

**Status Characteristics and Expectation States Theory:
A Priori Model Parameters and Test***

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Status Characteristics and Expectation States Theory: *A Priori* Model Parameters and Test

The theory of status characteristics and expectation states (Berger, Cohen and Zelditch, 1972; Berger, Fisek, Norman and Zelditch, 1977; Berger, Rosenholtz and Zelditch, 1980) addresses the formation of power and prestige orders in groups where actors are discriminated by external status characteristics such as gender and race. The theory is within the general conceptual framework of the expectation states theoretical research program (Berger, 1974; Berger, Wagner and Zelditch, 1985) and one of its formulations (Berger *et al.*, 1977) is mathematical in the sense that a mathematical model, couched in terms of the concepts of graph theory, is an integral part of the theory. The integration of substantive theory with mathematical model offers distinct advantages for theory growth: Consequences of the theory may be rigorously derived, the structure of the theory indicates the directions of extension, precise predictions enhance testability.

The advantages of the integrated mathematical model have, in fact, been realized to a large extent: A number of substantively important theorems have been derived from the theory (e.g., Humphreys and Berger, 1981), it has been extended to cover sequences of task situations rather than a single situation (Berger, Fisek and Norman, forthcoming), and to cover reward expectations as well as task expectations (Berger, Fisek, Norman and Wagner, 1985). The fit of the model to data from twelve experiments in the standardized experimental situation associated with the theory (see Berger *et al.*, (1977) for a description of the standardized experimental situation) was evaluated by the authors at the time of the initial publication of the formulation, and a few years later by Fox and Moore (1979) using different techniques for assessing goodness of fit. Since then we have found twelve other published experimental studies in the literature, which we believe constitute tests of the theory.

This research activity could be accelerated, however, if the parameters of the mathematical model could be assigned *a priori* theoretical values. While one of the attractive features of the mathematical formulation is that it can make some interval level predictions without using parameter values, a general interval level prediction capability requires knowledge of

parameter values. At the same, time empirical estimation of parameters can involve problems, and empirical estimates are limited to the contexts in which they are estimated, thus narrowing the scope of theoretical analysis. Therefore it would be a real advantage to derive parameter estimates on theoretical grounds. In this paper we present a method for deriving *a priori* values for the core parameters of the formulation, and demonstrate that these *a priori* values fit the available data as well as the empirically estimated values. At the same time, the analyses we present constitute a new assessment of the goodness of fit of the model to data which include the results of twelve experiments conducted after model formulation.

In the following sections we present a brief statement of the mathematical formulation of the theory of status characteristics and expectation states, the method of deriving theoretical parameter values, and the evaluation of the fit of the model to the available data given the new parameter values.

The Theory of Status Characteristics and Expectation States

The theory applies to task-performing small groups where the actors in the situation have no previous history of interaction with each other, are collectively oriented, and are performing a valued task with well-defined success and failure outcomes. A situation of this type is referred to as an S situation, and the formulation describes how an S situation can be represented as a graph structure.

The following elements are the building blocks of graph structures: Actors are represented as points. The symbol "*p*" is used to indicate the focal actor from whose perspective the situation is analyzed. Other actors are represented by the symbol "*o*" and a subscript is used to differentiate the *o*'s when there is more than one. Although there may be any number of actors in the situation, at any one time only two of them are interactants, the other actors being "referent others". Characteristics, or rather states of characteristics, are also represented as points in the graph. *C*(+) and *C*(-) are used to symbolize states of specific status characteristics such as mathematical or artistic ability, and *D*(+) and *D*(-) are used to stand for states of diffuse status characteristics such as gender and race. Different

characteristics of the same type are differentiated by subscripts. Outcome states of the group task are also represented as points labeled $T(+)$ and $T(-)$, standing for success and failure respectively.

Activated elements such as states of abstract task ability, $\Upsilon(+)$ and $\Upsilon(-)$, generalized expectation states, $\Gamma(+)$ and $\Gamma(-)$, and specific task outcome states, $\tau(+)$ and $\tau(-)$, are also represented as points in the graph.

Relations are represented as lines of the graph, and they are signed. There are three relations: Possession, dimensionality, and relevance. Possession, a primitive term, is used to represent actors' possession of states of characteristics, or other status elements such as task outcome states, and has a positive sign. Relevance, which also has a positive sign, is defined as existing between two elements if an actor who possesses the first is expected to possess the second. Dimensionality, which is negatively signed, is defined to exist between the differentially evaluated states of the same characteristic possessed by actors in the situation.

Given these elements, any situation within the scope conditions of the theory can be represented as a graph. Situations have initial structures which consist of a number of points representing the actors in the situation, the two points $T(+)$ and $T(-)$ representing the outcome states of the group task, two other points, $C^*(+)$ and $C^*(-)$ representing the high and low states of the specific ability which is *instrumental* to task performance (the asterisk is used to distinguish instrumental characteristics from other specific characteristics), and two lines representing the relevance between the like-signed states of the instrumental characteristic and the task outcome states.

Given the initial structure, the theory describes how the structure is further completed. The first step is the introduction of status information in the situation through the salience completion process. The salience assumption provides for the salience of characteristics on the basis of initial task relevance or discrimination between actors. When task relevant characteristics become salient, their paths of relevance become salient with them, so that they provide actor-task connections which are bases for the formation of task performance expectations.

When status characteristics not initially relevant to the task become salient on the basis of discrimination between actors, no such paths exist. One of the fundamental notions of status characteristics theory is that

paths of relevance connecting states of characteristics to task outcomes will come into existence even when status characteristics are not initially relevant to the task. The process by which this occurs is called the “burden of proof” process. The burden of proof assumption asserts that for diffuse status characteristics, the generalized expectation states associated with them will become activated, and establish a task path through the instrumental characteristic. Similarly, for specific characteristics, the specific expectations associated with them become activated, and provide a task path through abstract task ability.

Figure 1 presents a graph structure for a situation with two actors discriminated by a diffuse status characteristic (say gender, with p being male and o being female) which is not initially relevant to the task, but which becomes task connected through the action of the burden of proof process.

Figure 1 about here

The structure in Figure 1 is a completed structure in the sense that there will be no further development unless there is a change in the situation while this task is being performed. The situation may change as actors in the situation change or as new information which makes new characteristics salient becomes available. The sequence of completion assumption specifies how changes in the situation will lead to further structure development for the interacting actors for a given task through the saliency and burden of proof processes. Given a completed structure, the remainder of the formulation is concerned with analyzing the structure to obtain self-other expectations for the actors in the situation.

The analysis of graph structures proceeds by tracing the paths which connect each actor to the task outcome states. The length of a path is the number of lines which makes up the path, and the sign of a path is the product of the signs of the lines in the path and the sign of the outcome state the path connects to. In the structure of Figure 1, p is connected to the task outcome states, $T(+)$ and $T(-)$, by two positive paths of lengths 4 and 5. And o is connected by two negative paths of the same lengths.

The strength, or contribution to expectations, of a path is given by a function $f(i)$, where i is the length of the path. The function is assumed to be continuous and monotonically decreasing, yielding values in $(0,1)$. To

find the aggregated expectations for an actor, the paths joining the actor to the task outcome states are first combined in like-signed subsets to determine their combined strength according to the following combining rule. This combined strength is given the sign of the paths in the subset. The combining rule for two like-signed paths of lengths i and j is

$$f(i \cup j) = f(i) + f(j) - f(i)f(j).$$

Then the positive and negative path strengths are algebraically summed to obtain the aggregated expectation value, e_p , for a given actor p .

Thus the aggregated expectations for actor p in the sample structure will be

$$e_p = f(4) + f(5) - f(4)f(5),$$

since he has only positive paths connecting him to the task outcome states. Similarly the aggregated expectations value for the actor o will be the negative of this value, as she possesses the same number of paths of identical length but of negative sign.

The combining function given above can be generalized to combine more than two paths at the same time:

$$f(i \cup j \cup \dots \cup n) = 1 - (1 - f(i))(1 - f(j)) \dots (1 - f(n)).$$

Any actual computation of expectation values depends on knowing the values of the function $f(i)$, and this is the problem we address. However, we will complete the statement of the theory before taking up the problem.

The above procedure describes how expectations can be computed for individual actors. However, expectation states are relative, comparing an actor's self-expectations with the expectations he holds for the actor he is interacting with. This relative aspect of expectation states is captured by the concept of *expectation advantage*. The expectation advantage of an actor (i.e. the focal actor) is the difference between his self expectation value, and the expectation value he holds for the actor he is interacting with, that is, $e = e_p - e_o$. The Basic Expectation Assumption asserts that p 's power and prestige position with respect to o is a direct continuous function of p 's expectation advantage over o .

Thus as p 's expectation advantage over o increases, his power and prestige position relative to o increases. Furthermore this function is interval-order preserving. That is, given two pairs of actors, if the expectation

advantage between the first pair is greater than that between the second pair, then the power and prestige difference between the first pair is greater than the power and prestige difference between the second pair.

The formulation of the theory includes a specific version of the basic expectation assumption which specifies a function relating expectation advantage to the proportion of stay responses. Proportion of stay responses is an observable measure of power and prestige position in the standardized experimental situation. Thus numerical predictions can be made in that context. This function is

$$P(S) = m + q(e_p - e_o).$$

The constants m and q in this equation are empirical parameters which are assumed to capture the properties of specific experimental procedures and given populations of subjects. The use of this function requires that the values of m and q be known, as well as the values of the function $f(i)$ (from which e_p and e_o can be determined). We now turn to this problem.

The Derivation of Theoretical Parameters

The original approach taken by Berger *et al.* (1977) was to treat the function values as empirical parameters to be estimated from data. Since the situational graphs these researchers have examined involve paths of lengths 2 through 6, five empirical parameters need to be estimated. To reduce the number of parameters to be estimated, Berger and his associates adopted the following strategy: In determining the aggregated expectations of an actor, a path of length i is equivalent to some number (not necessarily an integer), k , of paths of $i + 1$ of the same sign. They make the assumption that k is a constant, that its value is the same for all path lengths. Given the strength of a path of one length and the value of the constant k , the strengths of paths of all other lengths can be calculated using the combining rule. Thus the number of independent parameters is reduced to two. Using data from a number of different experiments these authors estimated the value of k as 3 and $f(4)$ as 0.1768, while noting that the model is remarkably insensitive to parameter values. These values were used in the original evaluation of the goodness of fit of the model, and the later tests of the theory (Webster and Driskell, 1978; Fox and Moore, 1979).

We first present a theoretical argument which determines the form of the function $f(i)$, and then generate specific values from this function by making assumptions about its shape.

The form of the function $f(i)$

We begin by demonstrating that the constancy of k is not a simplifying assumption but a natural consequence of the theoretical formulation itself. That k is constant follows from the way path lengths are counted. In keeping with the normal practice of graph theory, the length of a path is the number of lines in it, and a line belonging to more than one path counts in the length of each. Thus in Figure 2, two paths of length five join A and B , and also two paths of length five join A' and B' , sharing the path joining A' with C' .

Figure 2 about here

Assume k is the number of paths of length n which are equivalent to one path of length $n - 1$. Suppose A and B are joined by k paths of length n having no points other than A and B in common. Suppose C' and B' are joined by k paths of length i having no points other than B' and C' in common, and that A' is joined with C' by a single path of length $n - i$ having only the point C' in common with the others. (Figure 2 illustrates the idea for two paths with $n = 5$ and $i = 3$.) Our objective is to show that k paths of length i joining C' and B' are equivalent to one path of length $i - 1$.

Since A' and B' are joined by k paths of length n , it follows from the assumption about k that these are equivalent to one path of length $n - 1$ joining A' and B' , which is equivalent to one path of length $n - i$ joining A' and C' together with a path of length $i - 1$ joining C' and B' ; therefore it is clear that k paths of length i are equivalent to one path of length $i - 1$. Since i was chosen as an arbitrary length less than n , it follows that k is constant, independent of path length. This property of the model forms the basis of the following argument.

By definition,

$$f(i - 1) = 1 - (1 - f(i))^k.$$

Next, we ask how many paths of length i will be equal to a path of length $(i - 2)$? By appropriate substitution, we can obtain the intuitively obvious result,

$$f(i - 2) = 1 - (1 - f(i))^{k^2}.$$

Similarly, if we ask how many paths of length i add up to one path of length $(i - 3)$, we see that,

$$f(i - 3) = 1 - (1 - f(i))^{k^3}.$$

By induction, we can conclude that,

$$f(i - n) = 1 - (1 - f(i))^{k^n}.$$

Conversely it follows that

$$f(i + n) = 1 - (1 - f(i))^{k^{-n}}.$$

Replacing i by 0 we obtain,

$$f(n) = 1 - (1 - f(0))^{k^{-n}},$$

and if we let $1 - f(0) = e^d$, we have

$$f(n) = 1 - e^{dk^{-n}}.$$

The parameter k is, of course, our familiar constant, and d is a constant which determines where the graph of $y = f(n)$ crosses the y -axis - that is, it fixes the value of $f(0)$.

Thus the assumptions of the theory, in particular the combining function, and the path counting rules completely determine the form of the function $f(i)$.

The shape of the curve of $f(i)$

Specifying the exact function is a question of determining the values of the two parameters k and d . The meaning of the parameter k is the number of paths of any length equivalent to a single path of length one less. The theory requires that k be larger than 1. Similarly, the parameter d which, as we

have noted above, determines the strength of a path of zero length, has to be negative since the function is assumed to be constrained to the interval $(0, 1)$. We now ask if we can make meaningful theoretical assumptions which will lead to specific values for these parameters.

Figure 3 shows a plot of the function for values of k and d corresponding to the empirical estimates of Berger *et al.* (1977) where $k = 3$ and $d = -15.759$. This value of d is obtained by substituting 3 for k and 4 for n in the function, and equating it to the empirical estimate of $f(4)$.

Figure 3 about here

The function $f(n)$ has meaning for us only if $n \geq 0$, since negative path lengths do not have a substantive interpretation. Its graph for $n > 0$ has three identifiable segments separated by two points where it attains its maximum rate of change of slope. The first segment, beginning nearly horizontal at the y-axis, is relatively short and of mild, but increasing downward slope. The function then fairly quickly changes character to assume a sharp downward and nearly constant slope, after which its slope begins to decrease again. The third segment returns to a mild downward slope as the function begins to approach the x-axis asymptotically. We ask the obvious question: Can the substantive meanings of different path lengths be associated with the different segments of this curve?

Classification of basic path forms

A theoretical examination of the potential meaning of basic path forms naturally leads to a scheme with three categories. Each category represents a distinct decreasing degree of certainty of the link between actor and task outcome. Typical examples of paths of different lengths, and the category scheme are shown in Figure 4.

Figure 4 about here

The first category we label as "possession". Any path of length one starting with an actor must consist of a possession line. That is, a path of length one can be thought of as representing a "fact". The actor p has either succeeded or failed at the task. Further, we would consider any path

of length less than one—that is, a set of paths equivalent to a path of length less than one—as a corroborated fact. In other words it would indicate that there is additional evidence that this “fact” is true. It is also the case that a set of paths equivalent to a length greater than one cannot contain a path representing a fact.

The other two categories we would think of in terms of inferences. That is, any basic path of length two or more can be thought of as an inference based on an implication that an actor should succeed or fail. The two categories differ in the kind and strength of inference involved.

Paths of length two or three we would categorize as “direct inferences”. They represent the implications of the facts in the situation. For paths of length two, the inference is based on the fact that actor p possesses a state of a characteristic that is instrumental to the task. For paths of length three the inference is based on the facts that actor p possesses the state of a characteristic directly relevant to the instrumental characteristic, which is in turn directly relevant to the task outcome. A set of paths equivalent to a path of length greater than three cannot contain a path representing a direct inference.

Paths of length four or greater we would categorize as “indirect inferences”. That is, the link between the actor p and the task outcome is based on generalizations rather than facts. This is indicated by the presence of an induced element in the path. Paths of length four or longer typically result from a burden of proof process. The link between the status characteristic possessed by the actor and the instrumental status characteristic is formed by an induced element such as a generalized performance expectation state or a state of abstract task ability.

This classification scheme corresponds simply to the three segments of the function $f(i)$, so that we can reasonably assume that each segment of the curve gives the path strengths for one of the path categories.

The values of k and d

The identifiable points delimiting the three segments of the curve are the points where the rate of change of slope of the function is locally maximized. Since the rate of change of the slope is the second derivative of the function, to find its maxima we set its third derivative equal to zero when $i = 1$ and

$i = 3$, obtaining a system of equations defining the values of k and d . The third derivative of the function $f(i)$ is

$$f'''(i) = (\ln^3 k)dk^{-i}e^{dk^{-i}}[1 + 3dk^{-i} + d^2k^{-2i}].$$

Since only the term in square brackets can take on the value 0, setting this term equal to zero is equivalent to setting the entire expression to zero, and we obtain the following equations:

$$1 + 3dk^{-1} + d^2k^{-2} = 0,$$

$$1 + 3dk^{-3} + d^2k^{-6} = 0.$$

This system of equations can be solved by elimination and substitution. Multiplying the first equation by k^4 and the second by k^6 , and subtracting the first from the second, results (after factoring) in

$$(k^4 - d^2)(k^2 - 1) = 0,$$

which gives us

$$k = \pm 1; d = \pm k^2.$$

We are interested only in values of k which exceed 1 and values of d which are negative. Therefore $d = -k^2$ is the only useful result. Taking the first equation above and substituting this result into it gives us

$$1 - 3k + k^2 = 0.$$

Only one of the two roots of this equation gives a value of k larger than one, so that the final result is

$$\begin{aligned} k &= (3 + \sqrt{5})/2, & \text{or approximately } k &= 2.618, \\ d &= -(7 + 3\sqrt{5})/2, & \text{or approximately } d &= -6.854. \end{aligned}$$

It is interesting to note that k turns out to be the square of the golden mean, a number well known to the ancient Greeks. It occurs, among other places, in the analysis of certain growth processes and in the proportions of pleasing architectural structures. Now the function $f(i)$ can be written as,

$$f(i) = 1 - e^{-2.618^{(2-i)}}.$$

This completes our task.

Comparison of the Theoretical Values and Empirical Estimates of the Parameters

Table 1 below gives the values of the strengths of path lengths obtained from the function we have derived and from the original empirical estimates.

Table 1 about here

The path strength values obtained from the function are generally lower than the empirical estimates, and this difference decreases both absolutely and relatively with increasing path length. The important question is how well these two sets of values fit the available data.

The available experimental data

As noted before, Berger and his associates (1977) have reported on the goodness of fit of the model to data from twelve experiments using the estimated path values given above, and Fox and Moore (1979) have presented a similar assessment using different techniques. We have searched the literature to find more recent experiments reporting relevant data. The required conditions are that the study be within the scope conditions of the theory, that it be conducted in the standardized experimental setting, and that the dependent variable be $P(S)$, the proportion of rejected influence. We have located twelve published studies satisfying these conditions, which were not included in the original evaluation. Thus the number of studies available for the assessment of goodness of fit is twenty-four, with a total of 127 different conditions. The twelve experiments reported by Berger and his associates are summarized and analyzed in Berger *et al.* (1977), and therefore we do not report on them in this paper. The twelve additional experiments we have located are briefly summarized in the appendix.

The method of assessing goodness of fit

The model predicts the proportion of rejected influence for each condition of an experimental study by the function below.

$$P(S) = m + q(e_p - e_o)$$

The quantity $(e_p - e_o)$ is the expectation advantage, computed from the strengths of the positive and negative paths in each experimental setting. The two parameters m and q are situationally determined, capturing the characteristics of particular subject populations and the effects of particular experimental variations. Therefore m and q are estimated separately for each experiment. Berger and his associates estimated these parameters using two of the conditions in each experiment, and then made predictions, comparing the predicted and observed values in terms of a binomial model. In the current case a condition-by-condition comparison for predictions generated by the two sets of parameters is unlikely to be very informative.

Fox and Moore (1979) adopted a different strategy for assessing goodness of fit. They note that the prediction function is linear and equivalent to a regression of $P(S)$ on expectation advantage. Hence regressing $P(S)$ values on the expectation advantages for the different conditions of an experiment serves the function of both estimating the parameters m and q (the constant is equal to m , and the regression coefficient of expectation advantage is equal to q) and assessing the goodness of fit at the same time. This technique offers advantages over the first, but still is not ideal for our purposes as it would yield a separate measure of goodness of fit for each experiment. Twenty-four different comparisons of the two sets of parameters would be difficult to summarize. Therefore, we modify this approach by fitting a single regression model to all the data from the twenty-four experiments, so that a very simple comparison of the goodness of fit produced by the two sets of parameters can be made. This approach does violence to the idea that m and q should be separately estimated for each experiment because the particular procedures (e.g., degree of collective orientation induced) and the characteristics of the subject population will affect how expectations will be translated into behavior. We partially compensate for this by introducing a number of dummy variables to capture differences in procedures and subject populations.

We have examined the twenty-four experiments for uniformly reported subject population and experimental procedure characteristics, and found a total of four such characteristics. Since the gender of the subjects is uniformly reported, with the majority being male, we use a dummy variable F which takes on the value 1 for females. There are rough indicators of age in all reports: Most studies have been conducted on undergraduates, some

have used high school students, and one study was done with a distinctly older group—Air Force personnel. Therefore we introduce two dummy variables, H , taking on the value 1 for high school subjects, and A , taking on the value 1 for the older group. The total and critical numbers of trials are also uniformly reported. Most studies have about 20 critical trials, some have over 30. We use a dummy variable, T , which takes on the value 0 for less than 25 critical trials, and 1 otherwise. All studies except one have 80 percent of the trials critical, and one has 60 percent. We use a dummy C to mark this single study. Since each of these characteristics can affect both m and q , all of these dummy variables are included in the regression model by themselves, and in interaction with expectation advantage. Thus the general model we start out with is as given below.

$$P(S) = [b_0 + b_F F + b_H H + b_A A + b_T T + b_C C] + [b_E + b_{EF} F + b_{EH} H + b_{EA} A + b_{ET} T + b_{EC} C] E$$

We use E to stand for expectation advantage. The first term in square brackets is equal to m and the second term in square brackets is equal to q for any one experiment. This general model cannot be expected to fit as well as a model involving separate m and q estimates for each study; however our main concern is with the relative goodness of fit of the two parameter sets, and neither set of parameters is going to have an advantage because of this simplification of the model.

We do our analysis on the average $P(S)$ for each condition, since subject by subject data for all studies are not available in the public domain. This means that we cannot estimate individual variation, but this is not a problem for our comparative purposes.

Goodness of fit

We do the regression analysis by forcing the expectation advantage as the first variable, and then let a stepwise procedure select the other terms to be included in the model. Table 2 shows the basic regression statistics for the simple regression equation with the expectation advantage alone, and for the final model generated by a stepwise procedure selecting from the variables of the general model. This final model includes the dummy variables for high school students, Air Force personnel, ratio of critical trials, and the interaction of the gender dummy with expectation advantage.

Table 2 about here

The results are extremely clear: The fit of the model for the two sets of parameters is essentially identical. So much so that one has to ask how this is possible given that the two sets of parameters appear quite different. The answer is that with respect to this data set the two sets of parameters are, in fact, not very different: It should be noted that since the expectation advantage is multiplied by the parameter q in the prediction function, smaller values of the function $f(i)$ lead to smaller values of e_p and e_o but to larger values of q . It is the relative value of the strengths of paths of different lengths which is important, and not their absolute magnitudes. Furthermore, in the set of twenty-four studies we are using, almost all experiments involve adjacent path lengths such as three and four, or four and five. The two sets of parameters are quite similar in terms of the ratios of adjacent path strengths, and therefore the two sets of parameters yield equivalent fits.

The theory of status characteristics and expectation states has recently been generalized to cover reward expectations (Berger *et al.*, 1985) and sequences of different tasks (Berger *et al.*, forthcoming). Both these extensions involve situations with more varied path lengths in their structures, and future experiments may yield data which can distinguish between the two sets of parameters. However, at this point we have demonstrated all that could be expected of our enterprise—the theoretically derived parameters fit the data fully as well as empirical estimates.

Considering the fit of the model in absolute rather than relative terms, expectation advantage by itself explains roughly 64 percent of the variance in $P(S)$. So even without taking into consideration the differences in subject populations and experimental procedures, expectation advantage is able to explain most of the variance in the data. When dummies for age, the ratio of critical trials, and the interaction of gender with expectation advantage are included, the model explains 82 percent of the variance. This can only be described as a good fit. There are certainly enough theoretically relevant aspects of experimental procedures and subject populations which we have not accounted for with dummy variables to account for the remaining 18 percent of the variance. On the other hand the standard error of the estimate is almost five percentage points—higher than one would like. However,

it would be too much to expect the model to make good point predictions without taking into account the conditions of the individual experiments by estimating m and q separately for each experiment. Twelve years and twelve experiments after the original formulation and test of this model, we feel that Fox and Moore's (1979) conclusion continues to be valid: ". . . [our analysis] has revealed the remarkable degree to which data from experiments conducted at different times and places with different subject populations are coherently organized by the linear expectation advantage model ..."

It is instructive to examine the coefficients of the final regression model generated by the stepwise procedure. The procedure started out with five dummy variables plus five interaction terms, one for the interaction of each dummy variable with expectation advantage. Four of these ten terms are included in the final model: three are dummy variables and one is an interaction term. The coefficients for both the included and excluded terms are given in Table 3. Since the results are almost identical for the two sets of parameters, we report the results for only the theoretical parameter values. First we should note that all included terms are significant at better than the .001 level, except for the interaction of gender with expectation advantage which is significant at roughly the .03 level. On the other hand none of the excluded terms has a probability value less than .1, so that there is a clean break between the significant and the non-significant terms.

Table 3 about here

The constant, which of course is the parameter m for undergraduate subjects in experiments with an 80 percent rate of critical trials, is equal to .637. This parameter is the rate of rejecting influence for status equals. The three dummy variables change this parameter for their respective groupings: The older group, the Air Force personnel, has an m .153 higher, and the younger group, the high school students, has an m .058 less. The other dummy variable affecting this parameter is the ratio of critical trials: For the experiment with a relatively low level of disagreement, the value of m increases by 12 percentage points. The parameter q is affected only by gender, its male value of .106 increasing by .025 for females. That is, females appear to change their levels of rejecting influence more than males for the same difference in expectations.

Concluding Remarks

We have presented a method for determining *a priori* values for the path parameters of the mathematical model of the theory of status characteristics and expectation states. We have demonstrated that these parameter values fit the available data about as well as the empirical estimates previously used. We believe the availability of these *a priori* parameters will significantly increase the applicability of the model to different interaction situations, as well as increasing the precision of theoretical analyses using this theory. Our analysis has also demonstrated that the status characteristics and expectation states model fits the data collected since its formulation quite well. The way to further theoretical developments and empirical investigation is open.

Appendix

Twelve of the twenty-four experiments we use to fit the model have been described and analyzed by Berger and his associates (1977). Therefore, we consider the other twelve experiments. Since all twelve have been published, our descriptions are very brief, and comments are confined to points of possible ambiguity in graphing situational structures.

Parcel and Cook (1977) report on two experiments on reward allocation behavior in the standardized experimental setting. The second experiment involves feedback on the correct response from the experimenter on each trial, and is outside the scope conditions of the theory. The first experiment involves two specific status characteristics which are either initially relevant, or non-relevant, to the task. These characteristics are manipulated in three different patterns, so that the subject can be high on both characteristics and face another who is low on both, or the reverse; or he can be high on one, low on the other and face another who is low on the first and high on the second. Thus this experiment has six conditions.

Webster (1977) also reports on two experiments dealing with the effects of equating characteristics. However, the first is one of the twelve experiments originally fitted by Berger and his associates; only the second

provides new data. The second experiment has four conditions. In two of these conditions the subject is manipulated to be high, and his partner to be low, on the characteristic instrumental to task performance. In the other two conditions the manipulation is reversed. In each pair of similar conditions, in one the two subjects are both manipulated to be high on two other characteristics, and in the other no information is given to the subjects on these characteristics.

Webster and Driskell (1978) studied the combining of diffuse and specific status characteristics initially non-relevant to the task. The study has three conditions: In one the subject is high on race (i.e., white), and her partner is low (i.e., black). In the second the subject is manipulated to be low, and her partner high, on two specific characteristics. In the third condition the subject is white and low on the two specific characteristics, while her partner is black and high on the two characteristics.

Harrod (1980) deals with the effects of goal object allocation on power and prestige position. The study has two conditions. In one the subject is given higher, and in the other lower, pay than her partner. The different rates of pay are not justified or related to the task in any way. Since the core formulation does not allow us to graph this situation, we use the reward expectations extension of the formulation (Berger *et al.*, 1985) to fit this experiment. Assuming that the ability referential structure becomes salient in the situation, the actor who receives the higher pay is task connected by two positive paths of lengths four and five, and the actor who receives the lower pay is connected by two negative paths of the same length.

Hembroff, Martin and Sell (1981) report on a study of the effects of total performance inconsistency on status generalization. There are seven conditions in the study. In two of the conditions the subjects are manipulated to be either high or low with respect to their partners in terms of age. In three of the conditions the subjects are manipulated to be equal to their partner in terms of a non-relevant specific status characteristic. The conditions differ in terms of the number of tests used in manipulating the characteristic, a variable which is not meaningful in terms of the theory,

and therefore we treat them as identical. Since this specific characteristic is neither relevant nor discriminating, it does not become salient and the graph of the situation is unconnected in each of these conditions. In the remaining two conditions the actors are either high or low in terms of age, and equal in terms of the specific characteristic. The specific characteristic is not salient in these conditions either, and they are graphed in terms of the diffuse status characteristic.

Hembroff (1982) studied the resolution of status inconsistencies. The experiment has 10 conditions; however, since two of these conditions are "borrowed" from the earlier study by Hembroff, Martin and Sell, we use only the data from the remaining eight conditions. The experiment involves one diffuse status characteristic, age, and one non-relevant specific status characteristic. The specific status characteristic is manipulated using different numbers of tests, but from our point of view this is immaterial. Thus there are two conditions where the subject is high-low, and two conditions where she is low-high with respect to the specific characteristic. There are two conditions where the subject is high-low with respect to age, but low-high with respect to the specific characteristic. Finally, there are two conditions where the subject is low-high with respect to age, and high-low with respect to the specific characteristic.

Pugh and Wahrman (1983) report two experiments on neutralizing sexism, the first of which is within the scope conditions of the theory. (The second is a sequence experiment and we do not attempt to fit it.) The first experiment has eight conditions, four with male and four with female subjects. Each subject interacts with a partner of the opposite sex. For each sex there is a "control" condition where there are no experimental manipulations; a "verbal" disclaimer condition where the subjects are told that their task is unrelated to sex (we graph this situation with the sex characteristic salient, since a verbal disclaimer cannot prevent either salience or burden of proof); a "demonstrated equality" condition where the subjects are manipulated to be both high on a relevant characteristic; and finally a "demonstrated superiority" condition where the female is manipulated to be higher than the male on a relevant characteristic.

Markovsky, Smith and Berger (1984) conducted a similar "sequence" experiment on the persistence of status interventions. The experiment involves two tasks performed in sequence, but since the conditions on the second task do not meet the scope conditions of the formulation, we use only the data from the first phase of the experiment. There are four experimental conditions to the first phase. The subject is an undergraduate who can be paired with either a junior high school student or a graduate student, making him either high-low or low-high in terms of a diffuse status characteristic. For half the cases where he is high-low in terms of the diffuse status characteristic the actor is manipulated to be low-high in terms of a specific characteristic relevant to the task. Similarly, in half the cases where he is low-high in terms of the diffuse characteristic, he is manipulated to be high-low in terms of the specific characteristic.

Martin and Sell (1985) studied the effect of equating characteristics on status generalization. The study involves one diffuse status characteristic—age and/or class standing—and one specific characteristic not relevant to the task. The diffuse status characteristic is always used to equate the subject with her partner; since it is not discriminating and not relevant to the task, it does not become salient. The specific characteristic is manipulated using two separate tests. However, as we have noted before in Hembroff, Martin and Sell, this does not have an effect on the way situations are graphed. The first two conditions have the subject either high-low or low-high with respect to the specific characteristic. The next two conditions are one of no information and one of equating diffuse status characteristics: Both are unconnected graphs. The last two conditions have the subject high-low or low-high with respect to the specific characteristic, and equal in terms of the diffuse status characteristic; their graphs are thus identical to the first two conditions.

Wagner, Ford and Ford (1986) carried out an experiment on reducing gender inequalities. Subjects are males and females, each working with a partner of the opposite sex on a task to which gender is relevant. For each sex there is one condition where gender is the only salient characteristic, one condition where the instrumental characteristic is manipulated so that

the actor is high and his partner is low, and one condition where the actor is low and his partner is high. Thus the experiment has six conditions.

Norman, Smith and Berger (1988) tested the inconsistency effect which is a feature of the combining process postulated by the theory. The experiment has four conditions and involves the manipulation of a number of specific status characteristics relevant to the task. In the first condition the actor is high on one characteristic and his partner is low. In the second condition the actor is high on two characteristics and his partner is low on both. In the third condition the actor is high on three characteristics, low on one; his partner is low on the three characteristics, high on the fourth. The fourth condition involves an actor who is high on two characteristics and low on two others; his partner is similarly low and high on two characteristics each.

Stewart (1988) studied the interaction between gender differences and differential pay rates in the standardized experimental situation. Male and female subjects are paired with partners of either the same or opposite sex to work on a task which is not gender typed. Furthermore, each subject can be paid more than, equal to, or less than his or her partner, resulting in twelve experimental conditions. This study also involves a situation requiring the use of the reward expectation extension of the formulation. Stewart concludes on the basis of this study and earlier studies using the same subject population, that gender is a diffuse status characteristic for males but not for females. We graph the situation according to this finding.

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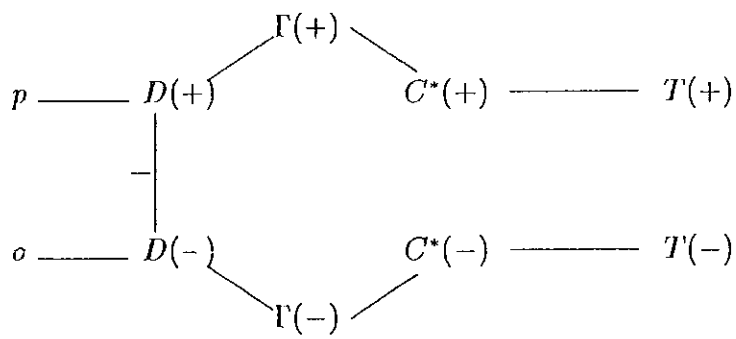


Figure 1: A Simple Structure

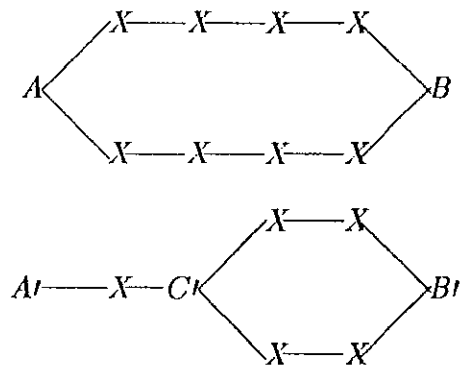


Figure 2: Two Equivalent Hypothetical Connections

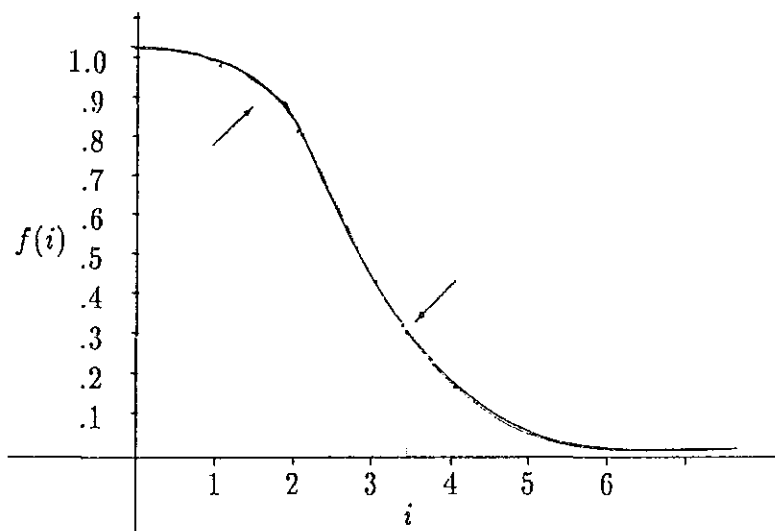


Figure 3: The Function $f(i)$

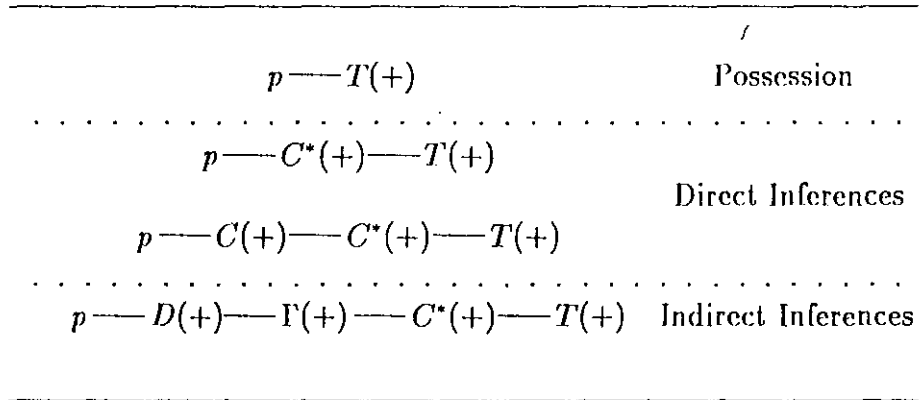


Figure 4: Paths of Different Lengths and Their Interpretations

Table 1: Path Strengths Obtained from the Function and the Original Empirical Estimates

Path Lengths	2	3	4	5	6
Function Values	.6321	.3175	.1358	.0542	.0211
Empirical Estimates	.8264	.4422	.1768	.0628	.0214

Table 2: Basic Regression Statistics

Expectation Advantage Only		
	Empirical Estimates	Theoretical Values
R	.797	.799
R^2	.636	.638
SE	.067	.067
F(1,125)	218.260	220.238

Final Model		
	Empirical Estimates	Theoretical Values
R	.905	.907
R^2	.820	.822
SE	.048	.047
F(5,121)	110.169	111.835

Table 3: Regression Coefficients for the Final Model with Theoretical Path Values

Included Terms				
	b	SE(b)	Beta	p
Constant	.637	.005		.000
Expectation Advantage	.106	.008	.742	.000
Air Force	.153	.020	.295	.000
Low Critical Trial Ratio	.120	.017	.266	.000
High school	-.058	.018	-.128	.001
Female X Expectation	.025	.011	.119	.028

Excluded Terms		
	Beta In	p
Many Trials X Expectation	-.067	.107
Air Force X Expectation	-.064	.114
Many Trials	.039	.373
L.C. Trials X Expectation	-.025	.512
High School X Expectation	.011	.829
Female	-.001	.982