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10 A Structural Equation Model of Impression Formation

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This chapter has two goals. First, it illustrates how theoretical ideas can be combined with psychological data in structural equation models. We show how to use a computer program, LISREL (Jöreskog & Sörbom, 1978), that allows the analysis of complex structural models. Our second goal is to show how structural equation models can further understanding of social cognition. We want to explore how people process information when they form impressions. To accomplish these objectives, the chapter briefly reviews the previous work that has been done on social cognition, concentrating on those studies that used data similar to ours. We then develop a theoretical model of how information about social events is processed when subjects are exposed to a short event description. The LISREL program is described, and we show how to represent our theoretical model with the program. Finally, the procedures for data collection are described, and we present the results of our analyses.

IMPRESSION FORMATION

Social psychologists usually assume that people use information about others to form impressions of them. Research on these processes is closely linked to work on attitude balance theory, attitude change dynamics, and the literature on attribution. Impression formation can be studied using a model in which nouns that identify actor-persons and object-persons are linked with verbs that describe some interpersonal behavior. Because the nouns and verbs are associated with specific, measurable attitudes or affective meanings, the event description can be presented to subjects to study the impressions they form about the people and the behavior involved in the simple event.

Gollob (1968) first developed an experimental paradigm to specify reactions to such events. He generated sets of simple sentences by combining actors that were either positively or negatively evaluated with object-persons that were either positive or negative. He linked the actor and the object with either a positive or negative behavior. For example, a sentence with a negative actor, a positive behavior, and a positive object-person would be "the cruel man helps the child." Gollob then attempted to predict the subjects' evaluative (good–bad) ratings of the actor within the context of each event-sentence.

Gollob found that the in-context impressions could be predicted very accurately as a function of the original attitudes associated with the actor (A), the behavior (B), and the object (0) in the sentence.[1] Eighty-six percent of the variance in the in-context impressions was explained by a simple regression model containing terms for the out-of-context variables—the original attitude toward the actor, the original attitude toward the behavior, and the product of the original attitudes toward the behavior and toward the object. (The multiplicative interaction represents a balance effect—doing good unto good or bad unto bad enhances the evaluation of an actor.)

Later studies by Gollob, Heise, and their associates (Gollob & Rossman, 1973; Heise 1969a, 1970, 1978, 1979; Heise & Smith-Lovin, 1981) have replicated Gollob's original findings. The following formula from Gollob (1968) can be used to predit in-context evaluations of an actor from out-of-context evaluations on seven-point scales:

$$A_e' = -.26 + .39\,A_e + .48\,B_e + .25\,B_eO_e. \qquad (1)$$

The effects described by this prediction formula can be applied interpretively to specific interpersonal events. For instance, the average out-of-context evaluative rating of a Child is 1.9 (quite good), of Pestering someone is −1.8 (quite bad), and of a Schoolgirl is 1.2 (slightly good—ratings and scales taken from Heise, 1978). A Child who has Pestered a Schoolgirl is viewed somewhat negatively, however; the rating of the Child (actor) within the context of this event is −0.92 (as compared with a 1.9 rating before the event). The formula indicates that this difference is a consequence of having engaged in a negative, irritating behavior and, especially, of having directed this negative act at someone who is basically a good, pleasant person.

Heise has expanded this impression formation paradigm to study changes in

[1]Gollob (1968) originally used the notation *SVO* to symbolize the subject, verb, and object of the event-sentence. More recently Heise and his associates (Heise, 1977, 1978; 1979; Heise & Smith-Lovin, 1981; Smith-Lovin, 1979) have used the *ABO* notation to emphasize the social nature of the described events.

impressions of potency (powerfulness versus weakness) and activity (liveliness versus quietness). Heise's studies also examined how events change impressions of object-persons and behaviors as well as impressions of actors.

The most recent studies (Gollob & Rossman, 1973; Heise, 1978; Heise & Smith-Lovin, 1981) have examined cross-dimensional effects in impression formation (e.g., effects of behavior potency on the evaluation of the actor). At least one significant cross-dimensional effect has been found in each prediction formula. For example, Heise and Smith-Lovin (1981) showed that the evaluation of an actor after an event can be predicted more accurately with the following equation, which includes effects from evaluation (e), potency (p), and activity (a) dimensions:

$$A_e' = .03 + .40\,A_e - .13\,A_p + .49\,B_e - .34\,B_a + .20\,B_eO_e \qquad .(2)$$

The effects of evaluation are very similar to those from studies that have explored only within-dimension effects (Gollob, 1968; Heise, 1969a, 1970). But now we see that powerful actors (high A_p) are evaluated somewhat more negatively when they engage in interpersonal behaviors, and that very active or frantic behaviors (high B_a) reflect badly on the actor.

Regression equations from earlier studies such as (1) and (2) summarize the total effects of the attitudes toward the event elements (A, B, and O) on the outcomes after the event. In the present analysis, we explore the possibility that these effects are not direct influences. Instead, a model is developed that treats impression formation as a feedback process. We suggest that a subject's out-of-context attitudes toward the event elements (obtained before an event is considered) set the initial attitudes or meanings within the context of the event description. Then, the impressions of (or feelings toward) each event element affects feelings toward the other elements until a stable final outcome is reached. In other words, the affective meanings or attitudes toward the actor, behavior, and object influence each other in indirect ways, as the meanings are modified by the context of the event description.

To illustrate the idea of impression formation as a feedback process, consider Heise's (1969a) finding that the object of a negative action is evaluated more negatively because he has been victimized (an effect of B_e on O_e'). This finding seems rather counter-intuitive as a direct effect. Why should we think less of someone who has *received* a negative action? It makes more sense to posit a feedback model that allows the attitudes toward event elements to affect one another. It may be the case that a negative behavior reflects badly on the *actor* within the event, and *then* the evaluation of the actor affects the attitude toward the object-person (i.e., the object-person must not be very nice, if he was associating with such a nasty person, the actor). Therefore, instead of having a direct effect of behavior evaluation (B_e) on object-person evaluation (O_e') negative behaviors may operate through actor evaluation (A_e') to injure the reputation of the object-person.

THE MODEL

A model including the types of indirect feedback effects described in the foregoing can be displayed conveniently using a path diagram (Fig. 10.1). Lowercase letters indicate observed variables, and uppercase letters indicate latent variables. The letters A, B, and O refer to the actor, behavior, and object-person; the subscripts e, p, and a refer to evaluation, potency, and activity. Primed variables (e.g., A_e') are impressions produced by an event; unprimed variables (e.g., A_e) indicate impressions of the actor, behavior, or object in isolation.

The model has nine outcome variables—the evaluation, potency, and activity ratings of actor, behavior, and object. It has 10 predictor variables, including B_eO_e, which is created by multiplying the evaluation of the behavior and the evaluation of the object. Impressions of actor, behavior, and object out of context are not influenced by the feelings resulting from exposure to an event description, so the nine out-of-context impressions and the B_eO_e interaction are exogenous variables. These original impressions of an element directly affect only the postevent feelings toward that same element; cross-element effects occur indirectly. For example, the out-of-context evaluation of a behavior (B_e) can only affect evaluation of that behavior within the context of an event (B_e'), which in turn may influence evaluation of the actor (A_e') or object-person (O_e') in the event. This theoretical restriction allows the prior impressions of actor, behavior, and object (the unprimed variables) to be used as instruments for disentangling relationships among the endogenous variables, the in-context impressions (see Heise, 1975, Chapter 5, for a discussion of instrumental variables). For example, the fact that B_e affects only B_e' directly allows us to estimate the effects of B_e' on the other primed variables: A_e', A_p', A_a', O_e', etc. We allow impression formation processes to involve cross-element effects but not intraelement effects. For example, O_e' is not allowed to affect O_p' and O_a', but it may influence B_e', (which then influences O_p').

THE LISREL PROGRAM

Structural equation modeling is a methodology that permits theoretical knowledge and empirical information to be combined in order to estimate parameters of large causal systems. Parameter estimates for structural equation models can be obtained from computer program LISREL, developed by K. G. Jöreskog (Jöreskog, 1969, 1970; Jöreskog, Gruvaeus, & Vanthillo, 1970; Jöreskog & Sörbom, 1978). A typical LISREL model incorporates a measurement model, which relates latent constructs to observed measures of these constructs, and a structural model that specifies the causal relationship among latent variables.

The LISREL approach has several advantages when compared with other approaches. First, we can examine theoretical systems that include a large

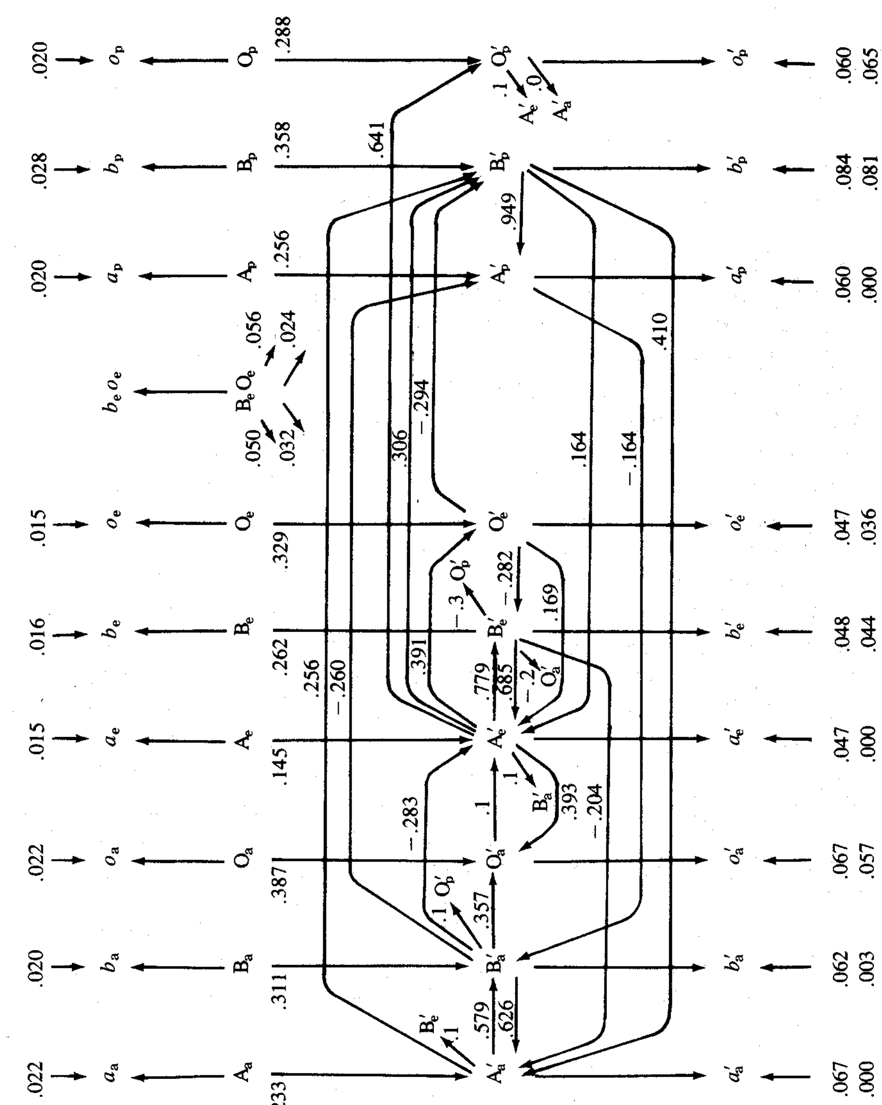

FIG. 10.1. A structural equation model of impression formation.

number of variables and relationships. For example, the impression-formation problem addressed in this chapter involves nine dependent variables, which have many interrelationships. Estimating the parameters of such a large, complex model is very difficult without a program like LISREL. Secondly, LISREL can use information that we have about the errors in our variables while it is estimating the structural parameters. In simple regression models like those used in earlier studies (Gollob, 1968; Heise, 1969a, 1970), the researcher must assume that all the errors in the variables are uncorrelated with one another. In addition, the independent variables must have no error if the estimated regression coefficients are to be unbiased. LISREL allows the researcher to specify a measurement structure in advance, so that assumptions about correlated errors can be tested. For example, in this study LISREL allowed us to test the hypothesis that the errors were uncorrelated. We estimated several models that allowed such correlations, and our results showed that the error correlations were not significantly different from zero. Therefore, we have set these parameters equal to zero for the model that we use as an illustration here.

In this study, we also have specific information about the amount of measurement error in our data (see discussion following). Using LISREL, we can set the measurement error variances at predetermined levels based on other analyses; the program then uses this information to compute more accurate, unbiased estimates of the effects in which we are interested.

LISREL produces the set of parameter values that are most probable, given the data and the theoretical model specification (i.e., it produces maximum likelihood estimates of model parameters). It constructs a theoretical variance–covariance matrix (Σ) by applying the model specifications and initial estimates of parameters, and searchers iteratively for new estimates of parameter values that best reproduce the observed variance–covariance matrix, S.

A chi-square value is computed to help judge how well the final model fits the data. When the chi-squre is small relative to the degrees of freedom, the model fits the data well. The level of fit that is considered to be "acceptable" is problematic. Ideally, a very small chi-square value is possible. In practice, however, a model that fits the data too well will contain a number of parameters that are not theoretically interesting but that only allow the model to represent sampling errors in the observed variance–covariance matrix. Unless a researcher is working with population data, some other criterion is needed for defining an acceptable fit. Three alternatives have been suggested:

1. A chi-square value that is equal to or less than the number of degrees of freedom may be considered a reasonable fit (Jöreskog 1969). In fact, for exploratory purposes any chi-square less than five times the degrees of freedom may be acceptable.[2]

2. Lawley and Maxwell (1971) suggest accepting models when the probability of the chi-square value is greater than or equal to .10. Others have used probability values of .05 or .15.

3. If a researcher is attempting to improve fit by removing constraints on a model's parameters, Sörbom (1975) proposes accepting the more parsimonious model when the difference in chi-square values produced by the two models is no longer significant. This criterion may be used when comparing models, because the difference in chi-square values also is chi-square distributed. The number of degrees of freedom for the comparison is equal to the difference in degrees of freedom for the two models.

Saris, de Piper, and Zegwaart (1979) apply each of these criteria and discuss differences in results. Obviously these are only rough guidelines. Theory and the plausibility of the estimates play an important role in evaluating a model.

In specifying a model for the LISREL program, any particular parameter may be treated in one of three ways: (1) as known a priori on theoretical or empirical grounds and therefore assigned a fixed value; (2) as unknown, but constrained to be equal to one or more other parameters; or (3) as an unknown quantity to be freely estimated by the program. Eight sets of parameters have to be considered in using LISREL, each set corresponding to an input matrix in setting up a problem.

The Θ_δ matrix is the variance–covariance matrix of the errors in measurement for the exogenous indicators. The Θ_ϵ matrix represents the same information for the endogenous indicators. In either case, the matrix diagonal defines the error variances of indicators. If the indicators were scales with known reliabilities, fixed values could be input as the diagonal entries in Θ_δ or Θ_ϵ. If errors in indicators are independent and random, then the off-diagonal elements of the Θ matrics are zero.

The Λ_x matrix represents the factor pattern for the indicators of exogenous variables. It shows which hypothesized latent variables influence each observed indicator. The corresponding factor matrix for the y indicators is Λ_y. Some elements in Λ_x and Λ_y always will be fixed, usually at zero or one. For example, if y_1 and y_2 are indicators of N_1, and y_3 and y_4 are indicators of N_2, then the parameters connecting the latent variable N_2 to y_1 and y_2 are set to zero on the theoretical grounds that their indicators measure only N_1, the construct that they are supposed to measure. Fixing a parameter equal to zero in a LISREL model is

[2]Because the chi-square value is a function of both the degrees of freedom *and* the number of observations, it may seem unreasonable that this ratio could be used to evaluate models at any sample size. It is appropriate, however, because the model's deviations from the observed variance–covariance matrix are a much more serious problem if the sample size is large. When the N is small, the matrix contains relatively large amounts of sampling error. The researcher does not want to fit this sampling error with his or her theoretical model. On the other hand, when the sample is large and the variances and covariances are very stable, deviations of the model from the observed interrelationships are more likely to be the result of theoretical misspecification. The use of a ratio of chi-square to degrees of freedom requires a theoretical model to fit a variance–covariance matrix from a large data set more closely than a matrix from a small data set.

equivalent to excluding the variable from the equation in regression or factor analysis. In models where only one indicator is available for each latent variable, the unobserved variables are considered to be the same as the observed indicators. In this case the Λ_x and Λ_y matrices will be fixed equal to an identity matrix.

The Φ matrix contains the variances and covariances of the latent exogenous variables. Usually these parameters are estimated by the program. However, if only one reliable indicator measures each unobserved variable, the Φ matrix is fixed equal to the observed variances and covariances of the indicators.

The structural coefficients relating the latent exogenous variables to the dependent variables are contained in the Γ matrix. If causal effects are eliminated on a theoretical basis, the corresponding parameters are fixed at zero. Again, fixing a parameter equal to zero is equivalent to excluding it from the equation.

The β matrix specifies the causal relationships among the latent endogenous variables. The diagonal entries in β will be 1.0 in most cases (unless a scale transformation in a latent variable is desired). The off-diagonal elements will be freely estimated unless there is theoretical knowledge which eliminates the possibility of particular effects.

The Ψ matrix contains the variances and covariances of unspecified determinants of the endogenous variables. The diagonal values indicate the size of the unexplained variances.

Specifying each parameter in each of the aforementioned eight matrices as fixed, constrained, or free defines a theoretical model. The parameter estimates that are obtained with LISREL provide the best fit to the data *given* that theoretical model. As a detailed example, the following description shows how the impression-formation model diagrammed in Fig. 10.1 is transformed into a set of LISREL matrices.

For our model, the Θ_δ matrix is 10×10 (because there are 10 observed exogenous variables) with all its values fixed. The diagonal values are the estimates of error variances (described in the following). The off-diagonal values are all 0.0, because measurement errors were found to be uncorrelated.

The Θ matrix is a 9×9 matrix with the same structure as Θ_δ.

The Λ_X matrix is a 10×10 matrix because there are 10 observed indicators for the 10 latent independent variables. Fixing all off-diagonal elements at 0.0 represents our assumption that measurements are not contaminated by the other dimensions (e.g., ratings of evaluation are not contaminated by potency and activity). A long tradition of research on the semantic differential (summarized by Osgood, 1962, and Heise, 1969b) supports this assumption; correlations among the three dimensions are close to zero in most studies (see Heise 1978, 1979, for a discussion of dimensional independence in ratings of social identities and interpersonal behaviors). The diagonal values of the Λ_x matrix are fixed at 1.0 to set the latent variables to the same scales as their indicators.

The Λ_y matrix (9×9) has a structure parallel to that of Λ_x.

The Φ matrix (10×10) is set equal to the observed covariances and variances of the exogenous variables, as there is only one indicator for each latent exogenous variable. If we had multiple indicators of one or more latent concept, the LISREL program could freely estimate the variance–covariance matrix of the exogenous latent factors.

The 9×10 Γ matrix shows relations of the nine endogenous variables to the 10 exogeneous variables. Because of the assumption that prior impressions of an element directly affect feelings only for that same element, most entries in Γ are set equal to 0.0 (Table 10.1). For example, whereas the coefficient for A_e to A_e' is to be estimated freely, the effects from A_e to A_p', A_a', B_e', B_p', etc, are set to 0.0. Initially, the column of effects associated with B_eO_e was completely free, permitting this variable to affect any of the endogenous variables directly. However, a first estimation revealed that only four of these effects were statistically significant. The small, nonsignificant effects were set equal to zero for the estimation presented here.

The β matrix (9×9) also contains both free and fixed values. Within-element, cross-dimensional effects (e.g. the effect of O_e' on O_p' and O_a') are fixed to 0.0 (Table 10.2). All cross-element parameters were left free initially, as none of these effects could be theoretically eliminated. Again, a first estimation revealed that some of these parameters actually are small and nonsignificant, and these parameters were set equal to 0.0 for the reestimation considered here.

The 9×9 Ψ matrix's diagonal is left free to estimate the variances-of-disturbance terms. The off-diagonal elements are fixed at 0.0, representing the finding that there were no correlations among the disturbances. (After the initial

TABLE 10.1
The Matrix Containing Estimates of the Relations of the In-context Ratings to the Ratings of the Social Identities and Behaviors in Isolation

Endogeneous, In-context Variable:	*Out-of-Context, Exogeneous Variable:* A_e	A_p	A_a	B_e	B_p	B_a	O_e	O_p	O_a	B_eO_e
A_e'	0.145	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.050
A_p'	0.0	0.256	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.024
A_a'	0.0	0.0	0.233	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B_e'	0.0	0.0	0.0	0.262	0.0	0.0	0.0	0.0	0.0	0.032
B_p'	0.0	0.0	0.0	0.0	0.358	0.0	0.0	0.0	0.0	0.056
B_a'	0.0	0.0	0.0	0.0	0.0	0.311	0.0	0.0	0.0	0.0
O_e'	0.0	0.0	0.0	0.0	0.0	0.0	0.320	0.0	0.0	0.0
O_p'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.288	0.0	0.0
O_a'	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.387	0.0

Abbreviations: *A*: actor; *B*: behavior; *O*: object; *E*: evaluation; *p*: potency; *a*: activity.

TABLE 10.2
The Matrix Containing Estimates of the Relations Among the In-Context, Endogenous Ratings of Evaluation, Potency, and Activity

		Causal Variables:								
		A_e'	A_p'	A_a'	B_e'	B_p'	B_a'	O_e'	O_p'	O_a'
Dependent Variables:	A_e'	1.0	0.0	0.0	0.685	0.164	-0.283	0.169	0.059	0.059
	A_p'	0.0	1.0	0.0	0.0	0.949	-0.260	0.0	0.0	0.0
	A_a'	0.0	0.0	1.0	-0.204	0.410	0.626	0.0	0.044	0.0
	B_e'	0.779	0.0	0.102	1.0	0.0	0.0	0.282	0.0	0.0
	B_p'	0.306	0.0	0.256	0.0	1.0	0.0	-0.294	0.0	0.0
	B_a'	0.064	-0.164	0.579	0.0	0.0	1.0	0.0	0.0	0.0
	O_e'	0.391	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
	O_p'	0.641	0.0	0.0	-0.281	0.0	0.109	0.0	1.0	0.0
	O_a'	0.393	0.0	0.0	-0.244	0.0	0.357	0.0	0.0	1.0
Unspecified Sources (Error)		0.0	0.0	0.0	0.044	0.065	0.003	0.036	0.065	0.057

Abbreviations: *A*: actor; *B*: behavior; *O*: object-person; *e*: evaluation; *p*: potency *a*: activity

estimation of the model, it became apparent that no disturbance terms were needed for the impressions of the actor (A_e', A_p', and A_a'; accordingly, these have been fixed at 0.0.) In Fig. 10.1, the disturbances of the endogenous variables have been deleted for graphic clarity; the unexplained variance in each latent endogenous term is shown in the bottom row of the figure.

Heise's (1978, 1979; Heise & Smith-Lovin 1981) data are used for the analyses here. The data collection procedures, stimuli, and data are very similar to those used in earlier impression formation research (Gollob, 1968; Heise, 1969a, 1970). In particular, notice that the *event* is the unit of analysis, rather than the individual subject's ratings. In the following, we outline the stimuli construction, the measurement scales, data collection procedures, scaling analyses, and the estimation of error variances for this study. More information about these topics is contained in Heise (1978).

Stimuli

The event stimuli for this study were constructed using social identities and interpersonal behaviors chosen from a dictionary of 1250 concepts with their average EPA (evaluation, potency, and activity) ratings (Heise, 1978). Identities and behaviors were chosen to represent nine EPA profiles (see the left-hand column of Table 10.3). For example, *hero* is an identity that most undergraduates

TABLE 10.3
Words Used to Construct Stimulus Sentence With Mean Evaluation, Potency, and Activity Profiles

Profile Type (EPA)	*Identities*	E	P	A	*Behaviors*	E	P	A
A (+ + +)	Athlete	0.9	1.8	2.2	Convince	0.7	2.0	1.1
	Champion	1.0	2.5	2.2	Protect	2.7	2.6	1.1
	Hero	1.9	2.3	2.1				
	Winner	1.1	1.6	1.7				
B (+ + -)	Boss	0.6	1.4	0.9	Contemplate	0.9	1.2	-0.1
	Judge	1.1	1.8	-0.3	Soothe	2.6	2.1	0.1
	Sheriff	0.9	1.3	0.3				
C (+ - +)	Child	1.1	-0.6	2.7	Amuse	2.2	1.1	1.8
	Infant	1.4	-1.5	2.3	Play with	2.1	0.9	1.8
	Schoolgirl	1.2	-0.5	1.5	Tickle	0.8	0.3	1.7
D (+ - -)	Cripple	0.4	-0.8	-1.3	Indulge	0.4	0.1	0.4
	Invalid	0.5	-1.3	-1.9	Serve	1.5	0.4	0.2
	Underdog	0.7	-0.7	0.3				
E (- + +)	Outlaw	-2.1	0.7	1.5	Attack	-2.3	0.0	1.6
	Roughneck	-1.5	0.8	1.6	Defy	-1.0	0.6	1.1
					Sock	-1.9	-0.4	1.3
F (- + -)	Disciplinarian	0.6	1.2	0.0	Grieve for	0.7	1.1	-0.6
	Orge	-2.5	0.9	0.3	Oppress	-2.6	0.3	0.2
	Warden	0.4	1.1	-0.1	Silence	-0.5	0.8	0.2
G (- - +)	Blabbermouth	-1.6	-1.5	1.0	Laugh at	-1.4	-1.1	0.9
	Gambler	-0.5	-0.4	1.6	Pester	-2.0	-1.1	0.9
	Maniac	-2.6	-0.6	1.3				
H (- - -)	Alcoholic	-1.4	-1.9	-1.2	Avoid	-1.2	-1.4	-0.2
	Beggar	-0.5	-1.5	-1.4	Betray	-2.8	-2.1	-0.2
	Coward	-1.5	-2.3	-1.0	Ignore	-1.8	-1.1	-0.7
O (0 0 0)	Boarder	0.4	-0.2	-0.4	Observe	0.4	0.3	-0.2
	Stranger	0.3	-0.2	-0.3	Tap	0.1	0.1	0.1
					Watch	0.2	0.1	-0.2

rate highly on evaluation, potency, and activity. Therefore, *hero* is used in some event descriptions where an *A*-profile (+ + +) identity is needed. In general, identities and behaviors were chosen so that they could be used to create a relatively large number of events (i.e., the identities would be reasonable interaction partners for a variety of others, and the behaviors could be reasonably enacted in a variety of roles.

Identities with certain EPA profiles were very difficult to find in the U.S. undergraduate culture. For example, the *F* profile (− + +) is represented by the identities *disciplinarian, ogre,* and *warden,* even though both *disciplinarian* and *warden* are slightly positive in evaluation. Bad, powerful but quiet roles are uncommon. Our inability to find identities and behaviors that perfectly represent each EPA profile would only create problems for the analyses if it produced low variance or high colinearity in the measures used. An inspection of the results here indicates that this is not the case.

The identities and behaviors that were chosen (Table 10.3) were then combined into sentences describing social events according to the 8 × 8 Latin square design shown in Table 10.4. Behavior EPA profiles and object-person EPA profiles are orthogonal (every behavior profile occurs with every object profile), whereas each actor profile appears once in every row and column of the square. This design minimizes the covariances among event elments. Thus, it enhances our ability to estimate linear effects and the behavior-object multiplicative interaction.

Each cell in Table 10.4 corresponds to a stimulus sentence. For example, a sentence representing the pattern *FHE* (the 8,5 entry in the square) would be "the warden (− + −) betrayed (− − −) the outlaw (− + +)." Obviously, several different event descriptions could have been created to represent each cell of Table 10.4, as there were several identities and behaviors that matched each profile. For example, another sentence representing the *FHE* pattern would be "the disciplinarian (− + −) avoided (− − −) the roughneck (− + +)." In general, event descriptions that were both reasonable (in the matching of interaction partners and behaviors) and interesting were chosen. The 70 event sentences

TABLE 10.4
Paradigm for Design of Stimulus Sentences

Verb				*Object*	*Profile*			
Profile	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*
A	C,A	D	E	F	G	H	A	B
B	D	E	F	G	H	A	B	C
C	E	F	G	H	A	B	C	D
D	F	G	H	A	B	C	D	E
E	G	H	A	B	C	D	E	F
F	H	A	B	C	D	E	F	G
G	A	B	C	D	S	F	G	H
H	B	C	D	E	F	G	H	A,H

Note: Each cell corresponds to a sentence. The EPA profile for the sentence Subject is is indicated within the cell; the profile for the Verb is shown as the row label; and the profile for the Object is given as the column label. Two sentences were created for two of the cells, as shown. Four additional sentences involved all-neutral profiles (*Q*) for the subjects, verbs, and/or objects: two *000*, one DOA, and one EOH.

Key (the three signs refer to high or low values on evaluation, potency, and activity, respectively):

A + + +	E - + +
B + + -	F - + -
C + - +	G - - +
D + - -	H - - -

used in this study are listed in the Appendix at the end of this chapter, along with the in-context ratings of the three event elements on the EPA dimensions. (The ratings shown combine male and female data.)

Ratings of the out-of-context impressions were obtained by presenting identities with an article (e.g., "a *schoolgirl*") and behaviors in an infinitive form (e.g., "to *avoid* someone"). The mean ratings of the out-of-context impressions are presented in Table 10.3. The in-context impressions were obtained by presenting a stimulus sentence and underlining the component to be rated (e.g., "The *schoolgirl* convinced the champion"). The mean in-context ratings for each actor, behavior, and object-person are presented in the Appendix.

Semantic differential scales were grouped below each stimulus, and five stimuli were rated on a page. A box containing a question mark was set next to each stimulus, to be used by subjects who did not know the meaning of a word.

Measurement

Semantic differential ratings were obtained on machine-readable forms using three scales to measure the dimensions: evaluation, potency, and activity. Each scale had nine rating positions with the adverbial anchors "infinitely," "extremely," "quite," and "slightly," on either side and "neither or neutral" in the middle. The "infinitely" category was an innovation in semantic differential technology that helped minimize ceiling-floor effects in ratings. The poles of the scales were defined by clusters of adjectives known from previous work to be associated with the semantic differential dimensions: *evaluation*—good, helpful, nice, sweet versus bad, unhelpful, awful, sour; *potency*—strong, powerful, big, deep versus weak, powerless, little, shallow; *activity*—hurried, alive, noisy, fiery, young versus slow, dead, quiet, stiff, old. The order of presentation of the three rating scales (evaluation, potency, and activity) and the orientation of each scale (left or right) were varied. More details on the scales, including validity assessments, are presented by Heise (1978) and Smith-Lovin (1979).

Data Collection

Subjects were students in introductory sociology classes at the University of North Carolina. Out-of-context ratings were obtained from all subjects; ratings of the identities and behaviors in the context of the event were obtained from three subsamples, with each subsample rating a different third of the actors, behaviors, and object-persons. The subsamples each contained 26 subjects, 13 males and 13 females. The three forms were distributed randomly in each class.

Each rating booklet consisted of a cover sheet, an instruction page for the out-of-context ratings, 11 pages containing out-of-context stimuli and semantic differential scales, an instruction page for the in-context ratings, 14 pages containing event sentences and semantic differential scales, and a final section containing the questionnaire for another study. After the booklets were distributed, instructions were presented verbally. Subjects were told that the project was attempting to develop "mathematical formulas that do a good job of describing how we react to events and how we develop ideas for new events." They were asked to record how they felt about different kinds of people, different kinds of behaviors, and different kinds of events. After being offered an opportunity to leave if they did not wish to participate, subjects were instructed meticulously in the use of the three semantic differential scales and presented with examples of completed ratings.

All subjects completed the rating task in the 1½-hour period allowed, except one who finished after an additional 15 minutes.

Preliminary Analyses

Cliff (1972) has shown that metric imprecision in equal-interval scoring of semantic differential scales can interfere with estimation of parameters in mathematical models. Preliminary analyses here confirmed Cliff's finding of more parsimonious models with proper scaling—fewer interactions were contained in models developed using a refined metric than in those using assumed-interval scaling. Therefore, a derived metric was used here, developing by applying the successive-intervals scaling procedure to ratings of 650 social identities and 600 interpersonal behaviors by 311 college undergraduates—the data for the dictionary of semantic differential profiles mentioned previously.[3] The values for coding rating positions are presented in Heise (1978, Table 4.7).

Mean ratings on the evaluation, potency, and activity dimensions were calculated for each of the stimuli using the derived metric. These means are

[3]The method of successive intervals as specified by Diederich, Messick, and Tucker (1957) was used to scale the data, employing a program prepared in 1972 by Gary Cox at the Thurstone Psychometric Laboratory, University of North Carolina, Chapel Hill. The procedure assumes that ratings of stimuli on a given scale are normally distributed, though the means and the variances of ratings vary for different stimuli. In an iterative process, category boundaries are adjusted until the normality assumption is maximally fulfilled for all stimuli. The final results reported by the program are optimized values for the boundaries between rating positions. The program also provides scale values for stimuli; these are not used here. Because the midpoint and range of the final scale are set arbitrarily in the program, results were standardized with regression formulas so that the boundary values from all analyses correspond as closely as possible to the boundary values of an assumed-interval scale (−3.5, −2.5, −1.5, −0.5, 0.5, 1.5, 2.5, 3.5). The results of the analyses for the EPA (evaluation, potency, and activity) scales are summarized in Heise (1978: Tables 4.3, 4.4, and 4.5). An analysis of variance was also conducted to address the question of whether or not scale metric is influenced by type of stimuli (noun or verb) or by orientation of scale (left or right). The metrics of evaluation, potency, and activity scales all are influenced to a slight degree by type of stimulus and by scale orientation (see a detailed description of these results in Heise, 1978, pp. 70–79). Therefore, the scales in this study have been adjusted very slightly to correct for the changes in the metric according to stimulus type and scale orientation.

presented in Table 10.3 and in the Appendix. Means within the male and female subsamples also were calculated in order to conduct tests for sex differences.[4]

The Variance–Covariance Matrix

The variance–covariance matrix used to estimate the parameters is presented in Table 10.5. This is the S matrix mentioned previously; it is compared to the theoretical variance–covariance matrix, Σ (which is generated by the parameter estimates), in order to evaluate the model's fit. The S matrix shows the relations among the *observed* variables, indicated in Fig. 10.1 by small letters.

For these impression-formation data, the variance–covariance matrix has several unusual properties that merit some discussion. For our data, the unit of analysis is the *event,* and each variance and covariance is based on the 70 event observations. Each data point for these statistics is a mean rating—an arithmetic average of the ratings of several subjects (26 subjects for each of the in-context ratings and 78 subjects for the out-of-context ratings, as all subjects rated all the out-of-context stimuli but only one of the three subsamples rated each in-context stimulus). Using the event as the unit of analysis is unusual. Normally, the number of observations (N) in a LISREL analysis would be the numbers of *individuals* from whom responses were obtained (e.g., in a social survey).

A second unusual feature of the variance–covariance matrix is that the data points involved in the computation of the matrix entries sometimes involve different subject pools. For example, all the out-of-context ratings were completed by all 78 subjects, so each of the data points for the calculation of these variances and covariances is a mean over 78 ratings. On the other hand, the variances and covariances of the in-context elements involve means calculated over a one-third subsample of the subjects. This could create problems for two reasons: (1) the means over the smaller subsamples are less stable (i.e., have more "error") than the means calculated from the entire sample; and (2) the different subsamples could use the ratings scales differently or have different attitudes toward the identities and behaviors, making the means from the different subgroups incomparable.

The first problem cannot confound our LISREL results, although it would be serious if ordinary regression were used. LISREL allows us to input the estimates of the error variances, which we base on the known reliability of the scales *and* the number of ratings involved in calculating each mean (see description of error estimation that follows). Therefore, LISREL "knows" which variances and covariances are based on less stable means (or data points) and can take this fact into account when producing its estimates.

[4]No sex differences were found in these impression-formation models (Heise & Smith-Lovin, 1981).

TABLE 10.5
Variance-Covariance Matrix of Observable Variables (S Matrix)

	a_e	a_p	a_a	b_e	b_p	b_a	o_e	o_p	o_a	b_eo_e	a'_e	a'_p	a'_a	b'_e	b'_p	b'_a	o'_e	o'_p	o'_a
a_e	1.679																		
a_p	0.657	1.742																	
a_a	0.122	0.828	1.727																
b_e	-0.245	-0.094	-0.065	2.767															
b_p	-0.080	-0.002	0.111	1.742	1.507														
b_a	0.001	0.063	0.094	0.293	0.242	0.556													
o_e	-0.042	-0.061	0.019	0.157	0.061	-0.021	1.413												
o_p	0.378	0.113	0.164	0.178	0.146	0.033	0.596	2.034											
o_a	0.268	0.205	0.071	-0.024	0.005	0.066	0.187	0.814	1.771										
b_eo_e	-0.513	-0.066	-0.191	-0.339	-0.274	0.169	-0.087	-0.212	-0.245	4.544									
a'_e	0.385	0.036	-0.059	1.178	0.786	0.019	-0.041	0.191	0.084	0.467	1.067								
a'_p	0.103	0.515	0.320	0.632	0.629	0.074	-0.160	0.004	-0.005	0.345	0.524	0.671							
a'_a	0.076	0.292	0.743	-0.001	0.189	0.253	-0.032	0.111	-0.030	0.055	0.024	0.236	0.530						
b'_e	0.129	-0.037	-0.022	1.517	1.026	0.083	-0.124	0.092	0.019	0.420	1.098	0.600	0.045	1.288					
b'_p	0.023	0.169	0.226	0.829	0.799	0.144	-0.125	0.112	0.064	0.211	0.561	0.549	0.229	0.697	0.622				
b'_a	0.066	0.143	0.405	-0.055	0.090	0.294	-0.017	0.128	0.020	0.098	-0.040	0.085	0.326	-0.015	0.120	0.326			
o'_e	0.068	-0.032	-0.035	0.506	0.320	0.017	0.449	0.247	0.154	0.211	0.387	0.139	0.013	0.380	0.175	-0.017	0.379		
o'_p	0.288	0.062	0.009	0.375	0.226	0.067	0.162	0.692	0.348	0.196	0.420	0.177	0.038	0.376	0.201	0.020	0.219	0.487	
o'_a	0.197	0.131	0.109	0.101	0.093	0.139	0.110	0.276	0.734	0.057	0.164	0.102	0.075	0.135	0.123	0.090	0.144	0.223	0.475

The second problem could not be corrected routinely in a LISREL analysis; it involves the possibility of nonrandom errors or subject differences. Therefore, we have explored in great detail the possibility that groups might differ in either their attitudes or their use of the rating scales. These results are discussed in Heise (1978, 1979); to summarize, the affective meanings of social identities and behaviors are largely shared, and subjects tend to use the semantic differential scales in similar ways. Furthermore, the small differences that have been found are not related to significant social or psychological factors. Therefore, it appears that we are justified in assuming that the three subsamples are not significantly different from one another, given that the subjects were randomly assigned to these subsamples.

Estimation of Error Variances

Because the data presented here were mean ratings by a number of subjects, the error could be estimated independently, then entered as fixed information for the structural equation procedure to use. Variances for measurement errors were estimated from standard errors of mean ratings, using pooled data on 650 identities and 600 behaviors (Heise, 1978). In the case of the independent variables, each observed value is a mean calculated over 78 respondents, so the variance of the mean (i.e., its error variance) is the within-concept rating variance (estimated from the pooled data) divided by 78. For ratings after the event presentation, division is by 26—the number of subjects that made each in-context rating.

The error term for the B_eO_e interaction cannot be calculated in this way, but it could be estimated using a formula proposed by Bohrnstedt and Marwell (1978, Equation 19). The error variance of this product term was estimated at .010; this value was not significantly different from zero, so the B_eO_e variable is considered to have no error in our analyses here.

RESULTS

The maximum likelihood estimates of parameters in our final structural model are presented in Tables 10.1 and 10.2. (Measurement models are not shown, as they are entirely fixed.) The results also are presented in graphic form as Fig. 10.1.

The probability associated with the chi-square value of 204.2 is .0006. Thus, portions of the observed variances and covariances still are unexplained. However, the ratio of chi-square to degrees of freedom in this solution is 2.08, indicating a fairly good fit. Another way of evaluating fit is to examine differences between observed variances and covariances and those reproduced using the parameter estimates. In this analysis, all but three of these residuals are below .130, and exceptions all involve one variable, A_p. Residuals of this size are not unusual given our small sample of events ($N = 70$) and the highly constrained specification of our model. After discussing our results, we propose strategies for improving the model in later studies.

Comparability to Earlier Studies

The LISREL program produces a matrix of reduced-form coefficients for the estimated model; these coefficients are given in Table 10.6. (Reduced-form coefficients evaluate the overall effects of the exogenous variables on each endogenous variable—any relationships among endogenous variables are ignored.)

The reduced-form coefficients in Table 10.6 allow us to check our present results to see if they are consistent with earlier studies. Because these coefficients represent total effects, they are comparable to the regression equations produced by other researchers. The values in one column of Table 10.6 represent the coefficients for one equation (e.g., the first column is the equation coefficients for predicting A_e' from A_e, A_p, etc.). The equation constants were calculated from the LISREL results and the means of the variables.

To illustrate the comparability of the reduced-form equations from the LISREL analysis and the results from earlier research, consider the A_e' results. The equation from Table 10.6 (ignoring coefficients that are not significantly different from zero) is:

$$A_e' = -.094 + .351\,A_e + .425\,B_e - .233\,B_a + .203\,B_eO_e. \tag{3}$$

These coefficients are quite similar to those in Equations 1 and 2 (from Gollob, 1968; Heise & Smith-Lovin, 1981).[5] The only difference in the pattern of results is that the A_p effect in the Heise and Smith-Lovin equation (our Equation 2) was not found in the current results. This is consistent with our examination of the residuals—recall that all the major residuals involved actor potency. We discuss these deviations from a good fit later; at this point we simply wish to illustrate the general similarity between the reduced-form equations from our model in Fig. 10.1 and the regression results of earlier studies. We now turn to the feedback model.

Impressions of Actors

The estimates of the direct effects (as specified in Fig. 10.1) are found in Tables 10.1 and 10.2. Again, equations can be constructed by multiplying the estimated coefficient by the variable with which it is associated. For example, the equation

[5]Although the coefficients are not identical, this is not disturbing, because all the impression-formation studies involved small samples of events. Estimates are expected to contain sizable amounts of sampling error. The more relevant comparison is whether or not the same coefficients are significantly different from zero in each study, and perhaps whether or not the coefficients for a given term are roughly the same magnitude. Although we report coefficients to three decimal places, this is not meant to imply that the estimates are this precise; it is merely a convention when reporting structural equation results.

TABLE 10.6
Coefficients for Impression Formation Equations
(Reduced Form of the Model in Fig. 10.1)

	Columns Contain Coefficients for Predicting								
from:	A_e'	A_p'	A_a'	B_e'	B_p'	B_a'	O_e'	O_p'	O_a'
Constant	-.094	-.139	.077	-.136	-.036	.267	-.069	-.430	-.113
A_e	.351	.060	-.010	.234	.065	.007	.137	.160	.083
A_p	.031	.268	-.050	.016	-.007	-.071	.012	.008	-.017
A_a	-.035	.034	.415	.019	.100	.233	-.014	-.003	.065
B_e	.425	.062	-.113	.535	.052	-.049	.166	.117	.018
B_p	.162	.401	.191	.128	.437	.055	.063	.074	.052
B_a	-.233	-.089	.372	-.118	.051	.526	-.091	-.059	.126
O_e	-.059	-.108	-.016	-.134	-.112	.005	.306	.000	.012
O_p	.039	.009	.021	.028	.013	.013	.015	.306	.013
O_a	.056	.009	-.002	.037	.010	.001	.022	.025	.400
B_eO_e	.203	.117	.008	.169	.097	-.002	.079	.083	.037

for predicting A_e' involves the following terms:

$$A_e' = .145\,A_e + .059\,B_eO_e + .685\,B_e' - .283\,B_a' + .169\,O_e' + .059\,O_p' + .059\,O_a' \tag{4}$$

The first two coefficients are found in Table 10.1; the others are from Table 10.2.

The A_e effect is basically a stability effect. It indicates that actors who occupy positively evaluated identities tend to maintain at least some of that positivity even after the event has influenced the meanings and impressions associated with the event elements.

The B_eO_e effect on A_e' is considerably smaller in the feedback model than in the regression (or total effects) models. This does not mean, however, that attitudinal balance is less important. Because of the potential for feedback among event elements, A_e' is affected by B_eO_e both directly *and* through its effects on B_e' and B_p'. Therefore, people who act in appropriate ways toward others seem more positive after the event is observed both because they have acted correctly *and* because their actions seem nicer and more powerful as a result of the event.

The effects of B_e', B_p', and B_a' indicate that actors are more positively evaluated when their actions seem nice (positively evaluated), strong, and quiet within the context of the event. Notice that these are the effects of *primed,* in-context variables. Because behaviors can acquire different evaluations, potencies, and activities within an event (depending on toward whom the act is directed and who does it), these effects must be interpreted differently than the total effects in Table 10.6 (and earlier research). For example, *helping* is a nice, powerful, and lively behavior, but it is seen as even more positive and strong if it is directed at a deserving, weak person (Equation 7). It is this evaluation within the context of the event that is the causal variable in our feedback model (Fig.

10.1). Behaviors that seem irritating, harassing, or aggressive in an event (low B_e', and high B_a') lower our evaluation of the actor.

Finally, actors are evaluated more positively if they are involved in an event with people who are nice, powerful, and lively (high O_e', O_p', and O_a'). This effect is quite intuitive and is more striking in our feedback results than in earlier regression studies.

The following equation describes the direct effects on an actor's potency within an event (again, the first two coefficients are from Table 10.1, the others from Table 10.2):

$$A_p' = .256\ A_p + .024\ B_e O_e + .949\ B_p' - .283\ B_a' \qquad (5)$$

Aside from the stability effect of A_p, we see that impressions of the actor's powerfulness within the context of an event are enhanced by the appropriateness of his or her actions (as summarized by the $B_e O_e$ balance term) and by the impression of the behavior itself within the context of the event. Acts that seem powerful and quiet (high B_p' and low B_a') make the actor seem more potent. These are usually behaviors that involve soothing, calming, or controlling another person.

The impressions of an actor's activity or liveliness after an event also are determined primarily by the impressions of his behavior, as can be seen in the equation derived from Tables 10.1 and 10.2:

$$A_a' = .233\ A_a - .204\ B_e' + .410\ B_p' + .626\ B_a' \qquad (6)$$

Aside from the stability effect of A_a, the perceived liveliness of the actor is increased if his or her behavior in the event is negatively evaluated, powerful, and active. Such actions are those that appear to be aggressive or threatening within the interaction described by the event. Notice that the appropriateness of the behavior ($B_e O_e$) will indirectly affect actor activity, because it affects B_e' and B_p'—inappropriate acts are more likely to be seen as immoral or aggressive within the context of the event and therefore will affect the activity of the actor.

Impressions of Behaviors

The equation predicting the direct effects on the evaluation of a behavior within the context of an event is:

$$B_e' = .262\ B_e + .032\ B_e O_e + .779\ A_e' + .102\ A_a' + .282\ O_e'. \qquad (7)$$

Acts appear more praiseworthy than usual if they are performed by a positively evaluated, lively actor—for example, an immature person (*baby, child, tot, youngster*) or an intimate (*friend, lover, pal*). Behaviors also are evaluated more positively if they are appropriate (the $B_e O_e$ effect), and if they are directed at nice people (high O_e').

The equation for predicting the potency of a behavior within the event is:

$$B_p' = .358\ B_p + .056\ B_e O_e + .306\ A'O_e' + .256\ A_a' - .294 \qquad (8)$$

An act's perceived power is among the most stable elements in an event (the coefficient for B_p is relatively high). However, an act can be strengthened somewhat by being directed at a stigmatized person (low O_e'), particularly when a harmful act matches the object's negative evaluation (the $B_e O_e$ effect). An act seems to have less than usual impact or potency when directed at a highly evaluated person (high O_e'), particularly if the act is harmful and thereby inconsistent with the receiver's evaluation. Acts also seem more potent when performed by good, lively actors (high A_e' and A_a').

The equation for predicting behavior activity within the context of an event is:

$$B_a' = .311\ B_a + .064\ A_e' - .164\ A_p' + .579\ A_a' \qquad (9)$$

Other than the B_a stability effect, the perceived liveliness of the behavior is influenced only by the impressions of the actor. The perception of the object-person only influences behavior liveliness indirectly, through its effects on A_e' and A_a'. Behaviors are seen as more lively if they are carried out by nice, weak, lively actors (high A_e', lowA_p', and high A_a'), Immature people, female identities, and amateurs usually have this profile. Any element of the event that tends to make the actor look immature or amateurish will also influence indirectly the impression formed of the behavior.

Impressions of Object–Persons

The impressions formed by object–persons are considerably simpler than those of actors and behaviors. For example, the evaluation of the object is directly affected by only one factor, other than the stability effect:

$$O_e' = .320\ O_e + .391\ A_e'. \qquad (10)$$

Object–persons who are acted on by positively evaluated people are viewed more positively because of the association. Because the actor's evaluation (A_e') is determined by so many factors (Equation 4), the evaluation of the object is actually influenced by a large number of factors indirectly. For example, objects of extremely negative acts will tend to be evaluated more negatively; such a victim is not rated more negatively because he or she is the object of an immoral act, however. Instead, he or she is rated lower on evaluation (and potency and activity) because he or she has associated with the type of person who would have committed such an offense. Thus, the feedback model of impression formation leads us to a new understanding of the ''derogation of the victim'' phenomenon: It is simply a generalization of the fact that we tend to evaluate people on the basis of those with whom they associate.

The formulas showing the direct effects on object potency and object activity are very similar to each other:

$$O_p' = .288\ O_p + .641\ A_e' - .281\ B_e' + .109\ B_a'; \qquad (11)$$

$$O_a' = .387\ O_a + .393\ A_e' - .244\ B_e' + .357\ B_a'. \qquad (12)$$

Both the perceptions of an object-person's potency and activity are based on a stability effect (of O_p and O_a, respectively), on the evaluation of the actor within the context of the event (A_e'), and on the evaluation and the activity of the act (B_e' and B_a'). Those who interact with positively evaluated or esteemed others have their power and liveliness enhanced. Those who are acted on by stigmatized (low evaluation) others are perceived as less powerful and lively. Those who have received acts that seem somewhat negative and lively are also perceived as more powerful and lively.

CONCLUSIONS

Overall, the estimated model does provide support for viewing impression-formation processes as a feedback system in which short-term affective reactions are Markovian in nature, with only current impressions affecting future outcomes. We have shown that such a model can largely account for the patterns of variances and covariances observed empirically.

Because all the residuals involve A_p, it seems likely that either the measurement of the actor's potency is distorted in some way or that some of the causal effects to or from A_p are misspecified. If a theorist wished to alter the model to improve fit, several strategies for revision are available (Byron, 1972; Sörbom, 1975; Saris et al., 1979). The most useful strategy involves examining the first-order partial derivatives associated with each constrained parameter and freeing those parameters associated with large derivatives (Saris et al., 1979). (These values are reported in the LISREL output.) The new model and its chi-square value could then be compared to the earlier run to determine whether or not the improvement was significant. In this impression-formation example, however, the fit is already quite adequate. Fitting the model to such a small sample without additional theoretical knowledge would not be advisable. Instead, this model should be tested and refined with a larger data base.

Although the parameter estimates presented here are exploratory, some of the patterns deserve comment. For example, the impressions formed about an object-person are relatively unconnected to the other event elements. On the evaluation dimension, the postevent view of the object is directly affected by just a single in-context variable (ignoring the direct stability effect from the original, exogenous object impression). Specifically, almost all effects on the object's evaluation and potency are mediated through the evaluation of the actor. This pattern is quite different from that observed in the reduced form (Columns 7 and 8 of Table 10.6) and in ordinary regression analyses of impression formation (Heise, 1970; Heise & Smith-Lovin, 1981) where the evaluation of the behavior has a major effect. The results here emphasize the impact that behavior evaluation and potency have on actor evaluation; the object's potency and activity are influenced by the prestige or evaluation of his or her interaction partner and therefore indirectly by what the interaction partner does. As described earlier, this interpretation leads to a new understanding of the "derogation of the victim" phenomena (i.e., the tendency for the objects of negative acts to be rated more negatively than the objects of positive acts).

It is also interesting that the object-person's potency and activity do not have a significant effect on any other postevent impressions. Again, this differs from the pattern obtained using direct-effect model specifications (Heise, 1978; Heise & Smith-Lovin, 1981). In these earlier analyses, object potency and activity had an impact on actor evaluation and on behavior impressions.

The relatively unconnected position of the postevent object impressions might allow experimental studies examining the theoretical assumptions involved in the model specification. For example, the feedback aspect of the structural model might be tested experimentally by selecting event stimuli that would cause very little shift in the evaluation of the actor but major changes in other event elements (e.g., A_p' and A_a'). Under such conditions, the impressions of the object's evaluation and potency should reach stability quite soon relatively to the other postevent impressions. Allowing subjects to provide time-varying ratings of event elements might provide a way to test predicted increments in postevent impressions.

A different test of the theoretical specification of the model will be possible on another corpus of events. Because many of the possible effects in the β matrix were found to be small and nonsignificant, these parmeters have been set to zero for reestimation. This "trimmed" model may now be estimated on a new data set. Because the model will now be overidentified, it would be possible to free some of the parameters that were theoretically set equal to zero in this specification (for example, the effect from the exogenous variable A_p to O_e'). Therefore, the new estimation will provide evidence whether or not the theoretical assumptions used to specify the original model are consistent with covariance patterns in multiple data sets.

Other questions also must be addressed by analyses using a larger corpus of events. The disturbance terms for impressions of the behavior and the object indicate that the determinants of these variables have not been exhausted. Probably more interaction terms (such as the B_eO_p effect noted by Gollob & Rossman, 1973) need to be included. A study using a corpus of 515 events is currently exploring this possibility.

APPENDIX 1

Event Sentences and the Mean Ratings of In Context Actor, Behavior and Object-Persons on the Evaluation, Potency and Activity Dimensions

	ACTOR	BEHAVIOR	OBJECT-PERSON	A_e'	A_p'	A_a'	B_e'	B_p'	B_a'	O_e'	O_p'	O_a'
1.	Child	Ignore	Judge	-0.6	-0.8	0.7	-1.1	-0.5	0.6	0.0	0.2	-0.5
2.	Schoolgirl	Tickle	Gambler	0.1	-0.2	1.4	0.3	0.0	1.1	-0.2	-0.6	1.0
3.	Sheriff	Attack	Cripple	-2.6	-1.1	1.1	-3.0	-0.6	1.1	-0.4	-2.2	-0.9
4.	Ogre	Contemplate	Schoolgirl	-1.3	0.7	-0.2	0.5	0.4	0.7	0.5	-1.2	0.9
5.	Maniac	Play With	Infant	-0.0	-0.4	-0.1	0.5	0.4	0.7	0.5	-1.2	0.9
6.	Warden	Betray	Outlaw	-0.6	0.0	-0.2	-1.2	-0.9	-0.3	-0.3	-0.7	0.2
7.	Alcoholic	Protect	Disciplinarian	0.8	0.5	0.0	1.2	1.1	0.5	0.5	0.1	-0.5
8.	Disciplinarian	Sock	Coward	-0.9	0.4	0.6	-1.1	0.1	1.2	-1.1	-1.2	-0.1
9.	Champion	Indulge	Underdog	0.7	0.9	0.7	0.1	0.2	0.2	0.6	-0.0	0.1
10.	Roughneck	Laugh At	Outlaw	-0.7	0.1	0.8	-0.8	-0.2	0.6	-0.7	-0.3	0.2
11.	Cripple	Protect	Judge	1.9	0.7	0.5	1.6	1.5	0.5	1.2	-0.1	-0.4
12.	Winner	Laugh At	Champion	-0.8	-0.4	1.3	-1.3	-1.0	1.1	0.2	0.3	-0.0
13.	Athlete	Contemplate	Disciplinarian	0.5	0.9	0.4	0.3	0.4	-0.1	0.2	0.7	-0.3
14.	Invalid	Indulge	Blabbermouth	0.6	-0.4	-0.9	0.3	-0.2	-0.1	-0.4	-0.3	0.6
15.	Maniac	Silence	Coward	-0.8	0.4	1.0	-0.4	0.5	0.5	-0.8	-1.7	-1.2
16.	Judge	Avoid	Champion	-0.2	-0.6	-0.9	-0.7	-0.9	-0.4	-0.2	0.2	0.5
17.	Outlaw	Soothe	Sheriff	0.7	0.7	0.4	1.0	1.0	0.3	-0.0	-0.6	-0.6
18.	Beggar	Indulge	Child	0.2	-0.4	-0.1	0.1	-0.2	-0.4	0.6	-0.4	0.3
19.	Schoolgirl	Grieve For	Cripple	1.6	0.5	0.3	1.8	0.7	0.6	0.7	-0.9	-0.8
20.	Gambler	Protect	Outlaw	-0.3	0.1	0.8	-0.5	0.9	0.4	-1.0	-0.6	-0.2
21	Roughneck	Silence	Disciplinarian	-1.6	0.5	1.0	-1.0	0.4	0.9	-0.4	-0.6	-0.1
22.	Alcoholic	Betray	Gambler	-1.2	-1.3	-0.8	-1.7	-1.3	0.0	-0.4	-1.2	-0.2
23.	Schoolgirl	Contemplate	Coward	0.8	-0.0	0.6	0.3	0.3	0.3			
24.	Warden	Indulge	Athlete	0.2	0.2	-0.2	-0.4	0.3	0.2	0.3	0.6	1.1
25.	Hero	Opress	Boss	-0.6	0.7	1.0	-1.0	0.5	0.9	-0.5	-0.6	-0.8
26.	Invalid	Ignore	Infant	-0.8	-1.3	-1.5	-1.3	-1.0	-1.3	0.4	-1.3	0.3
27.	Blabbermouth	Soothe	Cripple	1.1	0.8	0.9	2.1	1.2	0.1	0.6	-0.8	-0.8
28.	Child	Defy	Roughneck	0.5	0.6	1.4	0.7	1.4	1.7	-0.8	0.2	0.9
29.	Orge	Laugh At	Disciplinarian	-1.6	0.4	0.8	-1.4	0.2	0.5	-0.3	-0.2	-0.3
30.	Athlete	Protect	Maniac	0.9	1.4	1.4	1.1	1.2	0.6	-0.7	-0.8	0.6
31.	Cripple	Amuse	Beggar	0.9	-0.2	0.0	0.9	0.1	0.6	0.0	-0.7	-0.6
32.	Gambler	Sock	Winner	-1.6	-0.9	0.6	-1.9	-0.7	1.2	-0.4	-0.5	1.0
33.	Sheriff	Laugh At	Judge	-0.8	-0.3	0.6	-0.9	-0.4	1.1	0.2	-0.6	-0.5
34.	Roughneck	Protect	Infant	2.1	1.7	1.1	2.2	2.0	0.8	1.9	-0.1	1.4
35.	Alcoholic	Tickle	Invalid	-0.8	-1.1	-0.1	-0.5	-0.4	0.7	-0.7	-1.3	-0.7
36.	Cripple	Grieve For	Outlaw	0.7	-0.8	-0.9	1.4	0.5	-0.1	-0.3	-0.4	-0.1
37.	Blabbermouth	Ignore	Disciplinarian	-0.9	-1.1	0.6	-1.7	-1.0	0.4	-0.1	-0.9	-0.4
38.	Judge	Contemplate	Gambler	1.0	0.2	-0.6	1.0	1.0	0.0	-0.4	-0.5	0.0
39.	Outlaw	Indulge	Beggar	-0.2	0.5	0.8	-0.2	0.1	0.1	-0.8	-1.3	-1.3
40.	Alcoholic	Silence	Champion	-0.7	-0.3	0.0	-0.9	0.2	0.4	0.1	-0.6	0.2
41.	Schoolgirl	Convince	Champion	1.1	0.6	1.5	0.8	1.2	1.1	1.0	0.3	0.5
42.	Warden	Amuse	Sheriff	0.8	0.7	0.4	1.0	0.4	0.6	0.8	0.4	0.5
43.	Athlete	Sock	Child	-2.7	-1.2	0.8	-2.5	-1.1	1.6	-1.0	-2.0	0.9
44.	Cripple	Laugh At	Underdog	-1.1	-1.5	-0.3	-1.8	-1.7	-0.3	-0.4	-0.7	-0.7
45.	Coward	Soothe	Roughneck	0.6	0.3	-0.4	1.4	0.9	-0.2	-0.3	-0.3	0.2
46.	Schoolgirl	Serve	Disciplinarian	1.2	-0.1	0.6	1.4	0.0	0.5	0.4	0.4	0.1
47.	Warden	Silence	Blabbermouth	0.7	1.7	0.6	0.6	1.2	0.4	-0.3	-0.7	0.5
48.	Hero	Ignore	Coward	-0.1	0.3	0.6	-0.7	-0.2	0.0	-1.0	-1.4	-1.1

(continued)

APPENDIX 1—*Continued*

	ACTOR	BEHAVIOR	OBJECT-PERSON	A'_e	A'_p	A'_a	B'_e	B'_p	B'_a	O'_e	O'_p	O'_a
49.	Underdog	Contemplate	Champion	0.8	0.1	0.1	0.5	0.3	0.0	0.4	0.7	0.8
50.	Gambler	Indulge	Judge	-0.7	-0.2	0.5	-1.0	-0.1	0.4	-0.3	-0.5	-0.5
51.	Judge	Silence	Schoolgirl	-0.0	1.2	-0.2	-0.0	0.9	-0.0	-0.0	-0.8	0.9
52.	Outlaw	Ignore	Invalid	-1.9	-0.6	0.0	-1.6	-0.7	-0.0	-0.1	-1.8	-1.4
53.	Sheriff	Protect	Beggar	1.7	1.9	0.6	1.8	1.5	0.8	0.6	-0.4	-0.7
54.	Underdog	Attack	Ogre	0.8	1.1	1.5	0.2	1.0	1.4	-0.9	0.5	0.6
55.	Blabbermouth	Pester	Gambler	-1.0	-1.0	1.0	-1.4	-0.8	1.0	-0.2	-0.4	0.2
56.	Outlaw	Amuse	Champion	0.5	-0.0	0.8	0.9	0.7	1.2	0.2	0.5	0.3
57.	Beggar	Defy	Sheriff	-1.1	-0.0	0.0	-0.9	0.3	0.4	-0.5	-0.0	-0.6
58.	Child	Pester	Schoolgirl	-0.9	-0.8	1.8	-1.3	-0.5	1.1	0.2	-0.0	1.1
59.	Blabbermouth	Convince	Invalid	-0.5	-0.2	0.9	-0.6	0.1	0.9	0.0	-1.1	-0.9
60.	Judge	Indulge	Outlaw	-0.3	-0.2	-0.3	-0.4	-0.2	0.1	-1.0	-0.4	-0.5
61.	Sheriff	Amuse	Warden	0.8	0.4	0.3	1.2	0.5	1.2	0.7	0.3	0.0
62.	Outlaw	Sock	Blabbermouth	-1.1	0.7	1.4	-0.5	0.7	1.2	-0.5	-1.0	0.5
63.	Boarder	Watch	Stranger	0.3	-0.1	-0.2	0.3	-0.1	-0.6	0.1	-0.1	-0.5
64.	Athlete	Tickle	Roughneck	0.2	0.7	1.0	0.6	0.4	1.4	-0.3	-0.2	0.6
65.	Beggar	Pester	Alcoholic	-1.3	-1.3	-1.0	-1.2	-1.1	-0.1	-0.8	-0.8	-0.9
66.	Champion	Convince	Athlete	1.3	1.5	1.6	1.2	1.1	0.9	1.1	1.0	1.4
67.	Stranger	Tap	Boarder	0.1	0.1	0.3	-0.1	0.1	-0.2	0.4	-0.2	-0.2
68.	Alcoholic	Avoid	Beggar	-0.8	-1.2	-1.0	-0.8	-1.3	-0.1	-0.4	-1.2	-0.9
69.	Cripple	Watch	Winner	0.7	-1.1	-1.1	0.4	-0.1	-0.2	1.0	1.2	1.1
70.	Outlaw	Observe	Coward	-0.5	0.3	0.4	-0.0	-0.1	-0.2	-1.2	-1.6	-0.6

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