

DOCUMENT RESUME

ED 227 413

CG 016 546

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**TITLE** Methodological Explorations of Counselor-Client Interaction.  
**PUB DATE** Aug 82  
**NOTE** 2lp.; Paper presented at the Annual Convention of the American Psychological Association (90th, Washington, DC, August 23-27, 1982).  
**PUB TYPE** Reports - Research/Technical (143) -- Speeches/Conference Papers (150)

**EDRS PRICE** MF01/PC01 Plus Postage.  
**DESCRIPTORS** Behavior Change; Behavior Patterns; \*Counseling; \*Counseling Effectiveness; \*Counselor Client Relationship; \*Evaluation Methods; \*Interaction; Interpersonal Communication

**ABSTRACT**

In contrast to the usual counseling outcome assessment procedures, which rely on individual change scores on selected outcome instruments, this paper proposes a contemporary interactional perspective which suggests that the assessment of outcome should focus on determining changes in the counseling process itself, i.e., a change in the interaction patterns between the counselor and the client. Three analytic approaches for assessing pattern (and pattern change) are presented: (1) Markov chain analysis; (2) lag sequential analysis; and (3) information theory analysis. The specifics of each approach are described and their relationship to the sequential dependencies among the events in the counseling process are discussed. The contemporary interactional perspective is contrasted with earlier views which concentrated on behavior within the interview. A reference list and tables illustrating the interactional dependencies are appended.  
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METHODOLOGICAL EXPLORATIONS OF  
COUNSELOR-CLIENT INTERACTION

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### Abstract

In contrast to the usual counseling outcome assessment procedures which rely on individual change scores on selected outcome instruments, the contemporary interactional perspective would suggest that the assessment of outcome should focus on determining changes in the counseling process itself, i.e., a change in the interactional patterns between the counselor and client. Three analytic approaches for assessing pattern (and pattern change) are presented in this paper: Markov chain analysis, lag sequential analysis, and information theory analysis. While the specifics of each of the approaches differ, each is derived from the conditional, sequential dependencies among the events of the counseling process (interaction sequence).

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A distinction has generally been made between "process" and "outcome" research in the counseling and psychotherapy literature -- the two being differentiated from one another in terms of their respective foci. Process research, on the one hand, has attended primarily to the nature of the therapeutic encounter or "within interview behavior." On the other hand, outcome research has focused upon the effects of that encounter or on the relatively enduring changes in the client as a result of the therapy process. (Cartwright, 1957; Kiesler, 1966, 1971; Strupp & Luborsky, 1962). In recent years, however, this distinction has blurred, and recent speculations in the therapy literature lead one to question where process ends and outcome begins (Kiesler, 1971).

In contrast to earlier views of disturbed or disordered client behavior which postulated intrapsychic or situational determinants of that behavior (and the disrupted interpersonal relationships that followed), the contemporary interactional perspective (Watzlawick, Beavin, & Jackson, 1967; Watzlawick & Weakland, 1977) focuses on client "symptoms" as habitual and problematic patterns or sequences of interpersonal behavior -- patterns which are perpetuated by the way clients behave and by the influence of others intimately involved with them (Weakland, Fisch, Watzlawick, & Bodin, 1973). Cashdan (1973, 1981) refers to these patterns as "strategies." As traditionally conceived, a strategy refers to certain tactical maneuvers used to achieve some goal. Applied to interpersonal relationships, whether within counseling or outside of



counseling, a strategy refers to the relatively discrete modes of behavior through which a person develops and maintains ongoing interpersonal relationships. Specifically, they are the behavioral (communicative) maneuvers that clients use to try to meet their interpersonal needs. Strictly speaking, the maladaptiveness of a client's strategy is not a function of the strategy itself, but of the way it meets or fails to meet the expectations of the recipient. When a person's strategies are extreme in their effect on others (and held to be outside of the person's volitional control), these strategies are labeled as "symptoms" (Haley, 1963).

It is an extension of this view that in the therapeutic relationship, like other interpersonal relationships in which clients become involved, similar interactional patterns and sequences will emerge; and that ultimately it is the role and responsibility of the counselor to alter these interpersonal sequences. Indeed, while counseling involves many factors (including support, encouragement of self-expression, education, etc.), it is of crucial importance that the counselor deal successfully with changing the client's usual interaction pattern as it emerges in counseling. Unless this is accomplished, the counseling process will simply model and perpetuate those same problematic (symptomatic) response sequences which initially brought the client in for counseling (Anchin, 1982).

It follows from this perspective that, in contrast to the usual counseling outcome assessment procedures which rely on individual change scores on selected outcome instruments, assessment of outcome should focus on determining change(s) in the counseling process itself, i.e., a change in the interactional patterns between the counselor and client.

The issue of pattern in counselor-client interaction rests fundamentally on an assumption of behavioral interdependency or the mutual and reciprocal communication between participants. In a general sense, communication is said to occur between persons whenever they behave in a non-random manner with respect to each other. More specifically, it means that one person's actions are dependent (at least to some degree) on the preceding behaviors of the other. Indeed, were this not the case, (i.e., were the participants to not respond differentially/nonrandomly to each other), it would be impossible to say that there was any exchange process as such between the participants (Barnlund, 1981). By this definition of communication, it should be understood that communication is not simply the response one person to another, but essentially the relationship that is set up between their responses (Cherry, 1957) -- a relationship of mutual and reciprocal constraint upon the behavioral variability of both the counselor and the client. By virtue of this constraint, the interactive behaviors of the counselor and client, which are the "stuff" of the counseling process, become predictable, at least to some extent -- and it is this predictability that is referred to as "pattern" (Bateson, 1973).

The raw material for studying these patterns are the various counselor-client interactive behaviors as they occur and order themselves over time (i.e., across the process). It has been noted (Raush, 1969) that while the observational protocols or codings of these events are gathered in a temporal order, generally it is simply because the events occur that way. Most often in the conversion to data for analysis, the ordering of these events is either lost or ignored. Hertel (1972) has noted the major failing of most process research methods employed to investigate/

explicate the counseling process has been their inability to incorporate the temporal or sequential relationships among the chosen process units. The unfortunate consequence of such failing is that the notion of "process" as operationally defined by those methods is rendered little more than a metaphor to the construct purportedly under investigation.

Hertel (1972) and Raush (1969) have both noted the desirability of models and methods for process research whereby researchers could capture and investigate the temporal nature of counselor-client interaction through analysis of the sequential ordering of its events. Such models and methods would potentially move process research from investigation premised on static states to one more capable of dealing with both structural continuities and continuous changes, and toward the illumination and documentation of the kinds of sequential phenomena (i.e. patterns) that provide the inference base for our views of counseling process and change.

The approaches presented in this paper may generally be referred to as "sequential analyses". Sequential analysis is the term given to a number of statistical techniques used for analyzing sequences of behavior. Common to each of these techniques is the search for sequential patterns or redundancies among events/behaviors. While the specifics of each of the approaches differ, each is derived, at least conceptually, from the conditional, sequential dependencies among events in the sequence.

For example, suppose one observes a sequence of counselor-client exchanges using two observational codes (A and B). If one observes the interaction sequence

ABAABABBABBAAABABBABAAABBAABB

one can describe the interaction nonsequentially by simply observing that the frequency of occurrence of A is 16, and the frequency of B is 14. The unconditional probability of A is thus  $p(A) = 16/30 = .53$ ; and the unconditional probability of B is  $p(B) = 14/30 = .47$ . The conditional probability of the occurrence of B, given that A has occurred just prior to B, is the proportion of time that B occurs immediately after A: A occurs 16 times and of those 16 times B occurs after A nine times. Thus the conditional probability of B given A is  $9/16 = p(B/A) = .56$ . Hence one can reduce the uncertainty in our knowledge of B's occurrence by knowing the immediately preceding event in the interaction was A. Sequential analysis may thus reveal the interaction patterning (redundancies) between two individuals (Rausch, 1965). That is, to the degree that the actions of one person "depend" on (i.e. are constrained by) the immediately preceding behavior of the other, the first person's response probabilities have altered in response to the behaviors of the other. In the methods presented here, the dependency need not necessarily be limited to the effect of the immediately preceding event, but instead may allow for the discovery of more complex patterns of interactive dependency among the communicative events of both the counselor and client.

#### Markov chain analysis

Using the above example of a "counselor-client interaction sequence," it is possible to describe the sequence of coded events by specifying the likelihood of the various event to event transitions. These probabilities can then be arranged in a matrix called a transition matrix in which the rows (i) represent the antecedent events and the columns (j) are the consequents. The matrix summarizes the probabilities of each

state following every other state at the next ( $t$ ) instance. For each antecedent event at time  $t-1$ , the sum of the probabilities for each of the possible consequent events equals 1.0.

To the extent that the probabilities within each row are not equal (i.e., are non-random), the antecedent events may be said to constrain or modify the distribution of probabilities of the various consequents -- and the probability of occurrence of any given consequence is said to "depend on" the prior event. If the occurrence of an event is dependent on (constrained by) only the immediately preceding event, and if the probabilities are stationary across the sequence, the sequence is said to exhibit first-order (one-step) dependency and constitute a first-order Markov chain.

It is possible, and some would say probable, that the interaction among events would show greater or higher-order dependency among events; i.e., events are constrained by (or the probability of occurrence depends on) more than the immediately preceding event. Rather it is constrained by a sequence of some  $r$  number of preceding events.

The procedure for testing the order of dependency among events under this model is essentially to test a series of models (of dependency) in which the number of events in the sequence on which the events are considered dependent is increased by one event in each subsequent test. That is, a 1st-order (one-step) dependency model is compared to a random (0-order) model with respect to its "goodness of fit" to the contingency data; a 2nd-order model is compared with the first-order model; a third-order model with a second-order model; etc. To do so, of course, requires the construction of successively larger contingency tables which consecutively present the contingencies between events from the 1st to the  $r$ th

order. Table 1 presents examples of such contingency tables for the 3 category system presented earlier. Given such contingency tables as a data base, there are two methods generally employed to estimate the order/constraint of the sequential data summarized by the tables: the Chi square approach and the maximum likelihood approach.

(a) The first approach is based on a comparison of observed and expected frequencies for each consecutive increase in the order of dependency. The difference between the values is subjected to a  $X^2$  goodness of fit test for determining which model best describes/explains the contingent relationships among the data (Suppes & Atkinson, 1960; Chatfield, 1973).

(b) The maximum likelihood approach is similar to the  $X^2$  approach but employs the log-linear ratio statistic ( $G^2$ ) rather than the  $X^2$  statistic. Generally speaking, the maximum likelihood approach is better than the  $X^2$  approach (Bishop, Feinberg & Holland, 1975), but both are susceptible to difficulties associated with  $X^2$  when applied to complex data. In particular, as should be clear from Table 1, as the order of the sequential dependencies to be tested increases in number, the number of possible combinations of contingent events increases in a multiplicative fashion. Unless the number of actual events in the interaction sequence is quite large, this results in an increase in the number of empty cells in the tables, thus weakening the  $X^2$  test (see Chatfield & Lemon, 1970).

Given a Markov chain of some of  $n$ th order, it is possible to determine patterns of recurrence of events (Howard, 1971; Gottman, 1978). Digraph's of chains -- graphs of the probabilistic interrelationships among events (or if a higher-order chain, among sets of events) -- can



also be made in order to visually present the patterns inherent in the transition probabilities (e.g., Brent & Sykes, 1979).

### Lag sequential analysis

An alternative to the Markov chain approach to the study of contingency relationships (constraint) in interaction sequences is the lag sequential analysis method (Sackett, 1979a). As presented by Sackett, the particular advantage of this technique over the Markovian methods outlined above is that it allows for obtaining measures of contingency among events which are far apart in the sequence (i.e., higher order dependency) without the concern of "empty cells" which plagues the previous approaches.

The basic procedure for lag analysis is as follows: Each interaction event/code serves as a criterion code. For each specified criterion, the conditional probability of each other event (including itself) is calculated as a function of the successive lags (n-steps) of each code from the criterion.

To present an example, return to the original sequence of three interaction codes. To start, code A is initially set as the criterion. The next step in the procedure is to determine the number of times that each event code (including A) follows the criterion as the next event (lag 1), as the second event after criterion (lag 2) . . . and so on up to the largest sequential step of interest. Table 2 gives the probabilities for event lags for each criterion in the sequence (A and b), up to lag 5 (5-step dependency).

Having determined these conditional lag probabilities, they can be tested for statistical significance against the null hypothesis of equivalence to the unconditional probabilities of the events -- a "match"

of the conditional and unconditional probabilities suggesting independence of sequential events, rather than dependence (or constraint), at that lag.

Using these lag probabilities, it is possible to then identify patterns among those events within the sequence. This involves a three step procedure, referred to by Gottman (1979) as the "lag-one connection rule." First, starting with a criterion code, select for the next event the code with the highest lag-1 conditional probability from the criterion. Then select the code with the highest lag-2 probability from the criterion, the highest lag-3 probability, etc. Using the lag data summarized in Table 2, the generated pattern or probable sequence (up to lag-5) would be ABBABA.

Next, note that this sequence is a likely or common pattern only if the lag-1 probability from event 2 to event 3 is the highest conditional probability for that two-event sequence (with the second event now serving as the criterion). (Note: For these data, the highest lag-1 probability event for the second event (B) is not another B, but rather an A.) This process of verification continues -- successively checking the one-step connections generated within the identified sequence.

Finally, the last step in identifying a probable sequence pattern is to determine at any lag whether the conditional probability of occurrence of an event differs significantly from the unconditional probability of the event. Even if an event code is the most likely code at some lag from the criterion, if it is not more probable (statistically speaking) than its simple unconditional likelihood of occurrence, that event should not be entered into the identified common sequence. A computer program for determining lag probabilities and for testing the significance may be found in Sackett, et al. (1979b).

Despite growing interest and use of lag analysis as a method for identifying contingency relationships in interaction data, recent criticism regarding the statistical methods proposed by Sackett and Gottman for testing lagged dependence (Allison & Liker, 1982) raises question as to the statistical validity of this approach.

### Information theory

The previously presented techniques have addressed the issue of "pattern" as a function of constraint or dependency among events. Information theory takes a somewhat different, but analogous, approach to the study of pattern in sequences of events. An interaction sequence (as a stochastic process) may be characterized by some degree of redundancy between 0 and 100 percent -- redundancy being essentially synonymous with the notion of pattern (or patterning). At the zero-redundancy extreme, all events have an equal likelihood of occurrence -- the history of the sequence prior to any given event has no effect on the predictability of the event. That is to say, there is complete uncertainty with respect to the patterning within the sequence (or even more specifically, to the extent that events in the sequence are equally probable, there is no patterning at all). At the other extreme -- that of 100 percent redundancy -- the sequence is entirely predictable (redundant) and one can predict with complete certainty what each subsequent event will be.

The information theory approach consists of calculating the average conditional uncertainty for the sequence for differing lengths of strings of antecedent events. The decrease in uncertainty as the number of antecedent events increases may be used to assess the sequential dependency in the interaction sequence (Penman, 1980). A sequence has  $n$ th-order redundancy (or  $n-1$  dependency) whenever some of the possible patterns of a successive events/codes are more probable than others.

To calculate the degree of redundancy or patterning in a sequence, a decision must first be made on how high an order of redundancy one wishes to take into account. In a process similar to that in the Markov analysis, determination of the order of dependency involves calculating the average conditional uncertainty for successive orders of dependency and subtracting the average uncertainty of the previous order (Attneave, 1959).

The difference between successive values of conditional uncertainty provides a measure of how much information is gained (i.e., how much uncertainty is reduced) by basing predictions for a given event on the previous  $i$  events rather than the  $i-1$  previous events. The statistical significance of these sequential differences can be tested using a  $X^2$  approximation approach (Chatfield, 1973). Alternatively, it is often possible to see the point at which the conditional uncertainty starts to decrease relatively slowly (after a sudden decrease) and thereby determine the order of dependence among the events. This graphical technique is often more reliable than a series of significance tests based on the  $X^2$  approximation.

Returning to the previously presented sequence of events, Table 3 presents the conditional uncertainty for the sequence for the first three levels of sequential dependency. The value  $H$  is Shannon's measure of information or average uncertainty. The maximum value of  $H$  is equal to the  $\log_2$  of the number of categories--in this case,  $\log_2 2 = 1.0$ . This occurs when the outcomes (A and B) are equally likely or probable. In the previous sequence  $p(A) = .53$  and  $p(B) = .47$ --they are very nearly equal and  $H$  therefore approaches 1.0 ( $H_1 = .991$ ). (See Attneave, 1959

for computational formulae.) In a similar manner, the average uncertainty is computed for two-event (digram), three-event (trigram)... n-event (n-gram) "sequences." The amount of information (reduction in uncertainty) achieved by considering successively longer sequences of prior events is determined by subtracting  $H_1$  from  $H_2$ ,  $H_2$  from  $H_3$ , etc.

As can be seen from Table 3, little information is gained by knowing only one preceding event ( $H_2$ ). Consideration of two preceding events does bring about a reduction in uncertainty ( $H_3 = .842$ ), but knowing the previous three events greatly reduces the uncertainty of prediction ( $H_4 = .570$ )--suggesting this sequence to be of at least 3rd-order dependency.

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Table 1 First-, second-, and third-order transitions for the two category sequence.

First-order transitions

		<u>t</u>	
		A	B
t-1	A	7	9
	B	8	5

Second-order transitions

		<u>t</u>					
		A	B				
t-2	A	t-1	A	3	4	4	5
		B	4	4	4	0	

Third-order transitions

			<u>t</u>			
			A	B		
t-3	t-2	t-1	A	B	A	B
			A	0	2	3
A	A	2	4	2	0	
	B	3	0	2	3	
B	A	2	0	2	0	
	B					

Table 2 Lag matching frequencies and probabilities for the two category sequence

Lag	Number of Matched Occurrences			Probability	
	A	B	Total	A	B
Overall	16	14	30	.53	.47
<u>A</u> as criterion					
1	7	9	16	.44	.56
2	7	8	15	.47	.53
3	8	7	15	.53	.47
4	5	9	14	.36	.64
5	8	5	13	.62	.38
<u>B</u> as criterion					
1	8	5	13	.62	.38
2	7	5	12	.58	.42
3	6	6	12	.50	.50
4	8	4	12	.67	.33
5	5	7	12	.42	.58

Table 3 Conditional uncertainty for the two category sequence for successive levels of dependency.

Tetragram	Trigram	Digram	Symbol
AAAA AAAB	AAA	AA	
AABA AABB	AAB		
ABAA ABAB	ABA		A
<del>ABBA</del> <del>ABBB</del>	ABB	AB	
BAAA BAAB	BAA		
BABA BABB	BAB	BA	
BBAA BBAB	BBA		B
BBBA BBBB	BBB	BB	

$$H(\text{tetragram}) = 3.366$$

$$H(\text{trigram}) = 2.796$$

$$H(\text{digram}) = 1.953$$

$$H_1 = .991$$

$$H_4 = H(\text{tetra}) - H(\text{tri}) = .570$$

$$H_3 = H(\text{tri}) - H(\text{di}) = .843$$

$$H_2 = H(\text{di}) - H_1 = .962$$