; Darlington, 1990, Appendix 3; Dupont & Plummer, 1990; NCSS, 1991; Rothstein, Borenstein, Cohen, & Pollack, 1990). Researchers requiring frequent power calculations for diverse designs might maintain a potpourri of power software.

*Which should I use, a parametric or nonparametric test?*

Most classical statistical tests are based on the highly useful assumption that the data have been randomly sampled and are normally distributed. However, researchers are often faced with data sets that contain discrete measurements that are not normally distributed or are not randomly sampled. The critical issue in deciding whether to use parametric or nonparametric tests is whether the assumptions of the parametric tests can be met. Under the leadership of Kendall (1962) and Siegel (1956), interest arose in the use of nonparametric statistics. According to Siegel and others (Edgington, 1969; Gaito, 1970; Gibbons, 1971; Marascuilo & McSweeny, 1977), nonparametric statistics can provide useful alternatives to parametric tests and, in some cases, provide unique analyses that could simply not be achieved with traditional parametric methods.

Proponents argue that nonparametric tests require fewer assumptions about distributions, especially those of normality and equal variance within groups. Most advocates of nonparametric tests agree that, whereas parametric tests should be used with data that are "truly numeric" (i.e., data that fit interval and ratioscale measurement), because nonparametric tests require only ranking and/or counting, they may be more appropriate for nominal and ordinal scale data.

Given the fact that desk calculators were hardly affordable in the 1950s, early proponents of nonparametrics believed that the less laborious hand computation required by nonparametric tests was an advantage but this is of minor importance in the age of personal computers. Mc-

Sweeny and Katz (1978) stated that since many nonparametric tests require only rank orders, they are less sensitive to outliers. Some tests of contingency tables and some tests of ordinal data can be performed only as nonparametric tests.

Randomization tests provide a useful class of nonparametric tests (Edgington, 1969, 1987). In general, these tests provide all possible sortings and permutations of an observed data set. By tallying the occurrence of data patterns, the exact probability of specific data patterns can be assessed. Then the pattern of scores in the actual data set can be compared to the frequency of possible chance sortings. Thus, a researcher can offer a statement about the likelihood that the observed data pattern occurred by chance alone.

With very small data sets (i.e., $\leq$ 10 observations), it is possible to list all permutations by hand. The amount of computation needed for sorting large data sets can be prohibitively extensive. However, with the advent of faster computers and sampling techniques in which a sample of some but not all possible combinations is used, the task becomes more manageable.

Edgington (1980) and Harwell (1988) stated that when data are randomly sampled, parametric tests are most powerful. However, when a population has not been randomly sampled, even when the subjects are randomly assigned to groups, they argue that nonparametric randomization tests provide more power. Harwell (1988) stated that nonparametric tests do well in controlling for Type I error with nonnormal distributions and are more powerful than parametric tests when nonnormality is present. Gaito (1970) added that one can often make probability statements that are "exact" in nonnormal distributions regardless of shape. Furthermore, for samples with as few as 6 cases, there may be no alternative to using a nonparametric test.

Given the claims of the lack of restrictions and flexibility of nonparametric tests, it might be concluded that they should be used under all circumstances. However, it can be shown that the use of nonparametric tests may have serious drawbacks. Gaito (1970) and Harwell (1988) voiced a strong series of warnings against the unselective use of nonparametric tests. Cohen (1965) concurs and does so with such flair that we suspect many readers of his section titled "Nonparametric Nonpanacea" will find it as entertaining as informative.

The reasons for these authors' reluctance toward nonparametric methods are several-fold. First, a large body of research has demonstrated that $t$ and $F$ tests are fairly robust to assumption violations, especially if sample sizes are equal and large ($>$ 30 or so). Moreover, it cannot be said that all distribution-free tests are insensitive to distribution shape dif-

ferences. For example, the commonly used Wilcoxon/Mann-Whitney *U* test is more sensitive to skewness and kurtosis than is the *t* test. Although there have been attempts in recent years to solve complex designs with nonparametric procedures, Cohen's (1965) argument that there are few tests available for complex designs still holds.

Most important, nonparametric tests often have lower power efficiencies than their parametric analogues. That is, all else being equal, more cases will be needed to reject the null hypothesis with a nonparametric test than with a parametric test. If the assumptions of a parametric test are met, then a corresponding nonparametric test will be less powerful. Finally, when estimates of parameters are needed, then parametric tests must be used.

It can also be shown that a middle ground can be achieved. For example, nonnormal distributions can be transformed to normality (see Tukey, 1977b). They also can be ranked and analyzed with more traditional parametric techniques, substituting the ranks for interval and ratio scale scores. Harwell (1988) demonstrated that methods devised by Puri and Sen (1969, 1971) provide a conservative method for analyzing complex designs. In these methods, rank orders are substituted for scores, and the data are submitted to parametric analyses. Summary statistics such as *F* ratios and *t* values based on the ranked data are then converted to proportions of explained variance measures and tested for significance by conservative chi-square statistics. In a similar vein, Rassmussen and Dunlap (1991) have shown that when data depart from normality, parametric analyses of transformed data result in fewer Type II errors than nonparametric analyses and fewer Type I errors than parametric analyses of raw (untransformed) data.

It appears that if sample sizes are large, if assumptions are not seriously violated, and if data are at least ordinal, then researchers should consider staying with traditional parametric tests. On the other hand, if the data are of nominal scale, the assumptions of parametric tests are severely violated, and specialized small-sample techniques are available, then a nonparametric test might be employed. Alternatively, a researcher might attempt to transform data to meet the assumptions of parametric tests and submit data to more traditional tests or use the Puri and Sen (1969, 1971) approach.

We suggest that if the researcher is in doubt, parametric analyses of both raw and transformed data and nonparametric analyses be performed. As with the handling of outliers described earlier, if all analyses give essentially the same results, this can be mentioned and those results obtained with the parametric analysis of raw data can be reported. Again, in our experience, this is usually the case. In the event that dif-

ferent results are obtained with different analyses, results should be interpreted with considerable caution and all should be reported, if only parenthetically, in a footnote.

*How many predictor variables can I use in multiple regression?*

There is no rule written in stone for this response. Theoretically, one can have as many as $n - 2$ predictors, where $n$ is the number of subjects. However, in practice such a rule would result in ridiculously low power (because only one degree of freedom would remain). Moreover, any regression weights and $R^2$ values obtained would be highly unstable.

Stevens (1986) provides an excellent discussion of the issue. He makes a convincing argument that a good rule of thumb is: "No more than one predictor for every 15 subjects." Stevens bases his argument on two main points of evidence. One is Herzberg's (1969) formula for estimating validity shrinkage. Validity shrinkage is defined as the difference in the $R^2$ based on sample data and the $R^2$ that would be obtained using the sample regression equation in the population. Stevens showed that when the sample $R^2$ is .50 (a reasonable estimate for applied research) validity shrinkage begins to become small (i.e., about 12% of the sample $R^2$) when the ratio $n/k$ is 15, and $k$ is the number of predictors. Finally, Stevens cites a study by Park and Dudycha (1974) showing that, assuming an $R^2$ of .50, when $n/k \geq 15$, there is a 90% probability that validity shrinkage will be less than 5%.

*What are the differences among all these different types of variable selection procedures in multiple regression (e.g., forward, backward, stepwise, simultaneous, hierarchical, all subsets) and which should I use?*

Drawing heavily on an article by Hocking (1976), Rawlings (1988, chap. 7) offers an overview of the different purposes of regression, how these different purposes lead to different variable selection criteria, and how the various selection criteria work. Although there is little of Rawlings' presentation that cannot be found in Hocking, we find the former to be a more palatable offering to nonstatisticians. Other readable discussions can be found in Darlington (1968) and Wampold and Freund (1987).

The most important issue in determining which method to use is the reason that the analysis is being undertaken. Rawlings (1988) distinguishes six purposes of regression. On a broader level, we distinguish between three general purposes: a) description; b) model testing; and c) prediction/estimation.

> When the object is *simple description* of the behavior of the response variable in a particular data set, there is little reason to be concerned about elimination of variables from the model, about causal relationships, or about the realism of the model. The best description of the response variable, in terms of minimum residual sum of squares, will be provided by the full model, and it is unimportant whether the variables are causally related or the model is realistic. (p. 169)

Thus in this situation, "simultaneously entry" of all variables into the equation in a single step is appropriate. In practice, we rarely, if ever, encounter researchers with this goal in mind.

Often, researchers wish to use multiple regression to test theoretical models. For example, an investigator may believe that physical exercise improves mood solely by improving self-concept; that is, that self-concept completely *mediates* the relationship between exercise and mood. The investigator surveys 1,000 subjects and derives estimates of the degree to which they exercise, their self-concept, and their "average mood." Under these circumstances, hierarchical regression is the appropriate technique. In this procedure, the researcher decides in what order predictor variables will enter the regression equation based on the hypotheses being tested.

Given this example, the researcher would first enter self-concept into the regression equation (with mood as the criterion variable). Then, exercise would be entered into the equation. If exercise explained a significant amount of variance in mood when self-concept was in the model, the researcher's hypothesis would be disconfirmed. If exercise did not explain a significant amount of variance in mood when self-concept was in the model, the researcher's hypothesis would be supported (confirmation is beyond correlational data).

Finally, some researchers are interested in prediction or estimation. For instance, obesity researchers usually need measures of adiposity (fatness) for their studies. Although adiposity can be measured very accurately by dissection, underwater weighing, or dual photon absorptiometry (DPA), such methods are impractical for many investigators. However, skinfold thickness often correlates with total adiposity and is quite practical to measure. A researcher who measures skinfolds at 10 to 20 sites could probably combine these measurements to yield a highly accurate estimate of total fatness. This could be tested by collecting the skinfold measures and correlating them with a more direct measure of adiposity (e.g., from DPA). Two questions can then be answered in the regression analysis. Are all of the skinfolds necessary or can time and money be saved by dropping some of them without losing any accuracy

in the estimation? What are the optimal weights for each of the skinfolds (predictor variables)?

In this situation, two broad alternatives are available —all-subsets regression and stepwise regression. All-subsets regression is exactly what it sounds like. All possible subsets of predictor variables are tried. The researcher may then select the best subset. "Best" is usually defined by a mathematical criterion (Rawlings, 1988, describes several) that tries to achieve the best "compromise" between maximizing $R^2$ and minimizing the number of predictors. One drawback to all-subsets regression is computational demand. As the number of predictors becomes large, computational time can become great even for modern high speed computers. Some computer programs (e.g., SAS) contain an algorithm called the "leaps and bounds" algorithm, which provides an approximation to all-subsets regression with less computational cost.

The major alternatives to all-subsets regression are the stepwise procedures, which include forward selection, backward elimination, and stepwise selection. In forward selection, the variable entered first is the variable with the largest zero-order correlation with the criterion. The next variable entered is that with the largest first-order partial correlation when the first predictor is already in the model. This is repeated until some prespecified "significance level to enter" fails to be reached.

Backward elimination is the reverse. All variables are simultaneously entered into the regression. Then the predictor whose removal would produce the least rise in the residual sum of squares is removed. This process is repeated until some prespecified "significance level to remove" is reached.

The procedure most often labeled "stepwise" is designed to take advantage of the effects that the addition or deletion of one variable can have on the contributions of other variables (Rawlings, 1988). It is a selection process that can switch from forward to backward and back at any step in which the addition or elimination of any predictor will enhance the model.

Two caveats should be mentioned regarding all subsets and stepwise procedures. First, these procedures often capitalize on chance relationships in the sample data and may "overfit" the data. Therefore, when they are used to generate prediction/regression equations it is essential that the resulting equations be validated with independent data (Rawlings, 1988). Second, the ordinary $F$ tests of $R^2$ values are not applicable because a greater number of predictors have actually been "tried" than are included in the tested model (Henderson & Denison, 1989). These two facts are often ignored. Consequently stepwise regression has been

referred to as not only one of the most used but also one of the most misused statistical techniques (Henderson & Denison).

*How do I interpret interaction effects?*

Rosnow and Rosenthal (1989) provide a very brief and readable description of how to display and interpret interaction effects in the analysis of variance (ANOVA). A more detailed account and an excellent exposition of the possible reasons for interaction effects are provided in their chapter devoted exclusively to interactions (Rosenthal & Rosnow, 1991). Defining an interaction effect is simple. An interaction effect is the multiplicative effect of two (or more) variables after controlling for the individual additive effects (i.e., main effects) of the independent variables.

In truth, there are many different types and definitions of interaction effects. Although the multiplicative variant is only one, it is by far the most commonly discussed. For an excellent and detailed (though admittedly demanding) article on the many types of interaction, see Southwood (1978). Conceptually, an interaction effect occurs when the effect of one variable depends on the level of another. It should be noted that in this context we are considering interactions among independent (predictor) variables (e.g., Treatment × Treatment interactions) and not Subject × Treatment interactions.

Describing and explaining a particular interaction is somewhat more difficult. One controversy surrounds graphical presentation in the ANOVA context. Rosenthal and Rosnow (1991; Rosnow & Rosenthal, 1989) describe methods for graphically displaying the residual means after removing main effects. However, Meyer (1991) disputed the necessity of Rosenthal and Rosnow's suggestions and argued for graphing raw means, which is the procedure advocated in the vast majority of standard ANOVA texts (e.g., Winer et al., 1991). It is our opinion that the disagreement stems from two distinct issues being conflated; the *analysis* of interaction effects and the *interpretation* of interaction effects. The former is essentially a statistical problem over which there is no disagreement. The latter is a problem in human factors and needs to be treated as such.

In some complex designs, residual means may be tabulated to reveal patterns (Rosenthal & Rosnow, 1991, p. 375). Alternatively, we find that inspection of raw means often provides the viewer with rich information regarding such factors as whether the interaction is ordinal or disordinal. Winer et al. (1991) extensively describe the "geometric" interpretation of plots of raw means. In short, interpretation of an interaction effect that

has already been shown to be statistically significant is no longer a statistical problem but rather a problem in human perception. We believe this problem is best addressed empirically by researchers in graphical perception rather than analytically. In the meantime, we offer the simple suggestion that researchers plot interaction effects in the manner they find most aids their understanding.

An additional interpretive strategy was proposed by Mood (1950, p. 337). Mood suggested that the $F$ ratios of main effect mean squares over interaction mean squares can be taken as indices of the relative magnitudes of these effects. Thus interaction effects can also be interpreted in relation to the other effects present.

Regarding explanation, Rosenthal and Rosnow (1991) provide an explanation of several different patterns of interaction and discuss possible explanations for these effects. These explanations include both substantive interpretations and interpretations of interactions as possible measurement artifacts.

An important consideration regarding possible artifactual interaction is scale of measurement. Many statistically significant interaction effects disappear if the dependent variable is subjected to a nonlinear monotonic transformation (e.g., a log transformation). Two considerations apply here. First, if dependent variables are measured on an ordinal scale rather than on a ratio or interval scale, then the scaling is arbitrary and any monotonic transformation is permissible. In that event, if a transformation eliminates nonadditivity, the data can be described more parsimoniously with only additive effects, and the interaction effect may be artifactual.

The second obvious consideration is whether a transformation can eliminate the nonadditivity. As Winer et al. (1991) state:

> Not all interaction effects can be regarded as functions of the scale of measurement. In cases where profiles cross, or . . . have quite different shapes [i.e., disordinal interactions], transformations on the scale of measurement will not remove interaction effects. (p. 445)

Finally, researchers using multiple regression should be aware that interaction terms can be analyzed and interpreted here as well. In regression analyses, interactions are usually coded as product terms and are entered into regression equations after partialing out the "main effects" of the individual predictor variables. An interaction occurs when the slope of the regression between two variables depends on the value assumed by a third. A comprehensible presentation of interaction effects in the context of multiple regression can be found in Darlington (1990, chap. 13).

We are inclined to agree with Rosenthal & Rosnow (1991), Darlington (1990), Southwood (1978), and the majority of the research community that meaningful and scientific interpretations can be ascribed to many interaction effects.

*If I have pretest-posttest control group design, should I do repeated measures ANOVA, an ANCOVA with pretest as the covariate, or something else?*

Cole (1988) and Huck and McLean (1975) render excellent discussions of this issue. Given the pretest-posttest control group design (i.e., split-plot design), one can discern at least four options: (a) ignore the pretest data and analyze the posttest scores only with a simple one-way ANOVA; (b) use a repeated measures ANOVA with one between-groups factor (treatment assignment) and one within-groups factor (trials); (c) analyze change scores (e.g., posttest minus pretest) in a oneway ANOVA; or (d) analyze the data as an ANCOVA with one between-groups factor (treatment assignment) and one covariate (pretest scores).

The first method, ignoring the pretest data, is generally not recommended for two reasons. First, it discards information, arguably the most precious commodity researchers have (Cohen, 1990). Second, it is generally the least powerful of all the approaches.

The repeated measures approach utilizes all available information and is more powerful than the posttest-only approach. However, it is frequently misinterpreted (Huck & McLean, 1975). The crucial effect in this analysis is the Treatment × Trials interaction. However, many researchers mistakenly interpret one of the main effects in this situation (Huck & McLean). Thus this method may not be ideal. Regarding the analysis of gain scores, it can be shown that the Treatment × Trials interaction in the repeated measures approach is mathematically equivalent to the main effect for treatment in the change-score approach (Huck & McLean). As this approach is more easily interpreted, it may be preferable to the repeated measures analysis.

The repeated measures ANOVA or gain score analyses are equivalent to the ANCOVA when the pretest-posttest correlation = 1.0. However, as this is rarely the case, the ANCOVA, which corrects posttest scores via the actual sample pretest-posttest correlation, provides a more accurate representation of treatment effects and is therefore usually more powerful (Huck & McLean, 1975). The superior power of the ANCOVA increases as the pretest-posttest correlation decreases. Thus, the ANCOVA is generally recommended as the preferred method of analyses in these designs. The one exception to this may be when power is already high

and ease of interpretation is crucial. Although we are generally quite reluctant to recommend any procedure with inferior power, under these circumstances, the gain score approach may be preferred due to its more obvious meaning.

Two final points are noteworthy. First, when planning such experiments, we recommend considering Maxwell, Delaney, and Dill's (1984) "alternate ranks" procedure. This procedure assigns subjects to treatment conditions on the basis of rankings on pretest scores and will further increase the power of the subsequent ANCOVA. Second, if posthoc tests are to be done following an ANCOVA, additional procedures need to be used with covariate adjusted means (See Stevens, 1986, for a discussion).

## Conclusion

These responses will certainly not answer every question that a researcher facing a data set will have. Nor do they even represent responses to all the questions we are commonly asked, but space limits our presentation. However, we hope they will be helpful to researchers embarking on a data analysis, and we think the responses, and especially the suggested readings, will be helpful to fellow consultants, teachers, and researchers in answering the questions of their consultees, students, and associates. Finally, we do not intend for these suggestions to be taken as "written in stone." Like all fields of scientific inquiry, statistics is an evolving discipline, and the future will undoubtedly bring new insights.

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DAVID B. ALLISON conducts research at the Obesity Research Center, St. Luke's/Roosevelt Hospital, Columbia University College of Physicians and Surgeons. BERNARD S. GORMAN is a member of the Department of Psychology at Hofstra University. LOUIS H. PRIMAVERA is a member of the Department of Psychology at St. John's University.

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# Talking About Sexual Abuse: The Value of Short-Term Groups for Women Survivors

SANDRA TURNER

ABSTRACT. Many women who are adult survivors of childhood sexual abuse suffer long-lasting and devastating consequences. Some of the lasting effects are low self-esteem, depression, a sense of guilt and shame, feelings of isolation and loneliness, and unsatisfying personal relationships. Talking about the abuse with other women survivors can have a substantial therapeutic impact. This article describes the value of short-term groups as a means to help heal the scars of childhood sexual abuse, particularly incest.

IN THE UNITED STATES TODAY, sexual abuse is not really a taboo; talking about it is. Whereas sexual abuse at any age and in any form is extraordinarily traumatic, numerous studies have shown that the younger the age at which the abuse occurs and the more violent it is, the more pernicious are the effects on the survivor (Gomes-Schwartz, Horowitz, & Cardarell, 1990; Herman, 1981). Survivors abused at a very early age are likely to be silent for the longest time. Statistics show that anywhere from 1/3 to 1/2 of all the women in the United States will be sexually abused sometime in their lifetimes (Russell, 1986). Statistics also show that 16% of adult American women will experience incest before the age of 18 (Jackson, Calhoun, Amick, Maddever, & Habif, 1990). Despite these statistics, our society prohibits women from talking about what has been done to them.

The term *sexual abuse* applies to both rape (assault by a nonfamily member) and incest (assault by a family member or close relative), with the broadest definition of sexual abuse being any kind of unwanted sexual contact. Sexual abuse of a child may take the form of fondling, masturbation, exhibitionism, or intercourse that occurs between a child

and someone in a position of power or authority who is at least five years older than the child. (Greenwald, Leitenberg, Cado, & Tarran, 1990; Knight, 1990). Some experts consider anyone under the age of fifteen a child (Russell, 1986).

There is some disagreement in the sexual abuse literature about the perniciousness and pervasiveness of the effects of childhood sexual abuse. The survivors themselves, however, do not disagree about the effects: They are devastating. Group treatment can help survivors heal the effects of this devastation.

Survivors of incest generally feel a tremendous sense of isolation and alienation. They have not been encouraged to talk to each other. Belonging to a group that enhances survivors' communication with each other and focuses specifically on healing the scars of sexual abuse can not only lessen feelings of isolation and alienation but also foster a sense of empowerment, connection, and trust.

## Psychological Effects of Sexual Abuse

Researchers disagree about the psychological impact of childhood sexual abuse. Some studies report that "abuse itself makes little difference among those who have experienced good parenting" (Parker & Parker, 1991, p. 184). Others report findings that abused women do not experience more sexual dysfunction as adults than do those who were not abused (Tsai, Feldman-Summers, & Edgar, 1979).

Most research studies and clinical observations, however, report that depression, feelings of worthlessness, a sense of guilt and shame, anxiety, and, in many cases, a lower sense of self-esteem are problems that many women who have suffered sexual assault experience (Gordy, 1983; Jackson et al, 1990; Yassen & Glass, 1984). There are many variables that will affect measures of psychological functioning: the victim's age when the abuse occurred, as well as her age at the time of the study; her economic and vocational status; and any decision to seek treatment. Although it is true that abuse at a younger age is more injurious, it is also true that children who are questioned about abuse soon after it occurs are likely to minimize its psychological effects. They are especially unlikely to self-report depression (Shapiro, Leifer, Martone, & Kassem, 1990). This may be because of a sense of guardedness and an ability to deny and block out the experience.

Most women who were abused as children internalize the blame for the abuse, and this internalization of blame often leads to guilt, shame, and some degree of depression and feelings of worthlessness.

## Cultural, Social, and Economic Factors

The psychological or developmental explanation for the internalization of blame is that young girls are incapable of seeing that what happened to them is not their fault and that they did not cause it. The cultural explanation is that girls are taught to internalize blame and not to express anger: "Most women have not even been able to touch this anger, except to drive it inward like a rusted nail" (Rich, 1979, p. 309). In discussing spouse abuse, Wodarski states that the "basis for maintaining silence is a shared belief in a patriarchal society that seems to cut across all socioeconomic, religious, and racial planes" (Wodarski, 1987, p. 172). This statement is also true for childhood sexual abuse.

Of all the forms of sexual abuse, father-daughter incest is the most traumatic (Gomes-Schwartz, Horowitz, & Cardarell, 1990; Herman, 1981), for one of the most cherished beliefs in our patriarchal society is that fathers and father figures are our chief protectors. An incest survivor has had to give up this belief and to deal with the fact that not only was she not protected by her parents or older siblings, she was actually violated by one or more of them. The deep betrayal that survivors of childhood sexual abuse experience can lead to a sense of loneliness, isolation, and alienation. There is no group to which they feel they belong. Even girls who might be considered in the mainstream of society by virtue of class, race, and education feel alienated. Those who are also discriminated against because of class or race feel doubly alienated and isolated.

Socially, these feelings of alienation may have kept the survivors from joining groups or teams. They often find it difficult to develop meaningful friendships or relationships because of feelings of isolation.

## Group Therapy

L.C. Marsh, perhaps one of the first group workers in the United States, was known for his motto: "By the crowd they have been broken, by the crowd they shall be healed" (Gazda, 1982, p. 9). Marsh was an Episcopal minister who ran groups in mental hospitals in the 1920s. Karl Marx provided some conceptual underpinnings for group work in *Das Kapital.* He argued: "A dozen persons when working together will in their collective working day of 144 hours produce far more than 12 isolated men, each working 12 hours, or than one man who works 12 days in succession." (Moreno, 1956, p. 11).

A group provides a forum in which clients can use each other as well as

the leader to heal themselves. Shulman (1992) describes an "all-in-the-same-boat" phenomenon, in which the process of sharing feelings with others and realizing that other people feel the same way, provides a sense of relief and makes people feel less frightened and not so alone.

The mutual aid model, developed by Schwartz (1961), is particularly effective in working with sexual abuse survivors. Creating an atmosphere in which the group members need each other is the core of the task of the leader. Fostering a sense of connection could also be considered the essence of the emerging feminist theory of Baker-Miller (1993). The group leader can spark a feeling of connection among the members, as well as offer a vision of recovery and of hope.

Baker-Miller and her colleagues at the Stone Center in Wellesley, Massachusetts, contend that for women, self-knowledge and self-acceptance develop largely by interacting with others in a positive way. This conceptualization is an extension of the Social Learning Theory that sees human behavior as a continuous reciprocal interaction between cognitive, behavioral, and environmental factors (Bandura, 1977). According to proponents of the Social Learning Theory, people learn by observing other people's behavior as well as from direct experience, and that behavior is structured through positive and negative reinforcement. Baker-Miller believes it is the task of the therapist to become the positive role model and forge the connection.

Moreno contends that encounter, in which two or more people experience and understand each other, is the core of group process (Gazda, 1982). It is not just the meeting and the sharing of experiences, but the actual experiencing or the comprehending of the other that allows change or healing to take place. It is this kind of supportive encounter that victims of abuse have an opportunity to experience in small group work.

The main reason why a group is so effective in helping to heal survivors of sexual abuse is that the participants are allowed and encouraged to talk to each other about what they have not been allowed to articulate—namely, what happened to them. Each time women speak to each other about their experiences, they put more distance between themselves and the pain, and the more they continue to talk, the less victimized they feel (Bass and Davis, 1988). Talking about incest and other forms of sexual abuse is the real taboo that must be broken. Girls who have been abused, particularly incest survivors, are carefully taught by their aggressors and by other adults in positions of authority not to mention their abuse. And they don't. They seal themselves off from other people and, however much they may appear to be a part of the world, they are lonely and isolated.

## The Healing Process for Members of Short-Term Groups

The vignettes presented here are primarily taken from two 6-month groups that I ran with a co-leader.

One group member, Amy, related that there were two people she was told she could trust completely—her father and her parish priest. Because her father had been sexually abusing her since she was 4 years old, she confided in her priest when a stranger came into her school and forced her to touch his genitals. She talked to her priest, in what she thought was confidence, but he told her father, who accused her of making the incident up or having a bad dream.

Amy dealt with this double sense of betrayal and violation by those to whom she turned for protection by spending hours in her room, staring at her flowered wall paper and imagining herself disappearing behind the daisies and irises. For many years, her only source of comfort and of feeling of being in control was to make herself disappear among the flowers on the wallpaper.

Carol recounted that she had been sexually abused as a child, had told some people, and had talked about it in individual therapy. Yet, she continued to feel that it was her fault and that she was a bad person. About 20 years after the abuse, she was called for jury duty and during the selection process was asked if she had ever been the victim of any crime. "Yes, a crime was committed against me," she told the lawyer and the judge. "I was raped." The judge was obviously so stunned that a woman would say this out loud that he called her to his bench and asked her in a whisper to repeat what she had said. This was the first time she had stated that a crime had been committed against her, and it was the first time that she believed that it had been.

With Carol and the others in the group, talking about abuse was extremely important, but it is not enough. When clients recognize that someone else can stand to hear—or in fact shares—an experience they think is unbearable and intolerable, their process of healing and changing their self-image and self-esteem begins. In a group, other members as well as the leader can help members shed their sense of isolation and alienation and their feeling that they "don't deserve to be listened to." Group members can also actively encourage and help each other to change negative self-images and to replace them with positive ones (Trimpey, 1989).

## Shifting the Blame

A feminist or woman-centered approach to working with sexual abuse survivors is critical because their whole world is telling them that they are

bad or masochistic or blameworthy, and they need to be permitted to realize that what happened to them was really not their fault. Incest survivors have difficulty putting their personal victimization into the larger context of the mores of a patriarchal society that shows more sensitivity to the perpetrators than to the victims and that either denies anything happened or does not take what happened very seriously. In one group, for example, three women had been abused by their fathers or stepfathers, one of whom was a prominent professor at an Ivy League school and the other two were ministers. Staff at the clinic where the professor's daughter had gone for help was reluctant to prosecute her father because his school sponsored the clinic. The message that the perpetrator deserves more protection was driven home to this young girl and her mother, who probably did the best that she could by sending her daughter away to boarding school the next year.

The authors of the famous Kinsey Report of the 1950s were horrified at many of the sexual practices they uncovered in the United States, but they were not particularly alarmed by incest. A member of the Kinsey team, discussing incest, stated: "It is difficult to understand why a child, except for its cultural conditioning, should be disturbed at having its genitalia touched, or disturbed at seeing the genitalia of other persons, or disturbed at even more specific sexual contacts" (Kinsey, 1953, p. 121). What is the incest survivor to do who grows up in an environment that either blames her or trivializes the tragedy of which she is the unwitting and usually inarticulate victim? It is nearly impossible for her to learn how to take care of herself, for she has not learned how to distinguish an insult from an act of abuse.

Rebecca started off the fourth group session by describing how, when she was 6, her 13-year-old brother started sexually assaulting her in a very violent way. She felt from that moment on that she had lost her childhood and any sense of joy. These sexual assaults continued for 7 years while she was being overprotected by her parents in many other ways—not allowed to go outside by herself, and not allowed to ride a bike because it was too dangerous. She grew up with no sense of what is really dangerous and what is not. All she knew was that she felt unprotected and not valued. When, in one session, another group member, Ann, described being fed drugs by her mother's lover so he could sexually abuse her, Rebecca was truly horrified, much more so than by her own horrifying experiences.

The group was able to help Ann and Rebecca accept that what had happened to each of them was equally abusive and that neither of them had been at fault. Ann then related how she had taken a summer job working with young kids and how spending time with 4-, 5-, and 6-year-

olds had helped her to internalize how young they were and "What little babies they are!" Her visualizing how young and defenseless small children are was curative for Rebecca. Everyone else in the group was helped by her description.

## Stages of the Group

### *Beginning*

It is often surprising how quickly a group of women who have felt isolated for many years can bond with each other. Their relief at being able to talk about feelings in connection with sexual abuse is great, and group members feel very close to each other after having shared such vulnerable feelings. It is particularly important for the leader to be emotionally available to the members during this stage. Sometimes, however, this initial bonding gets shaken when someone expresses anger or feels too exposed. For instance, Ann almost did not return to the group after the first session because she felt the group was angry at her for implying that her own abuse was less harmful that someone else's. Occasionally, someone does drop out of the group, and if that does occur, it usually happens very early on. A person may leave because she is not able to tolerate the intensity of the exposure and the resulting closeness she feels. During this time of bonding, members may miss a session or two if they are feeling too vulnerable.

It is helpful if the leader calls a group member who has cancelled a session or who is going through a difficult time with feelings of depression or with problems in a relationship or at work. Encouraging members to reach out to each other is also empowering during this initial stage of emergent trust.

At a recent conference entitled "Learning From Women," Jean Baker-Miller spoke of the importance of the therapist's ability to empathize with clients (Baker-Miller, 1993). It is especially important for a group leader to connect emotionally with the group members who, as survivors of sexual abuse, tend to feel that no one else can possibly understand them or share their pain. Baker-Miller (1993) believes it is the therapist's responsibility to let the client know she, the client, has an impact on the therapist. This is what lets the client experience a longing for connection and risk making herself vulnerable. Baker-Miller also points out that therapists feel enhanced when they realize they have made an impact on clients. Such interaction can create a sense of mutual empowerment.

*Goal Setting*

The third or fourth session is a good time for the therapist to introduce the idea of establishing the individual goals that each member most wants to achieve by the end of group. These goals could seem small: Teresa, who had been assaulted as a child on the staircase landing of her apartment building, wanted to be able to walk down stairs rather than take the elevator; Grace, who had been told she was being raped because she was provocative, wanted to feel comfortable tucking in her shirt. Other specific goals set by group members have involved sleeping with the light off, sleeping without a knife under the pillow, taking a vacation, writing a letter to an abuser or to an unprotective mother, stopping a behavior pattern of binging and purging, and sustaining a friendship with another woman.

Ann, who was abused by her mother's lover starting at age 12 and who had spent the next 20 years being the family caretaker of her seven siblings, wanted to learn how to say no. This she did. She also wanted to stop wishing that she had "put a gun to her head." She was able to achieve these goals as she learned to value herself enough to reject others' demands.

By urging clients to have a specific goal that they want to achieve, the therapist helps to foster a task-oriented atmosphere. A time-limited group is valuable for creating the members' sense of urgency to work on specific goals. In almost every case, the members achieved their goals by the end of the group.

*Middle Phase*

During this phase, ongoing issues and themes are discussed: low self-esteem, guilt, shame, feelings of isolation and alienation, extreme anxiety, difficulty in developing satisfying sexual relationships and friendships, being unable to finish things such as school or training programs, and generally not living up to one's potential.

It is especially important that members trust each other at this stage, even if their trust is tenuous, for this phase comprises the major portion of the program and is the segment when most of the work gets done. It is critical that members be able to support each other as they bring up painful issues. Supported by each other and the leader, group members can take risks both in group and in the outside world and try out new behaviors in old settings and situations.

One of the suggested tasks for the leader to introduce after the first two months is the writing of a letter to the abuser or to someone else who

was not protective (Bass & Davis, 1988). Many women write to their abusive fathers, stepfathers, grandfathers, uncles, or brothers, telling them how angry and hurt they are and how their lives are still being affected by the sexual abuse. What is a startling response to this task is how often group members write first to their mothers, expressing their rage for not protecting them—and then never get to writing to their abusers. Their being angry at an unprotective mother is not surprising, but their being able to express feelings of rage and hurt only at their mothers, rather than at the assailant or perpetrator, is bewildering, at first. This response is no longer bewildering once the leader recognizes that this is exactly what survivors of sexual abuse are taught by a patriarchal society—to protect the perpetrators and blame the mothers. As one author points out: In our society, everything that is female is denigrated, and everything that is male is exalted (McIntyre, 1981). It is less risky to express anger at mothers because they are less powerful and not so likely to take revenge or disappear altogether.

The recent ruling in several states to extend the statute of limitations, which allows survivors to sue for damages many years after the abuse, may well have far-reaching influence. If it is possible that a woman as an adult survivor might be believed and actually have the power to prosecute her childhood abuser, more women will dare, one hopes, to get angry at the person who actually assaulted them.

*Termination*

Most of the work on goals takes place during the middle phase of sessions, and members find it is hard to face ending the group when they feel they are accomplishing so much. The last month of group can be difficult. Abby, who started off the first session saying she did not know how she was going to get through 24 sessions of this group and who spent the first 5 months counting down the weeks, said she was astonished to realize how sad she was that the group was ending. Others, who form attachments more easily, often get angry at the leader for ending and try to bargain for a few more months or weeks. It is often tempting to extend a group that is working well, but the contract stipulated that the group would end in six months. The terms of the contract exist for a good reason: Knowledge that there is a time limit acts as an important catalyst to change. It is particularly important to stick to this agreement with women who have already experienced too many broken contracts.

Ideally, what happens in the last stage of a group is grieving. To some extent, group members grieve the loss of the group, but more important, they grieve their lost childhoods. If members can allow themselves truly

to mourn the loss of their childhoods as they would have liked them to have been, and if they can achieve acceptance of what happened to them, they will begin to feel much better about themselves, and their lives will change. This is obviously not an easy task, and the more support people feel from each other and from the leader, the better they will be able to accomplish it.

In the last few sessions, it is important to talk over the goals achieved and other accomplishments. Thus, for example, not only was Sarah able to sleep without a knife under her pillow, she also was able to dream differently. For years she had had dreams of being chased, of not being able to scream when she was scared, and of drowning. As her group was coming to an end, she reported a dream in which she was being chased by two men. As usual, she was running and running and was about to try to get in her front door, when suddenly she stopped, turned around, and yelled at them to go away. And they did.

Jane's explicit goal had been to wear a dress she'd always felt too uncomfortable to put on. She wore the dress, asked for a promotion at work, and wrote a letter of protest to the editor of a New York newspaper that had run a story about how racism was the primary factor in the Central Park jogger case. She eloquently pointed out that women of all colors live in danger of being assaulted in the same way as that jogger and that sexism, not racism, is the real issue involved in most rapes. Several of the other group members signed the letter.

Not every group member will achieve all her goals as dramatically as Jane did, but for most people, just being in the group will help lessen their feelings of isolation and alienation. Most feel better about themselves by the end of the group. They are more self-accepting, and their relationships improve. Those who are in abusive relationships that do not improve find the courage to leave them. Many group members become more assertive; for many, their physical health improves. Even the women who feel that their only accomplishment is to have stayed in the group to the very end realize that they no longer feel so guilty or shameful and that their anger is not driven so strongly inward. They have accomplished a daunting task: They have learned to talk about what happened to them.

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SANDRA TURNER is an assistant professor in the School of Social Service at Fordham University in New York.

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Address:
Sandra Turner, Ph.D.
290 West 12th Street
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# BRIEF REPORTS

These brief reports were written by psychodrama trainees who have been working with Antonina Garcia, an executive editor of this journal. The editors of the journal invite psychodrama trainers to have their trainees write brief reports and submit them for review.

## A Year of Psychodrama Training

Our group of 14 met for 2½ hours weekly. For the first 2 months, our director–trainer taught us various warm-up exercises and directed several of our own psychodramas. Then it was up to us to lend ourselves to the learning process.

At first, I thought I could only learn psychodrama from watching my instructor work as an experienced director–trainer. I was amazed and pleased to find out how much we in the group could learn from each other, acting as inexperienced directors, and trusting in our supportive process.

I learned to trust that each person's psychodrama would go where that person needed to go. I did not need to waste energy worrying about whether that person was having a deep enough experience. This was often borne out by how much happened in the protagonist's life in the week following the drama.

I began to relax and trust the reality of "tele" and its contribution to such aspects of psychodrama as the choosing of group members for particular roles and the members' capacities to be creative, astute, and empathic auxiliary egos. I became aware of the importance of the warm-up segment, not only to connect individuals to their issues but also to reveal group themes. I realized that the director has to keep both individual and group themes in mind while helping the protagonist flesh out the drama.

I saw how important it is for a director to believe that it is possible to construct a safe environment for any issue that is being explored. By this, I mean that the director must take the time needed to set up roles; to create actual safe places within the drama; and to work toward some sort of healing, empowering, and corrective experience.

I learned about the possibilities and responsibilities of the auxiliary ego. In these roles, I began to trust that I could work from a hypothesis and that I could offer statements that revealed what I was feeling in the

role with the reassuring knowledge that the protagonist was free to accept and reject, according to his or her needs.

I began to understand about the importance of the positioning of the director, who needs to be at once supportive of the protagonist and able to double with empathy, but who also needs to have enough perspective to see the entire drama as it unfolds. Moreover, the director must know when his or her issues are being evoked by the psychodrama and how to distinguish these feelings from empathy.

I continued to be impressed by the reality of the molding of our beings in the crucible of our families of origin. I recognized that one can experience the possibilities beyond these boundaries through psychodramatic renderings of past, present, and future.

I realized how useful props can be in providing concrete representations of issues first presented as vague abstractions. I want to begin to collect scarves, hats, masks, musical instruments, stuffed animals, or anything else that would contribute to this purpose.

I experienced the importance of motion and physical action to the uncovering of the protagonist's feelings and insights and realized that this physical energy is very powerful and has to be used by the director in close cooperation with the wishes, instincts, and intentions of the protagonist.

I became aware of the difference in quality and purpose between the personal sharing at the end of the psychodrama and the in-depth processing of the psychodrama the following week. For me, it was very satisfying to be able to explore all aspects of the drama from differing points of view. Our trainer was an important model here, one who demonstrated the power of "I statements" without judgment or advice and showed us how to discuss an inexperienced director's work with sensitivity to what was accomplished through intuition, creativity, spontaneity, and intelligence, in spite of the expected technical flaws.

I came to appreciate Jacob Moreno's contribution as the creator of the concepts and techniques of psychodrama in an era in which most of the medical profession were unprepared either intellectually or emotionally to understand the significance of his work. I am only sorry that he insisted on doing the English translation himself, because his insufficient knowledge of the intricacies of English vocabulary and syntax obscures his meaning and makes it necessary for others in the field to interpret him to the rest of us.

In the final meeting of the group, we reviewed all the psychodramas we had shared as directors, auxiliaries, and audience. We highlighted our favorite roles and moments. We acknowledged what roles and dramas we still wanted to experience. Many of us will have the opportunity to

continue our training for another year. It is exciting to imagine how far we can now stretch ourselves within the framework of trust, support, and enthusiasm for our own growth.

HELEN GREVEN

# Discovering the Healthy Self: The Use of Future Projection in Acute Care Settings

The average length of the stay of inpatient hospitalization is 21–28 days. After patients have been assessed and referred, they may attend four or five psychodramas. Patients warm up differently to the groups, depending on size, population, and severity of treatment issues. Future projection has become a valuable tool in helping patients at all levels of treatment.

The technique of future projection of the healthy self offers a safe and structured means to work with the inpatient population. It helps the patients to build psychodramatic roles that will aid in their recovery process. Patients begin to build hope and set achievable goals. Aside from its treatment values, future projection also offers the psychodramatist a diagnostic tool and a measure for reality testing.

The therapist instructs patients to project what they will be like when they are healthy. It is important that the clinician chooses the descriptor for the projection carefully. Descriptors such as happy or all better can be misleading for patients. It encourages them to believe that once they have completed treatment they will always feel good. This sets them up for disappointment and relapse. It also sets the therapist up for negative projections and transferences. Healthy, as a descriptor, allows for more balance in the projection. It permits the patient more freedom in creating a definition for being healthy and aids in the development of hope.

In developing hope, the therapist should help the patient set realistic goals but should never disparage what the patient projects. Although some patients may not have realistic future roles, the fantasies projected can serve as a diagnostic tool for the therapist. For example, a patient may see himself or herself as receiving the Nobel Prize for discovering a cure for depression. This may not seem realistic but does display the patient's commitment to his or her recovery.

The qualities ascertained in the activity may be population warranted. Clinicians may wish to focus on disease-related issues for both treatment

and diagnostic reasons. For example, with eating-disorder patients, the clinician may want to find out the patients' ideal future body weights or how they are dealing with food issues. If a patient projects continued activity of eating-disorder behaviors, he or she displays diminished hope for recovery. This is important information for the therapist.

With patients who suffer from flashbacks and dissociative disorders, the clinician may question the frequency or severity in which these continue to occur in the future. A clinician may check to see if the patient is still in therapy and what other supports and coping skills the patient will be using. This helps both to explore the patient's expectations and to plant the seed for continued work. The focus of the projection depends on how the therapist wishes to use the information gained. I have found that patients respond well when they are asked specific questions about family, job, and relationships. For example, I may ask if they are in relationships and then ask them to describe their significant other. This gives much information about how the patient sees recovery and about the patient's ability for trust and intimacy. Questions about job and/or school help the patients to focus on their personal goals.

The length of time that the patients project for their recovery is important for both treatment and diagnostic reasons. Patients who give themselves a few years for recovery have a stronger base in reality. They also have a greater chance for integration of treatment and a more successful recovery. Patients who give themselves a hospital stay or a few months of treatment are less founded in the reality of full recovery and have a greater chance for relapse. Patients also reveal much in their aspects of dependency and intimacy. Patients may project a love interest as a necessity for recovery or project counterdependence. Adolescents often want a baby, which is indicative of their desire to be loved and have a corrective experience. Any information gained from these projections will help the therapist in future sessions.

It has been my experience that patients at all levels of treatment become stuck in the "when" and "why bother" phase. This is a time when they feel that there is no end in sight and that it is useless for them to continue to work. Future projection builds hope for these patients. Even the most traumatized patients benefit from imagining what they will be like when they have achieved their goals for emotional recovery. It is also a way for them to set concrete goals. Patients in acute stages of treatment are often indecisive and abstract in their goal setting. They make such statements as "I want to feel better," or "I don't want to feel this way anymore." Without having a concrete means of measuring their progress, these patients can easily become caught in the nothing-is-happening frame of mind. For patients who are stuck in their patient

role, it often helps to give them a more-concrete time frame for their projection. When they have achieved a goal, they can then repeat the exercise. It has been my experience that as they achieve these goals, their spontaneity begins to increase and they can eventually imagine the healthy self as a possibility.

Occasionally, patients are unable to project because of their hopelessness or suicidality. Future projection can be approached in a few different ways. As mentioned above, the therapist may wish to give time frames for the more hopeless patients. As with any patient feeling stuck, any movement within the role is beneficial. Future projection for a set time can help patients begin to set small, achievable goals. With each goal achieved, they can then set another. With each step in the process, the patient learns success, builds new roles, and increases spontaneity. Eventually, the patient may be able to project the healthy self. This may take more than one hospitalization or continued intensive outpatient treatment.

For patients who are suicidal, one may wish to suggest they enact what they would like their lives to be like if they continued to live. When patients are able to express this, I reinforce the fact that they're imagining a healthy, happier life could make that possible. Patients usually respond positively to this tactic.

Although I use it less frequently, I have found success in permitting patients to project their deaths. Adolescents, because of their limited sense of mortality, often enjoy playing such a scene out. This can lead to many other dramas, such as acting out the funeral or playing out situations similar to those in *It's a Wonderful Life*. Playing dead also allows individuals to use the voice they felt they could not use when alive. Once given voice and catharsis, patients generally decrease in suicidality. Future projection works well even in these seemingly hopeless cases.

Future projection serves as an excellent group warmup. When future projection is the result of the group warmup and patient's act hunger, it is extremely effective as the group activity. As with the dramas resulting from the "dead" projections, patients may wish to move into more intensive psychodramas. Individuals may find voice through their healthy selves. They enjoy enacting reunions so they can showcase their healthy selves. Patients benefit greatly by speaking to their healthy selves and asking themselves questions. They can explore what their journey will be like and what roads they need to follow. The healthy self is often confrontational and empowering to the hospitalized self. Patients usually leave the group with a new sense of direction.

Classical psychodrama during inpatient hospitalization can be difficult to achieve because of the acuity of the patients and safety issues. Future

projection has proved to be a valuable tool on many levels. The groups are always moved to action by the nature of the activity, and the activity almost always sets the stage for futire psychodramas.

COLLEEN LOGAN BARATKA

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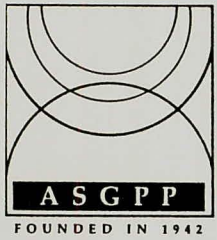


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