4. Reality Therapy Programs in Schools

Glasser’s book, *Schools Without Failure*, presents an understandable way to apply these ideas to schools. Published in 1969, it was the largest selling American book on education during the 1970s. Enthusiasm from educators who were using these ideas helped Glasser to found the Educator Training Center in 1968, to teach how to use the concepts in schools.

Starting with educational films and in-service training programs, the Educator Training Center has expanded until the staff now help universities. For example, the University of Wisconsin at LaCrosse offers master’s degrees on these concepts. At least 250,000 teachers in the United States have been specifically trained by the Educator Training Center staff and countless others have taken courses by those who have had this training. In translating reality therapy to schools, educators have recognized that the most important concepts to be learned are: (a) to base instructional programs on success practices— increase the student’s success within the curriculum; (b) use the classroom meeting as a device for involvement between teacher and student, and student and student. The class and teacher sit in a circle to communicate in a nonjudgmental way and discuss values, goals of the class, how to live together successfully in the classroom, and anything else that can increase involvement and help students to know someone cares. Use of these meetings shows significant improvement in behavior and increase in learning. This process is best described in the book *Schools Without Failure* (1969). In *Focus on Guidance*, Thompson and Cates (1976) quote a study in Tennessee showing specific data for frequency of inappropriate behavior and how it decreases as the classroom teacher uses these methods. Along with this comes increased learning.

The Educator Training Center has developed programs which help school personnel discipline students and involve them in their learning in a way that helps them to accept responsibility for all their behavior. A description of how this can be done can be studied in a pamphlet called “Glasser’s Approach to Discipline” (Educator Training Center 1977). It is a 10-step program. The first 3 steps use the process of reality therapy to look at how one deals with disruptive students. Steps 4 to 7 are specific ways to deal with children having difficulty, and the last 3 steps bring in other resources within the school and/or community. Schools which have applied this program report decreases in suspensions by 50–80 percent in junior and senior high schools, and vandalism by 40–90 percent. Improvement in teacher morale and professional growth were also cited as being significant gains by schools using this program. Administrators gained time to be the educational leaders they were meant to be. The implementation of this program can be further understood by reading a book by a principal, Bill Borgers, *Return to Discipline* (1979), who applied it to the students, teachers, and counselors in his school. He found that by having everyone understand how to help students take responsibility for their own behaviors, schools could function in a way that produced more learning.

Another book, *Loneliness in the Schools* by Marc Roberts (1973) shows how to use the schools-without-failure principles to establish more effective interaction within schools. His plan to encourage humanness and growth within the school environment was created out of his concern for the loneliness of people who spend many hours each day in school.

Although the Educator Training Center works throughout the United States, its main office is in Long Beach, California.

See also: Counseling Theories

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**Reciprocal Effects, Analysis of**

The analysis of reciprocal effects consists of the study of mutual influences between two (or more) variables. Often, researchers attribute causality to the influences among variables and speak of reciprocal causal effects. Examples from educational research include analyses of the reciprocal effects between: teacher expectations and student achievement, student self-concept and academic achieve-
ment, and vocabulary and comprehension skills. Also, among the many studies of reciprocal effects in psychology are analyses of mother-child interactions, infant intelligence and behavior, and aggressive behavior and viewing of violent television shows. Often, research questions about reciprocal effects have been simplified to, does X cause Y or does Y cause X? Consequently, many researchers have sought only determinations of causal predominance or of the causal ordering of the variables.

Longitudinal data are crucial to the analysis of reciprocal effects, because the temporal ordering is needed to unravel the influences linking the variables. Typically, observations on a large number of cases are obtained for each variable on a few (two or more) occasions. (Each case may be an individual or a unit such as a student-teacher or mother-child dyad.) Much of the empirical research and methodological discussion on reciprocal effects has been limited to the two-wave, two variable (2W2V) panel design, in which measures of X and Y are available on each of two occasions.

Four different approaches and statistical methods for quantitative data have been used in analyses of reciprocal effects. These methods are cross-lagged correlation, structural regression models, continuous-time feedback models, and multiple time series. Separate methods for dichotomous and categorical data, which have not been much used in educational research, are Lazarsfeld’s 16-fold table, log-linear models for contingency tables, and continuous-time Markov models (see Structural Equation Models; Log-linear Models; Contingency Tables).

1. Cross-lagged Correlation

Cross-lagged correlation has been the most popular procedure in educational and psychological research for the analysis of reciprocal effects. Most often, cross-lagged correlation is used to determine a predominant causal influence. Figure 1, which presents the population correlations among the variables in a 2W2V panel design, is the diagram that accompanies expositions of cross-lagged correlation. The population cross-lagged correlations are $\rho_{X_1 Y_2}$ and $\rho_{Y_1 X_2}$.

![Figure 1](image)

Population correlations for a 2W2V panel. The variables at time 1 are $X_1$ and $Y_1$ and the variables at time 2 are $X_2$ and $Y_2$.

The difference between the population cross-lagged correlations, $\rho_{X_1 Y_2} - \rho_{Y_1 X_2}$, is the basis for attributions of a predominant causal influence. If the data indicate that $\rho_{X_1 Y_2} - \rho_{Y_1 X_2}$ is positive, the predominant causal influence is concluded to be in the direction of X causing Y. If the data indicate that $\rho_{X_1 Y_2} - \rho_{Y_1 X_2}$ is negative, the predominant causal influence is concluded to be in the direction of Y causing X. Usually, attributions of predominant causal influences are made only when the null hypothesis of equal population cross-lagged correlations is rejected. If this null hypothesis is not rejected, the usual interpretation is that no direct causal influences exist between X and Y; in particular that a common causal influence may be responsible for their observed associations. This interpretation has been adopted as a null hypothesis of spuriousness, which is represented through a model allowing no direct influences between X and Y but with an unmeasured third variable influencing both X and Y at each time (Kenny 1979 Fig. 12-2, Rogosa 1980 Fig. 3).

The extension of cross-lagged correlation to determinations of causal predominance when more than two waves of data are available is to compare the cross-lagged correlations from all possible two-wave combinations. Rogosa (1980) showed that this strategy of using the multiple waves for replication of differences between the cross-lagged correlations is more likely to generate confusion than corroboration.

A related statistical procedure for 2W2V panel data, which has seen a number of applications in educational research, is the frequency-in-change-in-product–moment procedure developed by Yee and Gage (1968). Although the Yee–Gage procedure differs from cross-lagged correlation in many important details, this procedure for the analysis of reciprocal effects suffers from the same basic deficiencies as cross-lagged correlation.

Cross-lagged correlation does not provide dependable information as to the causal structure underlying the data. Building upon earlier analyses by Duncan (1969) and Heise (1970), Rogosa (1980) demonstrated that, when there are no reciprocal causal effects, the difference between the cross-lagged correlations may be small or may be large; and when there are considerable reciprocal causal effects, the difference between the cross-lagged correlations may be small or may be large. Furthermore, a zero difference between the cross-lagged correlations (indicating spuriousness in cross-lagged correlation) is consistent with large reciprocal causal influences or with small or nonexistent causal influences between the variables. Moreover, cross-lagged correlation may indicate a causal predominance opposite to that of the actual causal structure of the data. Hence, neither determinations of spuriousness nor causal predominance can be trusted.

A basic deficiency in cross-lagged correlation is
the lack of an explicit definition of a causal effect. Without a clearly defined quantity to be estimated, it is not surprising that cross-lagged correlation fails to provide sound inferences. Also, the emphasis on causal predominance in cross-lagged correlation is unwise. The reciprocal nature of many social and educational processes makes determination of only causal predominance a serious oversimplification of the research problem. Measures of the strength and duration of the reciprocal relationship and of the specific causal effects are needed.

2. Structural Equation Models

Structural regression formulations of reciprocal effects in longitudinal panel data were originally introduced in the path analysis literature (Wright 1960, Duncan 1969, Heise 1970). The term causal model is popular for describing both the path analysis and the more general structural equation models. In these models, a causal effect is represented by the change in an outcome variable that results from an increment to an antecedent variable. For two variables, \( X \) and \( Y \), the reciprocal influences are represented by the regression parameters of the path from a prior \( X \) to a later \( Y \) and from a prior \( Y \) to a later \( X \).

Previous formulations of regression models for panel data with reciprocal causal effects have focused on models for 2W2V data. Figure 2 represents a specific regression model for 2W2V data, given by the regression equations:

\[
X_2 = \beta_0 + \beta_1 X_1 + \gamma_2 Y_1 + u
\]

\[
Y_2 = \gamma_0 + \beta_2 X_1 + \gamma_1 Y_1 + v
\]

The parameters \( \beta_2 \) and \( \gamma_2 \) represent the lagged, reciprocal causal effects between \( X \) and \( Y \) and thus are of central importance in the investigation of reciprocal causal effects.

Although the structural regressions do provide a model that defines reciprocal effects among the variables, the validity of inferences about the reciprocal effects depends crucially on the validity of the model. Foremost among the important assumptions built into Fig. 2 and Eqns. (1) and (2) is that \( X \) and \( Y \) constitute a closed system so that no important influences have been omitted from the regression model. Also important is the assumption that all causal influences are lagged; simultaneous causal influences between \( X \) and \( Y \) are not included. With only 2W2V data, frequently it is not possible to distinguish between different underlying models, which makes the determination of reciprocal effects very difficult. Additional observations can aid in the formulation and testing of the regression models; one example of the use of regression models for three waves of data is the analysis of the influences between economic development and educational expansion in Hannan et al. (1974).

A generalization of these path analysis models is to specify \( X \) and \( Y \) to be latent variables having multiple indicators at each time point. The influences among the variables are represented by the parameters of the structural regression equations that relate the latent variables. (A measurement model connects the latent variables with their indicators.) For example, recasting Eqns. (1) and (2) in terms of latent variables, \( \beta_2 \) and \( \gamma_2 \) would then represent the reciprocal effects between the latent variables \( X \) and \( Y \). Examples of the use of structural equation models for the analysis of reciprocal effects are: the analysis of attitudes and behaviors in Bentler and Speckart (1981), the analysis of intellectual flexibility and complexity of work in Kohn and Schooler (1978), and models for home environment and intellectual development in Rogosa (1979).

3. Continuous-time Feedback Models

An alternative formulation of reciprocal effects is to model the rates of change of the variables. A simple two variable continuous-time model that incorporates reciprocal influences between \( X \) and \( Y \) is:

\[
\frac{dX(t)}{dt} = b_0 + b_1 X(t) + c_1 Y(t)
\]

\[
\frac{dY(t)}{dt} = c_0 + c_1 Y(t) + b_2 X(t)
\]

Equations (3) and (4) are coupled differential equations which stipulate that the rates of change of \( X \) and \( Y \) at any time depend linearly on the levels of \( X \) and \( Y \). The parameters \( b_2 \) and \( c_1 \) represent the cross effects or couplings between \( X \) and \( Y \). Note that Eqns. (3) and (4) are deterministic. Similar models for change can be formulated which include stochastic components, exogenous variables, and other generalizations. Many applications of these models are presented in Hannan and Tuma (1983).

Rates of change are not directly observable. However, the solution of the system of differential equations in Eqns. (3) and (4) yields equations, in terms of the observable variables, of the same form as Eqns. (1) and (2). The parameters \( \beta_2 \) and \( \gamma_2 \) in

![Figure 2](image-url)
Eqns. (1) and (2) are nonlinear functions of the time between observations and the parameters of Eqns. (3) and (4). That the solutions of Eqns. (3) and (4) have the same form as the regression model for 2W2V data allows models for 2W2V data to be thought of as reflecting a more general process, that of causal influences and resulting adjustments that are continuous in time.

4. Multiple Time Series
The statistical analysis of reciprocal effects, or feedback, between two time series has been an active area in econometrics, with most applications investigating reciprocal effects between money supply and income or those between advertising and sales. The statistical methods are based on predictability criteria. Loosely speaking, one time series, \( X(t) \), is said to cause another time series, \( Y(t) \), if present \( Y(t) \) values can be predicted better using past values of \( X \) than by not using past values of \( X \), other relevant information (including past values of \( Y \)) being included in the prediction. This definition encompasses both lagged and instantaneous influences between \( X \) and \( Y \). A comprehensive classification of the possible patterns of causal influences was provided by Pierce and Haugh (1977) who also presented data analysis procedures based on the correlations of residuals between the separately filtered time series for detecting these reciprocal effects. In addition, useful measures of linear dependence and feedback among multiple time series were developed by Geweke (1982).

In most economic research on reciprocal effects, the data consist of a single extensive time series of observations for each variable. The minimum number of observations over time needed for the application of time series statistical models is far beyond the usual design of longitudinal research in education. The longitudinal data for which methods commonly used in education (cross-lagged correlation, structural regression, and continuous-time feedback models) are applicable consist of a collection of many replications of very short time series (often with only two observations). Of course, such limited temporal data cannot support the complex time-series models used in the econometric analyses of reciprocal effects. One psychological application of models and analyses of reciprocal effects in time series data is the analysis of play behavior of individual mother–infant dyads in Gottman and Ringland (1981).

5. Methods for Categorical Data
Analyses of reciprocal effects using dichotomous or polychotomous variables have not been common in educational research. Lazarsfeld's 16-fold table for analyzing reciprocal effects among dichotomous variables is the best-known method for categorical data; Lazarsfeld (1978) provided a history of the development and application of this procedure. A natural extension of the 16-fold table analysis is the application of log-linear models for contingency tables (Goodman 1973). A third approach to the analysis of reciprocal effects is the use of continuous-time stochastic models, in particular, discrete-state, continuous-time Markov models. For additional references and for applications of these methods, see Coleman (1968), Hannan and Tuma (1979, 1983), and Markus (1979).

6. Conclusion
The investigation of reciprocal effects is an extremely difficult enterprise. Questions about reciprocal effects are some of the most complex in the design and analysis of longitudinal research. A humbling reality for research on reciprocal effects is that much simpler, preliminary research questions, namely those connected with the measurement of individual change and the assessment of correlates of change, remain controversial and unsolved. Clearly, reciprocal effects cannot be studied cheaply. Extensive, high-quality longitudinal data and theoretically based, explicit models of the reciprocal effects are absolutely necessary.

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