JOURNAL OF APPLIED BEHAVIOR ANALYSIS 1987, 20, 273–278 NUMBER 3 (FALL 1987)

FURTHER GENERALIZATION TECHNOLOGY: ACCOUNTING FOR NATURAL COVARIATION IN GENERALIZATION ASSESSMENT

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In recent years, the assessment of generalization effects has become a major priority of applied behavior analysis. In this paper we propose a set of procedures to increase the accuracy of generalization assessments by accounting for the degree of *natural covariation* between treated and untreated behaviors. Scatterplot analyses were used (a) to assess the amount of baseline and postbaseline covariation betweeen behaviors, (b) to determine if the observed generalization effect was due to a preexisting covariation between the behaviors, and (c) to assess if there is a significant change in the strength of the relationship between the behaviors as a function of the intervention. Six hypothetical sets of data are used to demonstrate how these procedures provide more accurate and detailed generalization assessment.

DESCRIPTORS: generalization assessment, natural covariation, response covariation

In the past decade, researchers such as Stokes and Baer (1977) have exhorted behavior analysts to abandon a passive "train and hope" approach and develop a more "active" pragmatic generalization technology. Central to the development of such a technology is the design of more accurate methods of describing the effects that different treatment strategies have on the relationship between treatment and clinically relevant nontreatment behaviors. In other words, the primary question is, to what extent does a particular intervention strategy uniquely produce positive changes in desired nontreatment variables? Before answering this question, researchers must first explicitly and conclusively reject the null hypothesis—that the observed relationship between treatment and nontreatment behaviors (generalization effect) was due primarily to the preexisting (baseline) covariation between these behaviors and not a unique function of the intervention. Rejecting the null hypothesis involves a careful analysis of the baseline data of both treatment and nontreatment behaviors to account for any naturally occurring interdependency.

Interdependencies and covariations of responses are currently receiving long overdue attention in the behavioral assessment literature (Kazdin, 1982; Nordquist, 1972; Parrish, Cataldo, Kolko, Neef, & Egel, 1986; Russo, Cataldo, & Cushing, 1981; Wahler, 1975; Wahler, Berland, & Coe, 1979; Wahler & Fox, 1981). For example, Wahler (1975) found that each of his subjects' behavior repertoire contained responses that covaried predictably across four different school settings and over a 3-year period. The responses covaried from .27 to .90 and ranged from sustained schoolwork and disruptive behavior to adult social interaction. Because of the likelihood of covariation in studies of generalization, failure to assess and control for the degree of natural covariation can distort the evaluation of strategies designed to promote generalization and increase the likelihood of committing type 1 errors. Researchers may overemphasize the power of a

We thank Paul Clement and Donald Baer for their encouragement, consultation, and technical feedback in the preparation of this manuscript.

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specific strategy when the phenomenon they are reporting is primarily a function of the naturally occurring covariation between the behaviors.

The purpose of this paper is to propose a set of procedures that will allow researchers to describe observed generalization effects more accurately and thereby reduce the likelihood of Type 1 errors in generalization assessment. The objective of this proposed assessment is to use scatterplot analyses (a) to assess the amount of baseline and postbaseline covariation between treated and untreated behaviors, (b) to determine if observed generalization effects are due to a preexisting covariation between these behaviors, and (c) to assess whether the strength of the relationship between these behaviors changes as a function of the intervention. Six hypothetical data sets are used to illustrate the usefulness of these procedures.

METHOD

The proposed assessment uses a standard scatterplot analysis (Roscoe, 1975) to provide a visual assessment of the direction and strength of the relationship between treated and untreated behaviors of interest. The principle advantage of using scatterplot analysis over correlation coefficients (e.g., Pearson's r) is that the scatterplot allows researchers to examine *every* relationship point between treated and untreated behaviors. This provides a means to assess changes in the strength of the relationship *over trials* after the intervention has been implemented.

The assessment procedure requires a minimum of a baseline and postbaseline phase for both the treatment and nontreatment behaviors. As with any scatterplot analysis, sufficient data points are required to note any trends in the data. This assessment procedure involves the following steps:

Step 1. Using the baseline scores for the treated behavior for the x-axis and the baseline scores for untreated (generalization) behavior for the y-axis, construct a scatterplot of the baseline data.

Step 2. Next, visually assess the strength and direction of the relationship between the behaviors. The closer the pattern of points approximates a straight line, the greater the degree of correlation between the two behaviors.

Step 3. Again, using the scores for the treated behavior for the x-axis and the scores for the untreated behavior for the y-axis, construct a scatterplot for the postbaseline data or treatment phase data.

Step 4. Compare the baseline and postbaseline scatterplots for changes in the strength or direction of the relationship between the two behaviors.

Step 5. If you suspect changes in the relationship over treatment trials, conduct a more detailed analysis of the postbaseline scatterplot. This can best be accomplished by coding the later relationship points and comparing early with later relationship points to determine if one better approximates a straight line. Plotting the regression line (Roscoe, 1975) for either the early or later trial relationship points may assist in this comparison.

RESULTS

Figures 1, 2, and 3 present the baseline and postbaseline graphs and scatterplot analyses for the six hypothetical examples. In the first example, the scatterplot reveals little if any relationship between the treated and untreated behaviors during the baseline phase. The relationship points more closely approximate a straight line during the intervention phase. This indicates a substantial increase in the strength of the relationship between the behaviors. The null hypothesis can therefore be confidently rejected (provided the design was sound). The observed generalization effect was due to a "unique" contribution of the intervention. The intervention also appears to have strengthened the relationship between the behaviors.

The baseline scatterplot reveals a strong relationship between the treated and untreated behaviors in Example 2. The relationship points continue to approximate a linear relationship during the treatment phase. The null hypothesis cannot therefore be rejected. The observed generalization effect was most likely caused by the preexisting relationship between the two behaviors which continued during the intervention phase.

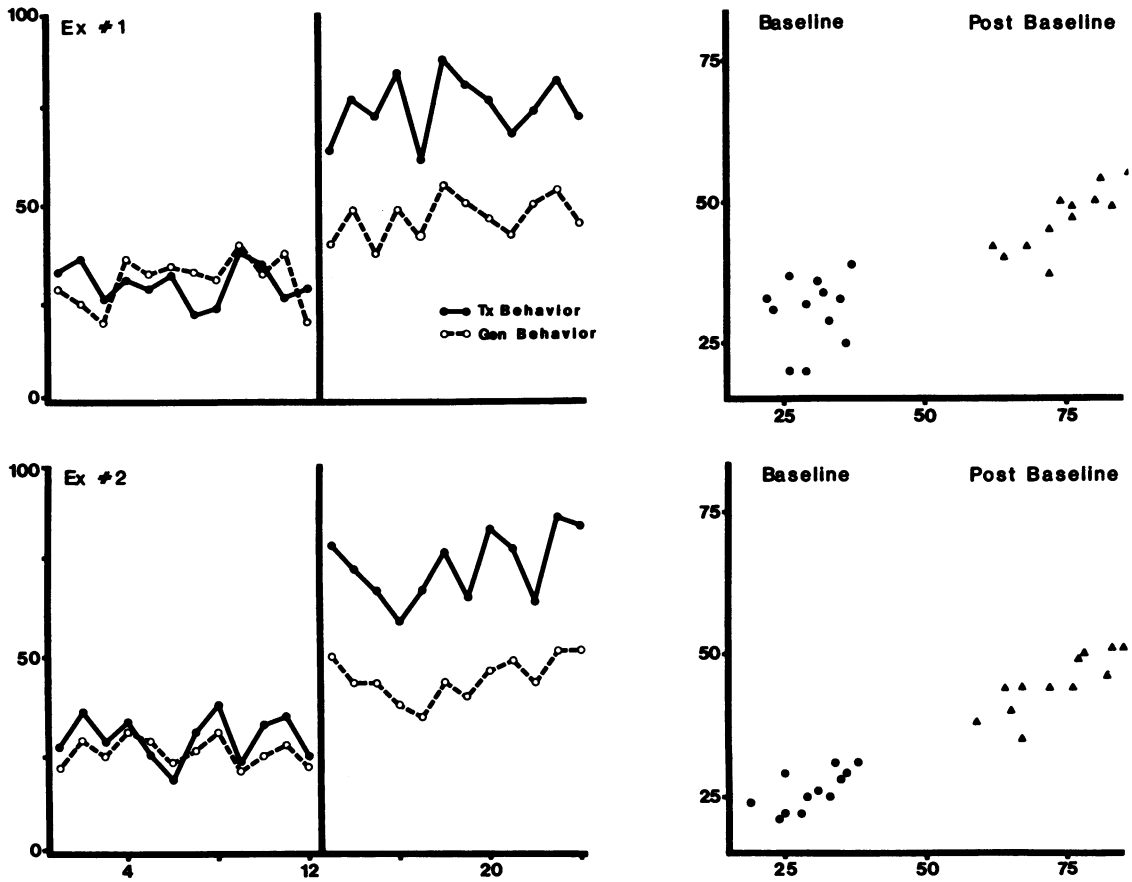

Figure 1. The graphs and scatterplots for hypothetical data Sets 1 and 2.

In Example 3, both baseline and postbaseline scatterplots reveal little if any relationship between the treated and untreated behaviors. Both scatterplots substantially deviate from a straight line. The null hypothesis can confidently be rejected. The observed generalization effect was not significantly affected by any preexisting interdependency between the behaviors. Neither was it fostered by a relationship that developed as a result of the intervention.

The baseline scatterplot reveals a strong inverse relationship between the treated and untreated behaviors in Example 4. The relationship lessens following intervention, as indicated by the increased dispersion of the relationship points in the postbaseline scatterplot. Because of the strong preexisting relationship between the behaviors, the null hypothesis cannot be confidently rejected.

In Example 5, the baseline scatterplot reveals minimal preexisting covariation between the behaviors. During treatment the later trial relationship points better approximate a straight line than do the initial data points. This indicates that a positive correlation gradually developed over treatment trials. Due to the lack of any significant baseline covariation, the observed generalization effect is attributable to the intervention. The intervention appears to have had a delayed but steadily increasing relevance for the generalization behavior.

In the final example both the treated and generalization behaviors are behavioral excesses. The baseline scatterplot reveals a strong positive relationship between these behaviors. This strong relationship continues during the initial treatment trials. The strength of the relationship then starts to lessen as shown by the later relationship points

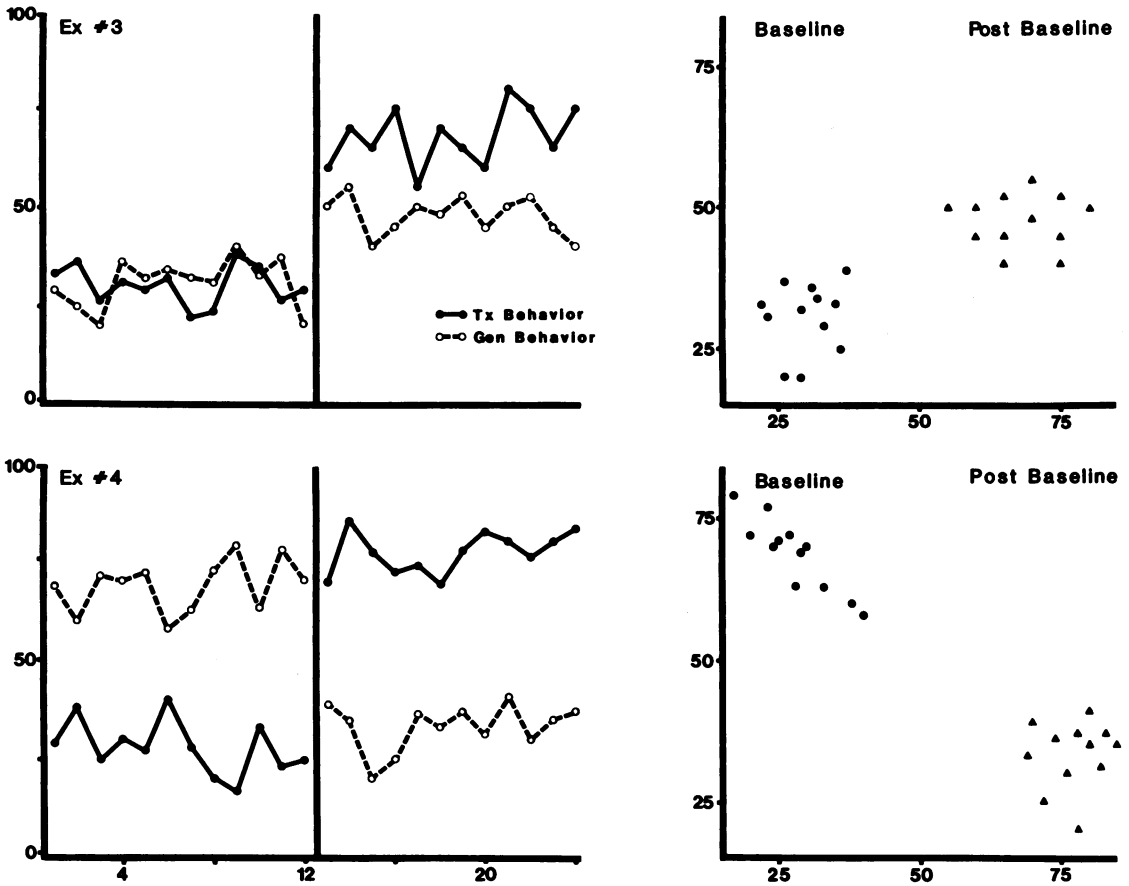

Figure 2. The graphs and scatterplots for hypothetical data Sets 3 and 4.

increasingly deviating from a straight line. The intervention appears to have had a delayed but steadily decreasing relevance for the generalization behavior.

DISCUSSION

These six hypothetical data sets demonstrate how the proposed procedures can extend our ability to describe in more accurate detail the relationship between treated and untreated behaviors as a function of varying treatment strategies. Three examples (2, 4, and 6) illustrate observed generalization caused by the natural covariation between the treated and untreated behaviors, and three examples (1, 3, and 5) reveal actual generalization effects that are independent of any preexisting relationship between the behaviors. In two examples (2 and 3) the degree of covariance between treated and untreated behaviors remained essentially unchanged following the introduction of the intervention. The intervention immediately altered the covariance in two other examples (1 and 4), and in two (5 and 6) the intervention had a delayed effect in altering the covariation between behaviors.

In each of the examples, the proposed visual analysis enhances our understanding of the *relative contribution* of the preexisting covariation between behaviors, and the intervention itself, in producing the observed generalization effect. In the three examples of observed generalization due to natural covariation, generalization is the by-product of the preexisting relationship between the behaviors, and is not the result of any "uniqueness" of the intervention. A different intervention that had the same impact on the target behavior would have most

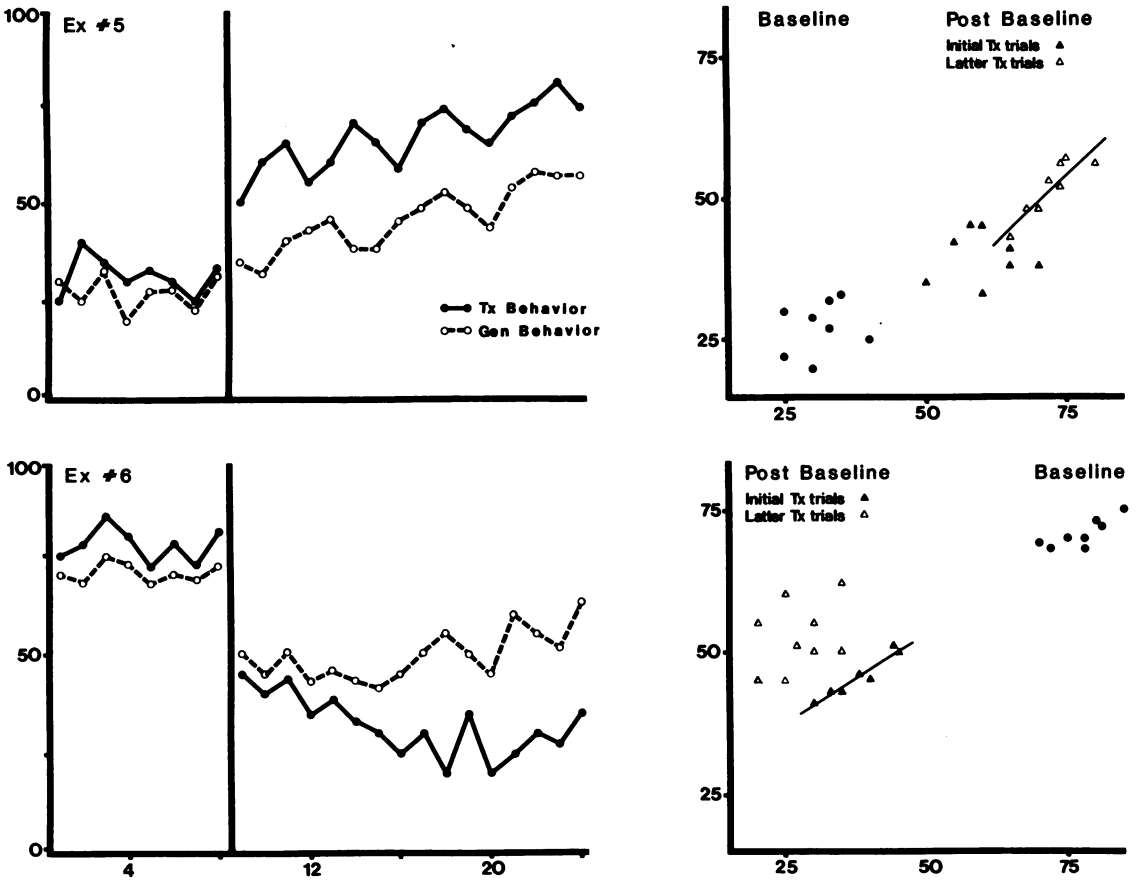

Figure 3. The graphs and scatterplots for hypothetical data Sets 5 and 6. In Example 5, the later trial regression line is plotted. In Example 6, the initial trial regression line is plotted. In Example 6, the baseline relationship points are in the upper right hand corner of the scatterplot because both behaviors are behavioral excesses.

likely produced the same amount of observed generalization (Parrish et al., 1986).

These procedures provide a means of studying the mechanisms involved in producing different types of generalization effects. To date, it is unclear to what degree the mechanisms involved in producing generalization are active or passive (Stokes & Baer, 1977). That is, are concurrent observed changes in untreated behaviors, subjects, or settings a function of a unique contribution of a specific intervention (i.e., active) or more a function of the preexisting covariation between the two variables? If specific interventions can be identified that produce significant observed generalization, then generalization would be enhanced by making these controlling responses readily transferable to other responses, settings, and subjects. If on the other hand, that generalization is primarily the result of preexisting covariations, then the focus should be on identifying the highly covarying clusters of clinically relevant behaviors and treating one of the behaviors with an intervention that yields the largest treatment effect. This latter strategy would still fulfill Stokes and Baer's call for an active generalization programming technology even though it relies on passive generalization mechanisms.

Without first controlling for the degree of preexisting covariation, it will be impossible to detect and test accurately the hypothesized mechanisms that account for observed generalization effects. Because the amount of preexisting covariation will always vary across studies, procedures similar to the

ones proposed here are necessary steps in the development of a robust generalization technology.

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Received April 25, 1986
Initial editorial decision July 28, 1986
Revision received December 3, 1986
Final acceptance April 21, 1987
Action Editor, Ron Van Houten